PALGRAVE STUDIES IN ENTREPRENEURSHIP AND SOCIETY

The Entrepreneurial Ecosystem

A Global Perspective

Edited by

Zoltan J. Acs · Esteban Lafuente
László Szerb

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Palgrave Studies in Entrepreneurship and Society

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This series offers to enhance and transform our understanding of entrepreneurship and its essential value in society.

The term 'entrepreneurship' enjoys a normative association with business start-ups and growth (with some concessions to large established entrepreneurial firms), and by extension, its contribution to economic growth and development. Meanwhile, the societal impact or the social value of entrepreneurship is a growing area of interest among scholars and policy makers, not least as a result of the UN Sustainable Development Goals, the impact of transformative technologies, the changing nature of work, and how we interact locally and globally.

Focusing on underexplored avenues for entrepreneurship development in different societies and cultures, the series covers topics from multiple geographical, sectoral and thematic perspectives. Titles will identify and explore different forms of entrepreneurship in society, with coverage of topics such as migration, citizen entrepreneurship, well-being and entrepreneurship, health and entrepreneurship, the politics of entrepreneurship and entrepreneurship and the arts, among others. Offering a global contribution to the development of the subject, the series offers a unique platform for engaging and promoting the wider social impact of entrepreneurship.

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László Szerb
Editors

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Editors
Zoltan J. Acs
George Mason University
Arlington, VA, USA

Esteban Lafuente
Business School
Costa Rica Institute of Technology (ITCR)
Cartago, Costa Rica

László Szerb
Faculty of Business and Economics
University of Pécs
Pécs, Hungary

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To Attila Varga

We dedicate this book to our friend Attila Varga, whose invaluable and remarkable work was instrumental in supporting the development of the Global Entrepreneurship Index project from the beginning. Besides encouraging us, he also helped to build the Europe's Regional Entrepreneurship Index and integrated it into his GMR model which allowed us to estimate the economic impact of improvements in entrepreneurship ecosystems across EU regions. Unfortunately, Attila is going through a very hard time since March 2021. We wish him a quick recovery. We are convinced his scientific legacy will endure and continue to inspire the work of many in the future.

Foreword

This is a book for those interested in how entrepreneurs exist within their ecosystems, and what the nature and evolution of entrepreneurial ecosystems means for economic development policy. This book offers a means to consider how entrepreneurial ecosystems and digital economies will look in the future, and what kind of actions are available to policymakers—nationally and regionally—to shape incentives that will enable productive activities.

The Path Forward

The COVID-19 pandemic and accompanying global economic shocks placed a spotlight on the role of productive entrepreneurship—and the entrepreneurial ecosystems in which it occurs—in mitigating damage, generating responses, fueling recovery, and building resilience to future vulnerabilities. The crisis demonstrated the power of entrepreneurship, with innovative and often local responses coming from entrepreneurs, like the production of protective equipment to fill regional health system gaps. At the same time, the crisis demonstrated difficulties when entrepreneurial ecosystems are not conducive, and when policies have either neglected entrepreneurs or favored established businesses.

In the digitized, post-COVID-19 world, entrepreneurial ecosystems matter more than ever. Well-informed and effective economic development policy is crucial to reset (and in some cases, set) entrepreneurial ecosystems such that they are conducive to productive entrepreneurship. This is not only about immediate crisis recovery. Rather, this is a question of getting things right: how can entrepreneurial ecosystems be configured so they will ultimately foster adaptability, flexibility, and resilience for productive entrepreneurs? Technology is a key part of any answer, and this book clarifies how regional innovation systems (RIS), clusters, entrepreneurial ecosystems, and digital entrepreneurial ecosystems are related. Acs and coauthors (Chap. 1) lay out how key characteristics related to industry, spatial boundaries, platforms, and the centrality (or not) of the entrepreneur are related and where they are different. The continued digitalization of the global economy can mean tremendous and new opportunities for potential entrepreneur and established firms, new offerings and value for users, and new approaches to interact for governments. It also presents governance and regulatory challenges: for example, platforms are available to users without geographic boundary, yet they are still embedded within local context. A large number of challenges around privacy, freedom, security, and access (among other things) continue to emerge from digitalization, putting pressure on the ability of current legal and regulatory frameworks to effectively understand and manage them. Sulyok's discussion of a "regulatory revolution" lays out some of these questions (Chap. 11).

Entrepreneurial Ecosystems Are Not All the Same

Many policy domains face a tension between what can be generalized and what must be tailored to local context. Entrepreneurial ecosystems are no exception. The consistent presence of some conditions in healthy entrepreneurial ecosystems, such as strong networks, suggests broad benefits. At the same time, the complex relationship between characteristics of a place, evolution of networks, knowledge, and technology in a place makes the replicability of policies difficult.

This book treats the uniqueness of entrepreneurial ecosystems as an opportunity for scholars and policymakers to consider how configuration could look in different contexts. Szerb and coauthors (Chap. 6) take on this challenge by applying a "benefit of the doubt" weighting technique to estimating the entrepreneurial ecosystem. Song and Waters (Chap. 9) discuss the shift in place-based economic policies in a digitalized context.

Policy Action

An important priority in the growing entrepreneurship ecosystems movement is clarifying and disentangling the effects of policies. While much is known about the economic benefits of entrepreneurship, the impact of policies is not always clear in direction or in magnitude despite a great deal of public funds in many countries being directed toward entrepreneurship. As many chapters in this book demonstrate, the measurement of entrepreneurial ecosystems is not only about capturing the size and magnitude of a key concept. It is also fundamentally about understanding what shapes relationships within the ecosystem as well as outcomes that come from it. Policy is at the heart of many of these relationships.

This book brings together established and newer steams of inquiry, focuses on practicality and action for economic development policy, and connects entrepreneurial ecosystems with the nature of digital transformation. It takes up difficult questions, such as Lafuente and coauthors' reconsideration (Chap. 4) of the *development tension* and the *policy tension* in the "entrepreneurship paradox," wherein entrepreneurship is good for the economy yet also appears to occur more in less-developed economies. And it analyzes multiple levels of action as the frame for thinking about entrepreneurial ecosystems, from Bosanquet's analysis of Elon Musk (Chap. 10) to Szerb and coauthors' (Chap. 2) country simulations on how alleviating ecosystem bottlenecks can improve the system and how policy recommendations can be developed by focusing on bottlenecks.

The blending of theoretical and empirical insights, practice and policy questions, and multiple levels of policy action in this book provides a unique—focused yet comprehensive—contribution.

Bloomington, IN, USA

Sameeksha Desai

Preface

The growing recognition of the importance of entrepreneurship at the end of the last century led scholars to study entrepreneurship at the economy level.[1] Prior to joining George Mason University, I was part of no less than four of these efforts. First, I was a member of the *Global Entrepreneurship Monitor* (GEM) project at the London Business School headed by Paul Reynolds. I was the leader and founder of the Hungary GEM team, served on the Board of GERA, and was research director of GEM Global publishing two executive reports, a U.S. report and several Hungarian reports. Second, I helped set up the institute for *Entrepreneurship, Growth and Public Policy* at the Max Planck Institute of Economics in Jena, Germany, headed by David Audretsch. Third, I was a research fellow at the *Kauffman Foundation* in Kansas City where I worked with William Baumol, Robert Litan, and Carl Schramm on entrepreneurship and public policy. Finally, I was part of a Swedish project headed by Pontus Braunerhjelm along with Bo Carlsson and David Audretsch at the *Royal Institute of Technology* and the *Swedish Entrepreneurship Forum*. This project gave birth to the Knowledge Spillover Theory of Entrepreneurship (KSTE) that cemented the connection between entrepreneurship and entrepreneurial ecosystems.

In 2005 I joined the faculty of the School of Public Policy at George Mason University. Both Roger Stough and Kingsley Haynes were interested in regional development, entrepreneurship, and economic growth.[2]

The fundamental question in this line of research was, "What is entrepreneurship at the economy level?" If it was difficult to define entrepreneurship at the individual or firm level, what chance did we have of answering the question at the economy level? In this endeavor, the GEM project was pivotal in that it created a unified data set across countries based on survey data that demonstrated that comparisons could actually be made measuring total entrepreneurial activity (TEA). This appeared to be a major breakthrough until it was discovered that the TEA was just one of many variables to measure entrepreneurship at the economy level and the different measures all gave conflicting results and, as a result, offered limited (if any) guidance to policymakers. The issue was one of measuring quantity versus quality.

László Szerb from the Hungarian GEM team and I started to explore ways to develop composite indicators to measure entrepreneurship at the economy level. We developed a method that used institutions to turn quantity measures into quality variables. Using this insight and following the GEM methodology we focused on entrepreneurial attitudes, entrepreneurial abilities, and entrepreneurial aspirations. We developed the Global Entrepreneurship Index (GEI) and released it in the *2008 Global Entrepreneurship Monitor: Executive Report*. In 2009 I took a sabbatical at Imperial College Business School and joined Erkko Autio in the entrepreneurship and innovation group. We continued to develop the idea of measuring entrepreneurship as an ecosystem, rather than measures such as rates of business formation. In May 2009 we organized a research conference at Imperial College on Entrepreneurship, Growth and Public Policy. The high-level conference was attended by leading scholars from around the world and they gave tentative acceptance to the idea of entrepreneurial ecosystems as a way to measure entrepreneurship at the economy level. With the details worked out, the GEI—a breakthrough advance in measuring entrepreneurial ecosystems at the economy level—was first published by Foundations and Trends® in Entrepreneurship in 2009 and the index was launched at the Heritage Foundation in Washington, D.C., in loose collaboration with George Mason University, the University of Pécs, Imperial College Business School, and the London School of Economics.

Out of our work, it became clear that a conceptualization of the entrepreneurial ecosystem was needed, and we realized that this ecosystem is characterized by multiple economic processes which are activated by different stakeholders. At the economy level entrepreneurship is an ecosystem that sustains economic growth by complex dynamic processes that drive resource allocation and productive entrepreneurship. The GEI started to gain recognition with articles in *The Economist*, *The Wall Street Journal*, and *MSNBC*, suggesting that a way forward might have been found. Moreover, businesses, banks, and global institutions like the World Bank and the United Nations started to pay attention. Research that used the GEI gave us insight into how countries at different levels of development pursued and fostered entrepreneurship. Several organizations including the World Entrepreneurship Forum at EMLYON Business School, the Global Entrepreneurship Network (GEN) headquartered in Washington, D.C., the U.S. State Department's program promoting entrepreneurship, and the U.S. Small Business Administration embraced the GEI and became major sponsors.

However, there was an issue that needed to be addressed. The KSTE suggested that knowledge spillovers that entrepreneurs exploited was local and places like Silicon Valley, Route 128 in Boston, Austin, and Seattle (among others) suggested the need for a local approach as well as a national one. Philip McCann at the University of Groningen introduced our project to the European Union that was interested in pursuing a European regional approach. In 2013 we received a grant from the European Directorate General for Regional and Urban Policy Analysis, and developed a regional version of the GEI. The Regional Entrepreneurial and Development Index (REDI) jointly developed by the University of Pécs, Imperial College Business School, and the University of Groningen was launched in 2014. REDI gave us a way to now compare regional economies across the European Union for over 100 regions.[3] In 2014 László Szerb, Erkko Autio, and I published a paper on the GEI in *Research Policy* that was the first article on entrepreneurial ecosystems that had an analytical core. In 2015 László Szerb, Raquel Ortega-Argilés, Ruta Aidis, Allicia Cardes, and I published a paper in *Regional Studies* dealing with the analysis of regional entrepreneurial ecosystems in Spain. The entrepreneurial ecosystem approach had now been established and it started a major reorientation of entrepreneurship at the economy level away from start-ups to ecosystems.[4]

These two papers led to two new strands of entrepreneurial ecosystems research. First, Attila Varga at the University of Pécs introduces the GMR modeling framework that targets two challenges ahead of these models: it incorporates the REDI as a measure of local entrepreneurial ecosystems and provides an estimated model through which changes in the REDI spill over to the broader economic environment. Second, Esteban Lafuente embarked on a project to develop further the relationship between entrepreneurial ecosystems and the global technology frontier using non-parametric methods and a DEA model to identify policy priorities published in *Research Policy* in 2022.[5]

The REDI research was also instrumental in a Horizon 2020 research project, Financial and Institutional Reform to build an Entrepreneurial Society (FIRES). Funded by an EU grant a consortium of eight universities led by the University of Utrecht, the London School of Economics, the University of Pécs, and the Research Institute of Industrial Economics in Stockholm carried out a multiyear study. The project's goal was to get the European Union back on a more sustainable growth path. The FIRES project results were published in a special issue of *Small Business Economics* in 2018 with one of the main findings on the importance of ecosystems written by Acs, Estrin, Mickiewicz, and Szerb. In 2017 *Small Business Economics* published a special issue on Entrepreneurial Ecosystems edited by O'Connor, Stam, Acs, and Audretsch. Over the past few years entrepreneurial ecosystem research has exploded with scores of articles across several disciplines published in leading journals by networks of scholars.[6]

To coordinate our efforts across multiple universities and international organizations in early 2000, we founded the Global Entrepreneurship and Development Institute (The GEDI Institute), a global organization that advances research on the links between entrepreneurship, economic development, and prosperity.[7] The GEDI Institute headquartered in Washington, D.C., was founded by leading entrepreneurship scholars from George Mason University, the University of Pécs, Imperial College Business School, and the London School of Economics. The GEDI methodology has been validated in rigorous academic peer reviews. The Institute's flagship project was the Global Entrepreneurship Index (GEI), a breakthrough advance in measuring the quality and dynamics of entrepreneurship ecosystems at a national and regional level. GEDI maintains the historical data on GEI, REDI, and the Digital Entrepreneurial Index (DEI). Its reports provide timely and detailed insights on the academic, business, and government events on the digital transformation.[8]

How does an economic system's architecture, the way it is put together and the way it is connected, affect its long-term stability? The question is especially relevant for entrepreneurial ecosystems. Economics before 1870 was concerned with two great problems: first, how prices are determined within and across markets and the other was formation within the economy: how an economy changes structurally over time. Since 1870 the former had defined neoclassical economics with the latter left to political economists. That has now changed—complexity economics provides a rigorous way to look at questions of how entrepreneurial ecosystems form and change over time. Complexity economics gives us a world closer to political economy than to neoclassical theory, a world that is organic, evolutionary, and historically contingent.

In the concluding chapter of this book Hilton L. Root gives an opening on how to think about entrepreneurial ecosystems.

Fairfax, VA, USA Zoltán J. Ács

Notes

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6. https://www.igi-global.com/article/entrepreneurial-ecosystem-research/259927
7. https://thegedi.org
8. https://vimeo.com/19955472 Interview with Zoltan J. Acs

Praise for *The Entrepreneurial Ecosystem*

"Entrepreneurial ecosystems, while having emerged as one of the most prominent policies for entrepreneurship and economic development, have confounded thought leaders in business and policy as well as the scholarly research community. No more. This pathbreaking new book offers the unequivocal analysis and framework explicitly clarifying what an entrepreneurial ecosystem is, can do and how best to create and sustain one. The book pulls together the top thinkers in the field to pave new ground on how and why no region can afford to ignore the power of entrepreneurial ecosystems, just as no researcher concerned with entrepreneurship, economic development and regional prosperity should ignore them."

—David Audretsch, Professor, *Indiana University*, *USA*

"Entrepreneurship is a key driver of wealth and rising living standards. Zoltan Acs has been a leader in entrepreneurship research for decades. In this timely and important volume, Acs and his colleagues shed light on the key role played by entrepreneurial ecosystems in driving innovation, business formation and economic development. It is a must read for business leaders and policy makers as well as economists, urbanists and social scientists interested in the dynamics of entrepreneurship and its impact on our economy and society."

—Richard Florida, Professor, *University of Toronto's School of Cities and Rotman School of Management, Canada*

"The Editorial team of Acs, Lafuente and Szerb is uniquely qualified to assemble a team of writers to provide a comprehensive and up-to-date picture of entrepreneurial ecosystems across a range of countries. The readership spectrum that will benefit from this volume ranges from those interested in how theories evolve, to policymakers charged with the responsibility for stimulating entrepreneurship in 'their' locality."

—David Storey, Professor, *University of Sussex Business School, UK*

"This important book, compiled by three of the world's leading thinkers on entrepreneurship, provides a comprehensive perspective on the development and importance of entrepreneurial ecosystems. Importantly, the contributors explain how the new digital technologies and the emergence of the platform economy have affected the social, spatial, and political dimensions of entrepreneurial ecosystems. This book is vital reading for both academics interested in understanding entrepreneurial ecosystems and policy-makers that wish to encourage the development of entrepreneurial ecosystems."

—Martin Kenney, Distinguished Professor, *University of California, USA*

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Notes on Contributors

Zoltán J. Ács is Professor Emeritus at George Mason University's Schar School of Policy and Government, USA. He founded Small Business Economics, where he served as co-editor in chief until 2021. He was also a visiting professor at Imperial College Business School in London. His career has focused on the link between innovation and entrepreneurship in industries and territories. Acs is a leading advocate of the importance of entrepreneurship for economic development. His policy initiatives take a broad view of public policy encompassing the individual, the economy, the region, and social policy. He received the 2001 International Award for Entrepreneurship and Small Business Research, on behalf of The Swedish National Board for Industrial and Technical Development. He has written more than 100 articles and 20 books, including articles in the *American Economic Review*, *Review of Economics and Statistics*, *Kyklos*, *Journal of Urban Economics*, *Research Policy*, and *Science Policy*.

Camilla Bosanquet is a Doctoral Student in Public Policy at the Schar School of Policy and Government, George Mason University, USA. Bosanquet retired as a U.S. Coast Guard Commander, following two decades' active-duty service. She also received distinction as a Cutterman, having served for more than nine years at sea in command positions onboard multiple cutters. She now conducts research within the Terrorism, Transnational Crime and Corruption Center (TraCCC) on homeland security, coast guard, seaport/shipping, and maritime trafficking issues. She holds an M.A. in Philosophy from Boston College and a B.S. in Government from the U.S. Coast Guard Academy. Bosanquet's research interests focus on illicit trafficking, the exploitation of legitimate transport systems to move illicit goods, and trafficking convergence crimes.

Dániel Kehl is an associate professor at the Faculty of Business and Economics, University of Pécs, Hungary. He teaches probability and statistics. His contribution in research projects is data analysis in very different fields from entrepreneurship to marketing, sports, education, or even medicine. His publications include close to 20 international journal articles (including *European Sport Management Quarterly*, *Energy Economics*, *Journal of Educational Computing Research*, *International Journal of Consumer Studies*, *Archives of Internal Medicine*, etc.), many Hungarian journal articles, and 1 book.

Éva Komlósi holds a Ph.D. in Economics from the University of Pécs in 2014. In her dissertation, she investigated various issues related to contemporary regional development policy in Japan. In 2010, she won a two-year scholarship funded by Japan's state. Between 2012 and 2022, Komlósi had a position in the MTA-PTE Innovation and Economic Growth Research Group at the University of Pécs. Since 2019, she has been working as an assistant professor at the Faculty of Business and Economics, University of Pécs. She teaches regional policy and regional economics. She has recently participated in a significant EU-financed research project, which focused on constructing the regional GEDI entrepreneurship index (REDI). Her current main area of research is the investigation of the effects of factors on entrepreneurship.

Esteban Lafuente is Professor at the Business School of the Costa Rica Institute of Technology (ITCR). He also serves as an editor of *Small Business Economics*. Lafuente's research is mostly devoted to the economic analysis of organizations and individuals, with special emphasis on managerial economics, entrepreneurship, and territorial development. Additionally, he is interested in the problems and possibilities of entrepreneurial activities and business creation, and their economic benefits from a territorial perspective. Lafuente's publication record includes various books and more than 40 articles published in a variety of journals including, among others, *Research Policy*, *Small Business Economics*, *Regional Studies*, *British Journal of Management*, *Journal of Business Research*, *Applied Psychology*, *International Journal of Production Economics*, *Technovation*, *Journal of Productivity Analysis*, and *Safety Science*.

Gábor Rappai is a Full Professor at the University of Pécs, Hungary, and he is the head of the Department of Economics and Econometrics at the Faculty of Business. He is also the leader of the Business Administration Doctoral School. He teaches statistics, multivariate statistics, time-series analysis, and financial econometrics. Since 2017 he is the Doctor of the Hungarian Academy of Science (D.Sc.); the title of his thesis was "The Specialties of the Modelling in Case of Anomalies in Time Series." His research areas are econometrics of causality, modeling financial time series, and sport economy. During his academic workmanship he authored 95 Hungarian and 21 foreign language articles, and participated in the preparation of 17 textbooks.

Hilton L. Root is Policy Specialist in International Political Economy and Development, and a member of the faculty at the George Mason University's Schar School of Policy and Government, USA. His current research examines three related areas: (1) global power transition and the challenge of legitimacy; (2) the comparative and historical dynamics of state-building; and (3) the use of complexity models to understand the evolution of social institutions. Root has lectured extensively and has authored more than 200 publications, including nine books. His latest book, *Network Origins of the Global Economy: East vs. West in a Complex Systems Perspective*, was published in 2020. Recent op-eds have appeared in *The Diplomat*, *The National Interest*, Real Clear World, and *U.S. News & World Report*. His writings have been translated into French, Chinese, Greek, Korean, Japanese, and Vietnamese.

Tamás Sebestyén is a Full Professor and research director at the Faculty of Business and Economics, University of Pécs, Hungary. He has been involved in the work of the Regional Innovation and Entrepreneurship Research Centre, and now he leads the EconNet Research Team, focusing on the analysis of economic networks. His main research interest is economic modeling; in addition to its mainstream techniques, he particularly focuses on connecting border areas such as network theory and agent-based modeling to standard approaches. He is actively writing in these areas for leading journals, while also participating in several research projects aiming at developing regional economic models for impact-evaluation of innovation policies.

Abraham Song is an assistant professor at the Graduate School of Education and Psychology, Pepperdine University, USA. He teaches courses on research methods and public policy. His current research examines state business incentives and digital platforms. In one stream of research, he conducts a program evaluation of state business incentives. In another stream of research, he studies the emergence of digital platforms and their implications for entrepreneurship and policy. Song is a research affiliate at the Milken Institute Center for Regional Economics and California Center, conducting research to inform and activate innovative economic and policy solutions to drive job creation and industry expansion. His research was awarded the Provost's Office Dissertation Fellowship, Wilkes Fellowship (D.C. Policy Center), Best Paper Award at the Association of Collegiate Schools of Planning (ACSP), and the Vernon E. Jordan, Jr. Doctoral Fellowship (Economic Club of Washington D.C.).

Márton Sulyok is head of the Public Law Center of Mathias Corvinus Collegium (MCC) and Senior Lecturer in Constitutional Law and Human Rights at the Institute of Public Law, University of Szeged, Hungary. He received his J.D. in 2007 and L.L.M. in 2012 from University of Szeged. He defended his Ph.D. in Law and Political Sciences in 2017 from University of Szeged. His dissertation focused on why states should increase constitutional protections for privacy in the online environment, with regard to the exclusion of evidence obtained in violation of privacy and confidence. Besides his academic work, he represented Hungary on the Management Board of the EU Fundamental Rights Agency (2015–2020), and since 2022, he represents MCC on the Board of Directors of the Athens-based European Public Law Organization.

Norbert Szabó is an assistant professor at the Faculty of Business and Economics, University of Pécs, Hungary. His research focuses on regional economic modeling and regional economic development. Most recently he is interested in modeling circular economy at the local level. His publications include 13 journal articles (e.g., *Regional Studies*, *Papers in Regional Science*) and 9 book chapters.

László Szerb is Full Professor at the Faculty of Business and Economics, University of Pécs, Hungary. In addition, he is the director of the Department of Management Science and the leader of the Regional Policy and Economics Doctoral School. Szerb is also an editor of *Small Business Economics* and serves in the editorial board of *Journal of Platform Economy*. His research focuses on entrepreneurship—in particular entrepreneurship ecosystems—and small business competitiveness. Most recently he is interested in digital entrepreneurship. His publications include 77 journal articles (including *Journal of Technology Transfer*, *Journal of Small Business and Enterprise Development*, *Regional Studies*, *Research Policy*, *Small Business Economics*, *Economic Inquiry*, and *Venture Capital*), 36 books, and 27 book chapters.

Attila Varga is the director of the Regional Innovation and Entrepreneurship Research Center and a professor in the Department of Economics and Econometrics at the Faculty of Economics and Econometrics, University of Pécs, Hungary. He holds a PhD from West Virginia University, USA, in 1997. His previous positions include a Research Assistant Professorship at the Regional Research Institute, West Virginia University (1997–1998), and Senior Research Fellowships at the Austrian Academy of Sciences, Vienna, and at the Vienna University of Economics and Business Administration (1999–2001). From 2006 to 2012 he served as the director of the Department of Economics and Regional Studies of Faculty of Business and Economics (FBE). Invited visiting research positions include the Institute of Public Policy, George Mason University (1997); Max Planck Institute, Jena (2004); Saint Etienne University (2005); Joint Research Centre-Institute for Prospective Technological Studies (JRC-IPTS) of the European Commission, Seville (2008); and Research Group in Theoretical and Applied Economics (GREThA) at the University of Bordeaux (2012). Attila Varga is internationally well-known for his research in the fields of regional innovation and economic development. He has written widely in major international journals of his research field. Attila Varga is also the director of the Doctoral School of Regional Policy and Economics.

Keith Waters is a postdoctoral researcher at Arizona State University (ASU) in the School of Complex Adaptive Systems at the ASU DC office. She is interested in regional economic geography from a complexity perspective, with special interest in inter-regional domestic migration, regional economic structures, and systems of cities as a whole. She is drawn to both network analysis and agent-based modeling of regional economic geography.

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Introduction to the Series on Entrepreneurship and Society

This new series on entrepreneurship and society aims to break new ground in our thinking and understanding of entrepreneurship and its essential value to society in which it is formed in its many incarnations. The term entrepreneurship enjoys a normative association with business start-ups and growth (with some concessions to large established entrepreneurial firms), and by extension, its contribution to economic growth and development. Although the word "social" is now embedded in entrepreneurship literature using concepts such as "social capital" and "social legitimacy," and the acceptance of "social enterprises" as forms of entrepreneurial organizations, the societal impact or the social value of entrepreneurship has not garnered sufficient interest among scholars and policymakers. The extant canon focuses attention on the disequilibrating role of entrepreneurs, their social interactions, and how communities create collective enterprises. Entrepreneurship is seen to be a handmaiden for economic growth, the ostensible elixir satisfying the desire for infinite progress and the resolution of gritty problems of opportunity and wealth creation.

Of late, we see an attempt to stretch the boundaries of knowledge through a growing interest in different geographies and the varied landscapes of peoples' endeavors. We are beginning to obtain early insights into the wider ramifications of entrepreneurial action in the digital age of machines, information, and creativity, where economic growth considerations might be tempered by issues of zero or minimal growth, and the greater significance of the ecosystem, and not just the individual or the firm, as a unit of analysis. Equally we find new discourse on well-being among entrepreneurs and in entrepreneurial organizations reflecting the Easterlin paradox of wealth creation not correlating well with happiness. In short, we are asking questions about how entrepreneurship impacts the societies in which we work, live, and play.

What this new series proposes is to review the literature on entrepreneurship and society as understood and observed currently while pursuing underexplored avenues for entrepreneurship development in different societies and cultures, such as Islamic Entrepreneurship, Entrepreneurship among the Global Majority, or the engagement of citizens with entrepreneurial activities for a better society. Many of these issues have antecedents which we often ignore. Obtaining a historical perspective on entrepreneurship in society is as important as identifying different types of entrepreneurship in society which reflect Schumpeter's idea of the catholicity of entrepreneurial value, thereby extending the scope of conceptual and ontological approaches to the study of entrepreneurship. We wish to cover different topics from multiple and intersectional geographical, spatial, sectoral, and thematic perspectives to provide for a more global, non-Eurocentric, contribution to the development of the subject and its importance for different societies.

I am delighted to present the first book in the series on Entrepreneurial Ecosystems—A Global Perspective by an exemplary team of scholars led by Zoltan Acs and his editorial team of Esteban Lafuente and László Szerb, together with the other contributors: Éva Komlósi, Tamás Sebestyén, Attila Varga, Norbert Szabó, Abraham Song, Keith Waters Szabó, Camilla Bosanquet, Márton Sulyok, Gábor Rappai, Dániel Kehl, and Hilton Root.

We welcome contributors and readers to this unique platform for engaging and promoting entrepreneurship in society.

Jay Mitra
Series Editor

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Introduction: Entrepreneurial Ecosystems

Zoltan J. Acs, Esteban Lafuente, and László Szerb

1 Introduction

This book is about the rapidly expanding field of entrepreneurial ecosystems and how it contributes to economic development. The topic of sustainable development is very broad and covers many topics including, but not limited to, sustainability of communities and the environment, the effect of work force on poverty divides, responsible consumption and production, and issues of environmental justice. While a holistic approach

Z. J. Acs
George Mason University, Arlington, VA, USA
e-mail: zacs@gmu.edu

E. Lafuente (✉)
Business School, Costa Rica Institute of Technology (ITCR), Cartago, Costa Rica
e-mail: elafuente@itcr.ac.cr

L. Szerb
Faculty of Business and Economics, University of Pécs, Pécs, Hungary
e-mail: szerb.laszlo@ktk.pte.hu

Z. J. Acs et al. (eds.), *The Entrepreneurial Ecosystem*, Palgrave Studies in Entrepreneurship and Society, https://doi.org/10.1007/978-3-031-25931-9_1

is laudable, the scope of this book is much more limited and focuses on the fundamental economic analysis of entrepreneurial ecosystems and productive entrepreneurship at the regional, national, and global levels. While the volume does deal with issues of inequality along the lines of the digital divide and reining in the digital expanse via regulation, its overall aims remain much more limited in scope. Its focus is first and foremost on understanding the question at hand, the role of entrepreneurial ecosystems in digital transformation, and to identify their economically meaningful implications for policy. Each chapter is an important manifestation that exhibits various challenges that exist 'on the ground' so to speak that influence the shaping and output of the economic analysis at the regional level.

This book *The Entrepreneurial Ecosystem* constitutes a *systematic* attempt to show how a substantial contribution to entrepreneurial ecosystem can be implemented. Building on the original contributions of many writers, the collection of chapters in this volume explores through a fine lens the economic, social, and policy approaches that characterize fruitful research on entrepreneurial ecosystems with economically meaningful implications for policy.

The temporal evolution of the entrepreneurial ecosystem, as a research stream, is a story strictly tied to the entrepreneurship field, and is characterized by significant advances in recent decades (see, e.g., Acs et al. (2017) and the recent surveys by Cao and Shi (2021) and Wurth et al. (2022)). Since Schumpeter's (1934) seminal work, academics, policy makers and strategy makers in general have awakened that societies need entrepreneurs to ignite new ideas that, in turn, can materialize in organizations with the potential to lift up the economy either by addressing specific market needs or by injecting potentially transformative innovations that otherwise may have gone unnoticed.

As a result of the natural evolutionary process of scientific fields, scholars have come to an agreement that, besides the entrepreneur, the multiple (and mostly complex) interactions that occur between entrepreneurs, other organizations, investors, and public administrations have the capacity to reshape local conditions and create an environment more conducive to productive entrepreneurship. This research stream, inspired in Marshall's (1920) work, found echo in subsequent research devoted to the study of national systems of innovation (Lundvall, 1992), regional clusters (Porter, 1998), and regional innovation systems (RISs) (Cooke et al., 1997).

Rooted in ecological metaphors originally proposed by Moore (1993) and popularized by Isenberg (2010), and in parallel to the institutional, technological, and industrial changes observed in many economies, it became clear that the accurate analysis of the entrepreneurship function needed to go beyond the entrepreneur. This way, the analysis of entrepreneurial ecosystems gradually started the journey toward becoming a research field in its own right.

As a result, the entrepreneurial ecosystem concept has rapidly gained legitimacy and become a 'trendy' topic that has entered the agenda of scholars from different disciplines as well as of policy-makers interested in comprehending how economic agents and local conditions interact to trigger productive entrepreneurship. Despite that the entrepreneurial ecosystem frame can be regarded as an integrative component of other existing theories (e.g., economics as well as the institutional and evolutionary theories), the ecosystem approach is proving itself effective in offering a solid theoretical apparatus for research and policy.

The dominant 'orthodoxy' in the entrepreneurship ecosystem literature clearly emphasizes an entrepreneurship function in which local conditions have a transformative role with the potential to support economic growth at the city, regional, and national levels. In this sense, we briefly present what we consider the two most prominent aspects guiding research on the entrepreneurial ecosystem, namely, the definitional and measurement issues of the ecosystem and the complementary role of the ecosystem framework, to analyze the rise of technology-led entrepreneurship in the digital economy.

The *first issue* relates to the definition of the entrepreneurial ecosystem. Scholars agree that, at territorial level, entrepreneurship is much more than mere business formation rates. Different from canonical work on entrepreneurship, the entrepreneurial ecosystem frame accentuates the role of the spatially bounded context backing entrepreneurial action, and how it affects both the ecosystem constituents and territorial outcomes. The academic enthusiasm for consolidating the entrepreneurial ecosystem as a research field not only has contributed to produce a uniform definition of this ecosystem, but also has materialized into a significant stock of scientific work that will continue to grow. Nowadays, the entrepreneurial ecosystem is conceived as a dynamic, spatially bounded umbrella that favors the interaction between multiple economic and political agents, which, in turn, supports productive entrepreneurship by enhancing resource mobilization processes and fuels territorial outcomes.

This renewed definitional approach, which is the result of a paradigm shift, has brought two interconnected consequences for ecosystem research. On the one hand, the entrepreneurial ecosystem approach entails a change in the unit of analysis to focus on the actors and factors affecting productive entrepreneurship. Contrary to new business counts, the entrepreneurial ecosystem is an artificial unit of analysis whose elements coexist and interact with different intensity at all spatial levels.

On the other hand, in a closely related manner, scholars are faced with a controversial issue linked to the measurement of the ecosystem and to the evaluation of ecosystem policies. By situating ecosystem constituents and productive entrepreneurship at the heart of the research agenda, the identification as well as the operationalization and quantification of ecosystem elements is a challenging task. In practical applications, research studies have used metrics based on either firm-level (e.g., stock or rate of new businesses) or individual-level (e.g., the GEM's entrepreneurial activity variables) data to equip policy-makers with means to understanding entrepreneurship at the territorial level. Because of the mismatch between the analyzed concept (i.e., entrepreneurial ecosystem) and the measurement approach chosen (firm- and individual-level data), studies based on this narrow view often produce little information on the configuration of the local ecosystem and the connection between ecosystem elements and territorial outcomes (e.g., Lafuente et al., 2020; Cao and Shi, 2021; Lafuente et al., 2022; Wurth et al., 2022).

Entrepreneurial ecosystems are not checklists, and what is desirable in one territory might not be so in another context. Underlying the holistic view of the entrepreneurial ecosystem frame is the need to critically evaluate this approach to policy-making. This is particularly relevant when considering the policy push for using the entrepreneurial ecosystem framework as an economic development tool in different geographies.

The competitive advantage of countries' entrepreneurship policy hinges on the capacity to match investments with available resources. Ecosystem scholars must therefore transcend the 'geographic barrier' resulting from researchers' excessive focus on developed settings and provide answers as to what is generalizable about entrepreneurial ecosystems, and as to whether the entrepreneurial ecosystem frame has the capacity to explain the configuration and dynamics of the entrepreneurship function in heterogeneous contexts or, on contrary, whether the ecosystem approach is limited to a reduced number of mostly developed territories.

The *second issue* relates to the capacity of the ecosystem framework to percolate through theories, as it happens with the economics, institutional, and evolutionary fields, and further fertilize the analysis of the digital economy by adding entrepreneurship to the equation. Rather than calling for a new theoretical apparatus, we argue that the ecosystem approach represents a fundamental insight with the potential of reworking digital economics by offering new viewpoints for studying observable phenomena of the digital ecosystem.

The entrepreneurial and the digital ecosystems share common properties (e.g., construct complexity and multilayered structure of participating agents). Besides, some theoretical overlaps can be identified: digital economics is rooted in solid policy-led disciplines such as economics, sociology, and strategic management (e.g., Goldfarb & Tucker, 2019), whereas the entrepreneurial ecosystem frame is anchored in economics and management studies in a broader sense (e.g., Acs et al., 2014; Lafuente et al., 2022; Wurth et al., 2022).

Many entrepreneurial businesses operate within the platform economy, and cross-regional and cross-national interactions, in terms of labor division and business operations, are archetypal characteristics of digital entrepreneurial ventures. Obviously, the relationship between digital economics and entrepreneurial ecosystem is complicated; however, there is increased interest in integrating the ecosystem approach into the analysis of digital economics for building joint knowledge and for better grasping the observed dynamics in the economy.

Opportunities for collaboration between the two fields might well emerge from the identification of common, economically relevant research questions. For example, following the Schumpeterian legacy of both fields, when theorizing about the connection between the entrepreneurial and the digital ecosystem, we argue that scholars should look beyond and enrich this emerging debate by addressing issues related to how the structure (i.e., connectivity, e-security, among others) and market configuration (i.e., oligopolistic competition among digital platforms) of the digital ecosystem affect the entrepreneurial ecosystem, and how high-tech ventures adapt to the digital ecosystem, especially if these high-tech ventures operate in multiple settings with heterogeneous digital ecosystems.

Policy-makers are increasingly regarding the entrepreneurial ecosystem approach as an economic development tool; therefore, the analysis of the abovementioned (and many more!) questions not only can stimulate a closer interaction between both fields, but also can unveil potentially new recovery pathways for territories in the post-Covid-19 pandemic.

2 Entrepreneurial Ecosystems

It is unquestionable that the intensive intellectual activity developed around the entrepreneurial ecosystem over the last decades has produced an impressive and well-organized stock of theoretical and empirical knowledge. Despite the immense value of existing work, it is obvious that the drastic changes observed in the global economic landscape, of which no territory and no industry is immune, demand a further revision of the theoretical predictions of the ecosystem framework. Thus, we argue that further integration between the entrepreneurial ecosystem and other disciplines is a prerequisite for producing what we believe would be a solid cross-disciplinary research frame that would open and/or enrich a debate that includes a more nuanced discussion of the entrepreneurial ecosystem constituents, as well as of the value of the ecosystem approach for policy.

Over the past decade, a research stream that focuses on a systemic approach to entrepreneurial ecosystems has emerged using data from the Global Entrepreneurship and Development Index (GEDI) project and the Regional Entrepreneurship and Development Index (REDI) project (Acs, Autio et al., 2015; Szerb et al., 2019). These papers can be classified

Table 1.1 Entrepreneurial ecosystems: Definitional and measurement issues

	Publications
1	Acs, Z. J., Autio, E., & Szerb, L. (2014). National Systems of Entrepreneurship: Measurement issues and policy implications. *Research Policy, 43*(3), 476–494.
2	Acs, Z. J., Estrin, S., Mickiewicz, T., & Szerb, L. (2018). Entrepreneurship, institutional economics and economic growth: An ecosystem systems perspective. *Small Business Economics, 51*(2), 501–514.
3	Lafuente, E., Acs, Z. J., & Szerb, L. (2022). A composite indicator analysis for optimizing entrepreneurial ecosystems. *Research Policy, 51*(9), 104379

Table 1.2 Entrepreneurial ecosystems: Empirical contributions

	Publications
1	Lafuente, E., Acs, Z. J.; Sanders, M., & Szerb, L. (2020). The global technology frontier: Productivity growth and the relevance of Kirznerian and Schumpeterian entrepreneurship. *Small Business Economics, 55*, 153–178.
2	Lafuente, E., Szerb, L., & Acs, Z. J. (2016). Country level efficiency and National Systems of entrepreneurship: A data envelopment analysis approach. *Journal of Technology Transfer, 41*(6), 1260–1283.
3	Acs, Z. J., Szerb, L., Ortega-Argilés, R., Coduras, A., & Aidis, R. (2015). The regional application of the global entrepreneurship and development index (GEDI): The case of Spain. *Regional Studies, 49*(12), 1977–1994.
4	Szerb, L., Lafuente, E., Horváth, K., & Páger, B. (2019). The relevance of quantity and quality entrepreneurship for regional performance: The moderating role of the entrepreneurial ecosystem. *Regional Studies, 53*(9), 1308–1320.
5	Szerb, L., Ortega-Argilés, R., Acs, Z. J., & Komlósi, É. (2020). Optimizing entrepreneurial development processes for smart specialization in the European Union. *Papers in Regional Science, 99*(5), 1413–1457.
6	Varga A., Sebestyén T., Szerb L., & Szabó, N. (2020). Estimating the economic impacts of knowledge network and entrepreneurship development in smart specialization policy. *Regional Studies, 54*(1), 48–59.

into three groups: the first group focuses on definitional and measurement issues of entrepreneurial ecosystems (Table 1.1), the second group focuses on empirical contributions to the literature (Table 1.2), and the third group covers the digital aspects of entrepreneurial ecosystems and the platform organizations that dominate them (Table 1.3).

Table 1.3 Entrepreneurial ecosystems: The digital platform economy

	Publications
1	Sussan, F., & Acs, Z. J. (2017). The digital entrepreneurial ecosystem. *Small Business Economics,* 49(1), 55–73.
2	Song, A. (2019). The digital entrepreneurial ecosystem—a critique and reconfiguration. *Small Business Economics, 53*(3), 569–590.
3	Acs, Z. J., Song, A., Szerb, L., Audretsch, D., & Komlósi, É. (2021). The evolution of the digital platform economy: 1971–2021. *Small Business Economics, 57*(4), 1629–1659.
4	Acs, Z. J., Szerb, L., Song, A., Lafuente, E., & Komlosi, E. (2022). Measuring the digital platform economy. In M. Keyhani, T. Kollmann, A. Ashjari, A. Sorgner, & C. Eiríkur Hull (Eds.), *Handbook of digital entrepreneurship*, chapter 5 (pp. 91–120). Edward Elgar Publishing. ISBN 978-1-800-37,362-4
5	Lafuente, E., Acs, Z. J., & Szerb, L. (2023). Analysis of the digital platform economy around the world: A network DEA model for identifying policy priorities. *Journal of Small Business Management*, in press, https://doi.org/10.1080/00472778.2022.2100895
6	Acs, Z. J. (2022). The global digital platform economy and the region. *Annals of Regional Science*, in press, https://doi.org/10.1007/s00168-022-01154-6

Perhaps the *first shot* was fired in 2014 with the publication of the National System of Entrepreneurship in *Research Policy* (Acs et al., 2014) (Table 1.1). Working at Imperial College Business School, the authors argued that the entrepreneurial ecosystem could be best understood as a system and the interrelated parts of the system could be optimized. It also laid out the different aspects of the existing literature on entrepreneurship at the individual, firm, and economy level. It was the economy level that posed the greatest challenge to the system. To overcome this challenge, they introduce a novel concept of National Systems of Entrepreneurship (NSE) and provide an approach to characterizing them. National Systems of Entrepreneurship are fundamentally resource allocation systems that are driven by individual-level opportunity pursuit, through the creation of new ventures, with this activity and its outcomes regulated by country-specific institutional characteristics.

This led to an important question, namely, 'Was the entrepreneurial ecosystem approach superior to one that only encompassed startups?' Of course that question was not accepted by much of the profession on systems, including national and regional systems of innovation and clusters who argued that what was the core firm focus was innovative/high-tech firms and export-based firms, not start-ups (Qian & Acs, 2013). To address this issue, Acs et al. (2018), at the London School of Economics, tested whether an entrepreneurial ecosystem approach contributed to total factor productivity (TFP). They analyzed conceptually and in an empirical counterpart the relationship between economic growth, factor inputs, institutions, and entrepreneurship. In particular, they investigate whether entrepreneurship and institutions, in combination in an ecosystem, can be viewed as a 'missing link' in an aggregate production function analysis of cross-country differences in economic growth. To do this, they build on the concept of National Systems of Entrepreneurship (NSE) as resource allocation systems that combine institutions and human agency into an interdependent system of complementarities. They explored the empirical relevance of these ideas using data from a representative global survey and institutional sources for 46 countries over the period 2002–2011. They found support for the role of the entrepreneurial ecosystem in economic growth.

The next question revolved around the issue of, how and if, the entrepreneurial ecosystem could be optimized for maximum economic benefit. Working at the University of Pecs and the Polytechnic University of Barcelona, Lafuente et al. (2022) employ the 'benefit of the doubt' approach rooted in nonparametric techniques to evaluate the entrepreneurial ecosystem of 71 countries for 2016. By scrutinizing the relative efficiency of countries' entrepreneurial ecosystems, their analysis of composite indicators allows the computation of endogenous (country-specific) weights that can be used for developing more informed policy-making. The results show that countries prioritize different aspects of their national system of entrepreneurship, which confirms that, contrary to homogeneous prescription, tailor-made policy is necessary if the objective is to optimize the resources deployed to enhance the local entrepreneurial ecosystem. The authors also found that significant improvements in the quality of this ecosystem can be realized by targeting the policy priorities of the local entrepreneurship system identified by their model. The three papers covered the key definitional and measurement issues of entrepreneurial ecosystems (Table 1.1).

Next, we turn to empirical studies that, at the national and regional levels, put to the test different postulates of the entrepreneurial ecosystem approach (Table 1.2). Two papers, Lafuente et al. (2020) and Lafuente et al. (2016), evaluate how countries' system of entrepreneurship is conducive to greater efficiency.

Concretely, in their study of 45 developed and developing countries during 2002–2013, Lafuente et al. (2020) built a world technology frontier and computed TFP estimates in order to evaluate how the national system of entrepreneurship—measured by the GEI indicator—triggers total factor productivity (TFP) by increasing the effects of Kirznerian and Schumpeterian entrepreneurship. The results of the common factor models reveal that the national system of entrepreneurship is a relevant conduit of TFP, and that this effect is heterogeneous across countries. Policies supporting Kirznerian entrepreneurship—for example, increased business formation rates—may promote the creation of low value-adding businesses which is not associated with higher TFP rates. Also, policy interventions targeting Schumpeterian entrepreneurship objectives—for example, innovative entrepreneurship and the development of new technologies—are conducive to technical change by promoting upward shifts in the countries' production function and, consequently, productivity growth.

While the above papers were at the national level, entrepreneurial ecosystems also operate at the regional level. The next set of papers focused on the regions of the countries of the European Union. The development of the methodology for studying regional entrepreneurial ecosystems that were comparable with national data was an important advance.

The *second shot* was fired in 2015 in a paper in *Regional Studies* in which Acs, Szerb, Ortega-Argilés, Coduras, and Aidis demonstrated that the systemic approach to entrepreneurship can also be applied at the regional level. Working with the European Union, the paper constructs a regional application of the methodology that captures the contextual features of entrepreneurship across regions. The resulting composite indicator—the Regional Entrepreneurship and Development Index (REDI)—identifies weaknesses in the incentive structure that affect regional development. Similar to the GEI indicator, the entrepreneurial disparities among regions are analyzed at the country and regional levels, using the penalty for bottleneck (PFB) methodology. This approach allows public policy action to be coordinated at both national and regional levels. It was found that the REDI indicator provides a valuable tool for understanding regional differences across Spanish regions. Three papers followed that expanded the results reported for the European Union: Szerb et al. (2019 in *Regional Studies*), Szerb et al. (2020 in *Papers in Regional Science*), and Varga et al. (2020 in *Regional Studies*) (Table 1.2).

The *third shot* across the bow happened in 2017 when *Small Business Economics* published a special issue on entrepreneurial ecosystems (Table 1.3). The introductory paper laid out a broad sweep of the topic, and the issue covered several topics (Acs et al., 2017). In one of the most provocative papers included in the special issue, Sussan and Acs (2017) argued that the entrepreneurship literature had ignored the role of technology, especially digital technology. According to the authors, a significant gap exists in the conceptualization of entrepreneurship in the digital age. This paper introduces a conceptual framework for studying entrepreneurship in the digital age by integrating two well-established concepts: the digital ecosystem and the entrepreneurial ecosystem. The integration of these two ecosystems helps to understand the interactions of *agents* and *users* that incorporate insights of consumers' individual and social behavior. The digital entrepreneurial ecosystem framework consists of four concepts: digital infrastructure governance, digital user citizenship, digital entrepreneurship, and digital marketplace. The paper develops propositions for each of the four concepts and provides a framework of *multisided platforms* to better grasp the digital entrepreneurial ecosystem. Finally, it outlined a new research agenda to fill the gap in our understanding of entrepreneurship in the digital age.

Acs (2022) and Acs et al. (2021) further developed the topic. The emergence of digital technologies has significantly reduced the economic costs of data—search, storage, computation, transmission—and enabled new economic activities (Goldfarb & Tucker, 2019). Over the years, firms able to create a platform-based ecosystem have become a force of 'creative construction'. Economic activities (C2C, B2C, B2B) have been reorganized around platform-based ecosystems for value creation, which are orchestrated by multisided platforms via the 'digital hand'. Acs et al. (2021) provide a conceptual framework consisting of three interrelated concepts: digital technology infrastructure, multisided platforms, and platform-based ecosystems (users and entrepreneurs). Using a unique database over five decades, the authors revisit the hypothesis that new firms were needed to introduce digital technologies.

Finally, Lafuente et al. (2023) integrate the platform economy and entrepreneurial ecosystems to evaluate the quality of the digital platform economy at the global scale by employing a network model rooted in nonparametric linear techniques (data envelopment analysis) on a sample of 116 countries for 2019. The proposed model is in accordance with the geographic diversity (country heterogeneity) and the multilayered structure characterizing the interactions between system participants: governments, digital platforms, platform-dependent firms, and end users. The core finding of the study is that the configuration of countries' platform economy is heterogeneous, which suggests that an informed, tailor-made approach to policy produces more effective outcomes. Policies aimed at enhancing the digital platform economy should emerge from the analysis of its main factors if the development of a strategy supporting qualitative changes in the system is the desired goal.

3 Digital Entrepreneurial Ecosystems

Entrepreneurial ecosystems are not a brand-new idea. In the context of regional economic development, it has its origins in regional innovation systems (RISs) and clusters (Qian et al., 2013; Acs et al., 2014; Acs et al., 2017; Szerb et al., 2019). In an attempt to clarify the relationships between RISs, clusters, and entrepreneurial ecosystems, Table 1.4 compares RISs, clusters, and entrepreneurial ecosystems using multiple criteria. The RIS approach focuses on regionally bounded resources and formal and informal institutions that underpin firm innovation, while highlighting the nonlinear and systemic nature of learning and firm innovation processes (Cooke et al., 1997; Asheim et al., 2011). Based on the so-called triple-helix model, firms, governments, and universities are often considered core players in an innovation system, where firms commercialize (typically) government-funded university research (Leydesdorff & Meyer, 2006). An RIS typically has an industry boundary and is often discussed in a particular industrial context, for example, biotechnology. Depending on the knowledge base of regions, the organization of RISs

Table 1.4 Key aspects of regional innovation systems, clusters, entrepreneurial ecosystems, and digital entrepreneurial ecosystems

	Regional innovation systems	Clusters	Entrepreneurial ecosystems	Digital entrepreneurial ecosystems
Components	Organizations; formal institutions; informal institutions (social capital, networks, culture)	Organizations; formal institutions; informal institutions (social capital, networks, culture)	Individuals; organizations; formal institutions; informal institutions (social capital, networks, culture)	Individuals; organizations; formal institutions informal institutions (social capital, networks, culture)
Functions	Learning and diffusion of innovation	Growing firm competitiveness	Entrepreneurial exploration of market opportunities	Exploitation of digital technologies for warranting firms' digital competitiveness
Measures of outcome	Product and process innovations	Nationally/ internationally competitive firms	Productive start-ups and scale-ups	Firm digitalization, social networking, and digitally led innovation
Regional knowledge base required	Technical knowledge; market knowledge; management knowledge	Technical knowledge; market knowledge; management knowledge	Technical knowledge; market knowledge; management knowledge; entrepreneurial process knowledge	Technical knowledge; digitalization; digital market knowledge; entrepreneurial process knowledge
Industry boundaries	Bounded by one industry	Bounded by multiple interconnected industries	Not bounded by industries	Not bounded by geography or industries
Core firm focus	Innovative/high-tech firms	Export-based firms	Innovative/high-growth start-ups	Digital platforms and platform-dependent firms

(*continued*)

Table 1.4 (continued)

	Regional innovation systems	Clusters	Entrepreneurial ecosystems	Digital entrepreneurial ecosystems
Role of entrepreneurs	Supporting	Supporting	Leading	Leading
Role of incumbent firms	Leading	Leading	Supporting	Leading
Role of government	Leading	Supporting	Supporting	Leading
Role of universities	Leading	Supporting	Supporting	Supporting

Source: Authors' summary based on Cooke et al. (1997), Porter (1998), Feld (2012), Qian et al. (2013), Spigel and Harrison (2018), Stam and Spigel (2022), Qian and Fu (2023), and Qian and Acs (2022) (i.e., the key players and their interactions) can be very different (Asheim & Coenen, 2005). Public R&D investment, support for universities, and fostering a culture of collaboration are common policies emerging from analyses based on the RIS framework.

Clusters are 'geographic concentrations of interconnected companies and institutions in a particular field' (Porter, 1998, p. 78). To a large extent, the clusters and RIS approach cover the same actors, which include firms, universities, and governments, but universities and governments play only supporting roles in clusters. Productive, export-based firms in a particular field are the core actors in a competitive cluster, which are also supported by other firms or industries through, for example, buy–sell relationships, shared specialized labor, and knowledge spillovers. Therefore, a cluster involves multiple industries that are economically interconnected. The popularity of clusters among economic development practitioners arises in part from some clear measures of clusters that make it possible to identify the scale of clusters at different geographical levels (Delgado et al., 2016). Echoing Porter (2007), regional economic development policy toward clusters includes building connections among cluster participants and investing in infrastructure such as universities. Interestingly, even though clusters are identified through industries, Porter advocates for an industry-neutral approach to cluster policy. Also, cluster-based policy efforts are not much different from those suggested by RIS scholars, and monotonous (repetitive) policy implications are considered the major weakness of the cluster theory (Motoyama, 2008).

How are entrepreneurial ecosystems different from RISs and clusters? The most remarkable difference for the entrepreneurial ecosystems approach perhaps lies in the shift from a focus on firms to a focus on people, including entrepreneurs, investors, dealmakers, and other entrepreneurship supporters (Acs et al., 2014; Motoyama, 2019; Qian et al., 2013; Stam & Spigel, 2022), even though the outcome of the entrepreneurial ecosystem is typically measured by productive start-up or scale-up businesses (Stam & Spigel, 2022; Wurth et al., 2022). Among all these actors, entrepreneurs should play a leading role in this ecosystem, either through their own entrepreneurial process or via engagement with the local start-up community (Acs et al., 2014). 'Blockbuster' entrepreneurs help sustain a strong entrepreneurial ecosystem when they invest their capital gains in local start-ups, mentor new entrepreneurs, and build a collaborative and giving culture. Networks developed through entrepreneurship events, support organizations, or even serendipitous meetings are of particular importance to the vibrancy of entrepreneurial ecosystem. Another notable distinction of entrepreneurial ecosystems is that they are not constrained by industry boundaries, as the same stock of entrepreneurial process knowledge circulated in the region benefits local entrepreneurs from all sectors (Wurth et al., 2022).

As shown in Table 1.4, even with some notable differences, entrepreneurial ecosystems share some features with clusters and RISs, such as the importance of organizations, institutions, networks, risk-raking culture, and the needs for technical, managerial, and market knowledge. These similarities may make economic development policy-makers wonder whether entrepreneurial ecosystems are substitutes for RISs and clusters. The answer is no. Entrepreneurial ecosystems should not be considered as a replacement of its two precedents, because they are interested and target different economic outcomes (see Table 1.4). The outcome of RISs is mostly linked to product and process innovation processes, clusters' outcome is measured by competitive firms and industries, whereas the outcome of entrepreneurial ecosystems is primarily measured by productive start-up and scale-up businesses. Therefore, entrepreneurial ecosystems should be considered complementary to RISs and clusters (Audretsch et al., 2021). Ideally, a region has a strong innovation system, competitive cluster, and vibrant entrepreneurial ecosystem at the same time (such as Silicon Valley), but most regions do not.

In parallel to the rapid development of the entrepreneurial ecosystem literature, academics and policy-makers have recently witnessed the emergence of a new research strand focused on the study of the digital entrepreneurial ecosystem. But, why do we need to update existing theories in order to study the role of digitalization in entrepreneurial ecosystems?

The world is today a more digitally integrated place. The accelerated digitization of the economy—in terms of drastic improvements in digital infrastructures and trade—is transforming the functioning of the economy, which has led to consolidate digital markets, ranging from smartphone applications to different forms of digital products and services (e.g., Brynjolfsson & McAfee, 2014; Lafuente et al., 2023). In this new economic scenario, it soon became clear that the entrepreneurial ecosystem literature was falling short in the conceptualization of entrepreneurship in the digital age, mostly because it ignores the decisive role of knowledge as a resource in the economy as well as how platforms govern and nurture platform-based ecosystems (Acs et al., 2021; Lafuente et al., 2023).

The digital entrepreneurial ecosystem literature is still evolving, but so far we can identify at least two features that distinguish conventional entrepreneurial ecosystems from digital entrepreneurial ecosystems: one institutional that puts digital platforms at the heart of this ecosystem, and one market-related that emphasizes the role of platform-dependent firms and digital entrepreneurs (Table 1.4).

This approach emphasizes the leading role of platforms in this ecosystem. Digital entrepreneurial ecosystems are developed and nurtured not by regions or governments but by multisided digital platforms (Sussan & Acs, 2017; Acs et al., 2021). Ecosystem governance, the rules by who gets on a platform, and the rules of good behavior are determined by the owners of multisided platforms (Goldfarb & Tucker, 2019; Lafuente et al., 2023).

Because digital platforms are powerful players of the digital economy connecting digital users, digital entrepreneurs, and incumbent digital businesses whose competitive advantage relies on their capacity to exploit digital technologies and platforms' offering (platform-dependent firms), governments are increasingly interested in interacting with platforms in order to safeguard public interests as platforms pursue their economic goals. In their effort to consolidate their position in digital markets and their product offering, platform organizations need to manage their ecosystem for billions of users and millions of entrepreneurs across the world. They are also embedded in local ecosystems, such as Silicon Valley, Seattle, and Beijing. Thus, a closer monitoring and updated regulation will likely contribute to ensure the efficient functioning of the system, in terms of the connections between platforms, platform-dependent firms, and end users (Lafuente et al., 2023).

Digital platforms offer important benefits to users, digital entrepreneurs, and platform-dependent firms, such as access to established markets, reliable transactions, and guaranteed operability. Indeed, platforms have dramatically lowered the cost of developing and distributing mobile applications and other complementary products that connect to platforms, which worldwide app developers and other agents can exploit using heterogeneous knowledge-based resources. In short, in a digital entrepreneurial ecosystem governed by multisided platforms, digitally led entrepreneurial innovation closes the gap between supply opportunity seeking, product development, and consumer needs.

To sum up, digital entrepreneurial ecosystems are environments characterized by the lack of regulation and monopolistic competition. In this setting, digital platforms dominate their relationships with platform-dependent firms and end users. The 'platformization' of the economy has undoubtedly produced large benefits to the market: platforms support innovation efforts of platform-dependent firms and digital entrepreneurs, and provide increased offering of digital goods and services at minimum search, reproduction, and verification costs (for example, Goldfarb & Tucker, 2019; Sussan & Acs, 2017). These benefits are also evident at the territorial level, in terms of the higher adoption of ICTs in urban settings (agglomeration effects), the increased flow of digital and physical goods in rural or low-density areas, and the reduced need for a task-specific workplace which favors that tech entrepreneurs locate their businesses in rural areas (Kolko, 2012; Lafuente et al., 2010).

4 Structure of the Book

As the reader will discover, the approach taken up in this book, *The Entrepreneurial Ecosystem,* is a systematic one oriented to understanding the aspects of the entrepreneurial ecosystem outlined in this introduction (i.e., definitional and measurement issues, and the complementary role of the ecosystem framework to analyze the digital economy), and to contrast these two aspects with positions reported by relevant contemporary empirical work rooted in different theoretical groundings. The rest of the book is as follows.

Chapter 2, titled 'Building Composite Indicators for Policy Optimization Purposes' by László Szerb, Zoltán J. Ács, Gábor Rappai, and Dániel Kehl, discusses the importance of composite indicators as valuable tools that capture the complexity and multidimensionality of a particular phenomenon and proposes an analysis based on the penalty for bottleneck (PFB) method to show how plausible policy recommendations can be extracted from composite indicators. The basic problem of the policy application of composite indicators lies on their incapability to handle the ingredients from the system perspective. The PFB methodology is based on the assumption that the performance of the system depends on the weakest link, that is, the variable that has the lowest value. The resulting PFB-based policy recommendation is clear: the bottleneck should be improved first because it has a magnifying effect on the other indicators in the system. Unlike other indexes or regression methods, the PFB provides a multivariate marginal analysis that allows to create a policy-portfolio mix that optimizes the use of additional resources. For a more precise policy application, the authors equalized the variable averages in order to derive homogeneous marginal effects over the averages of the variables. The authors present a practical application of the PFB methodology to the Global Entrepreneurship Index data with an exponential penalty function. Policy simulations with three country examples are also provided. The authors conclude that, compared to other methods that do not take a system-based bottleneck approach, the PFB can be successfully applied to numerous fields, thus facilitating the development of more accurate policy recommendations.

In Chap. 3, titled 'World Technology Frontier: Directed Technical Change and the Relevance of the Entrepreneurial Ecosystem', Esteban Lafuente evaluates the determinants of total factor productivity in a model that integrates differences in technology choices for a comprehensive sample for 73 countries during 2002–2013. The proposed TFP model is rooted in nonparametric techniques to compute the Malmquist productivity index and its components. The author finds that, for both OECD and non-OECD countries, technical change and total factor productivity growth is associated with higher rates of capital deepening. Results also indicate that the countries' technology choices (biased technical change) have an impact on productivity results. Public policies promoting economic growth should consider the national system of entrepreneurship as a critical priority, so that entrepreneurs can contribute to effectively allocate resources in the economy.

Chapter 4, titled 'The Entrepreneurship Paradox: The Role of the Entrepreneurial Ecosystem on Economic Performance in Africa' by Esteban Lafuente, László Szerb, and Zoltán J. Ács, discusses how increased globalization, economic complexity, and dynamism exacerbate contradictions between theoretical and empirical-driven arguments. Specifically, this chapter analyzes the entrepreneurship paradox—that is, entrepreneurship is good for the economy, but entrepreneurial activity is consistently higher in less developed and developing countries over time—through the lenses of two relevant tensions that underlie this paradox: the development tension (i.e., the inconsistent relationship between entrepreneurship and economic performance) and the policy tension (i.e., the unclear role of entrepreneurship policy on entrepreneurship outcomes). Building on a sample of 81 countries from Africa, America, Asia, and Europe for 2013–2014, the authors employ regression models and cluster analysis to scrutinize the effect of both the rate of entrepreneurial activity (quantity-based entrepreneurship) and the entrepreneurial ecosystem (quality-based entrepreneurship) on economic performance (GDP per capita). The analysis focuses on how the development tension and the policy tension shape the entrepreneurship paradox. In exploring these two elements of the entrepreneurship paradox, the proposed analysis defines and distinguishes quantitative entrepreneurship from the systemic, quality-based entrepreneurial ecosystem and sets forth alternative policies to reconcile the tensions between entrepreneurship and development that fuel the entrepreneurship paradox. The analysis proposed in this chapter contributes to a better understanding of the entrepreneurship paradox. The findings support the notion that African countries—and economies in general—do not need more entrepreneurs but rather a healthy entrepreneurship ecosystem that contributes to optimally channel the outcomes of entrepreneurial actions to the economy.

Chapter 5, titled 'The Monetization of the Regional Development and Innovation Index: Estimating the Cost of Entrepreneurship Ecosystem Policies in European Union Regions' by Tamás Sebestyén, Éva Komlósi, and László Szerb, provides a methodology to monetize the different pillars of the Regional Entrepreneurship Development Index (REDI). The REDI methodology provides a normalized value to describe the entrepreneurial ecosystem using natural units of the different measures as inputs to the calculation. To offer more informed policy analyses, the chapter adopted a two-step approach. First, the authors employ econometric techniques to assign a monetary value to the REDI variables. By entering the REDI scores into a production function explaining regional GDP levels, the authors estimate the marginal contribution of the REDI to monetized regional output, which they link to the marginal value of the REDI in a given region. Second, the authors employ a standard shadow pricing approach in which the resulting monetized REDI score is traced back to its components, thus offering a monetized approximation of the pillars that form the REDI composite indicator.

Chapter 6, titled 'Entrepreneurial Ecosystem in the European Union Regions: Identification of Optimal Ecosystem Configurations for Informed Policy' by László Szerb and Éva Komlósi, offers a direct empirical analysis of regional ecosystem measure based on complexity theory: the Regional Entrepreneurship and Development Index (REDI). The authors acknowledge that the REDI approach is based on homogeneous (across regions) and fixed (across pillars) pillar weights, thus ignoring part regions' heterogeneity. Therefore, they also enhance the REDI methodology by building on the benefit of the doubts (BOD) weighting technique. This weighting system reflects a value judgment on what are the optimal configurations of REDI constituents. If policy-makers are given objective, nonarbitrary information about the importance of REDI pillars, resource allocation should follow an economically meaningful process. Quantity improvements are ensured if additional resources are deployed, but for an equal quantitative change in the REDI score, enhancements will be qualitatively superior if policy-makers target a clear set of priorities. Based on the BOD enhanced REDI ($REDI^{BOD}$), the authors provide a score on the quality of the entrepreneurial ecosystem ($REDI^{BOD}$) for 125 European Union (EU) regions, conduct a grouping by cluster analysis, and offer policy suggestions for 23 large EU city regions.

Chapter 7, titled 'Measuring the Effects of Policies Targeting Entrepreneurial Ecosystems: An Application of the GMR Framework with REDI' by Attila Varga, Tamás Sebestyén, Norbert Szabó, and László Szerb, estimates the economic impact of entrepreneurship policy. Entrepreneurship policy should be added to the palette of public interventions promoting economic growth. Despite the growing evidence, it is still unknown to what extent a given policy intervention would affect economic growth in a particular country or region and how these effects might change over time. These effects can be estimated with economic impact models. In this chapter, the authors introduce the most recent version of GMR-Europe to determine the economic repercussion of policy interventions targeting entrepreneurship. To illustrate the capacity of the model, the paper provides a detailed policy impact assessment analysis.

The world is today a more digitally integrated place; however, digital inequality still prevails, and its repercussions (e.g., poor access to information, e-commerce, remote education, remote work, and remote healthcare) have aggravated with the Covid-19 pandemic. In Chap. 8, titled 'Digital inequality and the signature of digital technologies and the digital ecosystem: Analysis of deviations in the rank-size rule of Internet access data', Esteban Lafuente, Zoltán J. Ács, and László Szerb adopt a power-law approach to scrutinize global digital inequality on a sample of 107 countries between 2000 and 2019. Also, the authors take the digital inequality discussion to a more qualitative level by connecting their findings to the quality of countries' digital ecosystem. Building on the nuance that digital integration encompasses digital technologies and a healthy digital ecosystem, the scrutiny of rank deviations in the Internet access data shows significant progress in digital integration during 2000–2019; however, digital integration is slowing down since 2015. Investments in digital technologies support digital integration. The inspection of countries' digital ecosystem suggests that digital policies targeting governance (e.g., regulation and data privacy) and platforms' activities (e.g., social media and online payments) are critical to enhance the digital system and, consequently, reduce digital inequality and its negative manifestations.

Chapter 9, titled 'A Tale of Two Cities: How Arlington Won and Baltimore Lost in Battle for Amazon's HQ2' by Abraham Song and Keith Waters, narrates a tale of two cities, namely, Washington metropolitan area and Baltimore metropolitan area: about the rise of one and the fall of the other; about a metro that landed Amazon's distribution centers and the other, highly coveted HQ2. In today's knowledge economy where the most valuable companies are digital platforms, it's a winner-take-all when it comes to regional economic development. The paradigm of place-based policies of the industrial age that sought to attract large manufacturing plants with tax incentives is outdated. There is no better example of this paradigm shift in economic development from cost minimization to value maximization, from emphasis on physical capital to human capital, embodied in the case of Amazon HQ2 race, which ultimately landed in Crystal City, Virginia. Amazon HQ2 race represents a great lesson for what technology businesses value: talent. Virginia demonstrated a good understanding of tech firms' market needs, and its development strategy evidenced the importance of prioritizing the talent pipeline.

Chapter 10, titled 'Measuring the Modern Entrepreneur: An Evaluation of Elon Musk' by Camilla Bosanquet, qualitatively considers various arguments that characterize the entrepreneurial profile of Elon Musk. The chapter first contemplates entrepreneurship in an effort to develop baseline standards by which we might then evaluate Elon Musk. A secondary analysis compares Elon Musk against two of his predecessors, Henry Ford and Kiichiro Toyoda. Likewise, the author compares Tesla Motors with Ford Motor Company and Toyota Motor Corporation. Several accusations against Elon Musk will also be weighed, especially those which might challenge notions of Musk as an innovator, founder, and (ultimately) entrepreneur.

Chapter 11, titled 'How to Tame the Beast? Toward a 'Regulation Revolution' in the Digital Platform Economy' by Márton Sulyok, offers a broad frame to talk about legal and regulatory issues that arise in a 'platform context'. The author contrasts some of the natural drivers nurturing the digital platform ecosystem and incentivizing technological and digital progress, pushing the final frontier of law (understood as the means to create order) further, and testing the limits of states as regulators. The 'IT-debate', which today revolves around how to tackle growing pressures by recent IT-developments, in other words, how 'tame the beast', and the 'how' and 'when' to regulate digital platforms that are the foundations of the 'digital platform economy', has gained weight in public discourse. In discussing this essential function, relevant questions for legal scholars, regulators, and economists are addressed, including when and to what extent states should regulate digital markets to set rights and delimitate possible violations that range from privacy to freedom of speech. As states breach the digital barrier through technological evolution, the concept of sovereignty emerges in the digital sphere. Many actors with a marked economic footprint appear in the life of states which have different means to affect the 'analog context' of traditional sovereignty (i.e., population and decision-making). This leads to a 'regulatory revolution' that materializes in increased regulation of big data, actions of the 'big five', algorithmic decision-making, among others. A long-standing question in the legal community is whether law has primacy over politics and policy, or vice versa. In the current digital context, the question should rather be whether the platform economy has primacy over law (politics and policy), or whether it should be the other way around.

In the concluding chapter—Chap. 12, titled 'The Ecology of Innovation: The Evolution of a Research Paradigm'—Hilton L. Root proposes a framework in which complex system analytics plays a pivotal role for enhancing entrepreneurship scholarship and policy. Following a review of research on entrepreneurial ecosystems from an evolutionary perspective, the chapter forges a new research direction that pays close attention to the relationships between the decisions and strategies of agents and the structure of the environment in which choices are made. The chapter suggests new ways to evaluate the connections between system variables at their macroscopic scale, in the hope of defining global properties that are independent of the details at the microscopic scale. The analysis of entrepreneurial ecosystems through the complex adaptive systems lens has the potential to produce a literature that is richer in insights about the informal constraints, such as social norms, beliefs and ideologies, and the cognitive processes and cultural elements that underpin them, leading to a meta-theory that integrates a community's culture and its historical specificity with its entrepreneurship ecosystem.

In summary, this book on the entrepreneurial ecosystem is a timely intervention to document different shades of entrepreneurship which might be of value to scholars, policy-makers, strategy makers, students, as well as the general public.

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2

Building Composite Indicators for Policy Optimization Purposes

László Szerb, Zoltán J. Ács, Gábor Rappai, and Dániel Kehl

1 Introduction

In 2010, Carmen Reinhart and Kenneth Rogoff published a noteworthy and influential paper, arguing that the average gross domestic product (GDP) growth rate considerably falls down when the public depth to GDP exceeds 90% (Reinhart & Rogoff, 2010). Despite that the authors did not claim to prove a causal relationship between growth and debt, the paper soon become a blockbuster among fiscal austerity followers and turned out to be a reference point for such policy-makers like European Commissioner Olli Rehn, former US Vice-Presidential Candidate Paul Ryan, UK Minister of Finance George Osborne, and International

L. Szerb (✉) • G. Rappai • D. Kehl
Faculty of Business and Economics, University of Pécs, Pécs, Hungary
e-mail: szerb.laszlo@ktk.pte.hu; rappai.gabor@ktk.pte.hu; kehld@ktk.pte.hu

Z. J. Ács
George Mason University, Arlington, VA, USA
e-mail: zacs@gmu.edu

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Monetary Fund (IMF) CEO Christine Lagarde (Influential Reinhart-Rogoff Study, 2013; Mayeda, 2014). The effect of debt to growth relationship was first questioned by Thomas Herndon, Michael Ash, and Robert Pollin who find coding errors in the Reinhart/Rogoff Excel data set (Herndon et al., 2014). Moreover, the trio accused Reinhart and Rogoff with unreasonable omission of data as well as with unjustified weighting. In their reply, Reinhart and Rogoff (Reinhart, 2013) admitted the coding error but refused the other critics. Recalculating the result based on their renewed data set, the average growth rate over the 90% threshold was 2.3%, very close to Herndon et al.'s (2014) 2.2% (Reinhart et al., 2012). The debt to growth issue snowballed soon, leading to a huge and harsh debate in professional journals as well as in leading dailies and weeklies. While there was an agreement that growth and debt negatively correlate, many questioned the causal relationship (Panizza & Presbitero, 2014), find no evidence on the existence of any thresholds (Égert, 2015; Pescatori et al., 2014), and highlighted the presence of cross-country heterogeneity as opposed to a generally existing relationship (Kourtellos et al., 2013; Bell et al., 2014).

Having a closer look at beyond the veil of the debate, we can notice that the Reinhart and Rogoff public debt economic growth debate enlightened to a fundamental problem that is the limited practical applicability of the statistical/econometric methods. In particular, nothing robust and useful policy suggestion has emerged on how to optimize public debt. Even more notably, politicians and decision makers have become more suspicious about the usefulness of economic models and econometric methodologies. It seems that Nobel laureate Wassily Leontief long-back claim about the "inadequacy of the scientific means to solve" (p. 1) practical problems is still valid (Leontief, 1971). So, there is a time to look for alternative solutions that help us in decision-making about optimizing resources.

In this chapter, we are describing a composite indicator procedure that makes possible optimizing available resources in a system of multivariable setup. In order to do that we have developed two novel methodologies named as the equalization of the averages (EPA) and the bottleneck for penalty (PFB), both of them are vital for providing solid policy recommendation under certain conditions.

2 The Application of Statistical Methodologies Versus Composite Indicators in Decision-Making

The most important task of decision makers is to rank the available alternatives based on some evaluation criteria. This task is exponentially becoming more difficult when the number of potential alternatives and criteria increases. Decisions are also influenced by the availability of data. Over the last decades, parallel to globalization and the continued increased importance of the digital economy, the world has become an information-rich place. Facing to increased opportunities and challenges, data users from the public to experts demand clear, useful, and meaningful pieces of information and methods to solid decision-making (Saltelli, 2007). However, decision makers should also learn that their actions and decision have effect not only on the target but also on many other components. Decision cannot be evaluated in isolation, but rather in terms of the performance of the whole system (DeLaurentis & Callaway, 2004).

Statistical methods, in particular regression models, are frequently applied for decision-making. Nevertheless, even the proper setup of the model does not directly lead us to provide useful pieces of information to reach good (optimal) decision (Gelman et al., 2003). While the enormous development of statistical/econometric programs makes an easy thing to conduct cumbersome calculations, it did not prevent us to interpret the model results and predictive power properly (Soyer & Hogarth, 2012). Besides improper interpretation, the practical application of regression models is still problematic, underlined by the Reinhart/Rogoff debate. In the followings, we highlight three, closely interrelated, fundamental problems of the practical use of regressions and in more general statistical methodology:

1. *The neglect of the system perspective*. While theoretical models are often accused for disregarding empirical data, econometric models face other criticism that is the negligence of the system perspectives (Phelps-Brown, 1972; Sterman, 1989). As Nobel laureate Leontief claims: “By the time facts of everyday experience were used up, economists were

able to turn for bits and pieces of less accessible, more specialized information to government statistics. However, these statistics … fall short of what would have been required for concrete, more detailed understanding of the structure and functioning of modern economic system" (Leontief, 1982, p. 104). A straightforward solution to complex models is to increase the number of variables. In this respect, Milton Friedman's personal example of selecting alloys based on multivariate regressions also raises skepticism about the use of complex regressions (Friedman & Schwartz, 1991). Examining prior research papers, Green and Armstrong (2015) found that complexity increased the forecast error considerably, by 27% on average, just echoing to Friedman's doubts. Instead of more complicated methodologies, Green and Armstrong suggest looking for simple solutions.

2. *The* ceteris paribus *assumption*. A core tenet of most economic analyses is the basic postulate that we can change only one variable at one time and all the other variables remain unchanged. This approach completely neglects the system perspective, that is, the mutual dependence of all the elements in a given framework.
3. *Multicollinearity based on correlation of the variables.* Regression-based methods are looking for the best predictor. In the case of highly correlated variables, probably we select only one that explains best the target variable. However, using this result for policy could be very misleading. It does not mean that the other variables are not important, and even more importantly it does not mean that policy should neglect it.

In order to evaluate the usefulness of statistical/econometric methods, in particular regressions, to policy, we should go back to the very basics. Statistical methodologies are used to provide summary/aggregate pieces of information about a data set, variables, or phenomenon, and to demonstrate the connection between the variables. Perhaps the most popular statistical method, regression analysis, is seeking to assess the (casual) relationship between a dependent variable and the independent/predictor variables (Kleinbaum et al., 2013). Being more precise, regression analysis estimates the average value of the dependent variable under the conditions of fixed independent variables. Regressions are frequently applied for decision-making, including policy suggestions.

He also opined that "the more complex the regression, the more skeptical I am" (Friedman & Schwartz, 1991).

For policy application, the size and the significance of the parameters are crucial. While frequently used, many forget about the basic assumptions of multivariable regression applicability. One of these refers to the relation between the predictor variables that should be (linearly) independent from each other. However, finding the best, unbiased, consistent, and efficient parameters is becoming increasingly difficult when we have a set of closely correlated variables. It is even more problematic to interpret the parameters.

This task is becoming increasingly difficult as we move from one variable analysis to a multivariable setting. Despite continuous improvement efforts, traditional statistical tools, like regression analysis-based techniques, have not been able to provide satisfactory results; thus, they opened a way to new methodology developments (Hoerl & Kennard, 1970; Massy, 1965; Li, 1991). Having their roots in classification and dimension-reduction techniques, composite indices are becoming more and more popular in many fields from engineering to economics, political sciences, and environmental studies (Bandura, 2008; Handbook on Composite Indicators, 2008).

Based on Condorcet's early ideas, a group of scientists have focused on aiding decision makers by ranking, sorting, or classifying the number of available alternatives (Roy, 1996; Munda & Nardo, 2009). While these tools are very useful in making decisions under incomplete information, conflicting goals, and fuzzy environmental conditions, the computation and the interpretation of the results are becoming exponentially more difficult when the number of available alternatives and criteria increases. Drawings mainly, but not exclusively, on Borda's accomplishments, social scientists have been rather looking for index numbers that describe certain social or economic phenomena (Arrow & Raynaud, 1986; Fishburn, 1973). While the main national account indicators, like the most well-known gross domestic product (GDP), could also be viewed as composite indices, the United Nation's Human Development Index (HDI) was the first complex index, providing an alternative for expressing and interpreting development (Human Development Report, 1990).

By reducing the number of variables to basically one number, composite indices are appropriate tools for providing summary information about multidimensional phenomena. If the benchmark levels of the variables are properly selected, then the performances can be tracked over time, ranked, and compared to other units/countries of interest (Handbook on composite indicators, 2008). As compared to the outranking type of decision-making approach, indices applied mainly in the field of social sciences represent relatively simpler methodology and environmental conditions. Moreover, they are easier to calculate and interpret the results. However, index scoring and the associated ranks are sensitive to theory assumptions, and even small changes in different normalization, weighting, or aggregation methods could lead to significant changes in rank, causing instability (Jacobs & Goddard, 2007; Saisana et al., 2005). Note that this criticism could also be valid for regressions where parameter significances and sometimes even signs can change by adding or removing new variables in the equation. All index builders should keep in mind Arrow's theorem claiming that it is impossible to meet with all the conflicting criteria at one time (Arrow, 1963). Only a compromised solution can be achieved.

The most important drawback is that most social science index creators do not go beyond ranking, the comparison of the items, and the basic statistical analysis of the data. All well-known indices are able to calculate a unique index number and rank the units according to this number. It is also possible to compare units and track changes over time. However, the policy alternatives, that is, the potential and optimal way of improvement of the index, are left behind the veil of ignorance. Another frequent complaint about the statistical methodologies, including indices, is their limited capability to provide not only general but also case-specific solutions for improvements. Decision makers and politicians are particularly interested in solid methodologies that provide them with useful selection criteria and tailor-made public policy tools in a multilevel system setting. In addition, they want to understand the way of index construction, its advantages, and its drawbacks. To fulfill this requirement, we need a relatively simple way of calculation by avoiding cumbersome computation algorithms and evaluating a large number of alternatives. A central aim of this chapter is to provide a relatively simple index building methodology that is suitable for tailor-made policy recommendations.

An important issue and the main address of this paper is to clarify the ultimate connections among the variables and their influence on the index score and ranking of the particular unit. The interdependency problem exists on two levels. First, it is necessary to clarify the relationship among the variables. Since the index is supposed to apply for public policy purposes, the marginal change of all variables should be equal on average. However, the different averages of the normalized variables imply that reaching the same score requires different effort and consequently resources. Higher average normalized value variables could mean that it is easier to reach as compared to lower average value variables. The same is true for the marginal improvement—improving the higher average variable is relatively easier than lower average variables. Since we want to apply the method for public policy purposes, the additional resources for the same marginal improvement of the average of the variables should be equalized. A practical solution for this problem is a transformation to equate the average values of the variables.

Second, the interdependency issue is also present on the investigated unit level. If variables are independent from each other, then a change in one variable has no effect on any other variables (the rate of substitution is zero) in the unit level. This standpoint is hardly defendable from the system point of view. Strong dependences of the variables of a particular phenomenon are very common (Handbook on composite indicators, 2008). It is also widely held that the low score (weak performance) in one variable can be compensated with a better performance in another variable (Roy, 1996; Munda & Nardo, 2009). The key is the degree of compensability. Practically, the relative weights of the variables can be viewed as the rate of substitution. Non-weighting, that is equal weighting, implies perfect, one-to-one substitutability among the variables. However, it is more realistic to assume that the relative differences between the variable values have something to do with compensability. Configuration theory, applied frequently in the organizational sciences, provides a useful approach where the harmonization of the variables is more important than having excellent score in one variable and a low score in another one (Fiss, 2007; Miller, 1986). An important note is that the equation of the marginal effects of the average pillars does not mean equal substitution of the pillars over the units. On the contrary, the substitution changes from case to case, depending on the absolute and relative size of the bottleneck as well as on the magnitude of the whole composite index.

The primary aim of this chapter is to present a dynamic index construction methodology, called the penalty for bottleneck (PFB), that incorporates the interconnection of the variables in the index. The key principle of this approach lies in a set theory assumption that the system performance is determined mainly by the weakest performing variable. The PFB directly addresses the problem of unbalance of the variables. While the harmonization issue is directly addressed and solved in the Tarabusi-Palazzi-Guarini unbalance adjustment model (UAM), there are some differences. The center of adjustment is the average in the case of UAM and the minimum in the case of the PFB. Although the solutions are methodologically equivalent, the PFB is theoretically better supported. The core element of PFB is that the weak performance of a particular variable, called a bottleneck, has a negative effect on the other variables on the index scores, and hence on the whole system. Improving the weakest link has a magnifying effect on the index score. The newly developed, unique marginal analysis is particularly useful to provide tailor-made policy recommendations.

Practical application of the PFB methodology can be manifold, from performance measurement to ranking index improvement possibilities. Applying the logic of the PFB, it is also very easy to address other situations when the system performance is determined by the best performing variable. In this study, we provide a practical example by the Global Entrepreneurship and Development Index (GEDI). We also present a policy simulation with examples of three countries to improve an optimum policy mix to improve the GEDI score by 10.

3 The Problem of Compensability of the Variables in Composite Index Construction

Most indices are created to compare different units and a rank in terms of multiple features. Since one unit is stronger in one particular feature and the other in another feature, it is necessary to find a universal way to compare and summarize them in one index number. Technically, we want the following transformation:

$$\mathbf{P} = \left[z_{ij}\right] \rightarrow \mathbf{I} = \left[I_i\right] \tag{2.1}$$

P: is a matrix of the data set containing $n \times k$ elements
n: is the number of units (country, region, firm, etc.)
k: is the number of variables
z_{ij}: is the observed value of unit i with respect to feature j
I: is a vector of the indices
I_i: is the index associated to i^{th} unit ($i = 1, 2, \ldots, n$)

Building a composite indicator is a complex task, from selecting the proper theory and variable to normalization, weighting, and aggregation (Handbook on composite indicators 2008). While all phases of index-building involve several alternatives and possibilities that affect the final index number and rank order, the most problematic issues are probably weighting and aggregation (Munda & Nardo, 2003; Zhou & Ang, 2009). Even minimal changes in the methods can have major impact on the result (Jacobs & Goddard, 2007). The selection of the weighting and aggregation methods involves an important problem that all composite indicators have to deal with—that is, the variables' degree of compensability; eventually, weighting and aggregation are the two sides of the same coin (Munda & Nardo, 2009).

On the one hand, weights show the relative importance of the variable, and on the other, they imply the degree of trade-off between the variables. When equal weighting is applied, there is a one-to-one, complete compensability between the variables. From the public policy point of view, this implies a neutrality effect; that is, the same improvement of the index can be reached by increasing any of the variables with the same absolute value.

Basically, most index aggregation techniques have their roots in social choice and multi-criteria decision-making (MCDM) theories. These aggregation methodologies can be derived from Condorcet's and Borda's rules, keeping in mind Arrow's (1963) impossibility theorem, stating that no perfect aggregation rule exists (Munda & Nardo, 2005, 2009). The other important postulate comes from the MCDM, which also denies the possibility of optimizing with respect to all the criteria. Selection of the criteria can be based on the decision makers preferences and attributes, as highlighted by numerous MCDM development methods over the decades (Roy, 1996; Dyer et al., 1992; Zhou & Ang, 2009).

Like the weighting problem, the application of the MCDM or other linear aggregation techniques also requires dealing with the compensability issue. The simplest (trivial) and most frequently applied means of aggregation is to calculate the (weighted) averages of the normalized variables (Munda & Nardo, 2005). However, using linear aggregation requires the independence of the preferences, meaning that the change in one variable's preference should have no effect on the other variables' preferences (Keeney & Raiffa, 1976). Any models based on the non-compensability assumption deny the interdependence of the variables, synergies, and the feedback effects, which is hardly realistic from the system approach point of view.

There are some solutions. The Grey relational analysis developed by Deng (1989) is an analytical methodology that dynamically compares each variable in the system. The resulting relational grade could serve to calculate a ranking order. Another possibility is to introduce the analytic hierarchy process (AHP) structure (Saaty, 1996). AHP incorporates MCDM and derives a compensation structure that makes the different alternatives comparable. However, AHP initially requires setting up the weights and the decision-making criteria. One more option is to apply the fuzzy decision-making process (Yu & Tzeng, 2006); however, the usefulness of the relatively complicated fuzzy methodology is criticized even by the father of the AHP methodology (Saaty & Tran 2007). Munda and

Saisana (2011) suggest a nonlinear, non-compensatory, multi-criteria approach. In this case, the weights emphasize the relative importance of the variables and reject any compensability. While it is a solution for the independence problem, the elimination of compensability is not really constructive from the system point of view.

Index constructors frequently meet but many times neglect to recognize the imbalance of the variables (Tarabusi & Guarini, 2013). Imbalance means significant differences over the variables. It can happen that one country is very good in several variables (criteria) but has very low scores in other variables (criteria). How does it affect ranking, or what should be the trade-off if this disparity is present? One of the solutions to handle imbalance is provided by the outranking-based multi-criteria decision-aiding (MCDA) model. Veto threshold reflects a situation when the difference of the evaluation between a variable and another variable exceeds a certain threshold (Roy, 1996; Figueira et al., 2005). However, MCDA models are based on the non-compensatory assumptions of the variables, hence denying the possibility of trade-offs between the variables. Tarabusi and Palazzi (2004) and Tarabusi and Guarini (2013) introduce the idea of the harmonization of the variables. They claim that the (normalized) variable values should be equal for harmony. If the variables deviate from the ideal (arithmetic mean) position, either positive or negative directions, then they should be penalized. The penalty increases with enlarging the deviation from the "ideal" position. This model implies a partial (incomplete) compensability between the variables with decreasing marginal rate of substitution.

Over the years, weighting and aggregation techniques have become much more sophisticated. For example, the nonlinear methodology suggested by Munda and Nardo (2009) requires to examine $N!$ number of permutations, where N is the number of units (countries). Other methods also demand cumbersome and long computations (e.g., fuzzy methods). As a result, it is becoming more and more difficult to follow an algorithm to derive the index and interpret the findings results. This is particularly true if the interconnection of the variables is examined. Moreover, the issue of compensability leads us back to the original problem. It is hard to believe that the variables of a system are independent from each other. It is equally unreasonable to assume that the variables are perfectly compensable (complete compensability) with each other (under linear aggregation rules with equal weights). Other algorithms and methods should be developed that provide reasonable rules and assume only partial compensability in the line of Tarabusi and Palazzi (2004) and Tarabusi and Guarini (2013).

4 The Penalty for Bottleneck Methodology

First, we lay down the necessary assumptions about the system of variables.

All variables should positively correlate to the complex index. If the opposite is true, then the particular variable value should be multiplied by a −1 (see in Tarabusi & Guarini, 2013). As a corollary of this statement, an increase in one variable value should not involve a decrease in any other variable value. The performance of one unit in the system in terms of the variables is determined by the weakest performing variable. All other variables depend only on the weakest performing variable. In this sense, the weakest link variable behaves as a "dictator" over the other variables. The strength of dictatorship depends on the difference between the weakest link variable and the other variables.

The variables have a partial compensability with each other. The bad performance of the bottleneck (the lowest value variable) only provides an imperfect compensation with another better performing variable in the system.

Now, let's recall Eq. (2.1), where we have matrix **P** with n units and k variables. We want a transformation that condenses the k variables into one. To calibrate the different variables into the same range, we normalize the feature values to a [0,1] range as described in the following equation,[1]

$$x_{ij} = \frac{z_{ij}}{\max_i\left(z_{ij}\right)}, \tag{2.2}$$

where

x_{ij}: is the normalized value of j^{th} variable for unit i
z_{ij}: is the observed value of j^{th} variable for unit i
$\max_i(z_{ij})$: is the maximum value for j^{th} variable

The same normalization has to be done for all the k number of variables.

The different averages of the normalized values of the k variables imply that reaching the same performance requires different effort and consequently resources. Higher average values could mean that it is easier to reach as compared to lower average value. Since we want to apply the method for public policy purposes, the additional resources for the same marginal improvement of the average variable values should be the same for all the k variables. Therefore, we need a transformation to equate the average values of the k variables.

The arithmetic average of variable j for n units is

$$\overline{x}_j = \frac{\sum_{i=1}^{n} x_{ij}}{n} \text{ for all } j. \tag{2.3}$$

We want to transform the x_{ij} values such that the potential values stay in the [0,1] range, and the average of the transformed values is the desired $\overline{y}_j$

$$y_{ij} = x_{ij}^{r}, \tag{2.4}$$

where r is the "strength of adjustment." So, we have to find the root of the following equation for r

$$\sum_{i=1}^{n} x_{ij}^{r} - n\overline{y}_j = 0 \tag{2.5}$$

It is easy to see, based on previous conditions and derivatives, that the function is decreasing and convex, which means it can be quickly solved using the well-known Newton–Raphson method with an initial guess of 0. After obtaining r, the computations are straightforward. Note that if

$$\begin{aligned} \bar{x}_j &< \bar{y}_j \quad r < 1 \\ \bar{x}_j &= \bar{y}_j \quad r = 1, \\ \bar{x}_j &> \bar{y}_j \quad r > 1 \end{aligned}$$

that is r can be thought of as the strength (and direction) of adjustment. This transformation can be performed for all variables.

Now we define the variability with the range, called a bottleneck, which is the difference between the value of actual feature and the value of the worst feature.

The elements of the bottleneck matrix (**R**) can be defined as:

$$R_{ij} = y_{ij} - \min_j \left(y_{ij} \right) \tag{2.6}$$

The goal is to create an index that penalizes the bottleneck as:

$$\begin{aligned} \bar{y}_i^{(p)} &\le \bar{y}_i \\ \bar{y}_i - \bar{y}_i^{(p)} &\sim \max_j \left(R_{ij} \right) \end{aligned} \tag{2.7}$$

Starting from now, we are working with only one unit, so we are not representing index i.

Now, we apply a penalty function in general form:

$$y_j^{(p)} = \min_j \left(y_j \right) + f\left(R_j \right), \tag{2.8}$$

where $f(.)$ is the penalty function.

While this penalty function is similar to Tarabusi and Palazzi (2004) and Tarabusi and Guarini (2013), our approach calculates deviation from the minimum, and not from the arithmetic mean value, that is theoretically more correct. Among others, the Theory of Weakest Link (TWL) (Yohe & Tol, 2001; Tol & Yohe, 2006) and the Theory of Constraints (TOC) (Goldratt, 1994) provide solid theoretical arguments. In the line of the PFB, these theories argue that the performance of the system depends on the element that has the lowest value in the structure.

The basic implication of the penalty function is that bottlenecks, that is, large deviations in different variable values, can have a negative effect on the particular variable having higher value. The penalty function also reflects the compensation of the loss of one pillar for a gain in another pillar.

The marginal rate of compensation (MRC) is defined as:

$$MRC_{ij} = \frac{dy_i}{dy_j} \tag{2.9}$$

Full compensability means that a loss in one pillar can be compensated by the same increase in another pillar. However, this is not realistic. The MRC is the same concept as the Marginal Rate of Substitution for goods and to the Marginal Rate of Technical Substitution of inputs (Tarabusi & Guarini, 2013) that are reflected to the law of diminishing return. Therefore, the effect of the change of the penalty should not be proportional, reflecting to the increasing rate of MRC. It means that we require higher compensation for the loss in one pillar if the difference between another pillar value and the particular pillar is higher. The required positive value of the second derivative means that the pillars are just only partially, and not fully, compensable with each other. So the penalty should increase in an increasing rate:

$$\frac{dMRC_{ij}}{dy_j} > 0 \tag{2.10}$$

The penalty function must fulfill the following two properties: $f(0) = 0$ then $[\min_j(y_j)]^{(p)} = y_j$, and the slope measured as the tangent over the closed interval of [0; 1] is less than 1.

The index value representing the overall performance of one country over the k variables is calculated as the arithmetic mean (hereafter mean) after applying the PFB methodology[2]:

$$\bar{y}^{(p)} = \frac{1}{k}\sum_{j=1}^{k} y_j^{(p)} = \min_j\left(y_j\right) + \frac{1}{k}\sum_{j=1}^{k} f\left(y_j - \min_j\left(y_j\right)\right) \tag{2.11}$$

The value of the index is mainly determined by the variable with the worst value, which can be considered the weakest link among all the variables. The size of the penalty depends on the difference between the value of the worst variables and the value of the particular variable: the higher the difference, the higher the penalty.

Following from the above logic, the penalty function has good properties if it fits the aforementioned conditions, and if the average of the after-penalty values over the features is not larger than the initial average value of the features:

$$\begin{gathered} k \times \min_j\left(y_j\right) + \sum_{j=1}^{k} f\left(y_j - \min_j\left(y_j\right)\right) \le \sum_{j=1}^{k} y_j \\ \min_j\left(y_j\right) + \frac{1}{k}\sum_{j=1}^{k} f\left(y_j - \min_j\left(y_j\right)\right) \le \frac{1}{k}\sum_{j=1}^{k} y_j \end{gathered} \tag{2.12}$$

Now, we are defining a concrete penalty function as:

$$f\left(R_j\right) = a\left(1 - \mathrm{e}^{-bR_j}\right), \tag{2.13}$$

where $0 \le a, b \le 1$ are the penalty parameters, and the basic setup is $a = b = 1$.

Therefore, after penalty:

$$y_j^{(p)} = \min_j\left(y_j\right) + \left(1 - \mathrm{e}^{-R_j}\right) \tag{2.14}$$

Equation (2.14) represents the creation of a unique index number for each unit$i$ as calculated from k variables, by taking into account the one minus the differences between the value of variable j and the lowest value of all of the variables on the base of the natural logarithm.

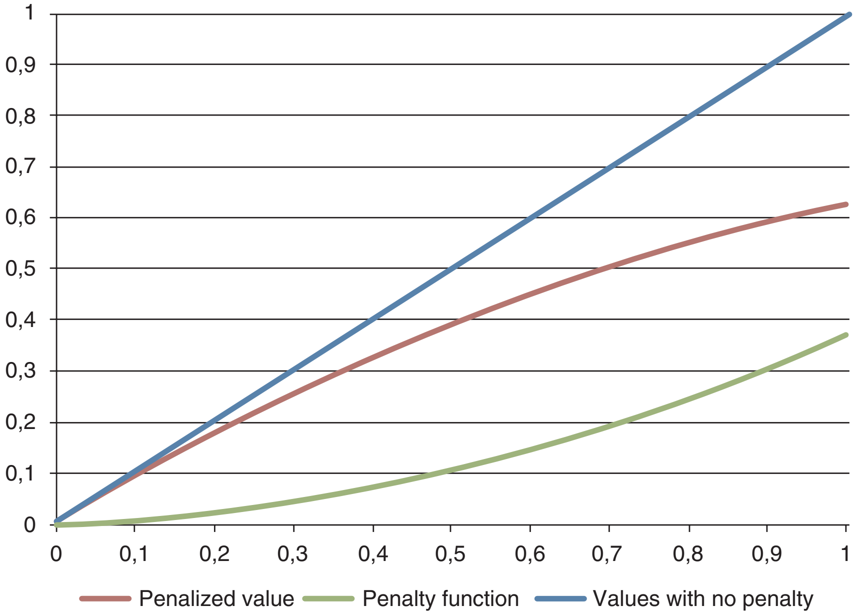

Fig. 2.1 Penalty function, the penalized values, and the values with no penalty ($\min_j(y_j) = 0, a = b = 1$)

If we illustrate it in a graph, then the original values (blue line) and the after-penalty values (brown and red lines) can be seen. The red line represents the case when the worst variable value is the minimum (0), and the green line represents the magnitude of the penalty. In this case, the maximum penalty is 0.368 (Fig. 2.1).

The bottleneck is not penalized any more:

$$\left[\min_j\left(y_j\right)\right]^{(p)} = \min_j\left(y_j\right) + \left(1 - e^0\right) = \min_j\left(y_j\right) \tag{2.15}$$

The slope of the penalty function is:

$$\frac{1}{e} \le \frac{\partial\left(1 - e^{-R_j}\right)}{\partial R_j} = e^{-R_j} \le 1 \tag{2.16}$$

The sum of the feature values after penalty is presented in Eq. (2.17) as:

$$\sum_{j=1}^{k} y_j^{(p)} = k \times \min_j\left(y_j\right) + \sum_{j=1}^{k}\left[1 - \mathrm{e}^{-\left(y_j - \min_j\left(y_j\right)\right)}\right] \leq \sum_{j=1}^{k} y_j \qquad (2.17)$$

because of the properties of the penalty function.

The range of the feature values after penalty is presented in Eq. (2.18)

$$\left[\max_j\left(y_j\right)\right]^{(p)} - \left[\min_j\left(y_j\right)\right]^{(p)} \leq \max_j\left(y_j\right) - \min_j\left(y_j\right), \qquad (2.18)$$

because

$$1 - \mathrm{e}^{-\left(\max_j\left(y_j\right) - \min_j\left(y_j\right)\right)} \leq \max_j\left(y_j\right) - \min_j\left(y_j\right). \qquad (2.19)$$

Now, let's summarize the properties of the PFB:

1. The bottleneck, that is, the worst performing variable, is unit-specific, changing from one unit to another.
2. The bottleneck is not penalized.
3. The size of the penalty depends on the difference between the particular variable and the lowest value variable; the larger the difference, the larger the penalty.
4. The index can be improved the most by increasing the lowest value, the "bottleneck" variable. The magnitude of the improvement has a multiplicative effect on all the other variables depending on the differences between the bottleneck and the second, the bottleneck and the third, and so on, variables. As a result, we have a multivariate rather than a univariate marginal analysis tool.
5. If all variables have the same value in the system, then there is no penalty; the system is optimal in terms of the PFB methodology.
6. Improving any other variable than the bottleneck has no effect on the other variables.

5 Distribution of the Additional Resources

Most index constructors finish when they calculate the index values and pay less attention to how it should be used for policy purposes. Basically, we want to answer to the following question: Which variable should be improved to achieve the largest increase in the index? If there is a complete compensability among the variables, then the same increase of any of the variables results in the same improvement in the index, under the conditions of equal weighing. However, this is not the case under the penalty assumption.

Let us assume that it is possible to involve new resources in the system. If we calculate the average value of the k variables, then it is not significant which variable we are improving. However, the situation is different if we apply the PFB methodology with the penalty function. In the following, we investigate the case of optimal additional resource allocation under the conditions of penalty function.

We assume that the features can be improved by Δ, altogether. The sum of the modified values denoted by y_j without penalty is given as follows

$$\sum_{j=1}^{k} \tilde{y}_j = \Delta + \sum_{j=1}^{k} y_j \tag{2.20}$$

The sum of the value of modified values represented by Eq. (2.20) is independent of which features are improved.[3]

However, the sum of the after-penalty modified value, denoted by $\tilde{y}_j^{(p)}$, depends on the preference of the distribution of the additional resource. Let's denote the value of the additional resource to the j^{th} variable by Δ_j

$$\sum_{j=1}^{k} \Delta_j = \Delta \tag{2.21}$$

In this case, the sum of the after-penalty modified values is given in Eq. (2.22):

$$\sum_{j=1}^{k} y_j^{(p)} = k \times \left(\min_j\left(y_j\right) + \Delta_{\min_j\left(y_j\right)}\right) + \sum_{j=1}^{k}\left[1 - \mathrm{e}^{-\left(y_j - \min_j\left(y_j\right) + \Delta_j - \Delta_{\min_j\left(y_j\right)}\right)}\right] \tag{2.22}$$

We want to maximize Eq. (2.22) with respect toΔ_j, maintaining the restriction described in Eq. (2.17), and to solve the following equation:

$$\frac{\partial\left[\sum_{j=1}^{k} y_j^{(p)}\right]}{\partial\left(\Delta_1, \Delta_2, \ldots, \Delta_k\right)}\Bigg|\left(\sum_{j=1}^{k}\Delta_j = \Delta\right) = 0 \tag{2.23}$$

If we assume that $k = 2$, then the solution is simple (let $y_1 \leq y_2$):

$$\begin{aligned}
\sum_{j=1}^{k} y_j^{(p)} &= 2 \times \left(y_1 + \Delta_1\right) + \sum_{j=1}^{2}\left[1 - \mathrm{e}^{-\left(y_j - y_1 + \Delta_j - \Delta_1\right)}\right] \\
&= 2 \times \left(y_1 + \Delta_1\right) + 1 - \mathrm{e}^{-\left(y_2 - y_1 + \left(\Delta - \Delta_1\right) - \Delta_1\right)} \\
\frac{\partial\left[2y_1 + 2\Delta_1 + 1 - \mathrm{e}^{-\left(y_2 - y_1 + \Delta - 2\Delta_1\right)}\right]}{\partial\Delta_1} &= 2 - 2\mathrm{e}^{-\left(y_2 - y_1 + \Delta - 2\Delta_1\right)} = 0 \\
y_2 - y_1 + \Delta - 2\Delta_1 &= 0 \\
\Delta_1 &= \frac{y_2 - y_1 + \Delta}{2}
\end{aligned} \tag{2.24}$$

and the result is

$$\begin{aligned}
\Delta_1 &= \frac{\Delta}{2} + \frac{y_2 - y_1}{2} \\
\Delta_2 &= \frac{\Delta}{2} - \frac{y_2 - y_1}{2}
\end{aligned} \tag{2.25}$$

From (25), the marginal rate of substitution between the two variables is the following:

$$\frac{\Delta_2}{\Delta_1} = \frac{\Delta - (y_2 - y_1)}{\Delta + (y_2 - y_1)} \leq 1 \tag{2.26}$$

The above relation is fulfilled, since $0 \leq \Delta$ and $y_1 \leq y_2$both have been previous assumptions. According to Eq. (2.26), the marginal rate of substitution decreases as the difference between the two variables increases, similar to standard microeconomic literature about the marginal rate of substitution between the goods and the technical rate of substitutions between outputs (Tarabusi & Guarini, 2013).

Since we want to apply all of the additional resources and do not want to allow redistribution of the resources, the modified values should not be negative. Therefore, we introduce a limit as $0 \leq \Delta_2$. Therefore, if $\Delta \leq y_2 - y_1$, then $\Delta_1 = \Delta$. Table 2.1 represents the solution for$k = 2$:

Applying the full induction, it can be proved that during the distribution of the additional resources, the methodology of filling from the bottom should be used. Improving the score of the weakest variable will have a greater effect on the index than improving the score of a stronger variable. Traditional marginal analyses are univariate, based on the ceteris paribus assumption, meaning that all other variables except one must hold constant. Our multivariable marginal analysis alleviates from the ceteris paribus assumption. It means that for reaching an optimal solution, we may need to change more than one variable.

Table 2.1 The redistribution of the additional resources in the case of two variables

Case	Δ	$\tilde{y}_1$	$\tilde{y}_2$	Sum with additional resources without penalty	Sum with additional resources with penalty
1	$\Delta \leq y_2 - y_1$	$y_1 + \Delta$	y_2	$y_1 + y_2 + \Delta$	$2\times(y_1+\Delta)+1-e^{-(y_2-y_1-\Delta)}$
2	$y_2 - y_1 < \Delta$	$y_1 + \frac{y_2 - y_1}{2} + \frac{\Delta}{2}$	$y_1 - \frac{y_2 - y_1}{2} + \frac{\Delta}{2}$	$y_1 + y_2 + \Delta$	$y_1 + y_2 + \Delta$

6 Application of the Penalty for Bottleneck to the Global Entrepreneurship and Development Index[4]

The GEDI project was initiated by Zoltán J. Ács and László Szerb in 2008 to provide a suitable measure of the national-level entrepreneurship. The first global report including the analysis of 71 countries appeared in 2011. Since then, there have been three reports of GEDI using former versions of the PFB methodology (Acs & Szerb, 2011, 2012; Acs et al., 2013b). The GEDI is based on the following four presumptions:

1. Since entrepreneurship is a multidimensional phenomenon, traditional single variables are not proper to measure it correctly. Hence, there is a need to develop a complex entrepreneurship measure.
2. Entrepreneurship components should reflect the quality rather than the quantity aspects. In addition, besides individual components, the contextual country-level environmental/factors are equally important. Basically, the institutional setup determines the effectiveness of the individual effort. As a consequence, we aim to measure not the whole supply of entrepreneurship but only its productive part.
3. The components of entrepreneurship constitute a system of mutually interrelated elements. The effectiveness of the system of entrepreneurship in the country level depends on its weakest performing component(s).
4. The “one size fits to all” entrepreneurship policy recommendations are misleading. On the contrary, index-based policy suggestions should be “tailor-made,” reflecting country-specific conditions.

Following Acs et al. (2013a), we define national entrepreneurship as the dynamic, institutionally embedded interaction between entrepreneurial attitudes, abilities, and aspirations, by individuals, which drives the allocation of resources through the creation and operation of new ventures. Attitudes, abilities, and aspirations are complex categories which include individual and institutional (contextual) measures.

According to this definition, we propose four-level index-building: (1) variables, (2) pillars, (3) sub-indices, and, finally, (4) the super-index. All three subindices contain several pillars, which can be interpreted as quasi-independent building blocks of this entrepreneurship index. The three subindices of attitudes, abilities, and aspiration constitute the entrepreneurship super-index, which we call the Global Entrepreneurship and Development Index.

The structure of the GEDI is described in Table 2.2.

While the abilities and aspiration subindices (outlined below) capture actual entrepreneurship abilities and aspiration as they relate to nascent and start-up business activities, the entrepreneurial attitude (ATT) subindex aims to identify the attitudes of a country's population as they relate to entrepreneurship. For example, the pillar known as opportunity perception potential is essential to recognizing and exploring novel business opportunities. It is also critical to have the proper start-up skills and personal networks to exploit these opportunities. Moreover, fear of failure to start a business can have a negative effect on entrepreneurial attitudes, even when opportunity recognition and start-up skills exist. Entrepreneurial attitudes are believed to be influenced by the crucial institutional factors of market size, level of education, level of risk in a country, the population's rate of Internet use, and culture, all of which are interaction variables of the indicator.

The entrepreneurial abilities (ABT) subindex is principally concerned with measuring some important characteristics of the entrepreneur and the start-up with high growth potential. This high growth potential is approached by quality measures, including opportunity motivation for start-ups that belong to a technology-intensive sector, the entrepreneur's level of education, and the level of competition. The country-level institutional variables include the freedom to do business, the technology absorption capability, the extent of staff training, and the dominance of powerful business groups. Moreover, gender equality of opportunities and female business start-ups are also desirable social and economic goals, so we included the share of female-to-male TEA ratio and the equal opportunity institutional variable in the entrepreneurial abilities subindex.

Table 2.2 The structure of the Global Entrepreneurship and Development Index

Global Entrepreneurship and Development Index									
Entrepreneurial Attitudes Sub-Index									
Pillars									
Opportunity Perception		**Start-up Skills**		**Nonfear of Failure**		**Networking**		**Cultural Support**	
Variables									
Market Agglomeration	Opportunity Recognition	**Tertiary Education**	Skill Perception	**Business Risk**	Risk Acceptance	**Internet Usage**	Know Entrepreneurs	**Corruption**	Career Status
Entrepreneurial Abilities Sub-Index									
Pillars									
Opportunity Startup		**Gender**		**Tech Sector**		**Quality of Human Resources**		**Competition**	
Variables									
Freedom	Opportunity Motivation	**TEA Femalr**	Female Opportunity	**Tech Absorption**	Technology Level	**Staff Training**	Educational Level	**Market Dominance**	Competitors
Entrepreneurial Aspirations Sub-Index									
Pillars									
Product Innovation		**Process Innovation**		**High Growth**		**Internationalization**		**Risk Capital**	
Variables									
Technology Transfer	New Product	**GERD**	New Tech	**Business Strategy**	Gazelle	**Globalization**	Export	**Depth of Capital Market**	Informal Investment

Note: The GEDI is a super-index made up of three subindices, each of which is composed of several pillars. Each pillar consists of an institutional variable (denoted in **bold**) and an individual variable (denoted in bold italic)

The entrepreneurial aspiration (ASP) subindex refers to the distinctive, qualitative, strategy-related nature of entrepreneurial activity. Entrepreneurial businesses are different from regularly managed businesses; thus, it is particularly important to be able to identify the most relevant institutional and other quality-related interaction variables. The newness of a product and of a technology, internationalization, high growth ambitions, and informal finance variables are included in this subindex. The institutional variables measure the technology transfer and R&D potential, the sophistication of a business strategy, the level of globalization, and the availability of venture capital.

For the 2012 year country investigation and ranking, the individual variables are calculated by including 377,648 individuals from 89 countries of the Global Entrepreneurship Monitor (GEM) Adult Population Survey. Sixty-seven countries' individual data are from the 2011–2012 years, and 21 countries have individual data from the pre-2010 years. We estimated the individual variables for 33 countries by using nearby and similar country GEM Adult Population Survey data. All the institutional variables are from surveys other than the GEM; most of them are from the Global Competitiveness Index (GCI), others are from the Doing Business Index or the Index of Economic Freedom, or from multinational organizations such as the United Nations, the Industrial Development Organization, or the Organization for Economic Co-operation and Development (OECD). While we tried to find a single institutional variable for each of the individual variables, it sometimes was not possible. Therefore, some of these institutional variables are themselves complex "indices." As compared to the previous versions, we changed the GCI-related venture capital variable to the depth of capital market variable (Groh et al., 2012) that is a more proper measure of the financial market development than venture capital.

For the calculation of the GEDI 2012 country scores, follow seven points:

1. We calculate all pillars from the variables using the interaction variable method, that is, by multiplying the individual variable with the proper institutional variable (see Table 2.2)
2. Pillar values are capped to the 95% value by using the whole 2006–2012 data with 355 observations.

3. Capped pillar values are normalized by using the distance method (using Eq. (2.2)).
4. The 15 pillar averages are equated to have the same marginal effect (using Eqs. (2.3) and (2.5)).
5. The PFB is applied to get the PFB adjusted values for all of the 15 pillars (using Eqs. (2.13) and (2.14)).
6. We calculate the values of the entrepreneurial attitudes, entrepreneurial abilities, and entrepreneurial aspirations subindex. The value of a subindex for any country is the arithmetic average of its PFB-adjusted pillars for that subindex multiplied by a 100. The maximum value of the subindices is 100 and the potential minimum is 0, both of which reflect the relative position of a country in a particular subindex.
7. Finally, the super-index, the Global Entrepreneurship and Development Index, is simply the average of the three subindices.

The received scores and the rank of the countries can be found in Table 2.3. By no surprise innovation-driven countries are on the top of the list. The United States leads the rank, followed by the Anglo-Saxon Australia. Nordic countries are also in a privileged position: Denmark, Sweden, and Finland are all in the top ten, and Iceland is eleventh. The Netherlands and Switzerland are also among the most entrepreneurial nations of the world. Taiwan, the best Asian country, is sixth place, and Singapore is tenth. At the same time, lower developed factor-driven countries with low GDPs, such as Pakistan, Uganda, most poor African countries, and Bangladesh, are on the bottom of the entrepreneurship ranking.

The connection between development, measured by the per capita GDP and GEDI scores, is depicted in Fig. 2.2. The mild "S" shape of the trend line and the high R2 of 0.76 imply a close relation between entrepreneurship and development.

7 A Policy Simulation for the Optimal Improvement of GEDI

Below, we present a further potential application of the PFB methodology. As proved previously, improvement of the whole index score depends on which component is selected to upgrade. The PFB simulates the

Table 2.3 The Global Entrepreneurship and Development Index (rank of countries for 2012)

Rank	Country	GEDI	Rank	Country	GEDI	Rank	Country	GEDI
1	United States	82.5	41	Czech Republic	44.6	81	Trinidad & Tobago	30.4
2	Australia	77.9	42	Hungary	44.5	82	Ukraine	30.2
3	Sweden	73.7	43	Kuwait	44.3	83	Morocco	29.5
4	Denmark	72.5	44	Malaysia	44.1	84	Ecuador	29.3
5	Switzerland	70.9	45	Saudi Arabia	43.5	85	Algeria	29.1
6	Taiwan	69.5	46	China	41.6	86	Swaziland	29.0
7	Finland	69.3	47	Peru	41.3	87	Paraguay	28.9
8	Netherlands	69.0	48	Italy	40.9	88	Angola	28.7
9	United Kingdom	68.6	49	Croatia	40.9	89	Philippines	28.5
10	Singapore	67.9	50	South Africa	40.4	90	Zambia	28.4
11	Iceland	67.5	51	Cyprus	40.3	91	Bosnia and Herzegovina	27.8
12	France	67.2	52	Montenegro	39.5	92	Venezuela	26.4
13	Belgium	66.5	53	Brunei Darussalam	39.3	93	Ghana	26.3
14	Norway	65.1	54	Lebanon	38.9	94	Egypt	25.2
15	Chile	65.1	55	Barbados	38.5	95	Senegal	24.8
16	Germany	64.6	56	Argentina	38.4	96	Benin	24.7
17	Austria	64.0	57	Mexico	38.2	97	Cameroon	24.7
18	Ireland	61.8	58	Greece	37.8	98	Liberia	24.5
19	Puerto Rico	61.7	59	Tunisia	37.2	99	Iran	24.2
20	Israel	59.7	60	Costa Rica	37.2	100	Honduras	24.0
21	Estonia	59.0	61	Namibia	36.8	101	Kenya	23.8
22	Slovenia	52.7	62	Macedonia	36.2	102	Tanzania	22.5
23	Qatar	52.7	63	Botswana	35.6	103	Nicaragua	22.1
24	Colombia	49.8	64	Thailand	35.5	104	Mozambique	21.1
25	Lithuania	49.6	65	Panama	34.8	105	Rwanda	21.1
26	Poland	49.1	66	Dominican Republic	34.3	106	Gambia	21.0
27	Latvia	48.4	67	Indonesia	34.3	107	Malawi	20.9
28	UAE	48.3	68	Serbia	34.0	108	Guatemala	20.7
29	Oman	47.6	69	Russia	33.2	109	Burkina Faso	19.9
30	Portugal	46.9	70	Gabon	32.8	110	Ethiopia	19.8
31	Spain	46.9	71	Albania	32.6	111	Madagascar	19.6
32	Korea	46.7	72	Jordan	31.7	112	Côte d'Ivoire	19.4
33	Hong Kong	46.6	73	Nigeria	31.6	113	Uganda	19.3
34	Slovakia	46.6	74	Jamaica	31.4	114	Mali	18.8
35	Japan	46.1	75	India	31.3	115	Pakistan	18.7
36	Bulgaria	45.5	76	Moldova	31.2	116	Mauritania	18.5
37	Bahrain	45.4	77	Bolivia	31.1	117	Sierra Leone	17.6
38	Uruguay	45.3	78	El Salvador	31.0	118	Burundi	15.5
39	Turkey	44.7	79	Kazakhstan	30.6	119	Chad	15.0
40	Romania	44.6	80	Brazil	30.4	120	Bangladesh	13.8

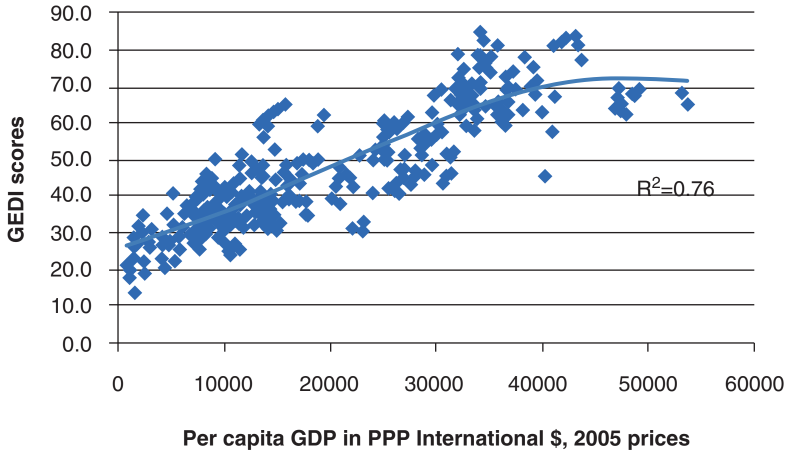

Fig. 2.2 The connection between GEDI scores and development, measured by the per capita GDP, 2006–2012 (third degree polynomial adjusted trend-line). Note: Per capita GDP in PPP in 2005 constant international dollars, World Bank. Number of observations = 347. The United Arab Emirates, as an outlier, has been removed while calculating the trend line

notion of a bottleneck; if the weakest pillar is improved, the overall GEDI should show significant improvement. The suggested policy recommendation is clear: improve the weakest pillar because it has a magnifying effect on the other variables and ultimately on the whole index. Remember, our methods allow the multivariate marginal analysis. However, the magnitude of the improvement is sensitive to the following assumptions:

1. The improvement depends not only on the weakest pillar value but also on the differences between the weakest and the second weakest pillar, the differences between the second and the third weakest pillar values, and so on. The largest improvement can be achieved if a country has one weak point, and after the adjustment there will be no other bottleneck pillar value. In cases where there are more bottlenecks, the additional resources should be divided among the weak pillars, if it is allowed.
2. Another question is whether we tolerate the additional resource to be distributed among the weaker pillars, or assume that only one pillar

value can be improved. If distribution is allowed, then the magnifying effect can be larger, depending on the conditions described in the previous point.
3. A different constellation emerges if we allow optimization of the whole system at the cost of worsening the best variable. The optimal solution is when there is no bottleneck—that is, all the pillar values are the same.
4. The improvement also depends on the relative weight of the pillars: Higher weight of the bottleneck could result in more significant improvement, while lower weight could mean minimal progress.

It is important to note that the following simulation has certain limitations, especially interpreting as a public policy recommendation. First, the applied 15 pillars of GEDI only partially reflect the whole national system of entrepreneurship. Therefore, the maximization of the GEDI score of a particular country does not mean maximizing the whole system. Second, while we have equalized the different pillar averages for all GEDI pillars to equate the marginal improvement effect over the 15 pillars, this might well not be true about the cost of improvement. In fact, these costs may vary significantly over pillars (Autio et al., 2012). Third, we set aside the differences in country size by presuming that the same effort is necessary to improve the GEDI over all the countries. Of course, the cost of an improvement of a pillar in larger country like Germany could be considerable higher than in a smaller country like Slovenia.

Here, we examine the result of the simulation to increase the GEDI scores by 10. We selected three countries as examples: Slovenia that has basically one bottleneck, Japan with more bottlenecks, and the United States where pillars are balanced. Table 2.4 shows the situation before the improvement has taken place, the required increase in the particular pillars (in absolute values and in percentages), and the improved version after adjustment.

Slovenia, a relatively small country of the European Union, has one major bottleneck, that is, opportunity perception (0.15 scores). Therefore, Slovenia should turn most of its new resources (93%) to improve its weakest pillar, and only 7% of the new resources should be spent to enhance the second weakest pillar, that is, gender.

Japan's entrepreneurial performance is more balanced than Slovenia's. However, balanced performance also means that Japan has more bottlenecks. Japan needs to alleviate first start-up skills, but then opportunity perception is becoming its bottleneck very soon. For optimization, 72% of the new resources are required to improve these two pillars. In order to reach the 10 point increase in its GEDI points, Japan needs to raise three other pillars: gender, networking, and internationalization. The required improvement of the latest two pillars is only marginal, 3 and 2%, respectively.

The United States, the leading country, has its entrepreneurial performance well balanced. Its weakest pillar value is networking, with 0.61 score. Altogether, the US needs to enhance eight of its pillars to improve its GEDI scores by 10. As a result, the weakest pillar values of the US would be 0.90. Moreover, due to the improvement, instead of one bottleneck, the US will have 10 bottlenecks. At the same time, the size of the bottleneck will be lower as compared to the previous situation.

Table 2.4 also prevails that the mitigation of one bottleneck requires significantly less resources as compared to the situation when two or even more bottleneck exist. Aside from the country-size effect and assuming the equal marginal improvement of the 15 pillars on average, Slovenia needs half of the resources for the same 10 point improvement as Japan does. The US has to turn 40% more resources as compared to Japan to improve eight pillars and increase the US GEDI score from 82.5 to 92.4.

8 Summary and Conclusion

The aim of this chapter is to present an amended methodology of composite index construction that takes into account the interrelation of the different elements (variables) under the assumption of imperfect compensability. The most frequently applied traditional way of combining the elements of the index is to take the arithmetical averages of the components. In this case, the enhancement of the index point therefore does not depend on which element is improved. Moreover, this methodology assumes the perfect compensability of the elements.

Table 2.4 Simulation: Required improvement of the pillar values to increase the GEDI scores by ten

	Slovenia				Japan				United States			
Pillar	1	2	3	4	1	2	3	4	1	2	3	4
Opportunity perception	**0.15**	0.28	93%	**0.43**	0.18	0.19	32%	**0.37**	1.00	0	0%	1.00
Start-up skills	1.00	0	0%	1.00	**0.13**	0.24	40%	**0.37**	1.00	0	0%	1.00
No-fear of failure	0.51	0	0%	0.51	0.69	0	0%	0.69	0.70	0.20	20%	**0.90**
Networking	0.76	0	0%	0.76	0.34	0.03	5%	0.37	**0.61**	0.29	28%	**0.90**
Cultural support	0.56	0	0%	0.56	0.43	0	0%	0.43	0.83	0.07	7%	**0.90**
Opportunity start-up	0.78	0	0%	0.78	0.62	0	0%	0.62	0.75	0.15	15%	**0.90**
Gender	0.41	0.02	7%	**0.43**	0.25	0.12	20%	**0.37**	0.89	0	0%	**0.90**
Tech sector	1.00	0	0%	1.00	0.79	0	0%	0.79	0.81	0.09	9%	**0.90**
Quality of human resources	0.61	0	0%	0.61	0.98	0	0%	0.98	0.95	0	0%	0.95
Competition	0.54	0	0%	0.54	0.48	0	0%	0.48	1.00	0	0%	1.00
Product innovation	0.64	0	0%	0.64	0.76	0	0%	0.76	0.86	0.04	4%	**0.90**
Process innovation	0.78	0	0%	0.78	0.99	0	0%	0.99	0.90	0	0%	**0.90**
High growth	0.64	0	0%	0.64	1.00	0	0%	1.00	0.88	0.01	1%	**0.90**
Internationalization	0.80	0	0%	0.80	0.35	0.02	3%	**0.37**	0.72	0.17	17%	**0.90**
Risk capital	0.52	0	0%	0.52	0.57	0	0%	0.57	0.97	0	0%	0.97
Sum		0.3	100%			0.6	100%			1.02	100%	
Number of pillars changed		2				5				8		
GEDI score	52.7		62.6		46.1			56.0	82.5			92.4

1. The original pillar values; 2. The required increase in the particular pillar; 3. The share of the required new resources in percentages; 4. The new pillar scores after adjustment. Bold: The bottleneck pillar. The dark shade reflects to the magnitude of the improvement: Darker color means more additional resources

The PFB method is based on the assumptions that (1) the elements of the system should positively correlate to the summary index number; (2) the performance of the system depends on the weakest link; and (3) the elements of the system cannot all be perfectly substituted for each other. The suggested simple analytical method of index construction has the additional advantage of not being sensitive to sample size. The PFB could rearrange the rank order of the investigated units in a particular feature. The level of the rearrangement depends on the differences between the bottleneck and the other variables. If every unit has similar differences in terms of features, then the rank order does not change much; if one unit is much less balanced than the others, then a lower rank can be expected for that particular unit. The policy message is that weak performance on a particular feature—that is, a bottleneck—should be handled first because it has the most negative effect on all the other features.

The first practical application of the PFB methodology was the creation of the Global Entrepreneurship and Development Index (Acs & Szerb, 2011, 2012). While we believed being the first with the idea of balanced performance and the application of the penalty function, later we recognized Tarabusi and Palazzi (2004) and Tarabusi and Guarini (2013) having the same idea. While the PFB and the Tarabusi-Palazzi-Guarini unbalance adjustment method (UAM) is very similar to each other, the major difference is that PFB calculates deviation from the minimum and not from the arithmetic mean value that first is being theoretically more correct. It is easy to create functions in addition to our weakest link assumption where performance is based not on the weakest link but on the best performance. However, this application requires solid theoretical foundation.

We believe that our PFB methodology has some advantages as (a) it is potentially more general, (b) the minimum adjustment is theoretically superior to the average adjustment principle, (c) the index calculation is simple, making it attractive even to nonexperts, (d) the interpretation of the results is straightforward, and (e) it is able to provide an additional multivariate marginal analysis for the optimal improvement of the index that is vital for tailor-made public policy recommendations. Moreover, we have provided an additional methodological improvement of the equalization of the variable averages technique to equate the marginal improvements of the pillars. The GEDI, the first complex, system-based entrepreneurship index, served as an example to present the practical applicability of average equalization and of the PFB, and to show the resulted public-policy portfolio that optimizes the GEDI scores. A simulation of three countries showed the potential of further policy application of the new technique.

Like any methodology, the PFB has also some disadvantages. First, the assumption of the measure of penalty is an axiom, but, for example, in the case of variance, similar ad hoc assumptions are made by economists. Further research and case-to case investigation are necessary to identify the best penalty function. Second, the methodology assumes that benchmarks are properly selected. Extreme values or outliers can result in particularly bad index values and incorrect rank order. To overcome this drawback, we used the 95% capping in the calculation of the GEDI scores. Note, the regression techniques, in a varying degree, are also sensitive to outliers. Third, all the variables should correlate positively to the overall index. Fourth, we provided a method to equalize the marginal effects of improvements. However, the equalization of the marginal effects does not mean the equalization of the cost of improvement since it would require including country-size effect and the equalization of the cost of the pillars on average. While the PFB seems to be a proper tool to identify bottlenecks, to set up policy proprieties, and to provide a policy-portfolio mix from the system perspective, these shortcomings somehow limit the sole and single use of PFB for public policy purposes. Indeed, PFB methodology results should be used together with other results and statistics. Autio et al.'s (2012) study about the analysis of the United Kingdom's entrepreneurial performance is a good example about the proper application of the GEDI methodology.

The further potential of the PFB methodology is enormous. This methodology is a proper tool not just for index-building but also for formulating strategy at the level of an individual firm. Szerb and Terjesen (2010) used it to present alternative penalty function cases to measure firm competitiveness. In any case, the PFB method can be useful when we want to measure and examine the performance of a complex system in which the elements are not independent of each other. A further major advantage of the method is the system-based multivariate marginal analysis that provides a policy-portfolio mix for optimizing the additional resources in a tailor-made manner, individually for all the individual units. Regression techniques are able only to identify the most important variables and make possible univariate marginal analysis. Moreover, PFB is a potential substitute for other data reduction methods like factor or principal component analysis. However, when statistical data reduction methods are used to maximize the explanation of variances, the PFB is a theory-based form of data reduction by "a priori" assuming strong connection among the variables. This means that whereas factor analysis builds on what the connection (correlation) *is* among the elements, the PFB shows what the connection among the elements *should be*.

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Notes

1. Here we do not want to go into other issues like outlier and skewness handling.
2. Weighting can also be applied, however, weighting changes the trade-offs between the variables.
3. Obviously, there is a limit to how to improve the features, that is $\tilde{y}_k \leq 1$; but we are not dealing with this case in the following.
4. The description of the GEDI structure and its component is based on Acs et al. (2013a, 2013b).

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3

World Technology Frontier: Directed Technical Change and the Relevance of the Entrepreneurial Ecosystem

Esteban Lafuente

1 Introduction

Productivity is heterogeneous not only across countries, but also in terms of the factors explaining productivity differences between and within territories over time (Barro, 1991). In this study, I build a world technology frontier based on a non-parametric technique to evaluate total factor productivity (TFP) trends among 73 countries during the period 2002–2013. The proposed model extends existing work on country-level productivity by integrating the entrepreneurial ecosystem in a technology that allows to scrutinize the effects on TFP of directed technical change that I associate with countries' technology choices (biased technical change) (e.g., Färe et al., 1994; Kumar & Russell, 2002).

Productivity has been invoked as a key factor contributing to economic growth, and, from a policy perspective, the analysis of the factors driving

E. Lafuente (✉)
Business School, Costa Rica Institute of Technology (ITCR), Cartago, Costa Rica
e-mail: elafuente@itcr.ac.cr

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TFP contributes to improve resource allocation policies and decision-making (Acemoglu & Zilibotti, 2001; Barro, 1991). Total factor productivity is often estimated by the Solow residual which captures technology shifts resulting from output growth that remains unexplained by growth in inputs (Van Beveren, 2010). Echoing the seminal work by Solow (1957), economists have devoted a great deal of efforts on evaluating the sources of productivity growth between and within countries over time. This literature supports the view that productivity differences across economies originate from differences in technology adoption or transfer, and from variations in technical change linked to the access to human capital, technological knowledge, and solid financial markets backing economic activity (see, e.g., Lucas, 1988, Romer, 1990; Barro & Sala-i-Martin, 1997; Mankiw et al., 1992; Parente & Prescott, 1994; Hall & Jones, 1999; Kumar & Russell, 2002; Griffith et al., 2004; Caselli & Coleman, 2006; Antonelli & Quatraro, 2010; Moll, 2014).

In this study I argue that, besides the differences in technology and production factors' availability, the institutional setting backing entrepreneurship—that is, the entrepreneurial ecosystem or the national system of entrepreneurship (NSE)—and the technology choices linked to the exploitation of productive factors play a decisive role in shaping countries' TFP.

At this point, two critical aspects that constitute the building blocks of this study are worth highlighting. The first issue deals with the definition of entrepreneurship as a national phenomenon. Entrepreneurship is a vital economic component present in any economy to a larger or lesser extent. At the national level, entrepreneurship is increasingly operationalized as the countries' capacity for creating and/or developing a local entrepreneurial ecosystem conducive to productive entrepreneurship by supporting the efficient allocation of productive resources to the economy (e.g., Autio et al., 2015; Wurth et al., 2021). Formally, Acs et al. (2014) define the national system of entrepreneurship (NSE) as 'the dynamic, institutionally embedded interaction between entrepreneurial attitudes, abilities, and aspirations by individuals, which drives the allocation of resources through the creation and operation of new ventures' (p. 479). Underlying this definition is the notion that the multiple, often complex, interactions that occur between countries' institutions and economic agents govern entrepreneurial activity. The analysis based on the NSE framework describes the territory's capacity to mobilize available resources to the market through new business formation processes by including the interactions between entrepreneurs and the multifaceted economic, social, and institutional contexts in which individuals develop their entrepreneurial activity. The NSE contributes to understanding the quality of the local entrepreneurial ecosystem as well as its constituents, and prior work shows that the systematic approach to entrepreneurship based on the NSE—operationalized via the GEI—seems appropriate to evaluate the role of the entrepreneurial ecosystem over productivity (Lafuente et al., 2020).

Therefore, if the local entrepreneurial ecosystem is instrumental for economic growth by promoting productive entrepreneurship (Cao & Shi, 2021; Wurth et al., 2021), it seems clear that the analysis of countries' TFP should include the combined effect of individual entrepreneurial action and the context within which these initiatives operate.

The second key aspect addressed in this study is related to the connection between the entrepreneurial ecosystem and TFP, and to the analysis of how specific input choices causing movements along the production technology affect countries' TFP. Prior studies on country-level productivity often compute TFP values under the assumption of Hicks neutrality of technical change, as in the classic study of technical change by Solow (1957) (see, e.g., Boussemart et al., 2003; Caselli & Coleman, 2006). Following Solow (1957, p. 312), neutral technical change is associated with a constant marginal rate of substitution between inputs that simply increase or decrease the output level of the focal unit of analysis. However, the technology choices of policy makers (as well as of individuals and organizations) are likely heterogeneous over time. In fact, Samuelson and Swamy (1974, p. 592) pointed that 'the Santa Claus hypothesis of homotheticity in tastes and in technical change is quite unrealistic'.

In practical terms, many considerations lead to believe that shifts in countries' production function are non-homothetic. Countries with different factors' endowments will take advantage of technological innovations that allow for a more intensive use of locally abundant production factors. It follows that countries better able to introduce technologies and entrepreneurship policies that match the local market conditions should show better productivity performances than countries that have put less effort in shaping policies based on the idiosyncratic characteristics of their local setting. Additionally, countries have differentiated productive and economic priorities, and the success of specific policies in one country might prove ineffective in other contexts with different local conditions of factor markets. These processes directly affect countries' rate of technical change (e.g., Acemoglu, 2002).

Technical change is a key factor to productivity growth, and it can be associated with input or output bias, so different policies may be implemented to address them. Besides purely technological aspects or variations in factor prices, differences in technical change across economies may result from specific policies associated with the greater (or lower) exploitation or specific resources (e.g., Kogan et al., 2017; Kumar & Russell, 2002). In the specific context of this study, by studying how changes in production factors—that is, capital and labor—as well as in the entrepreneurial ecosystem—measured by the GEI (Acs et al., 2014)—affect the directionality of technical change, this research is important in practice for understanding the value of 'appropriateness' of technology in ecosystem analyses. Besides the identification of inward or outward shifts of countries' technology function as a result of policies emphasizing changes in either economic factors or in the entrepreneurial ecosystem, the proposed analysis of technical change directionality is of crucial interest that contributes to the debate on how the entrepreneurial ecosystem contributes to economic performance.

This study relates to the large and growing stock of knowledge dealing with entrepreneurial ecosystems (see, e.g., the recent surveys by Cao and Shi (2021) and Wurth et al. (2021)), and the analysis of how variations in both production factors and the entrepreneurial ecosystem affect countries' technical change rate (i.e., input bias) is at the core of this chapter. For the empirical application, I employ a nonparametric technique (i.e., data envelopment analysis) to compute TFP estimates and its components (i.e., efficiency change, technical change, and the input bias term of technical change) on a sample of 73 countries during 2002–2013. The key findings reveal that the directionality of technical change—that is, GEI's input bias—impacts countries' TFP.

The proposed analysis of countries' TFP and its components offers valuable information on the sources of productivity change during growth and recession periods in developed and developing economies. Additionally, by examining the directionality of technical change, we are in a better position to assess whether the direction of technical change matches the technology choices of the analyzed countries, in terms of input usage.

The plan of the chapter is as follows. Section 2 offers the background theory. Section 3 presents the methodology used to compute TFP, technical change, and the input bias term of technical change. Section 4 describes the sample and estimation strategy, while the findings are presented in Section 5. Section 6 presents the discussion and concluding remarks.

2 Background Theory

Since the days of Schumpeter (1934), entrepreneurship is an attractive concept that has been mostly analyzed from the perspective of the individual (Baumol, 1996; Wurth et al., 2021). As a national phenomenon, entrepreneurship is more than variations in the stock of businesses in the economy, and its operationalization should incorporate the regulating effect of context-related factors on individual action (Acs et al., 2014; Autio et al., 2015). Countries cover a range of different institutional settings; thus, entrepreneurial entry is governed by complex interactions, and the economic effects of entrepreneurship differ across countries (e.g., Lafuente et al., 2021; Nightingale & Coad, 2014).

In this discussion, the academic passion for consolidating the entrepreneurial ecosystem frame, as a research field, has translated into a significant stock of scientific work nurtured by different literature frameworks (Wurth et al., 2021): the national innovation system (Lundvall, 1992), the theory of competitive advantage (Porter, 1998), and the regional innovation systems (Cooke et al., 1997; Fritsch, 2001). The convergence of these scholarly trends has relevant academic and policy implications.

The entrepreneurial ecosystem has been conceptualized as spatially bounded, evolving systems that support opportunity exploitation through the creation of new productive businesses (Acs et al., 2014; Spigel, 2017). Local resources made available and mobilized by institutional and market agents therefore constitute the key ecosystem inputs for entrepreneurs;

productive entrepreneurship will flourish in countries where institutional development and support policies are in sync with the needs of entrepreneurs, whereas inefficient or even destructive entrepreneurship characterize territories where institutions are weak (Baumol, 1996).

The entrepreneurial ecosystem is not a checklist of elements that can be organized hierarchically (Lafuente et al., 2021; Wurth et al., 2021). Rooted in the entrepreneurial ecosystem framework, I observe a shift in policy design from the standard quantitative view based on the count-number of new businesses to support new approaches that take into account relevant aspects of this ecosystem, such as the quality of institutions backing entrepreneurship and the interactions between ecosystem actors (Acs et al., 2014; Lafuente et al., 2020).

In this discussion, research on entrepreneurial ecosystems offers a comprehensive definition as well as a clear categorization of ecosystem constituents (see, e.g., the recent surveys by Cao and Shi (2021) and Wurth et al. (2021)). Furthermore, recent quantitative analyses (e.g., Giraudo et al., 2019; Lafuente et al., 2016; Lafuente et al., 2020) and case studies (e.g., Heaton et al., 2019; Shi & Shi, 2021; Spigel, 2017) suggest that ecosystem configurations are country-specific, and that the effectiveness of entrepreneurship policy is highly reliant on both resource availability and the interconnections between ecosystem actors.

In strict connection to the study objective (Section 1), these studies indirectly support the notion that the entrepreneurial ecosystem might be instrumental for supporting the economic activity of new and incumbent businesses and, subsequently, countries' economic performance.

The analysis of the entrepreneurial ecosystem permits to capture various interconnected effects related to territorial economic performance. First, the entrepreneurial ecosystem depicts the territory's capacity to mobilize available resources—in the form of interactions between individuals' attitudes, aspirations, and abilities—to the market through new business formation processes. Second, the entrepreneurial ecosystem portrays the interactions between entrepreneurial human capital and accumulated knowledge and the multifaceted economic, social, and institutional contexts in which individuals develop their entrepreneurial activity. Finally, the entrepreneurial ecosystem contributes to understand how entrepreneurship fuels territorial economic productivity through the efficient allocation of resources in the economy.

The relevance of the entrepreneurial ecosystem flows from the recognition that entrepreneurship is a vital component present in any economy to a larger of lesser extent. Therefore, the systematic analysis of countries' efficiency including variables that account for the effects of entrepreneurial activity—that is, through the national systems of entrepreneurship—helps not only to enhance the analysis of the factors that contribute to explain economic performance, but also to provide policy makers with valuable information on the economic contribution of entrepreneurship.

This is the core of this research. Instead of identifying ecosystem strengths and weaknesses, this study differs from earlier contributions to a large extent because it is focused on directed technical change and its implications for both the local ecosystem and the economy.

I directly stand on the shoulders of existing productivity models (i.e., Caves et al., 1982; Färe et al., 1997; Lafuente et al., 2020), and indirectly on the endogenous growth studies by Hicks (1932), Solow (1957), and Kennedy (1964), to formulate a model of directed technical change with a very applied purpose: I identify the sources of variation in countries' TFP at a global scale in order to inform policy makers on the specific role of the entrepreneurial ecosystem and related policies for improving the economic performance of countries. This objective is relevant to increase the knowledge on the response of the economy to different production factors, including the entrepreneurial ecosystem.

To move toward the model estimations, in the next section we present the details of our analytical approach.

3 Modeling Country-Level Total Factor Productivity

3.1 The Malmquist Total Factor Productivity (TFP) Index

The approach adopted in this study to construct the world production frontier and associated efficiency levels of each analyzed economy is non-parametric. When dealing with multiple inputs yielding multiple outputs, efficiency literature often makes use of data envelopment analysis

(DEA) frontier methods (see, e.g., Cooper et al., 2011). This data-driven method approximates the true but unknown technology through linear programming without imposing any restriction on the sample distribution. DEA is a complex benchmarking nonparametric technique that yields a production possibilities set where efficient units positioned on this surface shape the frontier. For the rest of units, DEA computes an inefficiency score indicating the units' distance to the best practice frontier. The fundamental technological assumption of DEA models is that, in a focal period (t), production units (i) use a set of $x = (x_1, \ldots, x_J) \in R_+^J$ inputs to produce a set of $y = (y_1, \ldots, y_M) \in R_+^M$ outputs, and that these sets form the technology (T): T{($\mathbf{x}$, $\mathbf{y}$, t): $\mathbf{x}$ can produce $\mathbf{y}$ at time t}.

In our case, for each country (i) in the sample (N), the best practice technology is modeled via an output distance function $D^t(x^t, y^t) = \inf(\theta > 0 : (x^t, y^t)/\theta) \in T^t$. The drawn technology exhibits constant returns to scale, is homogeneous of degree +1, and is convex in $\mathbf{y}$. The following linear program models the described technology and computes, for each country (i) and each period (t), the output distance function ($D^t(\mathbf{x}^t, \mathbf{y}^t)$):

$D^t(\mathbf{x}^t, \mathbf{y}^t) = \max \theta_i$

subject to

$$\begin{aligned} &\sum_{i=1}^{N} \lambda_i^t y_{i,m}^t \geq \theta_i y_{i,m}^t \quad && m = 1, \ldots, M \\ &\sum_{i=1}^{N} \lambda_i^t x_{i,j}^t \geq x_{i,j}^t \quad && j = 1, \ldots, J \\ &\lambda_i^t > 0 \quad && i = 1, \ldots, N \end{aligned} \tag{1}$$

The solution value of θ in equation (1) is the efficiency score computed for the country i at time t. Note that for efficient countries $\theta = 1$, while for inefficient countries $\theta > 1$ and $1 - \theta$ point to the degree of inefficiency. The term λ_i^t is the intensity weight used to form the linear combinations of the sampled countries (N).

Next, the distance functions can be used to compute changes in total factor productivity (TFP) between two periods through the Malmquist index ($M(\cdot)$). The Malmquist TFP index—first introduced by Malmquist

(1953) and formally developed in the pioneering work by Caves et al. (1982)—measures TFP variations between two periods. In a multiple input–output setting, this index reflects changes (progress or regress) in productivity along with changes (progress or regress) of the frontier technology over time. By using distance functions, the output-oriented Malmquist TFP index ($M(x^t, y^t, x^{t+1}, y^{t+1})$) is computed for each country (i) on the benchmark technologies in periods t and t+1 as follows (Färe et al., 1989):

$$M\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \left[\frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)}\right] \times \left[\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)}\right]^{0.50}$$

$$M\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = EC \times TC \tag{2}$$

In equation (2), productivity growth (progress) yields a Malmquist index greater than unity, while values lower than one point to productivity decline. Analogous interpretations hold for the components of the Malmquist TFP index. The term inside the first square bracket measures the effect of efficiency changes (EC), that is, whether the operating efficiency of a focal country is moving closer (catching-up) or farther from the efficiency frontier between periods t and t+1. The geometric mean of the term inside the second square bracket captures the effect of technical change (TC), that is, the shift in the technology function between the two periods. Improvements in the technical-change component are considered to be evidence of innovation (e.g., Färe et al., 1994; Kumar & Russell, 2002; Lafuente et al., 2020).

3.2 Modeling the Direction of Technical Change

Technical change (TC)—that is, shifts in the production function—can be neutral or non-neutral. Underlying many studies on technical change based on total factor productivity is the assumption of Hicks neutrality of technical change (see, e.g., Färe et al., 1994; Boussemart et al., 2003; Mahlberg & Sahoo, 2011), as in the classic study of technical change by Solow (1957). Nevertheless, prior studies have shown that technical change in many countries is non-neutral (Färe et al., 2006; Kumar & Russell, 2002).

Following Solow (1957, p. 312), technical change is said to be neutral if the marginal rate of substitution (MRS) between two inputs (x1, x2) stays constant and simply increases or decreases the output attainable between period t and t+1, that is, $x2^{t+1} / x1^{t+1} = x2^{t} / x1^{t}$. Mathematically, neutrality can be written as d/dt $MRS = d/dt\left(F_1^t / F_2^t\right) = -d/dt\left(dx2/dx1\right) = 0$, where F_1^t and F_2^t are the marginal products and the x2 / x1 ratio is held constant. Therefore, neutrality implies a homothetic inward shift on the unit isoquant (Binswanger, 1974).

Samuelson and Swamy (1974, p. 592) concluded that 'the Santa Claus hypothesis of homotheticity in tastes and in technical change is quite unrealistic'. Technical change is defined as non-neutral (x1-using or x2-using), depending on whether the MRS decreases or increases. That is, nonproportional shifts of the production frontier in the input–output space occur at different input mix points (Färe et al., 2006). For example, in the case of technical advance ($TC > 1$) and at a constant factor ratio, if the MRS rises so that $x2^{t+1} / x1^{t+1} > x2^{t} / x1^{t}$, then technical change is x2-using (x1-saving) as it favors the consumption of x2 via the increase of its output elasticity. Alternatively, when technical change is x1-using ($x2^{t+1} / x1^{t+1} < x2^{t} / x1^{t}$), it favors the use of x1 via greater increases in the output elasticity of x1 than that of x2. Table 3.1 summarizes the conditions for the direction of technical change bias.

Technical change is a key factor to productivity growth, and it can be associated with input or output bias, so different policies may be implemented to address them. Besides purely technological aspects or variations in the factor prices, differences in technical change across economies

Table 3.1 The direction of input biased technical change

Input mix	$IBTC < 1$	$IBTC = 1$	$IBTC > 1$
$x2^{t+1}/x1^{t+1} < x2^{t}/x1^{t}$	x2-using	Hicks neutral	x1-using
$x2^{t+1}/x1^{t+1} > x2^{t}/x1^{t}$	x1-using	Hicks neutral	x2-using

might result from development strategies or policy-driven factors associated with the greater (or lower) exploitation or specific resources (Kogan et al., 2017; Kumar & Russell, 2002). Therefore, other than the identification of the shift of the production function inward or outward (i.e., technology is progressing or regressing), the measurement of the direction of technical change biases is also important, since the directionality of the technology adopted by a focal country can amplify or reduce the shift of the production frontier.

Following Färe et al. (1997), the constant returns to scale measure of technical change (*TC* in equation (2)) can be explained by a magnitude term (*HTC*) and a bias term, which can be further decomposed in an input-bias (*IBTC*) and an output-bias (*OBTC*) component.

$$TC = \left[\frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)}\right] \times \left[\frac{D^{t+1}\left(x^t, y^t\right)}{D^t\left(x^t, y^t\right)} \times \frac{D^t\left(x^{t+1}, y^t\right)}{D^{t+1}\left(x^{t+1}, y^t\right)}\right]^{0.50}$$
$$\times \left[\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D^{t+1}\left(x^{t+1}, y^t\right)}{D^t\left(x^{t+1}, y^t\right)}\right]^{0.50}$$
$$TC = MTC \times IBTC \times OBTC \tag{3}$$

In equation (3), the magnitude term (*MTC*) is the measure of technical change under the assumption that the technology is Hicks neutral ($IBTC = 1$ and $OBTC = 1$). For the bias terms, values greater than one point to a positive effect of the biased technical change on the Malmquist index, while values below one indicate that the biased technical change shrinks productivity. Keep in mind that in models like ours—that is, where the constant returns to scale technology produces one output (see section 4.1)—$OBTC = 1$ and the *IBTC* term are independent of outputs, that is, the source of technical change bias exclusively comes from variations in the input mix (see Färe et al. (1997) for a detailed discussion on this issue). By taking these considerations into account, the technical change component (equation (3)) can be rewritten as:

$$TC = \left[\frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)}\right] \times \left[\frac{D^{t+1}\left(x^t, y^t\right)}{D^t\left(x^t, y^t\right)} \times \frac{D^t\left(x^{t+1}, y^t\right)}{D^{t+1}\left(x^{t+1}, y^t\right)}\right]^{0.50}$$

$$TC = MTC \times IBTC \tag{4}$$

Therefore, the three-way decomposition of the Malmquist TFP index used in this study is generated by inserting equation (4) into equation (2):

$$M\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \left[\frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)}\right] \times \left[\frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)}\right]$$

$$\times \left[\frac{D^{t+1}\left(x^t, y^t\right)}{D^t\left(x^t, y^t\right)} \times \frac{D^t\left(x^{t+1}, y^t\right)}{D^{t+1}\left(x^{t+1}, y^t\right)}\right]^{0.50}$$

$$M\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = EC \times MTC \times IBTC \tag{5}$$

In equation (5), a result of $IBTC = 1$ indicates that the technical change is Hicks neutral, while if $IBTC \neq 1$, the technical change is non-neutral. Therefore, by computing the change of the input mix and the value of the *IBTC,* it is possible to identify the direction of technical change. Figure 3.1—borrowed from Färe et al. (2006)—illustrates the direction of technical change. The figure draws the input set in period t ($L^t(y)$) and three input sets in period $t+1$ that capture the different types of technical change: Hicks neutral technical change $\left(L_{MTC}^{t+1}\left(y\right)\right)$, x1-using bias $\left(L_{x1}^{t+1}\left(y\right)\right)$, and x2-using bias $\left(L_{x2}^{t+1}\left(y\right)\right)$.

In Fig. 3.1, all input sets produce the same level of output (y) and the x2 / x1 ratio decreases, that is, $x2^{t+1} / x1^{t+1} < x2^t / x1^t$. Note that technical change is Hicks neutral ($IBTC = 1$) if $0b / 0c = 0f / 0e(h)$, meaning that the line through the points c and $e(h)$ is parallel to the line through the points b and f. Alternatively, a x1-using biased technical change occurs if technical change shifts the isoquant to $L_{x1}^{t+1}\left(y\right)$ ($0b / 0c < 0f / 0e(1)$) and $IBTC > 1$. If technical change shifts the isoquant to $L_{x2}^{t+1}\left(y\right)$, then $0b / 0c > 0f / 0e(2)$ and $IBTC < 1$, which implies a x2-using biased technical change.

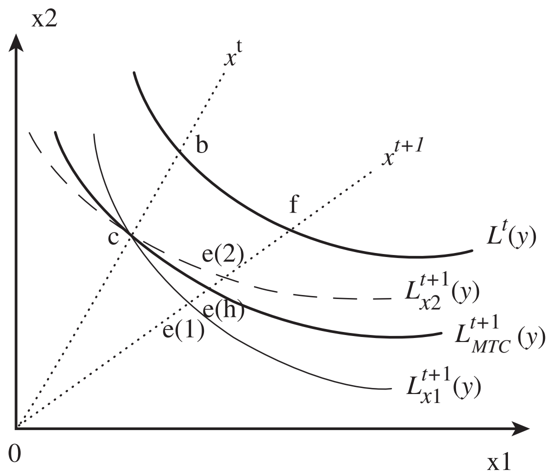

Fig. 3.1 Input biased technical change. Source: Author's elaboration based on Färe et al. (2006).

4 Sample, Variable Definition, and Estimation Strategy

4.1 Sample and Variable Definition

The data used in this study come from two sources of information. First, data on the macroeconomic figures of the analyzed countries were obtained from the World Development Indicators available from the World Bank data sets. Second, variables related to the country's demographic, educational, and economic conditions, as well as to the entrepreneurial activity used to estimate the Global Entrepreneurship Index (GEI), were obtained from different sources, including the Global Entrepreneurship Monitor (GEM) adult population surveys, the Global Competitiveness Index (GCI), and the Doing Business Index.

I compute productivity growth and its components on a sample of 73 countries over the period 2002–2013. Given the interest in evaluating productivity patterns at the world scale, I work with an unbalanced panel so that the total analyzed sample comprises 559 country-year observations. The full list of countries included in the analysis is presented in Table A1 of the Appendix. Note that the representativeness of the sample is ensured insofar as it includes 32 European countries (Belgium, Bosnia and Herzegovina, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Latvia, Lithuania, Macedonia, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, and United Kingdom), 18 American countries, including both North America and Latin America and the Caribbean islands (Argentina, Barbados, Brazil, Canada, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Jamaica, Mexico, Panama, Peru, Trinidad & Tobago, United States, Uruguay, and Venezuela), 11 Asian countries (China, India, Iran, Japan, South Korea, Malaysia, Pakistan, Saudi Arabia, Singapore, Thailand, and United Arab Emirates), 11 African countries (Algeria, Angola, Botswana, Ghana, Malawi, Namibia, Nigeria, South Africa, Tunisia, Uganda, and Zambia), and one Oceania economy (Australia).

Existing studies mostly evaluate country-level efficiency under the premise that capital and labor generate gross domestic product (see, e.g., Färe et al., 1994; Kumar & Russell, 2002; Boussemart et al., 2003; Färe et al., 2006; Mahlberg & Sahoo, 2011). Following the argument in Section 2, and similar to Lafuente et al. (2016), in this study the technology specification used to compute the world frontier defines an aggregate output (**y**: gross domestic product) that is produced by three inputs (**x**): labor, capital, and the entrepreneurial ecosystem. Table 3.2 presents the descriptive statistics for the input–output set.

The gross domestic product (GDP) is expressed at 2011 prices in millions of PPP international dollars. Labor is measured as the country's number of employees (expressed in millions of workers). Capital is defined as the gross capital formation, which represents the outlays on additions to the economy's fixed assets (public infrastructures, and commercial and residential buildings) plus net changes in the level of inventories held by firms in the economy.[1] This variable is expressed at 2011 prices in millions of PPP international dollars.

The third input, the Global Entrepreneurship Index (GEI), captures the multidimensional nature of the national system of entrepreneurship

Table 3.2 Descriptive statistics for the selected input–output set (period 2002–2013)

	Description	Mean (Std. dev.)	Q1	Median	Q3
Output					
Gross domestic product (GDP)	GDP equals the gross value added by country producers plus product taxes and minus subsidies not included in the products' value.	1,310,657 (2,681,693)	158,529	368,607	1,314,236
Inputs					
Labor force	The economically active population: people over 15 years old who supply labor for the production of goods and services.	38.96 (119.13)	2.74	8.23	24.57
Gross capital formation (GCF)	GCF consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories.	340,195 (835,411)	32,152	88,454	339,004
GEI score	Index that measures the country's systems of entrepreneurship	47.12 (17.45)	32.61	44.48	62.18

Data on labor and the economic variables were obtained from the World Bank, while the GEDI scores were provided by the International GEM Consortium.

at the country level. The GEI measures the dynamic and institutionally embedded interaction between entrepreneurial attitudes, entrepreneurial abilities, and entrepreneurial aspirations by individuals, which drive resource allocation through new business venturing (Acs et al., 2014). The GEI, which ranges between 0 and 100, is built on 14 pillars which result from 14 individual-level variables properly matched with selected institutional variables related to the country's entrepreneurship ecosystem.

The novelty of the Global Entrepreneurship and Development Index (GEDI) lies on the systemic view of countries' entrepreneurship in which the harmonization (configuration) of the analyzed pillars through the penalty for bottleneck (PFB) determines the country's systems of entrepreneurship (Miller, 1986, 1996). Through the PFB method, the system performance is mainly determined by the weakest element (bottleneck) in the system. The magnitude of the country-specific penalty depends on the absolute difference between each pillar and the weakest pillar. Also, pillars cannot be fully substituted through the PFB method, that is, a poorly performing pillar can only be partially compensated by a better performing pillar.

4.2 Estimation Strategy

I compute the total factor productivity measure and its components following equation (5) and using the input–output set specified in Section 4.1. At this point, two considerations are in order. First, similar to prior studies on country productivity (see e.g., Boussemart et al., 2003; Färe et al., 2006; Kumar & Russell, 2002; Lafuente et al., 2020), our productivity measures are based on discrete time estimations. This way, a TFP value is computed for each analyzed country for every adjacent pair of years.

The second consideration deals with the use of an unbalanced panel data to estimate the Malmquist index values. Underlying most research on productivity is the misconception that a balanced panel is a prerequisite to efficiently estimate TFP measures. This is surprising because some of the seminal works on the Malmquist index have clearly indicated that the use of unbalanced panels is possible (Färe et al., 1994, p. 73). More recently, in their analysis of the differences in TFP estimates generated from unbalanced and balanced panels, Kerstens and Van de Woestyne (2014) conclude that balancing an unbalanced panel might lead to lose relevant information about the units' productivity level (Kerstens & Van de Woestyne, 2014, p. 756).

On the basis of these considerations, I employ an unbalanced panel data to compute the TFP measures. Keep in mind that the value of the Malmquist index (equation (5)) will be undefined for missing observations. Details on the sample composition are presented in Table A1 of the Appendix, which shows that data for the whole analyzed period are available for 23 countries, including 18 OECD countries, Argentina, Brazil, China, Croatia, and South Africa. A group of 14 economies report information for more than six periods, while eight countries report information for six periods. Data for a five-year period are available for seven economies, and, finally, 22 countries report data for less than five time periods.

It should be noted that the panel used in this study is unbalanced because the data necessary to calculate the Global Entrepreneurship Index are missing for various countries over the analyzed period. Thus, this unbalancedness property is strictly linked to the phenomenon being modeled, which might represent a source of attrition bias (Baltagi & Song, 2006).

Therefore, I verified the validity of our estimations by scrutinizing the Malmquist index results for both the unbalanced panel including information for 73 countries and the balanced panel of 23 countries. Although the magnitude of the average productivity measures changes, the results of the Kolmogorov–Smirnov test of equality of distributions show that the differences in densities between both unbalanced and balanced data sets are not statistically significant (Combined K-S: 0.0801, *p-value* = 0.203). These results corroborate the robustness of our productivity estimations. Thus, in what follows, the productivity results computed for the full sample are analyzed in Section 5.

5 Results

5.1 World Productivity and Technological Catch-up

This section deals with the assessment of the world productivity results computed for the analyzed economies. Table 3.3 presents the summary statistics of the productivity measure and its components for the full sample, while the country-specific productivity values are presented in Appendix 2. Table 3.4 displays the results distinguishing the period 2003–2008 from the period 2009–2013. Additionally, Figures 3.2 and 3.3 break the sample into OECD versus non-OECD countries and plot the Malmquist TFP index and its components (*EC* and *TC*) between 2003 and 2013, respectively.

Table 3.3 Malmquist TFP index and its components

	Malmquist index	Efficiency change	Technical change
2003	1.0174	1.0018	1.0156
2004	1.0167	1.0165	1.0016
2005	1.0146	1.0036	1.0109
2006	1.0138	1.0080	1.0056
2007	1.0137	1.0134	1.0003
2008	1.0108	1.0011	1.0097
2009	0.9823	0.9742	1.0082
2010	0.9722	0.9946	0.9776
2011	0.9790	0.9644	1.0157
2012	1.0108	1.0161	0.9951
2013	1.0182	0.9995	1.0191
Total	1.0029	0.9981	1.0052

Table 3.4 Fixed-effects regression results: Convergence test

	Efficiency level (*t*-1)	Intercept	Time dummies	F-test	R2 (within)	Obs.
Panel A: 2003-2013	0.0947** (0.0422)	0.8722*** (0.0529)	Yes	5.49***	0.1558	470
Panel B: 2003-2008	0.1210*** (0.0427)	0.8670*** (0.0487)	Yes	4.43***	0.1507	202
Panel C: 2009-2013	0.1065*** (0.0387)	0.9062*** (0.0714)	Yes	7.19***	0.2048	268

Robust standard errors are reported in brackets. *, **, *** indicate significance at the 10%, 5%, and 1%, respectively.

Keep in mind that a productivity result higher than unity points to progress, while values below one indicate decline. For illustrative purposes, suppose that a hypothetical country reports the following productivity results between period t and t+1: Malmquist TFP index: 1.08, efficiency change: 0.90, technical change: 1.20. In this case, the result indicates that the fictitious country is moving farther away from the efficiency frontier (10%), and its productivity growth (8%) is attributed to technical progress (20%).

Results in Table 3.3 reveal that, on average per year, the analyzed economies experienced a productivity progress of 0.29% between 2003 and 2013. The reported productivity growth was mainly driven by improvements in technical change, which was, on average, 0.52% per year (average yearly efficiency change: –0.19%).

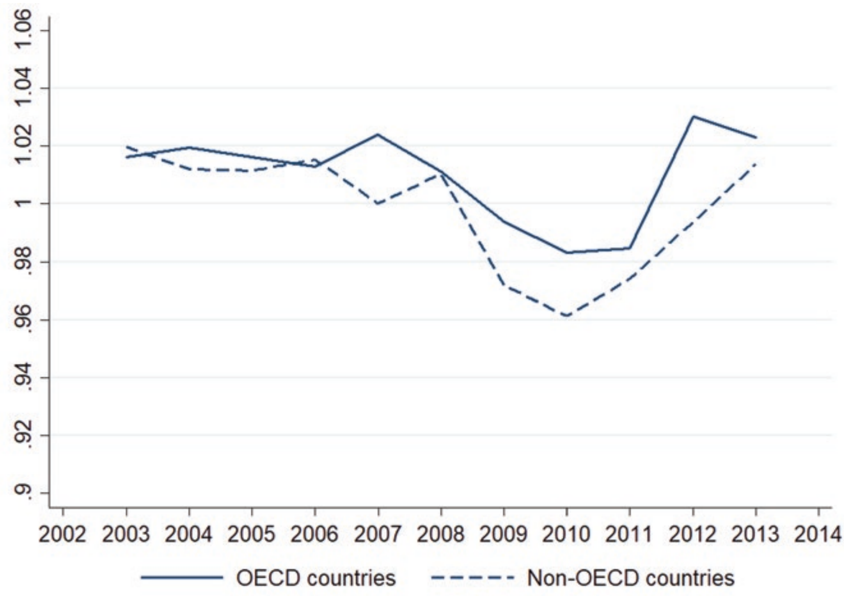

Fig. 3.2 Malmquist index in OECD and non-OECD countries

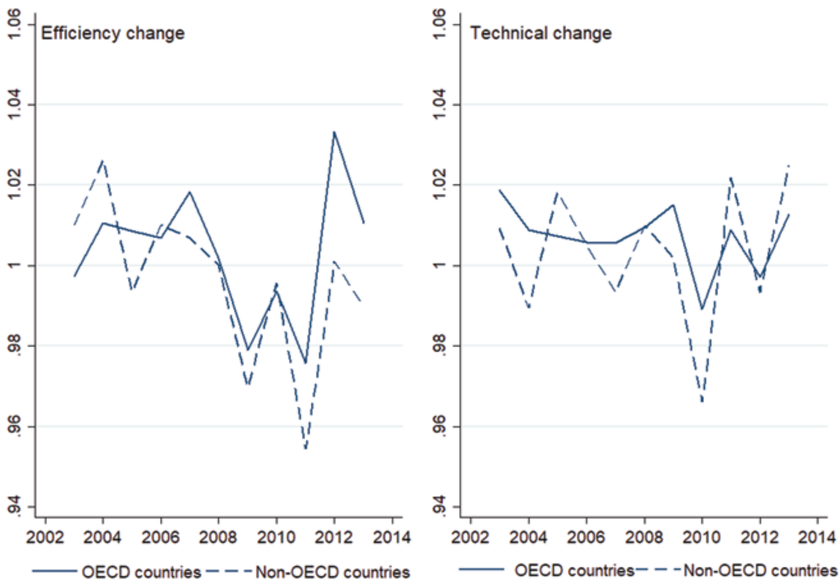

Fig. 3.3 Efficiency change and technical change in OECD and non-OECD countries

By looking at the configuration of the countries' efficiency level, it was found that the USA consistently shapes the efficiency frontier during the whole analyzed period. Also, I identified two groups of countries whose efficiency level places them on the frontier in different periods. The first group includes efficient countries in five or more periods: UK (efficient in ten periods), Norway (efficient in seven years), Germany (efficient in five years), and Singapore (efficient in five years). The second group includes Brazil (efficient in four years), Ireland (efficient in three years), and four countries located on the frontier in two periods (Argentina, Greece, Italy, and Nigeria).

Additionally, looking at the results in Table 3.3 and Fig. 3.2, one can notice two clearly differentiated periods. The first part of the analyzed period (2003-2008) is characterized by a consistent productivity growth (average yearly growth: 1.43%). This first period witnessed an evenly distributed contribution of both efficiency (0.74%) and technical change (0.70%) to country-level productivity progress. Note that in this period, the GDP of the analyzed countries grew, on average, 5.39% per year. The second half of the period is dominated by the downturn that affected the global economy after 2008. During this period GDP grew on average 2.85%, and country-level TFP experienced an average yearly fall of 0.56%, which was mostly caused by efficiency decline (average yearly decline: 0.90%).

By examining the differences between OECD and non-OECD countries, we note that these two groups have dissimilar patterns of TFP change, in which OECD countries grew faster than non-OECD countries with progressing technology and more efficient production. During the entire period, TFP values are higher among OECD countries (1.0105) viz-a-viz non-OECD countries (0.9944). However, differences in the distributions are only significant in the period 2008-2013. Figure 3.2 shows a slightly higher productivity growth in OECD countries (average: 1.67%) compared to non-OECD countries (average: 1.06%) during the pre-crisis period (2003-2008). Among OECD economies, the contribution of technical change to productivity growth (average: 0.91%) was greater than that of efficiency changes (average: 0.75%).

After 2008, results indicate that OECD recovered more rapidly from the worldwide economic meltdown, and that the average yearly productivity fall among non-OECD countries (1.50%) was mainly caused by a decline in operating efficiency (average decline: 1.74%) (Fig. 3.3).

Results in Fig. 3.3 might signal that non-OECD economies—mostly poor or developing countries—are losing the race for convergence. It has been argued that low technological catch-up is behind the slow convergence rates showed by economies (see e.g., Barro & Sala-i-Martin, 1992; Quah, 1997). In the context of our study, the world technology is represented by the production surface in the input–output space, and the potential catch-up effect is captured by movements toward the efficiency frontier, that is, improvements in the efficiency level (the term *EC* in equation (5)).

We ran two additional tests to verify whether poor and developing economies are catching-up with developed countries. First, we evaluated the distribution of the efficiency level across countries in the period 2003-2008 and in the period 2009-2013. Results in Fig. 3.4 point to a prominent shift in the probability mass away from the efficient reference value of one between the two subperiods, thus indicating that economies are predominantly moving away from the efficiency frontier over time.

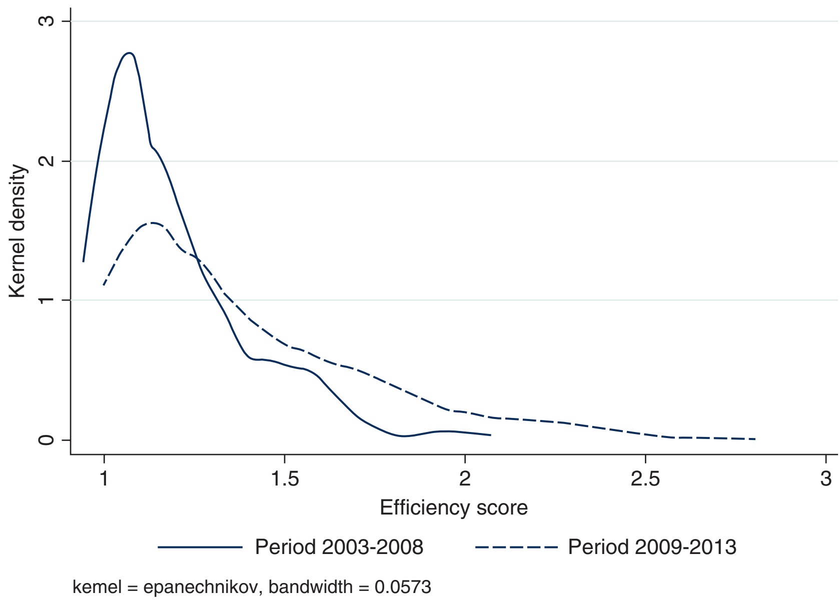

Fig. 3.4 Kernel density estimates of efficiency scores

This result is validated by the Kolmogorov–Smirnov test of equality of distributions which confirms that the difference in densities between the two periods is significant (Combined K-S: 0.1128, *p-value* = 0.004).

Second, we tested the convergence hypothesis by running a fixed-effects regression model in which efficiency variations—that is, *EC* in equation (5)—was regressed against the lagged efficiency level (equation (1)) and a set of time dummies which rule out the effect of time trends.[2] Building on the beta-convergence approach by Barro and Sala-i-Martin (1992), a positive relationship between the efficiency change term (*EC*) and past efficiency (in terms of distance to the efficiency frontier) would evidence that (poor) countries with higher inefficiency levels catch-up (rich) efficient ones.

The results of the fixed-effects model in Table 3.4 confirm that during the analyzed period, countries with greater inefficiency levels have, on average, benefited more from efficiency improvements than have more efficient countries. To further corroborate the robustness of this result, we estimated additional models for two subperiods (2003-2008 and 2009-2013). Although the coefficient for past efficiency remains positive and significant, the findings show a reduced speed of convergence after 2008, relative to that reported for the pre-crisis period. Also, the comparison of the efficiency level (equation (1)) between the two analyzed subperiods reveals that the distance to the frontier of non-OECD countries worsened from 24% (2003-2008) to 51% (2009-2013), while OECD economies show a lower average inefficiency increase from 16% (2003-2008) to 21% (2009-2013). This finding is in line with the result of the density test which suggests that, as a result of the global economic slowdown, non-OECD countries are not only lacking the resources necessary to consolidate their GDP, but also making an inefficient use of their available inputs.

Overall, this analysis yields mixed results on international convergence. However, these results do not necessarily imply that there is a tendency for technical change to modify (increase or reduce) the gap between rich and poor economies. Instead, results only indicate that OECD countries, which on average have also fallen short of the frontier, might have capitalized on their resources more efficiently than non-OECD countries after 2008. This is the point to which we turn in the next section where we examine how decisions linked to the utilization of inputs impact countries' technical change and, consequently, their productivity level.

5.2 The Direction of Technical Change

This section evaluates the results for the technical change component of the Malmquist index. By estimating the shift in the production frontier, the technical change term and its components indicate the evolution of the production possibilities allowed by the technology.

In this study, the modeled technology uses three inputs (capital, labor, GEI) so that the direction of the input bias term results from the analysis of the available input combinations (capital vs. labor, capital vs. GEI, labor vs. GEI). Recall that, for two given inputs (x1 and x2), if the x2/x1 ratio increases between period t and $t+1$, then $IBTC > 1$ implies x2-using bias, and $IBTC < 1$ implies x1-using bias. On the other hand, if the x2/x1 ratio decreases, then $IBTC > 1$ implies x1-using bias, while $IBTC < 1$ implies x2-using bias. The magnitude term (*MTC*) equals the technical change under joint Hicks neutrality ($IBTC = 1$).

The evolution of the technical change components and the distribution of countries according to the nature of input-biased technical change are presented in Table 3.5, while Table 3.6 summarizes the pattern of the Malmquist index and its components for OECD and non-OECD countries over the entire period (2003-2013) and two selected subperiods (2003-2008 and 2009-2013). Also, Table 3.6 reports the results of the Kolmogorov–Smirnov test which was used to detect differences in the distribution of the Malmquist index and its components between OECD and non-OECD countries.

Overall, results in Table 3.5 show that technical change (on average: 0.52% per year) has been mostly driven by a more efficient use of available inputs (average IBTC: 0.54% per year). Although the values of the technical change bias are relatively low, results in Table 3.5 indicate that, during the analyzed period, 54% of countries report an input bias value greater than unity. This is evidence that most countries are matching their technology choices with their input mix, which translates in a positive

Table 3.5 Malmquist TFP index and its components

	Technical change	Magnitude effect	Input bias term	Distribution of the input-biased technical change		
				IBTC > 1	*IBTC* < 1	*IBTC* = 1
2003	1.0156	1.0089	1.0069	18	6	5
2004	1.0016	0.9925	1.0097	18	9	5
2005	1.0109	1.0073	1.0038	13	3	14
2006	1.0056	1.0004	1.0051	24	6	4
2007	1.0003	0.9987	1.0019	18	13	6
2008	1.0097	1.0033	1.0066	17	4	19
2009	1.0082	0.9892	1.0197	31	4	9
2010	0.9776	0.9742	1.0035	26	12	10
2011	1.0157	1.0147	1.0011	23	20	12
2012	0.9951	0.9923	1.0029	39	14	7
2013	1.0191	1.0167	1.0023	26	17	18
Total	1.0052	0.9998	1.0054	253	108	109

effect of input bias on technical change and, consequently, on TFP levels. Also, the group of countries with neutral technical change decreased from 26% between 2003 and 2008 to 21% in the 2009-2013 period; however, the analysis of the country-level *IBTC* values reveals that the *IBTC* is different from zero for all countries. The proportion of countries with *IBTC* < 1 increased from 20% in the pre-crisis period to 25% in the 2009-2013 period, which suggests an increase in the number of countries employing an input mix that reduces the shift of the production frontier in the period following the economic downturn.

Concerning the direction of the input bias term, results in Table 3.6 point to significant differences in the technology choices and input usage conditions between OECD and non-OECD countries. During the period of economic growth (2003-2008), the technology adopted by economies was based on the intensive use of capital (capital-using bias), compared to labor and the entrepreneurship inputs. Also, the technology of most economies is biased toward the national system of entrepreneurship (GEI-using) over labor. Note that, in this period, countries with a positive input-biased technical change are mostly OECD countries (63 out of 108 observations). On contrary, I found a relatively balanced number of OECD and non-OECD countries with negative input bias values (17 and 24 out of 41 observations, respectively).

Table 3.6 Productivity and the direction of technical change

	Components of the Malmquist index (TFP)					Marginal rate of substitution					
						Capital / labor		Capital / GEI		Labor / GEI	
	Malmquist index	Efficiency change	Technical change	Magnitude effect	Input bias	Change	Direction	Change	Direction	Change	Direction
Panel A: 2003-2013											
OECD countries	1.0105	1.0037	1.0068	1.0013	1.0056	1.0067	Capital-using	1.0014	Capital-using	0.9941	GEI-using
Non-OECD countries	0.9944	0.9917	1.0034	0.9984	1.0051	1.0567	Capital-using	1.0639	Capital-using	0.9947	GEI-using
Total	1.0029	0.9981	1.0052	0.9998	1.0054	1.0270	Capital-using	1.0308	Capital-using	0.9944	GEI-using
Kolmogorov–Smirnov test	0.2340***	0.2304***	0.2267***	0.1625***	0.1001	0.2841***		0.1729***		0.1006	
Panel B: 2003-2008											
OECD countries	1.0167	1.0075	1.0091	1.0063	1.0030	1.0342	Capital-using	1.0201	Capital-using	0.9770	GEI-using
Non-OECD countries	1.0106	1.0073	1.0038	0.9946	1.0096	1.1275	Capital-using	1.0989	Capital-using	0.9646	GEI-using
Total	1.0143	1.0074	1.0070	1.0017	1.0056	1.0721	Capital-using	1.0521	Capital-using	0.9719	GEI-using
Kolmogorov–Smirnov test	0.1525	0.1293	0.2762***	0.2848***	0.2340***	0.3946***		0.2735***		0.1429	
Panel C: 2009-2013											
OECD countries	1.0045	1.0001	1.0045	0.9966	1.0082	0.9694	Labor-using	0.9840	GEI-using	1.0102	Labor-using
Non-OECD countries	0.9851	0.9827	1.0032	1.0001	1.0025	1.0149	Capital-using	1.0432	Capital-using	1.0124	Labor-using
Total	0.9944	0.9910	1.0038	0.9987	1.0053	0.9931	Labor-using	1.0147	Capital-using	1.0113	Labor-using
Kolmogorov–Smirnov test	0.2652***	0.2824***	0.1906**	0.1433	0.2190***	0.2001***		0.1722**		0.0956	

*,**,*** indicate significance at the 10%, 5%, and 1%, respectively (Kolmogorov–Smirnov test of equality of distributions).

For both OECD and non-OECD countries, technical change and TFP growth are associated with higher rates of capital deepening (Färe et al., 2006; Kumar & Russell, 2002). Additionally, results indicate that countries' economic conditions affect the substitution rate between labor and entrepreneurship inputs by facilitating the development and exploitation of resources linked to the entrepreneurial ecosystem, which arguably affects subsequent business creation rates and economic performance (Acs et al., 2014; Lafuente et al., 2020).

During the 2009-2013 period, the direction of the input bias term changed with labor accumulated worldwide, that is, the adopted technology becomes labor-using as compared to capital and GEI inputs overall. OECD countries show higher input bias results (1.0082) than non-OECD countries (1.0025), and their technologies are biased toward labor-using and GEI-using. Among non-OECD countries' technology, the only change is observed toward a labor-using technology, compared to the GEI input (Table 3.6). In this period, negative input bias values are mainly reported by non-OECD countries (44 out of 67 observations). This indicates that non-OECD countries are less prepared to either introducing a technology that adapts to their factor markets or promoting the provision of inputs that better contribute to exploit their technology. On the contrary, most economies with positive input-biased technical change are OECD countries (82 out of 145 observations). This result implies that OECD countries, which are often more technology innovator economies with access to more resources, are more capable of adopting a technology which is suitable for their factor endowments.

6 Concluding Remarks and Policy Implications

6.1 Concluding Remarks

This study has produced novel economic evidence on how the entrepreneurial ecosystem—that is, the institutional setting backing entrepreneurial action—triggers countries' total factor productivity, both by supporting a more efficient mobilization of resources and by enhancing the role of the entrepreneurs responsible for innovative actions that shift technology curves and translate into higher rates of technical change, and therefore, superior TFP growth rates.

Existing studies underline the relevance of technological barriers, factor accumulation, and the development of financial markets for explaining differences in total factor productivity across economies (e.g., Romer, 1990, Mankiw et al., 1992, Parente & Prescott, 1994, Caselli & Coleman, 2006, Caselli and Gennaioli 2013, Moll, 2014). In contrast, I have proposed that, besides technology and the availability of production factors, the entrepreneurial ecosystem plays a decisive channeling role that contributes to spur TFP.

In this sense, the main contribution of this study relies on the comprehensive analysis of the relationship between countries' entrepreneurial ecosystem and total factor productivity, while paying close attention to the critical role of directed technical change. Entrepreneurship is heterogeneous not only between countries, but also in terms of its effects on productivity.

Overall, the results in this paper provide robust evidence for a positive effect of the entrepreneurial ecosystem on TFP, thus suggesting that the entrepreneurial ecosystem is a relevant transmission channel that contributes to TFP by promoting entrepreneurial action and, subsequently, economic performance.

Productivity results from technological progress, which, in turn, results from the capacity of (new and incumbent) economic agents to generate and commercialize innovations, as well as to exploit business opportunities. Both innovation and the exploitation of market ideas are the main conduit of entrepreneurship attitudes, and the findings indicate that the main transmission mechanism through which the entrepreneurial ecosystem impacts countries' TFP is technical change. The results presented in this study help to reconcile the findings in theoretical models with the conflicting empirical results. Additionally, the systemic approach adopted in this study to measuring country-level entrepreneurship appears to provide a better measure of entrepreneurship than metrics based on individual-level or business-level data.

6.2 Policy Implications

The findings of this study have relevant policy implications. Policy makers often allocate large sums of public money in policies excessively oriented toward the stimulation of employment, capital accumulation, and knowledge generation in the economy, such as subsidies to support self-employment and human capital formation as well as investments in research and development. These policies—rooted in the endogenous growth theory—are conducive to economic performance and undoubtedly have translated into significant economic outcomes linked to increased levels of employment and education (Acemoglu et al., 2006; Aghion & Howitt, 1992). Nevertheless, the comprehensive analysis presented in this study supports the notion that a healthy entrepreneurial ecosystem has the potential to generate upward shifts in countries' technology function. This key result fuels the notion that policy should shift from a focus on capital and labor toward designs that match knowledge and capital formation programs, with policy interventions aimed at enhancing the local entrepreneurial ecosystem.

From a policy perspective, entrepreneurship support programs would become sterile if entrepreneurs navigate in contexts that do not guarantee the effective exploitation of their knowledge. Thus, policy makers need to turn their attention to the development of an appropriate entrepreneurial ecosystem and prioritize policies that promote the 'interconnector' role of this ecosystem so that the knowledge stock generated by local stakeholders (e.g., universities, support agencies, laboratories, among others) and available to entrepreneurs is efficiently channeled to the economy, which in turn has the potential to create economic growth. Additionally, in the long-run, successful productivity growth should be grounded in the creation and/or consolidation of policies that support Schumpeterian entrepreneurship, such as the development of mechanisms to finance innovations and incentives to develop new technologies (e.g., Lafuente et al., 2020).

Finally, many developed and developing countries implement policies to stimulate economic growth based on the mere formation of new businesses. However, the effects of such policies vary across countries with different levels of development. On the one hand, the strong growth effect of the entrepreneurial ecosystem on TFP through technical change suggests that for advanced countries—that is, those responsible of most innovations—explicit policies designed to improve the entrepreneurial ecosystem may prove themselves effective in supporting productivity, even if such policies discourage entrepreneurship indirectly (Litan et al., 2009). On the other hand, countries with a limited capacity to develop innovations that try to increase efficiency might benefit more from an investment policy that seeks to accommodate their existing resources to new technologies, rather than an entrepreneurial policy focused on the improvement of their entrepreneurial ecosystem. This argument is in line with Acemoglu et al. (2006) who stress that the optimal growth strategy depends upon the development process.

Appendix

Table A1 Countries included in the sample (period 2002-2013)

	Country	Number of observations		Country	Number of observations
1	Algeria	5	41	Malaysia	6
2	Angola	4	42	Mexico	10
3	Argentina	12	43	Namibia	2
4	Australia	7	44	Netherlands	12
5	Barbados	3	45	Nigeria	3
6	Belgium	12	46	Norway	12
7	Bosnia and Herzegovina	6	47	Pakistan	3
8	Botswana	2	48	Panama	5
9	Brazil	12	49	Peru	10
10	Canada	6	50	Poland	5
11	Chile	12	51	Portugal	6
12	China	12	52	Romania	7

(*continued*)

Table A1 (continued)

	Country	Number of observations		Country	Number of observations
13	Colombia	8	53	Russia	9
14	Costa Rica	3	54	Saudi Arabia	2
15	Croatia	12	55	Serbia	3
16	Czech Republic	4	56	Singapore	8
17	Denmark	12	57	Slovakia	3
18	Dominican Republic	3	58	Slovenia	12
19	Ecuador	7	59	South Africa	12
20	Estonia	2	60	Spain	12
21	Finland	12	61	Sweden	12
22	France	12	62	Switzerland	12
23	Germany	12	63	Thailand	7
24	Ghana	4	64	Trinidad & Tobago	4
25	Greece	11	65	Tunisia	4
26	Guatemala	5	66	Turkey	8
27	Hungary	12	67	Uganda	7
28	Iceland	9	68	United Arab Emirates	6
29	India	3	69	United Kingdom	12
30	Iran	6	70	United States	12
31	Ireland	12	71	Uruguay	8
32	Israel	10	72	Venezuela	9
33	Italy	12	73	Zambia	4
34	Jamaica	9			
35	Japan	12			
36	Korea, Rep.	7			
37	Latvia	9			
38	Lithuania	3			
39	Macedonia, FYR	6			
40	Malawi	2			

Table A2 TFP (Malmquist index), catch-up, and technological change

	Country	TFP	Efficiency change	Technical change	Magnitude term	Input bias
1	Algeria	0.9848	1.0016	0.9828	0.9862	0.9965
2	Angola	0.9539	0.9614	0.9916	0.9881	1.0037
3	Argentina	0.9770	0.9838	0.9929	0.9852	1.0083
4	Australia	1.0157	0.9959	1.0198	1.0197	1.0000
5	Barbados	1.0467	1.0422	1.0065	1.0076	0.9988
6	Belgium	1.0063	0.9995	1.0068	1.0042	1.0027
7	Bosnia and Herzegovina	0.9826	0.9896	0.9928	0.9933	0.9995
8	Botswana	1.1305	1.0783	1.0485	1.0435	1.0048
9	Brazil	0.9887	0.9994	0.9890	0.9810	1.0082
10	Canada	0.9882	0.9858	1.0024	1.0029	0.9996
11	Chile	1.0136	1.0003	1.0129	1.0139	0.9990
12	China	1.0534	1.0000	1.0534	1.0176	1.0354
13	Colombia	1.0073	0.9993	1.0097	1.0103	0.9994
14	Costa Rica	0.9856	0.9651	1.0213	1.0218	0.9996
15	Croatia	1.0170	0.9981	1.0190	1.0165	1.0026
16	Czech Republic	1.0379	1.0302	1.0075	1.0066	1.0009
17	Denmark	1.0312	1.0025	1.0289	1.0295	0.9994
18	Dominican Republic	0.9976	0.9740	1.0242	1.0252	0.9990
19	Ecuador	0.9833	0.9736	1.0102	1.0107	0.9995
20	Estonia	1.0589	1.0435	1.0148	1.0122	1.0025
21	Finland	1.0297	1.0204	1.0093	1.0083	1.0010
22	France	1.0075	1.0032	1.0044	0.9987	1.0059
23	Germany	1.0127	1.0048	1.0079	1.0022	1.0057
24	Ghana	0.9729	0.9739	1.0028	0.9959	1.0075
25	Greece	0.9988	0.9987	0.9997	0.9932	1.0067
26	Guatemala	0.9654	0.9574	1.0113	1.0064	1.0049
27	Hungary	1.0018	0.9934	1.0083	1.0033	1.0053
28	Iceland	0.9920	0.9905	1.0014	0.9928	1.0091
29	India	1.0872	1.0658	1.0196	1.0158	1.0037
30	Iran	0.9705	0.9759	0.9942	0.9973	0.9968
31	Ireland	1.0158	1.0020	1.0140	1.0029	1.0113
32	Israel	1.0000	0.9874	1.0129	1.0087	1.0042
33	Italy	1.0160	1.0094	1.0069	1.0007	1.0063
34	Jamaica	0.9846	1.0079	0.9772	0.9776	0.9996
35	Japan	0.9958	1.0014	0.9945	0.9944	1.0001
36	Korea, Rep.	1.0167	1.0102	1.0065	0.9977	1.0090
37	Latvia	0.9908	0.9943	0.9963	0.9925	1.0041
38	Lithuania	1.0671	1.0379	1.0309	1.0296	1.0013

(*continued*)

Table A2 (continued)

	Country	TFP	Efficiency change	Technical change	Magnitude term	Input bias
39	Macedonia, FYR	0.9623	0.9575	1.0055	1.0058	0.9997
40	Malawi	1.0182	0.9736	1.0458	1.0458	1.0000
41	Malaysia	0.9308	0.9438	0.9843	0.9840	1.0005
42	Mexico	0.9937	0.9997	0.9943	0.9946	0.9997
43	Namibia	0.9259	0.9098	1.0177	1.0096	1.0080
44	Netherlands	1.0200	1.0069	1.0132	1.0127	1.0005
45	Nigeria	1.0456	1.0424	1.0037	0.9991	1.0046
46	Norway	1.0111	1.0097	1.0014	0.9888	1.0130
47	Pakistan	0.9855	1.0000	0.9855	0.9758	1.0099
48	Panama	0.9709	0.9594	1.0129	1.0170	0.9960
49	Peru	0.9745	0.9657	1.0086	1.0086	0.9999
50	Poland	1.0746	1.0763	0.9984	0.9980	1.0004
51	Portugal	1.0895	1.0476	1.0406	1.0243	1.0158
52	Romania	1.0085	1.0045	1.0039	0.9988	1.0052
53	Russia	0.9464	0.9613	0.9842	0.9826	1.0017
54	Saudi Arabia	1.0118	1.0000	1.0118	1.0068	1.0050
55	Serbia	0.9938	1.0037	0.9905	0.9902	1.0003
56	Singapore	1.0273	1.0236	1.0032	0.9706	1.0347
57	Slovakia	1.0827	1.0684	1.0146	1.0071	1.0076
58	Slovenia	1.0191	1.0100	1.0098	1.0100	0.9999
59	South Africa	0.9841	0.9957	0.9887	0.9869	1.0019
60	Spain	1.0097	1.0087	1.0011	0.9946	1.0068
61	Sweden	1.0349	1.0150	1.0193	1.0213	0.9981
62	Switzerland	1.0252	1.0155	1.0097	1.0110	0.9988
63	Thailand	1.0078	1.0151	0.9928	0.9944	0.9984
64	Trinidad & Tobago	1.0124	0.9873	1.0261	1.0247	1.0014
65	Tunisia	1.0015	0.9910	1.0117	1.0089	1.0027
66	Turkey	0.9460	0.9601	0.9849	0.9849	0.9999
67	Uganda	1.0045	1.0478	0.9727	0.9731	0.9997
68	United Arab Emirates	0.9530	0.9827	0.9695	0.9471	1.0252
69	United Kingdom	1.0043	0.9999	1.0044	0.9942	1.0104
70	United States	1.0103	1.0000	1.0103	0.9745	1.0374
71	Uruguay	0.9847	0.9716	1.0144	1.0142	1.0002
72	Venezuela	0.9508	0.9766	0.9758	0.9695	1.0070
73	Zambia	0.9673	0.9482	1.0245	1.0266	0.9982

Notes

1. According to the World Bank, gross capital formation consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories. Fixed assets include land improvements (fences, ditches, drains, and so on); plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings. Inventories are stocks of goods held by firms to meet temporary or unexpected fluctuations in production or sales, and 'work in progress'.
2. Note that the proposed convergence test based on a panel data regression model is somewhat different to the convergence approach in cross-section regressions by Barro and Sala-i-Martin (1992) in the sense that our approach is now regarded as convergence toward the country's own maximum potential output level.

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4

The Entrepreneurship Paradox: The Role of the Entrepreneurial Ecosystem on Economic Performance in Africa

Esteban Lafuente, László Szerb, and Zoltán J. Ács

1 Introduction

Entrepreneurship is often invoked as a highly relevant conduit of economic growth, development, innovation and job creation (Acs et al., 2014; Aghion, 2017; Lafuente et al., 2016; Szerb et al., 2019). Despite entrepreneurship being an attractive concept usually linked to good news, descriptive data made available by the Global Entrepreneurship Monitor

E. Lafuente (✉)
Business School, Costa Rica Institute of Technology (ITCR), Cartago, Costa Rica
e-mail: elafuente@itcr.ac.cr

L. Szerb
Faculty of Business and Economics, University of Pécs, Pécs, Hungary
e-mail: szerb.laszlo@ktk.pte.hu

Z. J. Ács
George Mason University, Arlington, VA, USA
e-mail: zacs@gmu.edu

Z. J. Acs et al. (eds.), *The Entrepreneurial Ecosystem*, Palgrave Studies in Entrepreneurship and Society, https://doi.org/10.1007/978-3-031-25931-9_4

(GEM, 2018) and empirical studies (Block et al., 2017; Naudé, 2011) reveal that the rate of business creation is consistently higher in less developed economies over time, while developed countries show low levels of entrepreneurship. Therefore, the persistent contradiction between theoretical predictions and empirical findings over time constitutes an archetypal example of a paradox (Putnam et al., 2016; Smith & Lewis, 2011).

We argue that this paradox—that we call the entrepreneurship paradox—originates from, at least, two interwoven tensions that characterize country-level entrepreneurship research.[1] At the country level, entrepreneurship is much more than the mere creation of new businesses (Acs et al., 2017), and its operationalization should adopt a systemic approach that incorporates the regulating effect of contextual factors on individual actions (Acs et al., 2014; Lafuente et al., 2016). Because paradoxical tensions emanate from the interaction of the different domains that form complex systems (Smith & Lewis, 2011), it is not surprising that attempts for unveiling the role of entrepreneurship—a complex system—on economic performance usually yield competing and contradictory messages to scholars and policy makers (e.g., Acs et al., 2012; Bjørnskov & Foss, 2016; Desai, 2011; Shane, 2009).

Besides the definitional debate on what constitutes country-level entrepreneurship (Acs et al., 2017; Audretsch et al., 2015; Lafuente & Vaillant, 2016), we identify two broad, closely related tensions that underlie and fuel the entrepreneurship paradox. First, the development tension which emerges from the unclear effect of entrepreneurship on economic development: entrepreneurship is good for the economy, but less developed countries are 'more entrepreneurial' than developed economies. Although various economic arguments have been proposed to explain this contrasting relationship (see, e.g., Audretsch and Keilbach (2008), Braunerhjelm et al. (2010) and Acs et al. (2012); Acs, Audretsch, and Lehmann (2013a) for a discussion on the knowledge spillover theory of entrepreneurship), the debate is open, and empirical research on the entrepreneurship-development relationship is mixed. While some papers underline the positive role of entrepreneurship on economic development (e.g., Acs et al., 2012; Aghion, 2017; Bjørnskov & Foss, 2016), evidence consistently shows that the level of entrepreneurship is much higher in less developed and developing economies (resource- and efficiency-driven countries) than in most developed, innovation-driven countries (Larroulet & Couyoumdjian, 2009; Naudé, 2011).

The second element of the entrepreneurship paradox is the policy tension: many researchers and policy makers consider entrepreneurship as a general panacea that can solve many economic problems; however, public policy—mostly rooted in institutional isomorphism, that is, the replication of actions implemented in other, heterogeneous contexts—oriented to improve entrepreneurship often leads to unexpected and disappointing results, in terms of business creation rates, survival rates or contribution of entrepreneurship to the economy (Acs et al., 2016; Desai, 2011; Shane, 2009).

Underlying most entrepreneurship policies in less developed and developing countries are three widely shared premises: (a) what works in developed countries should work in less developed economies, (b) there is a general recipe (common rules) to improve entrepreneurship and (c) a policy focused on improving entrepreneurial activity is enough to improve country-level entrepreneurship. These presumptions ignore the systemic nature of country-level entrepreneurship in which the interaction between economic agents (entrepreneurs) and the environment where they operate (entrepreneurial ecosystem) plays a key role (Lafuente et al., 2016; Szerb et al., 2019).

In this paper, we analyze the entrepreneurship paradox through the lens of the development tension and the policy tension. By evaluating the connection between economic performance and countries' entrepreneurship ecosystem on a sample of 81 economies in Africa, America, Asia and Europe, we address the following research questions: (1) Why the high rates of entrepreneurial activity observed for Africa are not conducive to development? (2) What constitutes an appropriate entrepreneurship policy design for African countries? Entrepreneurship is still an understudied research field in less developed and developing countries and in Africa in particular (Dana et al., 2018; Devine & Kiggundu, 2016). Our study employs regression models and cluster analysis, seeking to produce insights on how entrepreneurship policy can be conducive to superior economic performance in African countries. Also, by scrutinizing the configuration of the entrepreneurial ecosystem in 14 African countries viz-a-viz other developing regions, we aim to produce novel evidence that contributes to clarifying the tensions that underlie the entrepreneurship paradox, as well as to reconcile the divergent views surrounding the role of entrepreneurship on territorial performance in Africa.

Although many African countries are making important economic progress, the results indicate that the analyzed African nations underperform compared to other developing countries in Asia and Latin America, in terms of GDP per capita. Additionally, the findings indicate that economic performance is not linked to high rates of entrepreneurial entry (quantity-led metrics), but rather to a healthy (quality-led) institutional setting—that is, entrepreneurial ecosystem measured via the GEI index—that supports entrepreneurial activities. In this sense, the results for the group of developing (low and middle income) economies show that Asian countries have the healthiest entrepreneurial ecosystem, whereas the analyzed African countries report the weakest results for the entrepreneurial ecosystem.

Our research offers two main contributions to the existing literature. First, by examining the entrepreneurship paradox through the lens of the development and policy tensions, our study presents new insights on the importance of adopting paradoxical frames in order to better understand how country-level entrepreneurship—operationalized via the entrepreneurial ecosystem—can contribute to a more effective channeling of resources to the economy and, subsequently, to the economic performance of countries. Poor institutional development and the lack of productive entrepreneurship opportunities are relevant challenges for African nations that call for effective policy design (Beugré, 2016; Gomes et al., 2011; Gomes et al., 2018). The overall performance of African countries is very modest compared to other developing countries in Asia and South America, which suggests that it is time to develop alternative policies (African Economic Output, 2017; Rodrik, 2016).

From a knowledge management perspective, prior work has emphasized different policy actions that may contribute to develop a knowledge-based economy at the territorial level, including, among others, the development of economic (fiscal) and noneconomic (infrastructures) incentives that attract high-tech multinational enterprises with the purpose to promote knowledge generation or acquisition processes (Lafuente et al., 2018; Wong et al., 2006), or investments in industry clusters that enhance knowledge sharing within and between industries via collaborations (Connell et al., 2014).

Second, the institutional approach adopted in this study contributes to extending the increasing stock of scientific work on paradoxes. The evolution of contradictions and paradoxes has been associated with institutional change (Putnam et al., 2016), and in this study we argue that a newly redefined entrepreneurship policy that emphasizes the role of the entrepreneurial system represents one of these alternatives. The relevance of studying paradoxes from an institutional perspective flows from the recognition that institutions are not monolithic socially created structures (e.g., Seo & Creed, 2002). Our arguments highlight the importance of challenging 'taken-for-granted' resource allocation rules if a new policy design emphasizing a more efficient resource mobilization that enhances country-level entrepreneurship and, subsequently, economic performance is the desired outcome.

In this sense, the approach adopted in this study proposes a shift in policy focus from actions directed to incremental entrepreneurial rates—that are assumed to take place in contexts dominated by monolithic institutions—to a more holistic view in which the systemic nature of country-level entrepreneurship—that is, focused on the interaction between entrepreneurs and the context—is at the heart of the analysis (Acs et al., 2014; Lafuente et al., 2016). In line with Putnam et al. (2016), we argue that institutional restructuration is necessary to encourage the development of new actions that contribute to mitigate and/or overcome the tensions that underlie the entrepreneurship paradox.

This paper is structured as follows. Section 2 introduces the development and policy tensions that trigger the entrepreneurship paradox. Section 3 evaluates entrepreneurship in Africa. The data, variables and methods used in the empirical analysis are presented in Section 4. Section 5 presents the results. Section 6 presents the conclusions, implications and limitations of the work.

2 The Entrepreneurship Paradox: From Development Tensions to Policy Tensions

There are two widely shared beliefs about the role of entrepreneurship and entrepreneurship policies on economic development. First, many researchers, practitioners and policy makers stress that the positive association between entrepreneurship and economic growth and development is unquestionable (Acs et al., 2016; Naudé, 2014; Shane, 2009). This notion dates back to Schumpeter's idea of innovative entrepreneurs who are responsible for creative destruction processes via the exploitation of new opportunities (Schumpeter, 1934). Growth theories also equate entrepreneurship with Schumpeterian entrepreneurship (Aghion, 2017; Lafuente et al., 2016; Szerb et al., 2019). However, a significant proportion of new firms is not innovative, and, on the contrary, only a minority (perhaps very few) of businesses matches the entrepreneurial profile described by Schumpeter and his followers (e.g., Henrekson & Sanandaji, 2014; Schumpeter, 1934). In sharp contrast to this view, Steyaert and Katz (2004) and Reynolds et al. (2005) state that entrepreneurship is a societal phenomenon, so anybody can be an entrepreneur. Yet, empirical evidence about the effect of everyday entrepreneurship on economic growth is not convincing, and the positive influence of entrepreneurship on economic growth is mostly limited to developed settings (Block et al., 2017; Van Stel et al., 2005).

The overwhelming majority of entrepreneurship studies in developing countries tend to cater to the tastes of canonical theories by encouraging the replication of theoretical arguments rooted in developed settings in emerging countries, regardless of the evident differences between developed and less developed economies (Bruton et al., 2008; Naudé, 2011).

This pattern has changed in the last decade, and research now acknowledges that entrepreneurship is not a universal but a context-specific phenomenon (Desai, 2011; Naudé, 2014). According to Baumol (1996), the productivity of entrepreneurship depends on the context: productive entrepreneurship will flourish in countries that provide favorable conditions for start-ups, while inefficient or even destructive entrepreneurship characterizes those nations where institutions are weak. Thus, the effects of entrepreneurship differ within and across countries. This has led to a policy change from a general 'one-size-fits-all' policy to country-specific tailor-made policies (Acs et al., 2014).

Institutional embeddedness is critical to explain differences in entrepreneurial behavior; however, the effect of institutions shows significant cross-country variations (De Clercq et al., 2010; Welter & Smallbone, 2011). Estrin et al. (2013) highlight the heterogeneous and complex effects of institutions on entrepreneurial growth aspirations. Acknowledging the role of institutions contributed to shift the focus of entrepreneurship policy from the narrow view based on promoting quantitative entrepreneurship (entrepreneurial activity) to a more holistic view in which the environment plays a decisive role in developed, emerging as well as transitional economies.

Besides formal institutions, informal institutions also influence entrepreneurship. Large informal sectors involving substantial informal entrepreneurial activity do not lead to economic growth. According to Henrekson and Sanandaji (2014), unproductive entrepreneurship can emerge because of the influence of entrepreneurs on the institutions. Evading and altering the existing institutions may lead to short-term rent-seeking entrepreneurship, instead of promoting innovative entrepreneurship with a long-term perspective. Informal institutions and rent-seeking behaviors are more pronounced in lower developed countries, which limit the capacity of public policy for modifying existing institutions and entrepreneurial behaviors (Autio & Fu, 2015; Thai & Turkina, 2014).

The second belief is associated with the way to measure entrepreneurship. While many researchers recognize the diversity of startups and small businesses, most comparable data are available only for self-employed and small business count numbers. Therefore, empirical studies tend to operationalize country-level entrepreneurship via measures based on the number of self-employed or new businesses (Beugelsdijk & Noorderhaven, 2005; Shane, 2009).

Since the 2000s, the Global Entrepreneurship Monitor (GEM) has made it possible to compare entrepreneurial activities around the world. The total early-phased entrepreneurship activity (TEA) rate—that is, the proportion of adult population aged 18–64 years who are actively involved in creating a business (nascent) or own and manage a new business (less than 42 month) (Reynolds et al., 2005)—has become a very popular, widely used entrepreneurship indicator (Amorós et al., 2013; Lafuente & Vaillant, 2016; Van Stel et al., 2005). As the number of participating countries in the GEM project grows, the limitations of TEA have become evident (Hindle, 2006). There are four fundamental problems with the TEA as a measure of entrepreneurship. First, TEA includes start-up intentions (nascent entrepreneurship) and new ventures with very different characteristics. Nascent (speculative) entrepreneurship represents an overconfident manifestation of individuals' entrepreneurship potential and growth opportunities. Because of the speculative nature of nascent entrepreneurship, about half of business intentions never materialize in new firms (Szerb & Vörös, 2018).

The second concern is that TEA mixes ventures with heterogeneous characteristics that follow very different distributions over different stages of economic development. In our view, this underlying property of the TEA ratio spurs the development tension of the entrepreneurship paradox. The TEA rate is typically high or extremely high in less developed countries and much lower in developed economies. Consequently, the TEA implicitly assumes that a new tech start-up in Silicon Valley has roughly the same economic importance as a new sheepherder business in Mali or a newly opened pension in the Croatian coast. In fact, similar to other self-employment measures, TEA correlates negatively with economic development (GDP per capita) (Acs et al., 2018; Baumol et al., 2007; Shane, 2009), while some scholars highlight a U-shape relationship between these two variables (Acs, 2006; Wennekers et al., 2010). It has been argued that local markets consolidation is a consequence of development so that as countries develop, more and more people leave self-employment and join organizations (Acs et al., 2017). Therefore, as the quantity of entrepreneurship declines, the quality of entrepreneurship increases. For example, the level of self-employment in the United States declined from 80% in the 1800s to less than 10% in the twenty-first century. A similar trend is observed in most developed economies (GEM, 2018).

Third, while entrepreneurship is believed to be a major determinant of economic growth, the connection between TEA and economic growth is insignificant or only positive among developed countries (Carree et al., 2007; Van Stel et al., 2005). The fourth problem is that TEA does not take into account the context within which businesses are created. The mostly negative correlation between TEA and the quality of the institutional setting generates another development paradoxical tension (Acs et al., 2014). Despite these fundamental discrepancies, TEA as a measure of entrepreneurship and as an effective target for entrepreneurship promotion policy is still used in many papers and policy reports (Amorós et al., 2013; GEM, 2018; Herrington et al., 2010; Parker, 2018).

To overcome the deficiencies of the TEA rate, alternative entrepreneurship measures based on GEM data (opportunity/necessity entrepreneurship, high growth startups) and other survey-based metrics (gazelles, high-impact entrepreneurship, innovative start-ups) have been developed (Amorós et al., 2013). These alternative entrepreneurship measures have very different effects on productivity, growth, job creation and development, thus opening up new challenges to effective entrepreneurship policy initiatives (Nightingale & Coad, 2014).

Traditional policy efforts oriented to increase the number of new businesses have proved to be ineffective (Acs et al., 2016), thus fueling the policy tension of the entrepreneurship paradox. The policy focus has started to shift from the quantitative approach to entrepreneurship based on mere numbers to develop quality-led measures that take into account important quality aspects of entrepreneurship like high-growth or innovation (Acs et al., 2014).

Entrepreneurship scholars have recently emphasized the need to account for the systemic nature of country-level entrepreneurship (e.g., Acs et al., 2014; Lafuente et al., 2016). In this sense, the entrepreneurship ecosystem (EE) approach has gained increased popularity. In this tradition, entrepreneurship is conceptualized as the interaction of entrepreneurs (agents) and the entrepreneurial environment (ecosystem) to produce goods and services (Acs et al., 2014). While the context view considers the entrepreneurial environment as the sum of different components, the EE approach is based on a multi-context perspective where the configuration of the components is also an important determinant of territorial economic outcomes. An intermediate output of the EE is entrepreneurial activity. Out of the many entrepreneurship measures, EE counts only those that yield high-impact, high-growth start-ups (Acs et al., 2014; Spigel, 2017).

This path-dependent evolutionary view, borrowed from the innovation systems approach, is another distinctive characteristic of EE. Because the mix of the EE components is heterogeneous across countries, entrepreneurship policy should also be country-specific rather than imitative (Isenberg, 2010; Spigel, 2017). This assertion has an important consequence and limitation on the adoption of the EE in less developed and emerging contexts. So far, only the Global Entrepreneurship Index (GEI) has provided a country-level measure of the quality of the entrepreneurial ecosystem. Consequently, most efforts oriented to provide economically meaningful policy recommendations to less developed, emerging or transition countries are based on GEI statistics (Acs, Audretsch, & Lehmann, 2013a; Atiase et al., 2018; Faghih & Zali, 2018; Sheriff et al., 2016; Szerb et al., 2017).

The GEI takes a slightly different view as compared to other EE scholars by claiming that it is possible to measure the EE in a uniform way via the use of a composite indicator (index). The GEI suggests that the relationship between entrepreneurship and economic development is positive, and that the curve is most likely S-shaped, contrary to the likely L-shaped curve theorized in research connecting rates of new firm or TEA measures and economic development. The three parts of the S-shaped curve show how productive entrepreneurship affects countries' economic performance at different stages of development. First, productive entrepreneurship is low in less developed, resource-driven countries and then rises as countries develop. How quickly countries modernize depends on the development of their institutions (Acemoglu et al., 2005). Political instability, corruption and rent-seeking predatory behavior characterize many developing countries. Under these conditions, entrepreneurs will be reluctant to make the (monetary and nonmonetary) long-term investments necessary to create productive, high-impact firms. If countries have extractive economies where only a few benefit at the expense of the others, development will not take place. As institutions become stronger, destructive and unproductive activities decline, giving way to more productive entrepreneurial activity, thus strengthening economic development (Acs et al., 2017).

At the country level, entrepreneurship is much more than 'more entrepreneurs'. The definitional debate on what is meant by country-level entrepreneurship jointly with the contrasting results reported by prior studies feeds both the development and policy tensions of the entrepreneurship paradox.

We argue that country-level entrepreneurship is more linked to 'better entrepreneurs functioning in settings with better institutions'. According to the GEI, optimal entrepreneurship policy that aims at improving the countries' entrepreneurial ecosystem should be country-specific and should focus on alleviating the weak components in the system (Acs et al., 2014).

3 Entrepreneurship in Africa

Little is known about entrepreneurship and the entrepreneurial environment in less developed and developing societies, such as African countries. This makes it difficult to understand the underlying factors that influence entrepreneurs in these resource-constrained economies (The entrepreneurship ecosystem of South Africa, 2017). In the past decade, efforts to creating reliable databases have intensified with the objective to measure the static, dynamic, qualitative and contextual factors of country-level entrepreneurship. There is a plethora of indices and reports that measure some aspects of entrepreneurship at the global level, but most African countries are not included (Sheriff et al., 2016).[2]

A relatively large number of studies focus on a few number of countries, mostly former British colonies (e.g., South Africa, Nigeria, Kenya and Tanzania). This may be due to a multitude of reasons including, but not limited to, the scarcity of local entrepreneurship scholars, the under-researched nature of the subject, the lack of interest in the subject or the lack of entrepreneurs to study. A notable exception is the work of Acs, Szerb, and Jackson (2013b)—*Entrepreneurship in Africa through the Eyes of GEDI*—who employ partially estimated data to analyze entrepreneurship in a relatively large number of African countries.

Africa is a large continent with highly heterogeneous countries. Northern Africa is mostly covered by Muslim nations that are part of the MENA countries. The most densely populated part of Africa—that is, sub-Saharan Africa—includes the poorest countries on the globe. Sub-Saharan Africa is also diverse by itself where different colonial histories and tribal heritages are still pronounced (Acs, Audretsch, & Lehmann, 2013a; Beugré, 2016; Taylor, 2012). Political instability exasperated with violent conflicts is not a fertile ground for development. Some MENA countries (Egypt, Morocco and Tunisia) and two sub-Saharan countries (Namibia and South Africa) are considered efficiency-driven countries, while the rest of countries are in the least developed, resource-driven cohort (World Economic Forum, 2017). This implies many similarities in macroeconomic figures from a certain distance (bird-eye view) as well as remarkable differences if we take a closer, analytical view.

Most African countries exhibit low standards of living, health problems, high-income inequalities, poor institutional development and macroeconomic instability in terms of foreign debt, inflation and unemployment (Gomes et al., 2018). To overcome these problems, a country needs to create economic growth with long-term orientation. Many suggestions to develop African countries have been proposed, including the attraction of Foreign Direct Investment (FDI), industry developments spanning agriculture modernization to industrialization and tourism, changes in institutions and regulatory environments, investments in physical infrastructure and human capital, development of small businesses and the private sector and science and technology development (Fields, 2014; Pieterse, 2010). While many of these broad development strategies could be related to entrepreneurship, we examine only three of them, namely the development of small businesses and the private sector, institutional development and industrialization.

The private business sector in most African countries is characterized by a few large businesses—often governed by foreign investors—and a large number of tiny small ventures mostly in the informal economy. Foreign businesses mostly operate in extractive sectors, and they are rather islands whose benefits do not percolate to the local economy (Hansen et al., 2016). Rather than following an innovation or value creation strategy, other large enterprises show a more rent-seeking behavior (sub-Saharan Africa, 2018; Taylor, 2012). New firm registrations are much lower in Africa as compared to similarly developed countries, thus suggesting that most local businesses operate in the informal economy (Munemo, 2012). According to a recent IMF report, informal economy contributes 25–65% of GDP and 60–90% of employment in sub-Saharan Africa (Sub-Saharan Africa, 2018). Additionally, informal businesses are very different from formally registered ones, in terms of growth and employment creation (Beugré, 2016; Rodrik, 2016; Williams et al., 2017). However, it should be noted that self-employment is not necessarily a manifestation of informal economic activity in less developed or developing economies (Fields, 2014).

Empirical studies connecting formal economic activity and economic performance show mixed results. While formal business activity has been found to positively impact economic growth in twelve African countries (Adusei, 2016), research also highlights that, although informal businesses are exposed to weakened property rights and higher risks, policies based on tax reforms oriented to reducing informal economic activities in developing contexts may have a negative impact on territorial welfare and labor market performance (Auriol & Warlters, 2005; Ulyssea, 2010).

Informal business activity is frequently associated with necessity-led entrepreneurship. Necessity entrepreneurship is not bad per se since it provides a potential to survive, but this type of entrepreneurship cannot help African countries to mobilize economic resources to economic growth and to get out of the deep pocket of poverty (Acs et al., 2017; Beugré, 2016; Naudé, 2011). In this scenario, the nature of entrepreneurship in Africa may explain the development tension of the entrepreneurship paradox.

Some researchers link entrepreneurship to small business development in African contexts. In their analysis of entrepreneurship in Nigeria, Nzewi et al. (2017, p. 176) state that 'small scale businesses can make to reduce poverty, create wealth, generate employment and enhance the development of infrastructures'. Others view African small businesses much less influential and more problematic given their lack of individual capabilities, human capital and supportive physical and regulatory environment (George et al., 2016; Ihugba et al., 2014).

Rooted in the institutional economics, institutional development has become popular in the last decade (e.g., Acemoglu et al., 2005). Institutional reforms have a positive effect on economic performance via the development of the private sector and small businesses. Properly targeted and enforced policy efforts could reduce corruption and the size of the informal sector as well as improve productive entrepreneurship (Gomes et al., 2018; Okey, 2011). While it is agreed that classical institutional reforms linked to property rights, economic freedom and ease of start-ups positively influence entrepreneurship in African countries (Kshetri, 2011), many other institutional effects remain unknown or understudied because of the lack of proper data.

According to a recent OECD report on Africa (African Economic Outlook, 2017), industrialization linked to local entrepreneurship could lead to improve productivity and induce employment. Most African start-ups operate in those sectors where entry is easy and human capital is not required (low skill sectors). Entrepreneurial skill development and high growth motivation are key factors for this new industrialization strategy. Previous, mostly unsuccessful African industrialization attempts heavily relied on foreign businesses or large publicly owned domestic firms (African Economic Outlook, 2017). Increased firm-level productivity can also be reached via technology developments to scale-up existing small businesses. However, this change should be coupled with institutional reforms as well as further skill and cluster development (Oyelaran-Oyeyinka, 2017).

Improvements in the entrepreneurial ecosystem as a way to achieve superior levels of development in Africa have recently gained attention, mostly as a result of the increased recognition on the need for productive entrepreneurship, instead of small, unproductive businesses (Beugré, 2016; Mwatsika, 2018; Sheriff et al., 2016). As we described previously, the EE approach focuses on the environment that induces high-impact entrepreneurship. Furthermore, the EE emphasizes the interrelation of environmental factors and aims to identify relevant elements at the country level.

The first work in this direction was conducted by Acs, Audretsch, and Lehmann (2013a) who found that human resources, entrepreneurship skills and networking and not innovation are the most inhibited factors in many African countries. Atiase et al. (2018) analyzed the factors affecting GEI. While financial institutions, political governance and access to electricity were found to be significant, access to credit had no impact on GEI.[3] A more accurate analysis was performed by Park et al. (2017) who examined a local ecosystem in Nairobi. These authors argue that 'for developing economies, which lack certain resources and formal institutions, support organizations of various origins can serve as a critical driving force in creating supportive entrepreneurial ecosystems' (p. 1).

Another lesson learned from the analysis of the entrepreneurial ecosystem approach is that policy implementation based on the replication of policies adopted by other successful and heterogeneous entrepreneurial ecosystems is not the way to enhance countries' development. Ecosystems, such as Silicon Valley, are complex and are formed by many components where developed institutions, infrastructure and innovative businesses play a key role. Thus, a policy designed to duplicate such system, or a few elements of it, constitutes a waste of money and resources. Even if knowledge is available, it would not automatically transfer to new businesses (Acs et al., 2012). Instead, African countries should rely on their actual local resources and absorptive technologies (Amankwah-Amoah et al., 2018; Cunningham et al., 2016).

Based on these arguments and results, it seems plausible to argue that the lack of appropriate institutions and market-led conditions nurture the policy tension of the entrepreneurship paradox.

An agreement exists among scholars and development experts that the free market forces that drive productive entrepreneurship in less developed and developing countries should not be left alone, and that governments should play an active role to consolidate such forces (Brixiová, 2010). However, contradiction and unclear aims could easily lead to policy misalignment (Edoho, 2015). Entrepreneurship support policy frequently falls into the fallacy of focusing on the 'more entrepreneurship' goal, instead of promoting the 'better entrepreneurship' objective. In Africa, the rising population figures induce policy makers to support any entrepreneurial activity in the short term, with the misleading notion that this policy would increase employment in the long term (Chiguntа, 2017; Gough & Langevang, 2016).

Several African countries have run programs to support youth start-up activity, including South Africa (Gwija et al., 2014), Swaziland (Brixiová et al., 2015) and Zambia (Chigunta & Mwanza, 2016). A common lesson from these programs is that low-quality, necessity-driven businesses may represent a short-term alternative (sheer survival), but this type of entrepreneurship does not help countries to get out of poverty. On the contrary, policies focused on the improvement of both the regulatory and institutional context and training programs were more successful than those that just aimed to increase the number of new firms in the economy (De Gobbi, 2014; Wiger et al., 2015).

According to Edoho (2016), effective entrepreneurship policy should aim to support opportunity entrepreneurship, shrink the informal activity, spur innovations, foster growth, expand opportunities and create jobs. From these arguments and evidence, it can be argued that African countries do not need more entrepreneurs, but better entrepreneurs. More entrepreneurs are not good for African economies, and what African countries need is a policy that stimulates the entrepreneurial ecosystem.

4 Data, Variable Definition and Method

4.1 Data

The data used in this study come from three sources of information. First, macroeconomic data were obtained from the International Financial Statistics available from the International Monetary Fund (IMF) data sets for the year 2013 and 2014. Second, the information used to measure the rate of entrepreneurial activity at country level was obtained from the Adult Population Surveys (APS) of the Global Entrepreneurship Monitor (GEM) for 2013. The GEM project began in 1998 as a joint initiative of the Babson College and the London Business School to create an international entrepreneurship research network. Today, more than 80 countries take part in this project, making the GEM a world reference in the entrepreneurship field and a highly valued source of information for scholars and policy makers in each of the participating countries. A comprehensive description of the GEM data and its methodology is presented in Reynolds et al. (2005). Third, variables related to the country's demographic, educational and economic conditions, as well as to the entrepreneurial activity used to estimate the 2013 Global Entrepreneurship Index (GEI) were obtained from different sources, including the Global Entrepreneurship Monitor (GEM) adult population surveys, the Global Competitiveness Index (GCI) and the Doing Business Index (see Acs et al., 2018).

The final sample includes information for a total number of 81 countries. Note that the representativeness of the sample is ensured insofar as it includes 14 African countries (Algeria, Angola, Botswana, Burkina Faso, Cameroon, Egypt, Ghana, Malawi, Namibia, Nigeria, South Africa, Tunisia, Uganda and Zambia), 20 American countries including both North America, Latin America and the Caribbean islands (Argentina, Barbados, Belize, Bolivia, Brazil, Canada, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Jamaica, Mexico, Panama, Peru, Suriname, Trinidad & Tobago, the United States and Uruguay), 14 Asian countries (China, India, Indonesia, Iran, Japan, Kazakhstan, the Republic of Korea, Malaysia, the Philippines, Qatar, Singapore, Taiwan, Thailand and Vietnam) and 33 European countries (Austria, Belgium, Bosnia and Herzegovina, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Ireland, Israel, Italy, Latvia, Lithuania, Luxembourg, Macedonia, the Netherlands, Norway, Poland, Portugal, Romania, Russia, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey and the United Kingdom).

4.2 Variable Definition

Dependent variable. Similar to prior work on countries' performance (e.g., Caselli & Coleman, 2006; Kumar & Russell, 2002; Lafuente et al., 2016), the territorial outcome variable used in this study is economic performance measured as the logged value of the GDP per capita for the year 2014. From the descriptive statistics presented in Table 4.1, we observe that average GDP per capita is 24,725 international dollars. As

Table 4.1 Descriptive statistics for the selected variables

	GDP per head	Total entrepreneurial activity (TEA)	Global Entrepreneurship Index (GEI)	Capital deepening ratio (Capital / labor)	Total population	Obs.
Full sample	24,725.78	0.1391	38.7061	72,595.01	70.14	81
	(20,807.25)	(0.0912)	(18.2267)	(61,677.16)	(209.62)	
Africa	6,813.45	0.2489	22.7315	21,374.42	38.16	14
	(5,050.61)	(0.1172)	(8.6091)	(17,646.21)	(44.97)	
Americas	17,820.30	0.1759	32.2237	46,536.68	44.40	20
	(11,900.47)	(0.0732)	(18.5889)	(35,502.41)	(81.62)	
Asia	31,231.32	0.1257	36.6845	72,518.95	250.65	14
	(32,860.53)	(0.0554)	(14.9301)	(71,047.82)	(461.67)	
Europe	33,750.16	0.0758	50.2694	110,150.10	22.72	33
	(16,629.86)	(0.0208)	(15.0704)	(59,648.74)	(32.39)	

Note: Monetary values (GDP per head and the capital–labor ratio) are expressed in international dollars, while total population is expressed in millions of inhabitants. The GDP per head variable is the value for 2014, while values for the rest of variables correspond to the year 2013.

expected, the highest (lowest) average GDP per capital is reported for European (African) countries. In the specific case of African nations, average GDP per capital is 6813 international dollars, and a further scrutiny of the data reveals that Botswana (15,914), Algeria (13,253) and South Africa (12,446) show the highest level of GDP per capita, while the lowest GDP per capital values are found for Malawi (1062) and Cameroon (726).

Rate of entrepreneurial activity. In this study, the first entrepreneurship variable is the total entrepreneurial activity (TEA) rate for 2013. Within the GEM framework, The TEA ratio measures the proportion of the adult population (individuals aged 18-64 years) involved in entrepreneurial activities. Because of the timing of the GEM adult population survey (individuals are interviewed between June and July), it should be noted that entrepreneurially active individuals include nascent entrepreneurs—who are actively involved in the business creation process (potential entrepreneurs working an entrepreneurial project during the last six months)—and new entrepreneurs who created a business in the previous 42 months (Reynolds et al., 2005). Table 4.1 shows that, on average, 13.91% of the adult population is involved in entrepreneurial activities in 2013. African countries report the highest TEA value (24.89%), while European countries are the least 'entrepreneurial' (TEA: 7.58%).

Also, Figure 4.1 shows that the relationship between quantitative-based entrepreneurship (rate of new entrepreneurs) and economic performance (ln GDP per capita) is negative (Pearson correlation= –0.6281, p-value < 0.000), that is, more entrepreneurs is associated with lower levels of development. As we mentioned before in the introduction and in Section 2, the contrasting relationship illustrated in Fig. 4.1 fuels the *development tension* of the entrepreneurship paradox analyzed in this study.

Entrepreneurial ecosystem. We employ the Global Entrepreneurship Index (GEI) for 2013 to evaluate the quality of the entrepreneurial ecosystem of the sampled countries. The GEI captures the multidimensional nature of entrepreneurship at the country level. The GEI index measures the dynamic and institutionally embedded interaction between entrepreneurial attitudes, entrepreneurial abilities and entrepreneurial aspirations by individuals, which drive resource allocation through new business venturing (Acs et al., 2014).

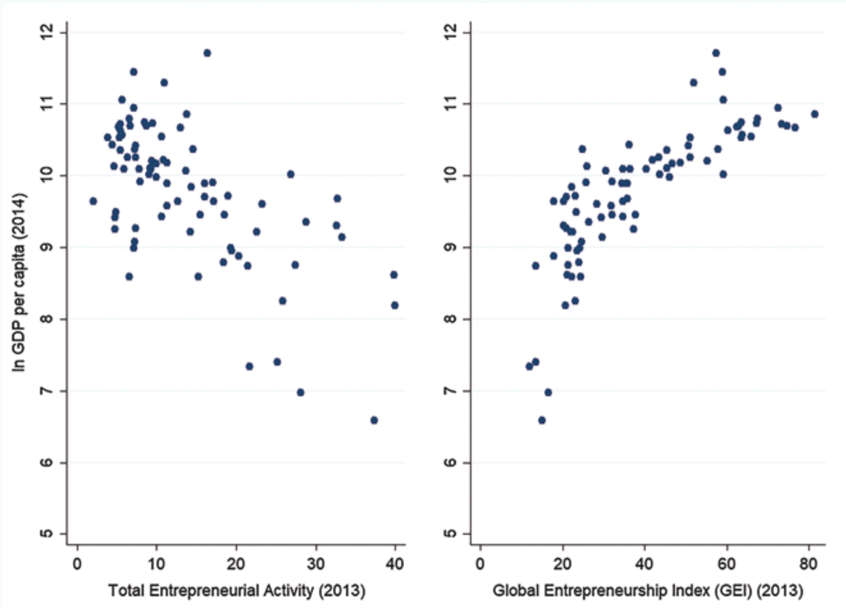

Fig. 4.1 The relationship between GDP per capita, the rate of entrepreneurial activity (TEA) (left: correlation = –0.6281, $p < 0.000$) and the entrepreneurial ecosystem (GEI index) (right: correlation = 0.7919, $p < 0.000$)

The GEI index, which ranges between 0 and 100, is built on 14 pillars, which result from 14 individual-level variables properly matched with selected institutional variables related to the country's entrepreneurship ecosystem (see Acs et al., 2018). The framework supporting the building of the GEI index as well as the full description of the methodology used to compute the GEI scores is offered by Acs et al. (2014) and Acs et al. (2018). The GEI values for the 81 countries included in the sample are presented in Table 4.2. Note that developed (OECD) economies are in the top-10 positions, while the five countries with the poorest entrepreneurial ecosystem—according to the GEI scores—are African. Also, the results in Fig. 4.1 show how the quality of the entrepreneurial ecosystem—measured by the GEI index—is positively correlated to economic performance (ln GDP per capita) (Pearson correlation= 0.7919, *p*-value

Table 4.2 The Global Entrepreneurship Index (GEI): ranking and score for 2013

N	Country	GEI index	N	Country	GEI index
1	United States	81.56	41	Malaysia	34.61
2	Canada	76.67	42	Barbados	34.59
3	Sweden	74.60	43	Uruguay	34.41
4	Denmark	73.30	44	China	32.15
5	Switzerland	72.41	45	Croatia	32.10
6	Ireland	67.57	46	Costa Rica	31.77
7	Netherlands	67.23	47	Kazakhstan	30.43
8	United Kingdom	65.85	48	Namibia	29.69
9	Finland	63.78	49	Macedonia	29.34
10	France	63.51	50	Thailand	28.43
11	Taiwan	63.45	51	Peru	26.40
12	Austria	62.92	52	Russia	25.87
13	Germany	62.43	53	Panama	25.67
14	Belgium	60.32	54	Trinidad & Tobago	24.78
15	Norway	59.11	55	Georgia	24.69
16	Chile	59.08	56	India	24.41
17	Luxembourg	58.97	57	Belize	24.12
18	Israel	57.88	58	Philippines	24.06
19	Qatar	57.44	59	El Salvador	23.43
20	Estonia	55.24	60	Algeria	23.24
21	Singapore	51.95	61	Ghana	23.14
22	Slovenia	51.05	62	Mexico	23.04
23	Japan	51.04	63	Egypt	22.49
24	Korea	50.59	64	Vietnam	22.22
25	Lithuania	48.78	65	Argentina	22.18
26	Portugal	46.60	66	Indonesia	21.94
27	Turkey	46.09	67	Bolivia	21.45
28	Spain	45.49	68	Jamaica	21.25
29	Poland	45.37	69	Nigeria	21.04
30	Latvia	43.55	70	Bosnia and Herzegovina	20.97
31	Czech Republic	43.38	71	Iran	20.88
32	Slovak Republic	41.88	72	Zambia	20.61
33	Hungary	40.38	73	Ecuador	20.34
34	Colombia	37.75	74	Brazil	20.31
35	Tunisia	37.24	75	Guatemala	17.95
36	Greece	36.38	76	Suriname	17.75
37	Italy	36.11	77	Malawi	16.52
38	Romania	35.73	78	Cameroon	15.08
39	Botswana	35.68	79	Uganda	13.51
40	South Africa	34.68	80	Angola	13.44
			81	Burkina Faso	11.88
				Full sample	**38.71**

< 0.000). In this sense, the analysis of country-level entrepreneurship based on metrics linked to the entrepreneurial ecosystem may contribute to reconcile the policy tensions that underlie the entrepreneurship paradox.

Control variables. We control for capital deepening, country size and location in the different model specifications. In line with previous studies on economic performance (e.g., Acs et al., 2017; Caselli & Coleman, 2006; Kumar & Russell, 2002; Lafuente et al., 2016), our models include the effect over GDP per capita of capital deepening, defined as the ratio of the capital stock (K) divided by labor (L). For the year 2013, capital is defined as the private capital stock which is computed through the perpetual-inventory method, while labor is the total number of workers in the country. Country size is proxied by the total population. Finally, a set of dummy variables was included to identify countries located in Africa, Latin America and Asia (the geographic reference groups include developed countries located in North American and Europe). Note that, similar to the case of the GDP per capita, the GEI score and the variables capital deepening and size are logged to reduce skewness.

4.3 Method

In line with the arguments that underpin this study, we first employ regression techniques (OLS) to estimate the model that emphasizes a relationship between country-level entrepreneurship and economic performance among the sampled economies. To evaluate the proposed relationship empirically, in the first stage analysis we propose a regression model with the following form:

$$\ln \text{GDP} / \text{capita}_i = \beta_0 + \beta_1 \text{Entrepreneurship}_i + \beta_2 \text{Control variables}_i + \varepsilon_i \quad (4.1)$$

In equation (4.1), entrepreneurship is measured as the canonical quantity-based rate of new entrepreneurs (TEA) and the GEI index that evaluates the quality of the entrepreneurial ecosystem, β_j is the parameter estimate computed for the set of independent variables (j)

and ε_i is the normally distributed error term estimated for each analyzed country (i).

Additionally, we propose a second-stage analysis to provide further results on the relationship between entrepreneurship and economic development in Africa. In this case, we employ a nonhierarchical cluster analysis (*K*-means) (Anderberg, 1973; Everitt, 1980) using as inputs the GDP per capital, the entrepreneurship measures (TEA and GEI scores), the capital deepening ratio and total population. Because the *K*-means cluster analysis requires a fixed number of clusters, we adopted two approaches to verify the number of cluster and the validity of our analysis. First, we used the Calinski and Harabasz (1974) statistic. This index is obtained as $CH\left(k\right)=\frac{B\left(k\right)/k-1}{W\left(k\right)/n-k}$, where *B(k)* and *W(k)* are the between and within-cluster sums of squares, with k clusters. Since the between-cluster difference should be high and the within-cluster difference should be low, the largest CH(k) value indicates the best clustering. In this study, the number of clusters that maximizes the CH(k) index is 4 (pseudo-F value: 47.86). Therefore, the final nonhierarchical cluster asks for a four-way division. Second, we ran a discriminant analysis to further validate the cluster results. The results of the discriminant analysis (Table 4.3) corroborate the appropriateness of the proposed approach to examine the relationship between entrepreneurship and economic development.

Table 4.3 Results: Discriminant analysis

	Classification according to the discriminant analysis				Total
True groups	Group 1	Group 2	Group 3	Group 4	
Group 1	17 (94.44%)	1 (5.56%)	0 (0.00%)	0 (0.00%)	18
Group 2	2 (10.00%)	18 (90.00%)	0 (0.00%)	0 (0.00%)	20
Group 3	0 (0.00%)	0 (0.00%)	20 (100.00%)	0 (0.00%)	20
Group 4	0 (0.00%)	0 (0.00%)	0 (0.00%)	23 (100.00%)	23

5 Empirical Results

5.1 Regression Analysis: More Entrepreneurship or a Healthy Entrepreneurial Ecosystem

Table 4.4 presents the results of the regression models that emphasize the relationship between entrepreneurship—quantitative (TEA) and qualitative (GEI score)—and economic performance (equation (4.1)). Regression models are estimated for the full sample (81 countries) and for the subsample of 43 less developed and developing economies located in Africa, Asia and Latin America.

Concerning the effect of the traditional quantitative entrepreneurship measure—that is, the total early activity measure (TEA) (model 1)—the findings in Table 4.4 indicate that, for both the full sample and the subsample of less developed and developing economies, increase in the rate of entrepreneurs is not associated with higher levels of GDP per capita in a significant way. In sharp contrast with theoretical postulates, this result is in line with previous studies highlighting a not-significant or an unclear effect of quantity-based entrepreneurship measures on economic performance (Block et al., 2017; Van Stel et al., 2005). As we indicated in Section 2, this contrasting result is the main factor explaining the *development tension* of the entrepreneurship paradox.

In the case of model specification 2 regressing GDP per capita against the GEI score measuring the quality of the entrepreneurial ecosystem, results in Table 4.4 strongly support the notion that economic development is not linked to the presence of more entrepreneurs, but rather to a better (high quality) institutional setting backing entrepreneurial activity (entrepreneurial ecosystem) (Acs et al., 2014; Lafuente et al., 2016). This result is consistent for the model applied to the full sample and to the subsample of less developed and developing countries located in Africa, Asia and Latin America.

Because country-level entrepreneurship is a complex system in which the institutions governing economic activity interact with the economic agents leading entrepreneurial activities (entrepreneurs), the poor and disappointing results of traditional policies oriented to increase the

Table 4.4 Regression results (dependent variable: ln GDP per capita)

	Full sample		Developing countries in Africa, Latin America and Asia	
	(1)	(2)	(1)	(2)
Rate of entrepreneurs (TEA)	0.3411 (0.6592)		0.3769 (0.7038)	
Global entrepreneurship index (GEI)		0.4324*** (0.1343)		0.5644** (0.2145)
Capital deepening (ln capital to labor ratio)	0.8222*** (0.0446)	0.6743*** (0.0671)	0.8920*** (0.0660)	0.7370*** (0.0875)
ln population	–0.0180 (0.0206)	–0.0171 (0.0185)	–0.0195 (0.0305)	–0.0059 (0.0266)
Africa	–0.4088*** (0.1395)	–0.2639** (0.1225)	–0.5095*** (0.1476)	–0.3862** (0.1458)
Latin America	0.0185 (0.1240)	0.0350 (0.0789)	–0.1343 (0.1267)	–0.0130 (0.1171)
Asia	0.1465 (0.1069)	0.0251 (0.0986)		
Intercept	0.9433* (0.5143)	0.9763* (0.5307)	0.3706 (0.7089)	0.0593 (0.7646)
F-test	106.23***	112.24***	52.50***	43.57***
Adjusted R^2	0.9088	0.9215	0.8579	0.8851
RMSE	0.2916	0.2705	0.3581	0.3219
VIF (min–max)	1.91 (1.27-2.57)	2.38 (1.26-3.86)	1.79 (1.45-2.35)	1.97 (1.46-2.44)
Number of countries	81	81	43	43

In the full model, the omitted geographic continent is Europe, while Asia is the omitted geographic dummy in the models that study the role of entrepreneurship in developing economies. *, ** and *** indicate significance at the 10%, 5% and 1%, respectively.

number of entrepreneurs—and ignoring the systemic nature of country-level entrepreneurship—fuel the *policy tension* of the entrepreneurship paradox.

5.2 Differences in the Entrepreneurial Ecosystem Within Africa

With the results of the baseline regression model presented in Section 5.1 as starting point, Figure 4.2 illustrates the configuration of the entrepreneurial ecosystem for the analyzed African, Asian and Latin American countries. Overall, we observe that, among less developed and developing economies, Asian countries show the healthiest entrepreneurial ecosystem. Additionally, we note that African countries underperform compared to other less developed and developing economies in Asia and Latin America in most pillars of the entrepreneurial ecosystem (the only exceptions are the opportunity perception and process innovation pillars). A third result from Fig. 4.2 deals with the differences in the configuration of the entrepreneurial ecosystem: for Asian countries, the core strengths of the entrepreneurial ecosystem are linked to human capital, innovation (product and process) and growth potential of new and incumbent firms, while in Latin America, the strongest pillars of the entrepreneurial ecosystem are opportunity perception, start-up skills and competition. On contrary, the entrepreneurial ecosystem of the analyzed African countries is relatively strong in the pillars related to opportunity perception, networking and cultural support (Fig. 4.2).

Figure 4.3 further examines the configuration of the entrepreneurial ecosystem among the 14 African countries analyzed, distinguishing MENA (Algeria, Egypt and Tunisia) from non-MENA countries (Angola, Botswana, Burkina Faso, Cameroon, Ghana, Malawi, Namibia, Nigeria, South Africa, Uganda and Zambia). In this case, two relevant differences emerge. First, the entrepreneurial ecosystem of MENA countries is strong in the pillars risk capital, growth potential, human capital and technology absorption, while the entrepreneurial ecosystem of non-MENA countries stands out for high levels of opportunity perception and competition. Second, and besides the relevance of the networking and the cultural

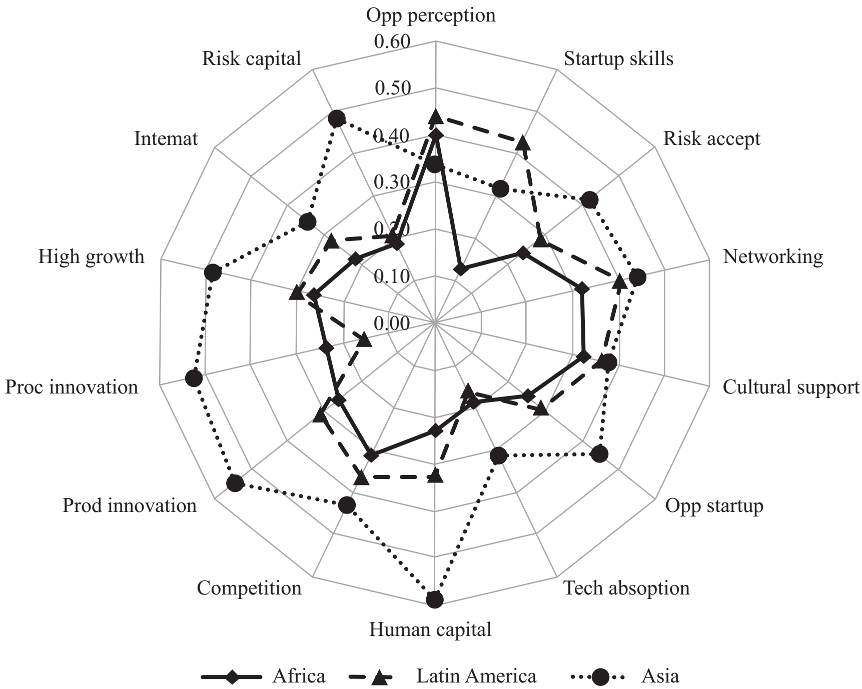

Fig. 4.2 The configuration of the entrepreneurship system in Africa, Latin America and Asia

support pillars in the entrepreneurial ecosystem of all African countries, MENA countries show a relatively balanced configuration of the entrepreneurial ecosystem, whereas the entrepreneurial ecosystem of non-MENA countries is skewed toward the pillars opportunity perception, networking and cultural support.

5.3 Cluster Analysis

This section presents the findings of the cluster analysis. Table 4.5 presents the results for the four groups that emerge from the cluster analysis: mostly developed economies with a healthy entrepreneurial ecosystem and low rates of entrepreneurship (Group 1), less developed and developing economies with a mid-level entrepreneurial ecosystem (Group 2),

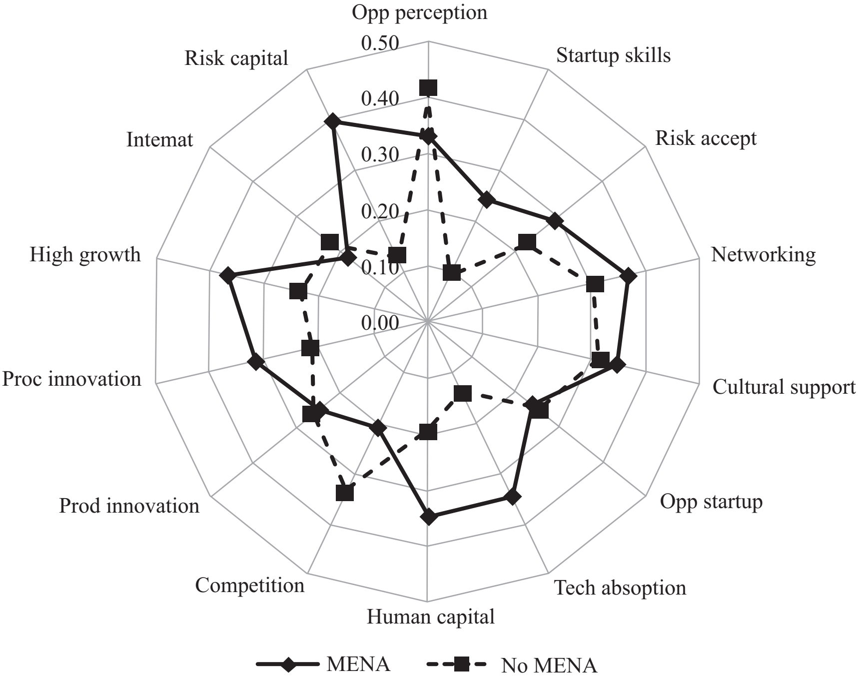

Fig. 4.3 The configuration of entrepreneurship system in Africa: MENA and non-MENA countries

Table 4.5 Results: Cluster analysis

	Group 1	Group 2	Group 3	Group 4
GDP per capita	42,512.28	28,165.96	17,122.72	6,624.02
Total entrepreneurial activity (TEA)	0.0763	0.1286	0.1337	0.2369
Global Entrepreneurship Index (GEI)	57.31	39.31	32.31	21.37
Capital deepening	136,558.50	73,184.93	48,041.78	17,489.75
Total population	162.53	51.26	10.79	38.99
Number of countries	23	20	20	18

mostly small developing economies with a mid-level entrepreneurial ecosystem (Group 3) and less developed and developing economies with a poor entrepreneurial ecosystem and high rates of entrepreneurship (Group 4).

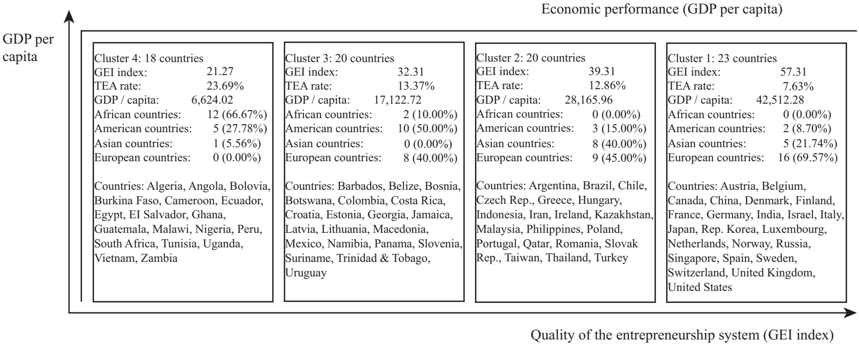

Fig. 4.4 The empirical relationship between the entrepreneurship system (GEI) and economic performance (GDP per capita)

Figure 4.4 illustrates the positioning of the four clusters according to their level of GDP per capita and the quality of their entrepreneurial ecosystem. The results point to an inverse relationship between (quantity-based) entrepreneurial activity and the quality of the entrepreneurial activity (GEI).

Group 1 mostly includes developed economies: 16 European economies, Canada, the USA, Japan, Korea and 3 large developing economies (Russia, India and China). This group reports the lowest rate of entrepreneurship (TEA= 7.63%) as well as the highest level of both GDP per capita (42,512 US$) and GEI score (57.31). Countries in Group 2 are mostly small European nations and large Asian developing economies. Also, three large Latin American economies are included in this cluster (Argentina, Brazil and Chile). On the contrary, Group 3 is formed by ten Latin American economies, eight Central and Eastern European countries and two high-performing African countries (Botswana and Namibia). Both Groups 2 and 3 show similar levels of quantitative (TEA) and qualitative (GEI) entrepreneurship; however, the differences in GDP per capital and population are remarkable.

Finally, Group 4 is formed by African nations (12 countries= 67%), five less developed and developing Latin American economies and one Asian country (Vietnam). This group shows the lowest average GDP per capita (6,624 US$), the poorest entrepreneurial ecosystem (average GEI = 21.37) and the highest rate of entrepreneurial activity (TEA= 23.69%).

The results of the cluster analysis reinforce empirically the prevalence of the *development tension* emphasized in this work: If entrepreneurship is good to the economy, why economic growth is not positively correlated with the rate of entrepreneurship at the global scale? In this case, we argue that less developed and developing countries do not need more entrepreneurs but rather a healthier institutional setting that helps to optimize the market-oriented efforts of entrepreneurial action.

Additionally, the findings corroborate the *policy tension* of the entrepreneurship paradox: Why governments allocate large amounts of resources to entrepreneurship policies whose long-term effects are uncertain or economically meaningless? Here, we propose that policies focused on increasing the number of entrepreneurs with the objective to improve the economic contribution of entrepreneurship will become sterile if the territory replicates policies implemented in other, heterogeneous contexts, and if the focal territory does not enjoy an institutional setting that supports the channeling of resources to the economy via entrepreneurial activities.

6 Concluding Remarks, Implications and Future Research Lines

6.1 Concluding Remarks

This study has produced novel evidence on the relevance of the entrepreneurial ecosystem for the economic prosperity of less developed and developing economies in Africa and other geographic settings. Overall, the results emphasize that more entrepreneurship—that is, higher rates of business creation—is not statistically associated with greater levels of economic development. This contradiction between theoretical predictions and the empirical findings fuels the entrepreneurship paradox analyzed in this study.

From the analysis of two tensions that underlie the entrepreneurship paradox—development tension and the policy tension—we argue that this paradox can be reconciled by engaging in a more holistic interpretation of the ways through which the outcomes of country-level entrepreneurship are channeled to the economy, that is, via a profound analysis of the entrepreneurial ecosystem.

By evaluating the entrepreneurship paradox through the lens of the development tension and policy tension, our analysis offers a comprehensive view of how entrepreneurship can contribute to the economic consolidation of African countries as well as of less developed and developing economies located in other geographic settings.

In this sense, the main conclusion emerging from our results is that less developed and developing economies, including African countries, do not need more entrepreneurs. Rather, the findings show that the presence of a healthy entrepreneurship ecosystem—that is, the institutional setting backing entrepreneurial activity—is a prerequisite to optimally channel the outcomes of entrepreneurial action to the economy and, subsequently, promote the economic consolidation of countries, regardless of their stage of development.

6.2 Entrepreneurship Policy in Africa: Reconciling the Tensions of the Entrepreneurship Paradox

What are the policy lessons that can be drawn from the proposed analysis of the entrepreneurship paradox? In an increasingly globalized and complex world, competing demands surface countries' environment, and policy makers grapple with tensions between coordinated policy efforts and meeting collective goals. The policy implications discussed in this section emerge from the results of the study and are strictly connected both to the two analyzed tensions (development and policy) of the entrepreneurship paradox and to our research questions.

Increased support to productive entrepreneurship—The higher rate of entrepreneurship reported among less developed and developing economies is good news; however, the analysis—based on the development tension of the entrepreneurship paradox—of the contribution of entrepreneurship to these economies reveals a less positive case. From a Kirznerian perspective (Kirzner, 1973, p. 74), the higher entrepreneurship rates in less developed and developing countries suggests that individuals—'entrepreneurially alert' individuals (Kirzner, 1997,

p. 71)—perceive and exploit business opportunities. Nevertheless, all types of entrepreneurs fall in the conception of entrepreneurship proposed by Kirzner.

Therefore, the null effect of quantitative entrepreneurship on economic performance found in this study indicates that entrepreneurship in Africa, and in other less developed and developing economies, is primarily unproductive (Acs et al., 2018; Aghion, 2017). This argument contributes to explain the development tension of the entrepreneurship paradox, which is also connected to our first research question ('Why the high rates of entrepreneurial activity observed for Africa are not conducive to development?').

The majority of entrepreneurship support programs implemented in Africa are based on the replication of (successful) policies adopted by other, heterogeneous territories. Instead of promoting 'better entrepreneurship', these 'duplication' policies often fall into the fallacy of focusing on generating 'more entrepreneurship', regardless of the state of the economy (African Economic Outlook, 2017; Chigunta, 2017; Gough & Langevang, 2016). The outcomes of these programs—for example, Gwija et al. (2014) for South Africa, Brixiová et al. (2015) for Swaziland and Mwanza and Chigunta (2016) for Zambia—are primarily linked to the promotion of low-quality necessity-driven businesses that only offer a short-term (and economically meaningless) solution to employment problems (sheer survival). But, this strategy does not help countries to get out of poverty.

In line with our results, African countries do not need more entrepreneurship but rather better entrepreneurship. Therefore, policy makers will be well advised to consider the long-term benefits of policies that endorse productive entrepreneurship. This logic and results suggest the need for rethinking the beneficiaries of entrepreneurship support programs.

At the country level, effective change in policy directions does not occur through the ideological confrontation of ongoing tensions, such as the development tension analyzed in this study. On the contrary, multiple actors interact in the fabrication of (productive and unproductive) entrepreneurship-led societies (see, e.g., Lafuente et al. (2017) for a recent discussion of the economic relevance of the interaction between new manufacturers and new knowledge-intensive firms).

We do not propose to disregard investments in unproductive entrepreneurship. Put briefly, the approach to entrepreneurship policy should not be a 'yes' or 'no' to new productive or new unproductive businesses, but rather to seek a new form of governance of entrepreneurship policy more compatible with both the characteristics of the focal economy and productive-induced growth. Existing work emphasizes the need for productive entrepreneurship in Africa (e.g., Beugré, 2016; Mwatsika, 2018; Okey, 2011; Rodrik, 2008). In our view, by encouraging productive entrepreneurship—for example, high-growth businesses, knowledge intensive businesses or firms with export potential—African countries can reconcile the development tension of the entrepreneurship paradox.

Formalization of entrepreneurial activity—In a closely related manner, we suggest that African policy makers need to turn their attention to the adoption of measures that combat informal economic activities. African contexts are characterized by a large informal economic sector that operates in corrupt environments (Gomes et al., 2018; Rodrik, 2016). In this sense, changes in the regulatory framework—for example, enhancing property rights and reducing market entry fees in order to optimize business creation bureaucracy and improve the ease of doing business—have been portrayed as effective mechanisms that may contribute to increase the economic impact of entrepreneurial activity in Africa (Auriol & Warlters, 2005; Kshetri, 2011; Ulyssea, 2010). Additionally, the shrinking of informal sectors constitutes an alternative way to encourage productive entrepreneurship and, subsequently, to help to reconcile the development tension of the entrepreneurship paradox.

Institutional change focused on the development of the entrepreneurial ecosystem—Contradictions and paradoxes are often seen as recursive patterns of change (Putnam et al., 2016, p. 37). In connection to our second research question ('What constitutes an appropriate entrepreneurship policy design for African countries?'), we argue that a newly redefined entrepreneurship policy that emphasizes the role of the entrepreneurial system constitutes an alternative pattern of change.

As we mentioned above in this section, African policy makers have traditionally allocated large sums of public money in entrepreneurship policies excessively oriented toward the stimulation of low-quality, low-impact entrepreneurship, such as subsidies to support self-employment and the access to financial resources by new businesses, regardless of their characteristics or market potential (African Economic Outlook, 2017).

These policies are rooted in an institutional isomorphic approach, that is, a convergence strategy based on mirroring what other, usually more developed peers do. In our view, this imitative strategy is evidence that a policy of complacency—characterized by the mere promotion of 'more entrepreneurship'—is infiltrating into the African policy circles and, consequently, is fueling the policy tension of the entrepreneurship paradox in these economies.

The disappointing outcomes of most entrepreneurship support policies in Africa (African Economic Outlook, 2017) illustrate what we consider a plausible, relevant cause of the policy tension of the entrepreneurship paradox. Entrepreneurship support programs would become sterile if entrepreneurs navigate in contexts that do not guarantee the effective exploitation of their knowledge and resources. Therefore, we suggest that policy makers need to turn their attention to the development of the country's entrepreneurial ecosystem. By prioritizing policies that promote the 'interlocking' role of the entrepreneurial ecosystem, the outcomes of entrepreneurial action can be efficiently channeled to the economy which, in turn, has the potential to generate sustainable economic development.

From a knowledge management point of view, the policy tension of the entrepreneurial paradox may result from the mismatch between resource allocation policies and territories' knowledge stock. For example, prior research has highlighted how various policy actions promoting the connection between countries' available resources (physical, technological and knowledge-based) and productive entrepreneurship are more successful in creating and/or consolidating a knowledge-based economy. These policies—which may be considered valid benchmark cases—include, among others, the joint promotion of human capital among the population and different incentives (economic such as fiscal bonuses and noneconomic linked to infrastructure development) that increase the presence of high-tech multinational enterprises in the focal territory which, in turn, increases the territories' knowledge stock via knowledge generation or acquisition processes (e.g., Lafuente et al., 2018; Wong et al., 2006). Additionally, Connell et al. (2014) show how investments in industry clusters (i.e., infrastructures, networks, ICTs) are valid mechanisms to enhance knowledge sharing across economic actors (i.e., businesses) through collaborations within and between industries and, subsequently, improve industry-level productivity.

Our results suggest that the development of start-up skills, human capital, risk capital and internationalization are the main weaknesses of the entrepreneurial ecosystem of the 14 African countries analyzed in this study. Also, African countries have a limited capacity to develop innovations (Acs et al., 2018), which is reflected in the low technological absorptive capacity of the analyzed African entrepreneurial ecosystems. Therefore, in the long-run, economic consolidation of African countries should be grounded in the creation and/or consolidation of country-specific policies that seek to accommodate the promotion of productive entrepreneurship to the characteristics of both the local entrepreneurial ecosystem and their existing technologies, rather than in policies that finance all types of entrepreneurship or that incentivize the adoption of disruptive technologies.

Such policies may discourage entrepreneurship indirectly by displacing low-quality necessity-driven potential entrepreneurs from the entrepreneurial career (Litan et al., 2009; Shane, 2009). However, the mere deployment of resources to promote 'more entrepreneurship' is not enough to successfully enhance territorial development. In this sense, the prescription for policy makers is to prioritize and redirect policy efforts toward the development of a solid entrepreneurial ecosystem. This way, African countries can break down the complacency policy that is leading them to fall into a 'catch 22' loop in which ineffective entrepreneurship policies perpetuate the policy tension of the entrepreneurship paradox. From our perspective, the proposed radical shift in policy patterns that emphasizes the harmonization between the development of local entrepreneurship and the elements shaping the local entrepreneurial ecosystem is conducive to economic consolidation. Also, these policy actions may contribute to reconcile the policy tension of the entrepreneurship paradox.

6.3 Lines of Future Research

As with any study, the results presented in this work are open to future verification. In this sense, it would be valuable to extend the proposed analysis in various directions. First, and similar to other studies dealing with the connection between entrepreneurship and economic performance in Africa (e.g., Beugré, 2016; Mwatsika, 2018; Sheriff et al., 2016), the data do not permit the direct analysis of the decision-making process underlying the generation and implementation of entrepreneurship policies in the analyzed African contexts. Further research can address this issue by exploring the economic response to (homogeneous and heterogeneous) entrepreneurship support programs in different geographic settings.

Second, and following the debate on the relevance of studying tensions and paradoxes from a processual approach (Putnam et al., 2016), future work should evaluate the evolution of the tensions underlying the entrepreneurship paradox using longitudinal data that permit a better understanding of the potential dynamics over time of the process outcomes linked to the entrepreneurship paradox.

Notes

1. Building on the terminology used by Smith and Lewis (2011) and Putnam et al. (2016), tensions—dualities or dichotomies that are inherent to complex systems or socially constructed—are underlying elements of paradoxes that seem logical individually, but irrational and inconsistent when juxtaposed. A paradox is a set of contradictory yet interrelated elements (tensions) that coexist and persist over time (Smith & Lewis, 2011, p. 382).
2. These include the Global Entrepreneurship Monitor (GEM), the World Bank Group Enterprise Survey (WBEGS), the Economic Freedom of the World Report (EFWR), Hofstede's Indicators (HI), the Global Competitiveness Report (GCR), the Legatum Prosperity Index (LPI), the Global Entrepreneurship and Development Index (GEDI).

3. We should note that the analysis by Atiase et al. (2018) probably suffers from endogeneity bias because many of the independent variables are part of the GEI components.

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5

The Monetization of the Regional Development and Innovation Index: Estimating the Cost of Entrepreneurship Ecosystem Policies in European Union Regions

Tamás Sebestyén, Éva Komlósi, and László Szerb

1 Introduction

Right from the beginning of its creation, the Regional Entrepreneurship Development Index (REDI) methodology has aimed to provide policy suggestions. This index can be used to describe the general stance of the entrepreneurial ecosystem of regions, based on proxies that measure different aspects/dimensions of the entrepreneurship ecosystem. The optimization targets the additional efforts to decrease the imbalances over the fourteen pillars of the entrepreneurship ecosystem. Since the examined 125 European Union (EU) regions differ in their pillar values and configurations therefore it suggests that policy to improve the REDI scores should be unique for each region. The REDI methodology

T. Sebestyén • É. Komlósi • L. Szerb (✉)
Faculty of Business and Economics, University of Pécs, Pécs, Hungary
e-mail: sebestyent@ktk.pte.hu; komlosi.eva@ktk.pte.hu; szerb.laszlo@ktk.pte.hu

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provides a normalized value to describe the entrepreneurial ecosystem using natural units of the different measures as inputs to the calculation while the monetary value of such units is unknown. In this chapter, we provide a methodology to assign monetary values to the different pillars of REDI. To conduct policy modeling, one needs to link monetary values to the different pillars/dimensions. This chapter presents a method to monetize the pillars of the REDI calculation and provides a practical application to the 125 EU regions.

The method we provide borrows from standard shadow pricing, which is a widely used approach to assign monetary values to factors which do not have a determined market price. In principle, this approach calculates the marginal contribution of a given resource to the outcome/objective of some optimization problem. If the optimization targets a monetary value such as cost or profit/payoff, the standard method is straightforward to be used. In the present setup, however, the REDI methodology starts from natural units for pillars and results in a normalized score which still does not have a monetary dimension.

Following from the challenge described above, we proceed in two steps. First, using econometric techniques, we assign a monetary value to the REDI scores. By entering the REDI scores into a production function explaining regional GDP levels, we are able to estimate the marginal contribution of the REDI to monetized regional output. This can be taken as the marginal value of the REDI in a given region. Then, we turn to the standard principles of shadow pricing where this monetized REDI score is traced back to its components, thus allowing for a monetization of the REDI pillars.

In what follows, we first describe the data, and then turn to the estimation procedure and results. After that, the shadow pricing method is described. For a more accurate cost estimation, we also calculate the fiscal multipliers for each country. In the following chapter, we provide a simulation for estimating the monetary costs of a uniform (all regions) 10% increase of the REDI scores. Finally, the paper concludes with mentioning the limitations of our approach.

2 The Econometric Model

Our unit of analysis is the region. Originally our cross-section analysis consisted of 125 "mixed" NUTS regions because the REDI has been calculated for 24 countries, which altogether contain a mix of 125 NUTS1 and NUTS2 regions. It was possible to create the REDI for 24 countries in the European Union, except Bulgaria, Cyprus, Luxemburg, and Malta. In the case of 10 countries, REDI data were calculated at NUTS1 level (Austria, Belgium, Greece, France, Germany, Italy, the Netherlands, Poland, Romania, and the United Kingdom). For four additional countries, only country-level classification was possible. These are the Czech Republic, Latvia, Lithuania, and Estonia. For the remaining 10 countries, REDI were calculated at NUTS2 level (Croatia, Denmark, Finland, Hungary, Ireland, Portugal, Spain, Slovenia, Slovakia, and Sweden). In the case of Portugal, only those five NUTS2-level data were available which belong to the Continente NUTS1 region. For Spain, the two small African continent NUTS1 regions, Ceuta and Melilla were also excluded.

First, we conducted the regression analysis alone for the 125 NUTS regions. However, it was problematic that in the case of 28 regions (5 Danish NUTS2, 12 British NUTS1, 2 Croatian NUTS2, 8 Swedish NUTS2, and 1 Spanish NUTS2), capital stock data were missing. Since the exclusion of the listed regions would have resulted in a significant loss of data (22.4% of the data set), we decided to calculate them. Finally, it was not possible to calculate capital stock data for three NUTS2 regions (for the Croatian HR03 and HR04, and the Spanish ES70). Thus, the final database included information for a mix of 122 EU NUTS regions. Note that the representativeness of the sample is ensured insofar as it includes 24 European countries (Table 5.1).

However, due to inconsistent regression results, a further modification of the sample was required. The analysis of the regression results highlighted the *low sample size* and the *low variability in some variables* that cause serious problems. In this problem, we are required to (1) collect *all*

Table 5.1 Number of analyzed regions by country

Country		Basic class	No. of regions
AT	Austria	NUTS1	3
BE	Belgium	NUTS1	3
HR	Croatia	NUTS2	3
CZ	Czech Republic	NUTS1	1
DK	Denmark	NUTS2	5
EE	Estonia	NUTS2	1
FI	Finland	NUTS2	5
FR	France	NUTS1	8
DE	Germany	NUTS1	16
EL	Greece	NUTS1	4
HU	Hungary	NUTS2	7
IE	Ireland	NUTS2	2
IT	Italy	NUTS1	5
LV	Latvia	NUTS2	1
LT	Lithuania	NUTS2	1
NL	Netherlands	NUTS1	4
PL	Poland	NUTS1	6
PT	Portugal	NUTS2	3
RO	Romania	NUTS1	4
SK	Slovak Republic	NUTS2	4
SI	Slovenia	NUTS2	2
ES	Spain	NUTS2	17
SE	Sweden	NUTS2	8
UK	United Kingdom	NUTS1	12
Total			125

NUTS2-level data for the 24 countries (consequently the sample size has increased to a total of 254), and additionally (2) *pool data* for the determined years, whereby we were able to achieve a satisfactory sample size (n = 508).

So far, the REDI has been calculated for two time periods: (1) the *REDI 2013* for 2007–2011 and the *REDI 2017* for 2012–2014. Thus, as regards other variables of the cross-sectional analysis, we collected data for 2011 and 2014 (i.e. for the last year of the two periods for which the REDI has been calculated).

This study measures territorial performance via purchasing power parity per capita GDP. The regression model consists of a simple production function complements (capital and labor) supplemented with the REDI. The explanatory variables used in this study come from two sources. First, regional figures related to *employment (L)* and *population density (DENSITY)* were obtained from Eurostat. Also, *capital stock (K)* data were derived from Eurostat's gross fixed capital formation data and calculated by using the PIM method.[1] Second, the variable measuring the quality of the entrepreneurial ecosystem across European regions is the *Regional Entrepreneurship and Development Index (REDI)* (Szerb et al., 2013, 2017). In the final model specifications, we included two control variables related to urbanization. Urbanization economies are a type of agglomeration externality that refers to considerable cost savings generated through the locating together of people, firms, and organizations across different industries (Parr, 2002; McCann, 2013). Therefore, location in large or densely populated cities may offer serious advantages. In our study, we follow the practice by Meliciani and Savona (2015) and assess the role of urbanization by introducing *regional population density (DENSITY)* and a dummy for regions with a *capital city (CAPITAL)*.

Our regression model variables can be found in Table 5.2.

The following general multiple linear regression model was tested in order to estimate the effect of the entrepreneurial ecosystem on territorial performance. The regression analysis departs from a model that includes

Table 5.2 The dependent and independent variables used in the regression model

Variable	Definition
GDP_PPS_percap	Per capita gross domestic product *purchasing power standard*[a] (2011, 2014)
L_perCap	Employment, per capita (2011, 2014)
K_perCap	Capital stock, per capita[b] (2011, 2014)
REDIunit_perCap	REDI2013 and REDI2017 values[c]
DENSITY	Population density (2011, 2014)
CAPITAL	Capital dummy (dummy 1 = yes, 0 = no)

Source: Own calculation

[a] "The purchasing power standard, abbreviated as PPS, is an artificial currency unit. Theoretically, one PPS can buy the same amount of goods and services in each country." (Eurostat)

[b] It is calculated from gross fixed capital formation data (million €) using PIM method

[c] REDIunit: calculated as the sum of the 14 average adjusted pillars

the basic factors (labor and capital) of a simple production function completed with the REDI, which reflects the interaction between individuals and their contexts that determines the weights of economic and societal benefits of entrepreneurship (Audretsch & Belitski, 2017). The econometric model used in this study has the following form:

$$\begin{aligned} LnGDP\_PPS\_perCap_i = \beta_0 + \beta_1 LnL\_perCap_i + \beta_2 LnK\_perCap_i \\ + \beta_3 LnREDIunit\_perCap_i \\ + \beta_4 LnDENSITY_i + \beta_5 CAPITAL_i + \varepsilon_i \end{aligned} \tag{5.1}$$

In Eq. (5.1), performance refers to the per capita GDP at the regional level, β_i is the parameter estimate estimated for the independent variables, and ε is the normally distributed error term that varies across regions. Before the estimation of the parameters, the necessary assumptions of linear regression were checked. First, we have checked the skewness of the variables. Since some of the variables indicated significant (positive) skewness, we used the log transformation method (Appendix *A1. table*). For measuring multicollinearity, we have calculated the VIF values for all of our variables. In our model, none of the VIF values exceeds the critical threshold. The average VIF value of the model is 1.172 (range: 1.108–1.279). The well-known tests of normality, the Kolmogorov–Smirnov test, indicates significant deviation from normal distribution. Applying the *Breusch–Pagan–Koenker test*,[2] we could identify the presence of heteroscedasticity in our data. Test results are presented in Table 5.7 of the Appendix. An alternative and highly appealing method of reducing the effects of heteroscedasticity on inference is to employ a heteroscedasticity-consistent standard error (HCSE) estimator of OLS parameter estimates (White, 1980; Hayes & Cia, 2007). With this approach, the regression model is estimated using OLSs, but an alternative method of estimating the standard errors is employed that does not assume homoscedasticity.

Table 5.3 shows the results using the HC3 estimators.[3] Note that the standard errors are quite similar for the predictors. We can be pretty

Table 5.3 OLS regression analysis: GDP estimations using standard error estimates assuming homoscedasticity (OLSE) and heteroscedasticity (HC3)

	OLSE			HC3	
	Coefficient	Std. error	*p*-value	Std. error	*p*-value
Independent variables					
Constants	1.515	0.150	*0.000*	1.5152	*0.0001*
Ln_K_perCap	0.524	0.026	*0.000*	0.5235	*0.0000*
Ln_L_perCap	0.794	0.069	*0.000*	0.7939	*0.0000*
Ln_REDIunit_perCap	0.058	0.012	*0.000*	0.0584	*0.0000*
Ln_DENSITY_perCap	0.094	0.008	*0.000*	0.0964	*0.0000*
CAPITAL	1.515	0.031	*0.003*	0.0939	*0.0149*
F-test	248.691			143.63	
Adjusted R^2	0.710				
Average VIF values	1.172				
Number of observations	508				

confident that there is a relationship between the explanatory variables (L, K, REDI, and DENSITY) and per capita GDP because the regression estimate is statistically different from zero, regardless of how the standard error is estimated. But conclusions about CAPITAL differ, when heteroscedasticity is managed using the HC3 estimator, the partial relationship between CAPITAL and the dependent variable is statistically significant only if the dependent variable is GDP_PPS.

In order to calculate the shadow prices for the REDI pillars, we must calculate the elasticity between REDI score units and regional GDP levels. For this purpose, we selected model HC3 with the estimated REDI regression coefficient 0.0584 (p-value < 0.000). Given this estimated elasticity between the REDI scores and GDP levels, we have a monetized value for the REDI. More precisely, we are able to calculate the effect if there is a marginal increase in the REDI on the monetary value of regional output, which serves as a starting point to monetizing the REDI pillars. In what follows, we show how the shadow pricing approach was implemented in this setting to assign monetary values to the REDI pillars.

3 Shadow Pricing

In this section, we describe how we calculated shadow prices for REDI pillars. The basic concept behind these calculations is that using the results from the estimations described previously, we are able to assign monetary value to the REDI pillar units. Given the econometric framework established in the previous section, we have an estimation of the elasticity between REDI score units and regional GDP levels. Let this elasticity be ε^{GDP}, showing the percentage change in regional GDP level given a 1% change in the regional REDI score unit. If Y_i is the GDP level in region i, then the monetary value of a 1% increase in regional REDI score unit is

$$v_i = \frac{\varepsilon^{GDP}}{100} Y_i \tag{5.2}$$

In what follows, we introduce the shadow pricing logic, starting with the relevant elements of REDI calculation, through how optimization can be interpreted in the REDI context, to the derivation of the final shadow prices.

3.1 The Starting Point: REDI Normalized Pillar Values

In this approach, we start from the REDI calculations. As described previously, the calculation of the REDI for all regions follows the steps below:

1. Start from individual and institutional variables for the 14 pillars, and normalize these values to the 0–1 interval.
2. Multiply the institutional and individual variables to get the raw pillar values.
3. A 95 percentile capping ensures that extreme values do not distort the results.
4. Capped pillar values are normalized to the 0–1 interval.

5. Capped and normalized pillar values are transformed in a way that pillar averages across regions are equalized (and equal to the average values across pillars).
6. The penalty for bottleneck method is applied to get penalized pillar values.
7. Pillar values are summed up to achieve REDI score units for regions.

In this exercise, we start from step 5. This means that for every region i and pillar p, we have a $y_{i,\,p}$ transformed pillar score between 0 and 1.[4]

Let's use the term $\hat{y}_i = \min\left(y_{i,1}, y_{i,2}, \ldots, y_{i,14}\right)$ to denote the minimal pillar value in region i. Then the penalized pillar values are calculated as:

$$h_{i,p} = \hat{y}_i + \left[1 - e^{-\left(y_{i,p} - \hat{y}_i\right)}\right] \tag{5.3}$$

Finally, the REDI score units applied in this exercise and also used in the econometric estimations is the sum of the penalized pillar values:

$$S_i = \sum_p h_{i,p} \tag{5.4}$$

3.2 The REDI as a Maximization Problem

The method we use takes advantage of the standard shadow pricing principle, which is based on the following extreme value problem:

$$f\left(\mathbf{x}\right) \rightarrow \max$$

$$g\left(\mathbf{x}\right) = b \tag{5.5}$$

where $\mathbf{x}$ is a vector of control variables, $f(\mathbf{x})$ is the objective function, b is some resource constraint, and $g(\mathbf{x})$ is a constraint function. The problem above imposes one constraint on the optimization, but it can be generalized to an arbitrary number of constraints. It is known from standard optimization theory that the shadow price with respect to the constraint b (also known as the Lagrange multiplier of the constraint) reflects the change in the objective function (given an optimal allocation of $\mathbf{x}$) if the constraint is relaxed by a unit. Given that the objective function describes a cost-minimization or profit-maximization problem, these shadow prices associate a monetary value to the natural resource units which constrain the problem.

Using the standard shadow pricing principle in our context, we must convert the REDI methodology into a maximization/minimization problem. In our approach, we start from the average equalized, normalized pillar values $y_{i,p}$ for every region. As a result of the average equalization procedure, these values can be regarded as brought to a common denominator, or in other terms, reflecting the scores of pillar elements on a common scale. Now, one maximization problem is set for each region i. The average equalized and normalized pillar scores $y_{i,p}$ for region i are considered as the control variables, so in the general setup (5.6), $\mathbf{x} = (y_{i,1}, y_{i,2}, \ldots, y_{i,14})$. Also, the resource constraint is the sum of observed pillar values: $b_i = \Sigma_p y_{i,p}$. To sum up, we interpret the REDI calculation logic as follows. Every region possesses some b_i amount of resources that can be used to enhance entrepreneurial activity in the region by allocating it to the different pillars of the model (entrepreneurship ecosystem). In this shadow pricing method, we are looking for an optimal allocation of the resources in a given region, which does not necessarily coincide with the actual observed allocation.

The objective function converts the equalized pillar scores into the REDI score units, using the penalty for bottleneck principle as follows. As a result, the optimization problem for region i is as follows:

$$\sum_p \hat{y}_i + \left[1 - e^{-\left(y_{i,p} - \hat{y}_i\right)}\right] \rightarrow \max$$

$$\sum_p y_{i,p} = b_i \tag{5.6}$$

where $\hat{y}_i = \min\left(y_{i,1}, y_{i,2}, \ldots, y_{i,14}\right)$ as before.

Given the objective function in (5.6), it is easy to show that for any constraint $b_{i,}$ the optimal solution is $y_{i,\,p} = b_i/14$ for all p, given that there are 14 pillars. The key to this result is the symmetry of the pillars in the objective function and the terms containing the minimal pillar value.

To prove this result, assume that we have an allocation which satisfies $y_{i,\,p} = b_i/14$ for all p. Then, impose a reallocation so that $y_{i,\,p}$ decreases by some Δb, while an $y_{i,\,q}$ increases by this same amount so that the resource constraint is still satisfied. All other pillars are unchanged. If the initial symmetric allocation was not optimal, this reallocation could increase the objective function. As the latter is additively separable in the $h_{i,\,p}$ penalized pillar scores, it is sufficient to analyze the change in the terms corresponding to pillars p and q. With the reallocation, the $\hat{y}_i$ minimum terms decrease by Δb, as it takes the smallest pillar value. As this enters the objective function symmetrically for all pillars, the value of the objective function decreases by 14 Δb. As pillar p (where the score decreased) becomes the bottleneck with the minimal value, the term in the bracket for this pillar is 0, because $y_{i,p} = \hat{y}_i$. As for pillar $y_{i,q} = \hat{y}_i + 2\Delta b$, the term in the bracket for this pillar becomes $1 - e^{-2\Delta b}$. Before the reallocation, the symmetric allocation rendered the terms in the bracket to 0 for all pillars, so it follows that the change in the allocation increases the bracketed term for pillar q, but less than $2\Delta b$. To conclude, the reallocation decreases the objective function by 14 Δb on the one hand, and increases it by less than $2\Delta b$ on the other, so the objective function definitely decreases. It follows that the symmetric allocation is an optimal allocation.

The logic above can be easily represented visually if we restrict the number of pillars to two. Figure 5.1 shows this solution. The black lines in the figure represent isoquants of the objective function in (5.6) with two arguments $y_{i,\,1}$ and $y_{i,\,2}$. This means that along a black curve, the different allocation of the pillars 1 and 2 yields the same REDI score unit. The closer a black curve is to the top-right corner, the higher the REDI score unit it represents. The blue lines represent the resource constraint given b_i. Again, the closer the blue line is to the top-right corner, the more relaxed the constraint is. Along the blue line, the sum of the two pillar values is the same, while its allocation on the two pillars changes.

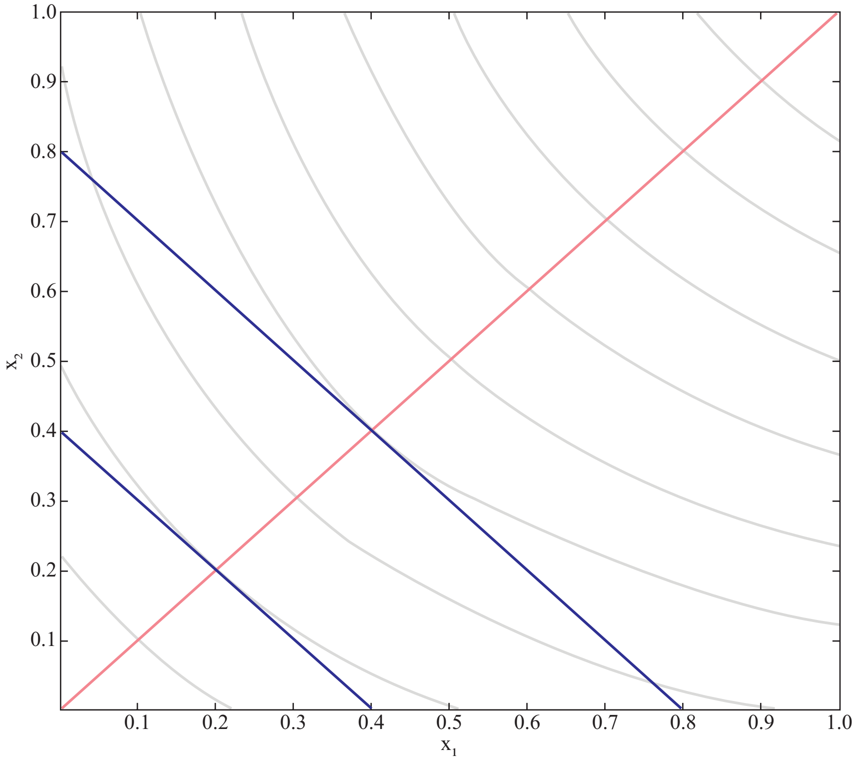

Fig. 5.1 A visual representation of optimal allocation

It is easily visible in Fig. 5.1 that due to the symmetry of the objective function, the resource constraints hit the highest REDI score unit in the middle of the graph, under a balanced allocation of the resources on the two pillars. The red diagonal line shows all the optimal allocations under different resource constraints. The penalty for bottleneck principle ensures that in an unbalanced allocation, one can always improve the REDI score with a reallocation toward a more balanced structure, while the symmetry of the pillars drives the optimal allocation to perfect balance.

4 Applying the Shadow Pricing Logic

As shown in the previous section, the structure of the REDI ensures that given b_i amount of resources in region i which can be allocated to the different pillars, the optimal allocation is $y_{i,p} = b_i/14$ for all pillars p. Now assume a change in the resource constraint from b_i to b_i'. As a result, the optimal allocation changes to $y_{i,p}' = b_i'/14$ for all pillars p. Using the objective function in (5.6), it is easy to show that given the optimal allocation, the REDI score is simply $S_i = \Sigma_p y_{i,p} = b_i$.[5] So if the resource constraint changes, the optimal REDI score also changes to $S_i' = b_i'$. As described in the previous sections, the monetary value of a percentage change in the REDI score units is v_i. If the change in the REDI score (assuming optimal resource allocation) is a result of a change in the resource constraint, the monetized change in the REDI score is the shadow price of the resource. The shadow price of the resource is then

$$V_i = \frac{S_i'}{S_i} v_i \tag{5.7}$$

An important difference between this solution and the forward logic is that the latter one provides a different shadow price for all pillars in a given region, while the optimization method presented here provides one shadow price for a given region for the "general" resource which is assumed to be allocated to the different pillars.

Table 5.8 contains the results for the shadow prices obtained with the optimization method described above. The average value across regions is 2.381 thousand EUR, while the minimal and maximal values are 1.512 and 4.059 thousand EUR, respectively. These values mean that if a pillar value (resource) changes by 1 basis point (0.01 on the 0–1 scale), per capita GDP in PPS in the region is expected to change by this amount.

5 Discounting with Fiscal Multipliers

The V_i values calculated in (5.7) and sampled in Table 5.8 show how the GDP per capita in a region is expected to change for a small change in the resource constraint. These values, although having monetary dimension, are more of an output or result of investing resources into the entrepreneurial environment than being the cost of these investments. How the cost of such investments can be determined is not a straightforward task.

Our approach in this respect is to use fiscal multipliers. As our interest is basically policy-driven, we concentrate on policy interventions resulting in improvements in the REDI pillars, which means relaxing regional resource constraints in the context of the shadow pricing (optimization) setup. Without directly assigning monetary costs to improving specific REDI pillars, we assume that there is a general efficiency of such policies—these are usually expressed in the form of multipliers: spending 1 EUR on specific purposes, what increase can be achieved in economic output/income. The merit of using multipliers is that such values are widely available, and they provide a general/aggregate measure of how policy efforts turn into economic outcome.

Given that the multiplier relevant for region i is m_i (meaning the one unit of government spending in region i results in a m_i unit increase in regional GDP), we can use this value to calculate backwards: how much spending is required in order to achieve a given amount of increase in the GDP. If the result of an investment in any pillar p in region i is V_i as in (5.7), then the "policy cost" of achieving this monetary result can be expressed as

$$MV_i = \frac{V_i}{m_i} \tag{5.8}$$

One challenge in determining the multipliers is that there are many of them. Multipliers typically differ with respect to the fiscal instrument (e.g. government consumption, different taxes), whether it is temporary or permanent, and also the horizon of the output effect taken into account (e.g. short- or long-term effects on GDP).

In this study, we take two comprehensive sources of country-level multipliers into account: a report of the European Central Bank (Kilponen et al., 2015), which uses country-level DSGE models to estimate multipliers, and the report of the OECD (Barrell et al., 2012), which uses a standardized econometric method for the same purpose. These reports provide country-level estimates of fiscal multipliers for a set of countries[6] and several fiscal instruments.[7] The ECB report provides estimates for temporary and permanent interventions, but the OECD estimations are given only for temporary policies.

This diversity in the reported fiscal multipliers requires a careful choice among them. First of all, our goal is to use as detailed data as possible, which drives the choice to use country-level multipliers wherever possible. A constraint in this respect is that the two reports contain different countries (with some overlap). In order to have the largest coverage, we take both reports and take the multipliers wherever the country is reported. If it is reported in both reports, the average of the two multipliers is used. Latvia, Lithuania, Hungary, Poland, Romania, and Slovakia are not covered by either of the reports. As the ECB provides values for the eurozone, these can be used for eurozone members within these remaining countries, while the rest is assigned an average value of the CEE countries.

This approach also narrows down the fiscal instruments to be used—only government consumption is comparably provided by both reports. This instrument is in line with our purpose on the other hand: the fiscal instruments used to promote entrepreneurial ecosystems are mainly (but of course not exclusively) expenditure-side tools which are accounted for as government spending.[8] Finally, as only the ECB report contains permanent multipliers and its long-run effects, the primary choice of using the most diverse set of reported values for different countries narrows down the time span as well only to temporary interventions and short-run effects.[9] Finally, the standard way of presenting multipliers is the estimated effect of a restrictive fiscal impulse—as we are working with a positive, expansionary effect with more resources spent on specific purposes, we use the assumption that the reported multipliers are symmetric so that the same, but opposite, effect is expected after a fiscal expansion as after a restrictive one.

Table 5.4 Estimated multipliers for different countries in the REDI sample

Country	ECB estimation	OECD estimation	Final value
Belgium	0.93	0.17	0.55
Czech Republic	0.54		0.54
Denmark		0.53	0.53
Germany	0.52	0.48	0.50
Estonia	0.83		0.83
Ireland		0.33	0.33
Greece	0.90	1.07	0.99
Spain	0.50	0.71	0.61
France	0.92	0.65	0.79
Italy	0.79	0.62	0.71
Latvia			0.98
Lithuania			0.98
Hungary			0.68
Netherlands	0.74	0.53	0.64
Austria		0.53	0.53
Poland			0.68
Portugal	0.85	0.68	0.77
Romania			0.68
Slovenia	0.66		0.66
Slovakia			0.98
Finland	0.78	0.64	0.71
Sweden	0.60	0.39	0.50
United Kingdom		0.74	0.74
Eurozone	0.98		0.98
New members in 2004	0.68		0.68
Average	0.74	0.58	0.69

Table 5.4 shows the original ECB and OECD estimations of multipliers, together with the final values used in our calculations. The values mean that given a 1% increase in government spending (as a ratio to the GDP), GDP is expected to increase by the given percentages. As these values lay below 1, they mean that spending 100 EUR from the government budget results in a less than 100 EUR increase in the GDP. Or reversely, in order to achieve a 100 EUR increase in economic output, the government has to spend more than 100 EUR.

Table 5.8 contains the results of these calculations. The Direct Shadow Price column shows the raw shadow prices according to (7), before

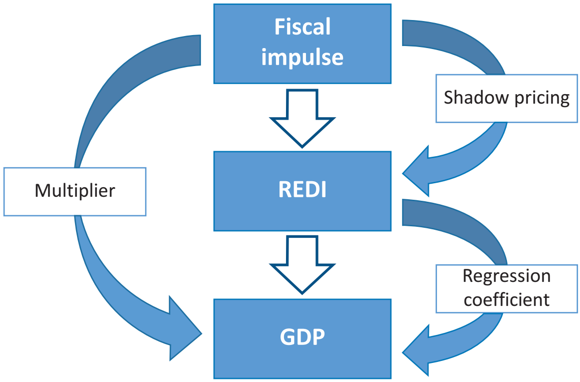

Fig. 5.2 The logic of the calculation of the shadow prices

accounting for the fiscal multipliers. On average, this comes out at 2.38 EUR per capita. After discounting with the multiplier, we get higher numbers (as described above, 1 EUR spent by the government yields less than 1 EUR on GDP), with an average of 3.75 EUR per capita (Discounted Shadow Price column) across the sample. Given the population level of regions, we can easily aggregate up these per capita levels (Aggregate Shadow Price column). This leads to a result of 14.64 million EUR shadow price for the average region: according to our logic, spending this amount of money equals the release of the REDI resource constraint by 0.01 unit. In other terms, this is the price of 0.01 REDI units.

Our logic behind the method is illustrated in Fig. 5.2. Fiscal impulse is assumed to affect the REDI score, which is then assumed to affect the GDP level. From the measurement point of view, multipliers grasp the relationship between fiscal impulses and the GDP. The regression coefficient reflects the relationship between REDI and GDP. Using these two values, our shadow pricing logic quantifies the third relationship between fiscal impulse and REDI, thereby allowing for an estimate of the fiscal cost of changing the REDI score in a region.

6 The Cost of Entrepreneurship Policy Action: Improving the REDI Scores

In this part of the chapter, we are estimating the costs of the entrepreneurship ecosystem improvement; that is, how much does it cost to increase the REDI scores by 10% in the EU regions? This exercise is based on the following assumptions:

1. the basis of REDI increase is the pillar level
2. we calculate the increase of the REDI scores based on the 10% uniform increase of each region's REDI scores
3. for optimization we are relying on the PFB methodology described in Sect. 3.1.
4. we assume that the marginal increase of 10% costs the same for all the 10%; that is, we are not calculating the possibility of increasing marginal costs.

According to our calculation, we need 30.15 units for a uniform 10% REDI score increase. The total cost of this improvement is estimated to be 45.77 billion EUR for the 125 EU regions. The simulation results for each region can be found in Table 5.8 of the Appendix. There are substantial differences among the regions. The per capita cost of 10% REDI increase ranges from 25.13 EUR/capita (Lithuania) to 388.38 EUR/capita (Ireland, Southern and Eastern), a 15 times difference. The per capita cost of improvement is mostly determined by two effects. First is the magnitude of the bottleneck: If there is only one or two bottlenecks, it is relatively easy to balance them, so it requires less resources. Second is the absolute increase of REDI scores; that is, better regions with higher REDI scores require higher amount of money for the same percentage increase of REDI as compared to regions with lower REDI scores.

For a more detailed analysis, we have selected five country regions that are Austria, Denmark, Hungary, Portugal, and Slovakia (Table 5.5).

Based on Table 5.5, the representative regions are substantially different in terms of both pillar composition and the development of the entrepreneurship ecosystem. Danish regions are the most developed, followed by Austrian and Portuguese regions. Slovakian and Hungarian regions are at the bottom of REDI ranking. Only one or two bottlenecks characterize Austria's, Denmark's, and Hungary's regions, while Portugal and Slovakian regions are more balanced. Most Danish regions should focus on improving the globalization pillar, while Austria's regions are weak in high growth. All Hungary's regions face problems in cultural support. Portuguese regions are more different than the previous three country regions. The variations over pillars in Slovakian regions concentrate mostly on the attitude- and ability-related components.

The required resources to increase the REDI scores and the associated costs substantially change over all regions and fluctuate within country regions in a varying degree. Within country, regional differences are the smallest in Hungary, larger in Slovakia and Portugal, and more substantial in Austria and Denmark. In terms of natural units, the Portuguese Lisboa (0.41) and the Danish Hovedstaden (0.40) need the most, while the Hungarian Közép Magyarország (0.10), Észak Alföld, Dél Alföld, and the Slovakian Bratislavsky kraj (all 0.11) need the least resource for REDI improvement.

The situation is slightly different if we examine the associated expenses: Hovedstaden's 10% increase in the REDI pillar costs 157.34 EUR/capita, followed by Lisboa with 136.95 EUR/capita. All Austrian regions are also expensive with over or close to 100 EUR/capita investment requirements to improve their entrepreneurship ecosystem. The two cheapest regions in terms of EUR per capita are the Hungarian Észak Magyarország (39.41 EUR/capita) and the Danish Midtjylland (39.45 EUR/capita). So, within Denmark, the per capita cost of 10% REDI increase over regions is almost fourfold.

The overall regional cost of entrepreneurship ecosystem improvement depends on the per capita costs and the size of the population. So, the total cost is the highest in the Austrian Ostösterreich (405.88 million

Table 5.5 The effect of a 10% improvement of the REDI in Austrian NUTS1, and Danish, Hungarian, Portuguese, and Slovakian NUTS2 regions

Code	Region	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10
AT1	Ostösterreich	0.675	0.858	0.341	0.620	0.525	0.637	0.724	0.549	0.932	0.735
		0.000	0.000	0.100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AT2	Südösterreich	0.345	0.609	0.362	0.584	0.614	0.608	0.606	0.414	0.658	0.568
		0.010	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AT3	Westösterreich	0.504	0.666	0.373	0.588	0.564	0.682	0.547	0.407	0.704	0.575
		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DK01	Hovedstaden	1.000	0.787	0.556	1.000	1.000	1.000	1.000	1.000	1.000	1.000
		0.000	0.000	0.040	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DK02	Sjalland	0.780	0.208	0.539	0.831	0.957	1.000	0.733	1.000	0.918	0.828
		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DK03	Syddanmark	0.889	0.282	0.581	0.826	1.000	1.000	0.637	1.000	0.924	0.980
		0.000	0.070	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DK04	Midtjylland	0.916	0.413	0.551	0.828	1.000	1.000	0.802	1.000	0.853	0.886
		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DK05	Nordjylland	0.845	0.315	0.556	0.773	1.000	1.000	1.000	1.000	0.587	0.592
		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
HU10	Közép-Magyarország	0.408	0.497	0.110	0.162	0.018	0.149	0.557	0.555	0.359	0.425
		0.000	0.000	0.000	0.000	0.100	0.000	0.000	0.000	0.000	0.000
HU21	Közép-Dunántúl	0.174	0.130	0.099	0.152	0.022	0.200	0.318	0.269	0.182	0.146
		0.000	0.000	0.020	0.000	0.100	0.000	0.000	0.000	0.000	0.000
HU22	Nyugat-Dunántúl	0.276	0.183	0.113	0.157	0.022	0.242	0.260	0.312	0.220	0.177
		0.000	0.000	0.000	0.000	0.100	0.000	0.000	0.000	0.000	0.000
HU23	Dél-Dunántúl	0.162	0.114	0.093	0.147	0.021	0.138	0.254	0.261	0.292	0.350
		0.000	0.000	0.010	0.000	0.080	0.000	0.000	0.000	0.000	0.000
HU31	Észak-Magyarország	0.159	0.100	0.104	0.132	0.019	0.168	0.324	0.284	0.142	0.070
		0.000	0.000	0.000	0.000	0.090	0.000	0.000	0.000	0.000	0.030
HU32	Észak-Alföld	0.132	0.118	0.099	0.142	0.020	0.120	0.200	0.273	0.156	0.294
		0.000	0.000	0.010	0.000	0.100	0.000	0.000	0.000	0.000	0.000
HU33	Dél-Alföld	0.152	0.134	0.096	0.131	0.020	0.157	0.281	0.246	0.174	0.198
		0.000	0.000	0.020	0.000	0.090	0.000	0.000	0.000	0.000	0.000
PT11	Norte	0.359	0.399	0.383	0.244	0.398	0.290	0.237	0.196	0.281	0.368
		0.000	0.000	0.000	0.060	0.000	0.000	0.060	0.100	0.020	0.000
PT15	Algarve	0.237	0.475	0.377	0.263	0.506	0.498	0.444	0.201	0.375	0.216
		0.000	0.000	0.000	0.060	0.000	0.000	0.060	0.100	0.020	0.000
PT16	Centro (PT)	0.121	0.375	0.379	0.241	0.415	0.339	0.275	0.234	0.250	0.495
		0.140	0.000	0.000	0.030	0.000	0.000	0.000	0.020	0.010	0.000
PT17	Lisboa	0.498	0.747	0.425	0.297	0.401	0.323	0.556	0.367	0.520	0.430
		0.000	0.000	0.010	0.150	0.030	0.110	0.000	0.070	0.000	0.010
PT18	Alentejo	0.296	0.342	0.351	0.244	0.621	0.593	0.188	0.205	0.329	0.484
		0.000	0.000	0.000	0.060	0.000	0.000	0.110	0.090	0.000	0.000
SK01	Bratislavsky kraj	0.641	0.630	0.191	0.472	0.051	0.160	0.944	0.558	0.211	0.957
		0.000	0.000	0.000	0.000	0.110	0.000	0.000	0.000	0.000	0.000
SK02	Západné Slovensko	0.158	0.055	0.178	0.396	0.065	0.194	0.310	0.224	0.095	0.426
		0.000	0.080	0.000	0.000	0.080	0.000	0.000	0.000	0.050	0.000
SK03	Stredné Slovensko	0.140	0.078	0.177	0.419	0.072	0.144	0.343	0.222	0.122	0.372
		0.020	0.060	0.000	0.000	0.090	0.000	0.000	0.000	0.040	0.000
SK04	Vychodné Slovensko	0.164	0.051	0.168	0.426	0.055	0.105	0.254	0.179	0.147	0.747
		0.000	0.080	0.000	0.000	0.080	0.030	0.000	0.000	0.000	0.000

Notes: For each region, the first line shows the pillar scores in a 0–1 potential range. The second line shows the required increase of the pillar scores by units. REDI pillars: Y1 = Opportunity perception, Y2 = Start-up skills, Y3 = Risk perception, Y4 = Networking, Y5 = Cultural support, Y6 = Opportunity start-up, Y7 = Technology absorption, Y8 = Human capital, Y9 = Competition, Y10 = Product innovation, Y11 = Process innovation, Y12 = High growth, Y13 = Globalization, Y14 = Finance. REDI sub-indicators: ATT = Attitudes, ABT = Abilities, ASP = Aspirations

Y11	Y12	Y13	Y14	ATT	ABT	ASP	REDI (old)	REDI (new)	Received resources	Required PPS EUR/ capita	Required PPS million EUR
0.571	0.238	0.695	0.451	53.4	60.8	48.5	54.2	59.7			
0.000	0.180	0.000	0.000						0.280	112.84	405.88
0.805	0.237	0.518	0.210	45.8	51.0	41.8	46.2	50.9			
0.000	0.080	0.000	0.160						0.250	117.91	207.91
0.486	0.198	0.612	0.485	48.3	51.4	42.8	47.5	52.3			
0.000	0.180	0.000	0.000						0.180	98.54	297.08
0.705	0.303	0.371	1.000	72.5	80.5	58.3	70.4	77.5			
0.000	0.180	0.180	0.000						0.400	157.34	271.31
0.066	0.290	0.079	0.047	48.6	62.4	20.9	44.0	48.4			
0.100	0.000	0.070	0.000						0.170	48.88	39.99
0.560	0.307	0.194	1.000	58.0	69.0	49.6	58.9	64.8			
0.000	0.000	0.150	0.000						0.220	79.04	94.97
0.682	0.365	0.090	1.000	55.5	64.9	45.7	55.4	60.9			
0.000	0.000	0.120	0.000						0.120	39.45	50.07
0.338	0.248	0.154	0.909	55.6	67.0	38.2	53.6	59.0			
0.000	0.030	0.140	0.000						0.170	54.18	31.45
0.371	0.371	0.555	0.288	20.3	32.9	33.4	28.9	31.8			
0.000	0.000	0.000	0.000						0.100	49.93	148.21
0.122	0.259	0.368	0.142	11.0	21.8	18.8	17.2	18.9			
0.000	0.000	0.000	0.000						0.120	58.69	63.48
0.123	0.264	0.696	0.107	13.9	23.2	22.7	20.0	22.0			
0.000	0.000	0.000	0.020						0.120	59.99	59.37
0.182	0.353	0.250	0.072	10.3	21.3	21.4	17.7	19.4			
0.000	0.000	0.000	0.040						0.130	47.11	43.77
0.172	0.355	0.331	0.137	9.9	20.7	19.0	16.5	18.2			
0.000	0.000	0.000	0.000						0.120	39.41	46.73
0.220	0.305	0.269	0.145	9.8	17.3	22.1	16.4	18.0			
0.000	0.000	0.000	0.000						0.110	41.40	61.40
0.185	0.206	0.357	0.097	10.2	19.6	18.9	16.2	17.8			
0.000	0.000	0.000	0.000						0.110	43.94	56.85
0.776	0.245	0.472	0.293	34.3	24.9	39.2	32.8	36.1			
0.000	0.010	0.000	0.080						0.330	94.29	345.94
0.282	0.274	0.404	0.248	35.3	35.9	27.9	33.0	36.3			
0.000	0.010	0.000	0.080						0.330	112.13	50.10
0.588	0.300	0.390	0.363	28.5	26.3	38.1	30.9	34.0			
0.000	0.000	0.000	0.000						0.200	61.33	141.46
1.000	0.297	0.446	0.572	45.0	42.7	49.8	45.9	50.4			
0.000	0.030	0.000	0.000						0.410	136.95	385.53
0.478	0.349	0.443	0.435	34.8	30.8	40.8	35.5	39.0			
0.000	0.000	0.000	0.030						0.290	89.51	67.22
1.000	0.419	0.944	0.612	32.3	36.1	55.8	41.4	45.5			
0.000	0.000	0.000	0.000						0.110	41.24	25.12
0.233	0.391	0.688	0.404	15.7	19.3	35.9	23.6	26.0			
0.000	0.000	0.000	0.000						0.210	58.96	108.35
0.315	0.405	0.453	0.392	16.5	19.6	34.2	23.4	25.7			
0.000	0.000	0.000	0.000						0.210	50.12	67.58
0.348	0.420	0.388	0.309	15.8	16.3	36.7	22.9	25.2			
0.000	0.000	0.000	0.000						0.190	42.53	68.44

EUR) that includes the capitol, Vienna. Lisboa and the Portuguese Norte require 385.53 and 345.94 million Euro, respectively. The cheapest regions are the small Bratislavsky kraj (25.12 million EUR) and the Danish Nordjylland (31.45 million EUR).

7 Summary and Conclusion

In this chapter, we have presented a potential way to estimate the cost of policy intervention that is the well-known shadow-pricing method. First, we applied econometric technique to estimate the per capita EUR monetary value to the REDI scores. Then, we put the REDI scores to a classical production function to get the marginal contribution of the REDI to regional GDP. Finally, we applied the shadow pricing principle to assign the monetary value of the REDI pillar units. For calculating the overall effect of policy intervention, we estimated the fiscal multipliers for all countries. In the final section, we provided the application of the shadow pricing cost estimates for the 125 NUTS1 and NUTS2 regions of the European Union.

The overall cost of the 10% REDI improvement for the 125 regions was estimated to be around 45.8 billion EUR. The average GDP for the 24 countries in the 2012–2014 time period was 12125.43 billion EUR. The 45.8 billion EUR is 0.35% of the total GDP, which seems to be an underestimation of the real full costs of improving the entrepreneurship ecosystem.

However, there are some important lessons that we could learn from this exercise. First, the costs of policy interventions vary substantially over the 125 regions. Within country regions, there are also differences; however, the magnitude of the differences varies. As presented, the differences are large in Denmark and in some other large EU country regions like Germany and the former member United Kingdom. This is just another reinforcement of the tailor-made policy intervention principle as opposed to a uniform policy. Second, policy makers should be careful about what kinds of policy aims to target. The costs estimated by the natural units are different from the per capita monetary expenses and again different if we calculate the overall regional monetary costs. We believe that the per capita cost is the most appropriate policy target.

Although the methods presented above provide relatively easy ways to assign monetary values to the pillars of the REDI, they have clear limitations.

- The values attained do not reflect real costs. Although the best way would be to systematically evaluate the cost of increasing the values of different pillars, this would require a substantial amount of information on how public and private resources spent on a diverse set of activities contribute to the improvement of the actually measured proxies of the different pillars. As this is a resource-intensive task with questionable results, we turned to the shadow pricing principle, which is used to assign somewhat "artificial" prices, values to the natural units of some resources.
- Although the best way to proceed in shadow pricing would be to focus on the cost side, that would mean setting up a cost function, which eventually results in the same problems as mentioned in the previous point. Our approach thus builds on a value-side calculation. By linking the REDI scores to regional GDP levels, we are able to estimate how much an increase in a given pillar's score (forward method) or the pillar scores together (optimization method) contribute to regional production in monetary terms. Instead of being a cost level, this estimate shows the value of the improvement in the pillars for the region.
- Although the optimization method is methodologically more compact and builds on standard shadow pricing, it requires the assumption that the resources are allocated in an optimal way across the pillars, that is, pillars are balanced. As a result, shadow price calculations use a situation (optimal allocation) as the starting point, which does not coincide with actually observed allocation/structure of the REDI pillars in the regions.

Appendix

Table 5.6 Descriptive statistics after log normalization

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
LN_GPD_PPS_perCap	508	2.01	5.13	3.2070	0.36304	0.272	0.108	2.237	0.216
LN_REDIunit_perCap	508	–7.73	–3.25	–5.5665	0.81064	–0.074	0.108	–0.123	0.216
LN_L_perCap	508	–1.64	–0.48	–0.8602	0.14230	–1.125	0.108	2.290	0.216
LN_K_perCap	508	2.85	5.33	4.2025	0.35137	–0.267	0.108	0.955	0.216
LN_DENSITY	508	1.19	9.29	5.0935	1.21384	0.631	0.108	1.664	0.216
CAPITAL	508	0.00	1.00	0.0906	0.28725	2.862	0.108	6.216	0.216

Table 5.7 Breusch–Pagan–Koenker test of heteroscedasticity

	OLS model
Breusch–Pagan test for heteroscedasticity (CHI-SQUARE df = P)	71.357
Significance level of Chi-square df = P (H0:homoscedasticity)	0.0000
Koenker test for heteroscedasticity (CHI-SQUARE df = P)	58.290
Significance level of Chi-square df = P (H0:homoscedasticity)	0.0000

Table 5.8 Results of shadow pricing per region with the optimization methods (million EUR)

Region Name	Region code	Direct shadow price	Country-level multipliers	Discounted shadow price	Population	Aggregate shadow price	Required PPS EUR/capita	Required PPS million EUR
		(PPS EUR per capita)	–	(PPS EUR per capita)	(Thousand capita)	(Million PPS EUR)	for 10% increase of REDI	for 10% increase of REDI
Ostösterreich	AT1	2.14	0.53	4.03	3596.91	14.50	112.84	405.88
Südösterreich	AT2	2.50	0.53	4.72	1763.329	8.32	117.91	207.91
Westösterreich	AT3	2.90	0.53	5.47	3014.925	16.50	98.54	297.08
Région de Bruxelles-Capitale	BE1	3.60	0.55	6.54	1154.765	7.55	366.05	422.70
Vlaams Gewest	BE2	2.35	0.55	4.27	6373.844	27.23	187.95	1197.94
Région wallonne	BE3	1.94	0.55	3.52	3562.131	12.55	81.05	288.70
Czech Republic	CZ	2.21	0.54	4.10	10499.58	43.05	81.99	860.90
Baden-Württemberg	DE1	2.41	0.5	4.82	10554.89	50.90	144.68	1527.12
Bayern	DE2	2.32	0.5	4.64	12493.82	57.92	162.25	2027.12
Berlin	DE3	2.00	0.5	3.99	3350.088	13.38	155.75	521.79
Brandenburg	DE4	1.98	0.5	3.95	2455.218	9.71	35.58	87.36
Bremen	DE5	3.02	0.5	6.03	654.429	3.95	193.03	126.33
Hamburg	DE6	3.27	0.5	6.54	1726.021	11.29	196.24	338.72
Hessen	DE7	2.23	0.5	4.47	6007.417	26.85	165.36	993.37
Mecklenburg-Vorpommern	DE8	2.47	0.5	4.94	1605.647	7.93	128.45	206.25
Niedersachsen	DE9	2.33	0.5	4.65	7784.694	36.22	158.21	1231.63
Nordrhein-Westfalen	DEA	2.37	0.5	4.73	17558.52	83.13	151.51	2660.24
Rheinland-Pfalz	DEB	2.09	0.5	4.18	3994.276	16.71	66.95	267.41
Saarland	DEC	2.44	0.5	4.87	996.2985	4.86	185.20	184.52

(*continued*)

Table 5.8 (continued)

Region Name	Region code	Direct shadow price (PPS EUR per capita)	Country-level multipliers –	Discounted shadow price (PPS EUR per capita)	Population (Thousand capita)	Aggregate shadow price (Million PPS EUR)	Required PPS EUR/capita for 10% increase of REDI	Required PPS million EUR for 10% increase of REDI
Sachsen	DED	1.97	0.5	3.94	4056.321	16.00	94.64	383.90
Sachsen-Anhalt	DEE	2.20	0.5	4.41	2270.982	10.01	52.90	120.14
Schleswig-Holstein	DEF	2.16	0.5	4.33	2808.045	12.16	82.25	230.95
Thüringen	DEG	2.34	0.5	4.69	2178.092	10.20	163.98	357.15
Hovedstaden	DK01	2.08	0.53	3.93	1724.396	6.78	157.34	271.31
Sjælland	DK02	1.52	0.53	2.88	818.2445	2.35	48.88	39.99
Syddanmark	DK03	1.90	0.53	3.59	1201.583	4.32	79.04	94.97
Midtjylland	DK04	1.74	0.53	3.29	1269.266	4.17	39.45	50.07
Nordjylland	DK05	1.69	0.53	3.19	580.443	1.85	54.18	31.45
Estonia	EE	1.73	0.83	2.08	1322.74	2.76	56.26	74.42
Voreia Ellada	EL1	3.09	0.99	3.14	3150.369	9.88	28.23	88.95
Kentriki Ellada	EL2	3.68	0.99	3.74	2783.278	10.40	41.09	114.35
Attiki	EL3	3.75	0.99	3.80	3928.338	14.94	34.22	134.43
Nisia Aigaiou, Kriti	EL4	3.40	0.99	3.45	1163.115	4.02	48.33	56.21
Galicia	ES11	2.85	0.61	4.72	2760.319	13.02	84.92	234.41
Principado de Asturias	ES12	2.65	0.61	4.39	1067.422	4.68	74.59	79.62
Cantabria	ES13	2.92	0.61	4.83	589.2745	2.84	86.89	51.20
País Vasco	ES21	3.12	0.61	5.16	2175.151	11.23	77.45	168.45
Comunidad Foral de Navarra	ES22	3.35	0.61	5.53	636.775	3.52	110.62	70.44
La Rioja	ES23	3.58	0.61	5.92	318.0405	1.88	118.34	37.64
Aragón	ES24	3.38	0.61	5.58	1337.843	7.47	100.52	134.48
Comunidad de Madrid	ES30	2.68	0.61	4.44	6386.275	28.34	133.11	850.10

Castilla y León	ES41	2.96	0.61	4.90	2520.495	12.35	142.09	358.14
Castilla-la Mancha	ES42	2.98	0.61	4.92	2087.131	10.28	103.42	215.85
Extremadura	ES43	2.64	0.61	4.36	1099.36	4.80	69.82	76.76
Cataluña	ES51	2.94	0.61	4.86	7454.75	36.23	131.21	978.15
Comunidad Valenciana	ES52	2.64	0.61	4.37	4977.81	21.75	109.24	543.76
Illes Balears	ES53	3.19	0.61	5.28	1103.753	5.82	121.36	133.95
Andalucía	ES61	2.34	0.61	3.87	8360.478	32.33	92.80	775.84
Región de Murcia	ES62	2.71	0.61	4.48	1460.439	6.54	85.12	124.31
Canarias (ES)	ES70	2.96	0.61	4.90	2089.843	10.24	102.86	214.97
Länsi-Suomi	FI19	1.98	0.71	2.79	1367.222	3.82	78.20	106.91
Helsinki-Uusimaa	FI1B	2.28	0.71	3.21	1558.891	5.00	96.17	149.92
Etelä-Suomi	FI1C	1.83	0.71	2.57	1159.337	2.98	56.58	65.59
Pohjois- ja Itä-Suomi	FI1D	1.87	0.71	2.63	1299.487	3.42	36.85	47.89
Île de France	FR1	2.65	0.79	3.38	11940.21	40.33	162.13	1935.92
Bassin Parisien	FR2	2.22	0.79	2.83	10796.94	30.55	62.26	672.17
Nord—Pas-de-Calais	FR3	2.00	0.79	2.55	4059.038	10.37	43.41	176.21
Est (FR)	FR4	2.12	0.79	2.71	5384.92	14.57	43.30	233.19
Ouest (FR)	FR5	2.13	0.79	2.71	3645.973	9.88	75.87	276.63
Sud-Ouest (FR)	FR6	2.13	0.79	2.72	6979.666	18.96	29.88	208.56
Centre-Est (FR)	FR7	1.77	0.79	2.26	7727.595	17.47	42.95	331.90
Méditerranée	FR8	1.99	0.79	2.53	7979.922	20.19	32.89	262.47
Jadranska Hrvatska (Adriatic Croatia)	HR03	2.22	0.79	2.83	1409.667	3.98	33.91	47.80
Kontinentalna Hrvatska (Continental Croatia)	HR04	2.25	0.79	2.87	2858.666	8.20	37.30	106.62
Közép-Magyarország	HU10	3.38	0.68	4.99	2968.33	14.82	49.93	148.21
Közép-Dunántúl	HU21	3.31	0.68	4.89	1081.647	5.29	58.69	63.48

(*continued*)

Table 5.8 (continued)

Region Name	Region code	Direct shadow price (PPS EUR per capita)	Country-level multipliers –	Discounted shadow price (PPS EUR per capita)	Population (Thousand capita)	Aggregate shadow price (Million PPS EUR)	Required PPS EUR/capita for 10% increase of REDI	Required PPS million EUR for 10% increase of REDI
Nyugat-Dunántúl	HU22	3.38	0.68	5.00	989.6095	4.95	59.99	59.37
Dél-Dunántúl	HU23	2.45	0.68	3.62	929.0385	3.37	47.11	43.77
Észak-Magyarország	HU31	2.22	0.68	3.28	1185.796	3.89	39.41	46.73
Észak-Alföld	HU32	2.55	0.68	3.76	1483.149	5.58	41.40	61.40
Dél-Alföld	HU33	2.70	0.68	3.99	1293.975	5.17	43.94	56.85
Border, Midland and Western	IE01	1.51	0.33	4.58	1242.653	5.69	229.06	284.64
Southern and Eastern	IE02	2.33	0.33	7.06	3361.714	23.74	388.38	1305.63
Nord-Ovest	ITC	3.66	0.71	5.19	15929.9	82.60	98.52	1569.33
Sud	ITF	3.14	0.71	4.45	14075.58	62.65	53.41	751.84
Isole	ITG	3.02	0.71	4.28	6703.067	28.71	59.95	401.87
Nord-Est	ITH	4.06	0.71	5.76	11541.47	66.46	103.65	1196.22
Centro (IT)	ITI	3.38	0.71	4.80	11823.66	56.74	100.77	1191.50
Lithuania	LT	2.24	0.98	2.28	2998.03	6.85	25.13	75.33
Latvia	LV	1.91	0.98	1.95	2038.037	3.97	29.24	59.59
Noord-Nederland	NL1	2.26	0.64	3.57	1717.881	6.12	153.31	263.37
Oost-Nederland	NL2	1.95	0.64	3.07	3545.193	10.89	58.35	206.85
West-Nederland	NL3	2.16	0.64	3.40	7891.41	26.80	64.53	509.23
Zuid-Nederland	NL4	2.08	0.64	3.28	3588.061	11.76	108.13	387.99
Region Centralny	PL1	2.14	0.68	3.16	7780.293	24.57	50.52	393.07
Region Poludniowy	PL2	1.92	0.68	2.83	7871.792	22.31	68.02	535.41
Region Wschodni	PL3	1.87	0.68	2.76	6659.861	18.38	46.92	312.46

Region Pólnocno-Zachodni	PL4	1.92	0.68	2.83	6135.988	17.39	39.68	243.48
Region Poludniowo-Zachodni	PL5	1.90	0.68	2.81	3840.447	10.78	50.54	194.10
Region Pólnocny	PL6	1.77	0.68	2.62	5751.908	15.06	57.60	331.30
Norte	PT11	2.19	0.77	2.86	3668.89	10.48	94.29	345.94
Algarve	PT15	2.60	0.77	3.40	446.831	1.52	112.13	50.10
Centro (PT)	PT16	2.35	0.77	3.07	2306.403	7.07	61.33	141.46
Lisboa	PT17	2.56	0.77	3.34	2815.143	9.40	136.95	385.53
Alentejo	PT18	2.36	0.77	3.09	751.0065	2.32	89.51	67.22
Macroregiunea unu	RO1	2.10	0.68	3.10	5092.878	15.81	65.19	331.98
Macroregiunea doi	RO2	1.79	0.68	2.65	6144.138	16.29	37.11	228.02
Macroregiunea trei	RO3	3.17	0.68	4.69	5444.597	25.52	51.56	280.73
Macroregiunea patru	RO4	2.15	0.68	3.18	3998.95	12.71	50.86	203.40
Stockholm	SE11	2.36	0.5	4.77	2108.693	10.07	214.79	452.93
Östra Mellansverige	SE12	1.63	0.5	3.30	1587.298	5.23	56.04	88.95
Småland med öarna	SE21	2.13	0.5	4.31	815.5185	3.51	150.78	122.97
Sydsverige	SE22	1.56	0.5	3.15	1411.691	4.45	110.23	155.60
Västsverige	SE23	1.80	0.5	3.64	1900.853	6.92	80.11	152.28
Norra Mellansverige	SE31	1.98	0.5	4.01	827.977	3.32	84.19	69.71
Mellersta Norrland	SE32	2.09	0.5	4.23	368.9665	1.56	42.29	15.60
Övre Norrland	SE33	1.93	0.5	3.90	509.2215	1.98	116.93	59.54
Vzhodna Slovenija	SI01	1.75	0.66	2.65	1096.608	2.91	100.73	110.47
Zahodna Slovenija	SI02	2.13	0.66	3.22	959.0295	3.09	132.08	126.67
Bratislavský kraj	SK01	3.67	0.98	3.75	609.1555	2.28	41.24	25.12
Západné Slovensko	SK02	2.75	0.98	2.81	1837.725	5.16	58.96	108.35
Stredné Slovensko	SK03	2.34	0.98	2.39	1348.26	3.22	50.12	67.58
Východné Slovensko	SK04	2.19	0.98	2.24	1609.058	3.60	42.53	68.44

(*continued*)

Table 5.8 (continued)

Region Name	Region code	Direct shadow price	Country-level multipliers	Discounted shadow price	Population	Aggregate shadow price	Required PPS EUR/ capita	Required PPS million EUR
		(PPS EUR per capita)	–	(PPS EUR per capita)	(Thousand capita)	(Million PPS EUR)	for 10% increase of REDI	for 10% increase of REDI
North East (UK)	UKC	1.70	0.74	2.29	2603.204	5.97	25.24	65.70
North West (UK)	UKD	1.89	0.74	2.55	7078.098	18.08	84.28	596.53
Yorkshire and The Humber	UKE	1.66	0.74	2.24	5310.291	11.89	31.33	166.40
East Midlands (UK)	UKF	1.61	0.74	2.17	4570.081	9.92	75.99	347.29
West Midlands (UK)	UKG	1.71	0.74	2.31	5640.755	13.01	59.95	338.18
East of England	UKH	1.54	0.74	2.09	5909.753	12.34	29.22	172.70
London	UKI	2.95	0.74	3.99	8305.947	33.12	195.37	1622.76
South East (UK)	UKJ	1.71	0.74	2.31	8724.452	20.15	78.54	685.25
South West (UK)	UKK	1.52	0.74	2.06	5340.771	11.00	84.45	451.04
Wales	UKL	1.69	0.74	2.28	3072.005	7.00	113.90	349.89
Scotland	UKM	2.02	0.74	2.73	5309.039	14.51	158.47	841.31
Northern Ireland (UK)	UKN	1.66	0.74	2.25	1822.415	4.09	114.52	208.70
Average		2.38	0.66	3.75		14.64	92.03	
Sum					488768.9			45768.49

Notes

1. The perpetual inventory method (PIM) is a method of constructing estimates of capital stock and consumption of fixed capital from time series of gross fixed capital formation. It allows an estimate to be made of the stock of fixed assets in existence and in the hands of producers, and it is generally based on estimating how many of the fixed assets installed as a result of gross fixed capital formation undertaken in previous years have survived to the current period (OECD, 2001).
2. http://spsstools.net/en/syntax/syntax-index/regression-repeated-measures/breusch-pagan-amp-koenker-test/
3. Hayes, A.F. and Cia, L. (2007): Using heteroscedasticity-consistent standard error estimators in OLS regression: An introduction and software implementation. *Behavior Research Methods*, 39(4), 709–722. http://www.afhayes.com/spss-sas-and-mplus-macros-and-code.html
4. The transformation procedure ensures that $\sum_i y_{i,p} / R = \bar{y}$ for all p (R is the number of regions).
5. The reason for this is that under the optimal allocation, bottlenecks are eliminated, so the bracketed term in the objective function in (6) vanishes.
6. From the 23 countries covered by the REDI, 17 appear in one of the reports, while 10 appear in both.
7. The OECD report contains government consumption, government benefits (transfers), direct and indirect taxes. The ECB report estimates multipliers for government consumption, labor income tax, capital income tax, and consumption tax.
8. Another approach could be using government transfers, but this would narrow down the basis for multiplier data to the OECD report.
9. Although there is some variation, the long-run effects do not differ too much from the short-run effects.

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6

Entrepreneurial Ecosystem in the European Union Regions: Identification of Optimal Ecosystem Configurations for Informed Policy

László Szerb and Éva Komlósi

1 Introduction

While the entrepreneurship ecosystem literature has gone through a rapid expansion over the last decade, it is still in an early phase in terms of its theoretical and conceptual development. Recent theoretical advances seem to crystallize in two directions as networking and complexity approaches. Complexity theory provides a suitable way to study the emergence of new structures, describe the relationship among the system elements, and examine the time-evolving dynamics of ecosystem constituents. In this chapter, we offer a direct empirical analysis of regional ecosystem measure based on complexity theory: the Regional Entrepreneurship and Development Index (REDI).

L. Szerb (✉) • É. Komlósi
Faculty of Business and Economics, University of Pécs, Pécs, Hungary
e-mail: szerb.laszlo@ktk.pte.hu; komlosi.eva@ktk.pte.hu

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We acknowledge that the REDI approach is based on homogeneous (across regions) and fixed (across pillars) pillar weights, thus ignoring part regions' heterogeneity. Therefore, we also enhance the REDI methodology by building on the benefit of the doubts (BOD) weighting technique. This weighting system reflects a value judgment on what are the optimal configurations of REDI constituents. If policy makers are given objective, nonarbitrary information about the importance of REDI pillars, resource allocation should follow an economically meaningful process.

Quantity improvements are ensured if additional resources are deployed, but for an equal quantitative change in the REDI score, enhancements will be qualitatively superior if policy makers target a clear set of priorities. Based on the BOD enhanced REDI ($REDI^{BOD}$), we provide a score on the quality of the entrepreneurial ecosystem ($REDI^{BOD}$) for 125 European Union (EU) regions, conduct a grouping by cluster analysis, and offer policy suggestions for 23 large EU city regions.

2 Entrepreneurial Ecosystems: From Concepts to Theories

Rooted in the innovation system and cluster theories, the concept of entrepreneurship ecosystem (EE) emerged in the 2010s to shed new lights on the role of entrepreneurship in national and regional economic development (Isenberg, 2010; Feld, 2012; Mason & Brown, 2014; Spigel & Harrison, 2018). Previous researches had biases to focus on (1) the individual- or firm-level characteristics, (2) self-employment type of entrepreneurship measurements, (3) looking for a single or a few important determinants of start-ups, and (4) identifying general, "one-size-fits-all" entrepreneurship policy instruments (Acs et al., 2014; Szerb et al., 2019, Stam, 2015). Policies to boost startups independently from development and local conditions or to create a new Silicon Valley where even preconditions were missing lead to mixed and sometimes disappointing results and called for new approaches to study entrepreneurship (Adams, 2020; Vivarelli, 2013; Isenberg, 2010).

The idea that neither individual nor environmental factors alone or in isolation are able to explain entrepreneurship-induced long-term growth had been known for long (Spilling, 1996; Neck et al., 2004; Cohen, 2006), but EE concept jumped to the forefront of entrepreneurship research in the 2010s by providing an overarching holistic view of individual and institutional factor combination of entrepreneurship. Based on Spigel and Harrison (2018) and Szerb et al. (2019), there are seven distinctive characteristics of EE research as comparing the individual entrepreneurship innovation system or cluster approaches.

- First, EE separates the EE components from entrepreneurial outputs and outcomes. Various entrepreneurial activities are intermediate outputs to spur economic growth and job creation (outcomes) (Stam, 2015; Szerb et al., 2019).
- Second, EE focuses on new start-ups and growing young businesses (scale-ups) instead of already existing incumbent firms and businesses. New firms are the key to novel Schumpeterian types of innovations and technology development (Acs & Audretsch, 2005; Hobijn & Jovanovic, 2001).
- Third, while being place-based, EE is industry-neutral by focusing on potentially high-growth businesses, and not on clusters (Stam, 2015; Spigel & Harrison, 2018). Technologies, in particular digital technologies, play an important role in EE development (Sussan & Acs, 2017; Elia et al., 2020).
- Fourth, EE puts the entrepreneur in the center of EE instead of some anchor firms or institutions. The entrepreneur has multiple roles as the disseminator of knowledge in the ecosystem and as an initiator of a start-up or a manager of a scale-up (Feld, 2012).
- Fifth, EE recognizes the interactions among the stakeholders and the institutional factors as the key mechanisms for knowledge spillover and resource exploitation capacity. Agency is important to understand why many institutional development efforts remain ineffective (Acs et al., 2014).
- Sixth, EE enriches the system components by adding entrepreneurship-specific factors, most importantly those that relate to opportunity recognition, exploitation, and start-up practices. Knowledge and knowledge spillover about the entrepreneurial processes and practices are particularly important factors (Spigel & Harrison, 2018).

- Finally, seventh, EE highlights the importance of tailor-made, bottom-up policies as appropriate tools to develop local entrepreneurship instead of top-down policies trying to replicate successful examples (Isenberg, 2010; Acs et al., 2014).

While scholars define EE partially differently, there is an agreement that EE is a complex, dynamic system (CAD) of individual and interdependent actors and the widely interpreted institutional structures that support entrepreneurial activity in a particular region or country. Acs et al. (2014) highlight the resource allocation feature of the ecosystem, and many others claim that EE should support only productive, high-impact or high-growth start-ups and scale-ups, and not generally start-ups (Stam, 2015; Alvedalen & Boschma, 2017; Spigel, 2017).[1] Initial EE publications focused on identifying ecosystem components (Isenberg, 2010; Mason & Brown, 2014), and on describing the relation among the components (Stam, 2015; Motoyama & Knowlton, 2017; Spigel, 2017). Governance issues and stakeholder network analyses just have been emerging as new trends in EE research (Colombo et al., 2019; Cunningham et al., 2019).

The entrepreneurship ecosystem literature has gone through a rapid expansion over the last decade; however, it is still in an early phase in terms of its theoretical and conceptual development (Acs et al., 2014; Alvedalen & Boschma, 2017; Cantner et al., 2021; Phillips & Ritala, 2019; Stam, 2015). In a recent summary paper, Cao and Shi (2020) find that EE research is mostly an empirical rather than conceptual focused. Recent theoretical advances seem to crystallize in two directions as networking and complexity approaches. Based on the weak and strong ties of social capital concept, network theory is appropriate to examine the connections among the ecosystem stakeholders (Neumeyer et al., 2019; Pittz et al., 2021).

Complexity theory provides a suitable way to study the emergence of new structures and to describe the relationship among the system elements and to examine the time-evolving dynamics of the constituents (Stam, 2018; Phillips & Ritala, 2019; Han et al., 2021). In fact, complexity theory is a branch of different scientific concepts, "each reflecting a different focal method or model or approach for exploring emergence in some way" (Lichtenstein, 2011, p. 475). Out of Lichtenstein's 15 distinct foci, the complex adaptive system (CAD) and the ecological system approaches seem to be applicable to EEs. The ecological system analogy, the dynamic balance of the living and nonliving constituents shaping EE, has appeared early in the EE research (Isenberg, 2016; Sussan & Acs, 2017; Cantner et al., 2021). The ecological analogy is useful to describe the connection and the evolvement of a system, but it is hard to operationalize. The CAD approach is based on the agent interaction and learning that lead to emergent, collective behavior. At the same time, agents' actions are highly unpredictable because of the complexity of interaction, forward and backward effects (Lichtenstein, 2011). Following Roundy, Bradshaw, and Brockman's (Roundy et al., 2018) pioneering study, some authors claim that CAD is an appropriate theory for studying EEs (Phillips & Ritala, 2019; Fredin & Lidén, 2020).

A methodologically underdeveloped field of EE research is the measurement issue. It is closely associated with the boundaries of EE. While many believe that the appropriate territory of EE is relatively small city or city-region, data are available mostly for larger, frequently artificial regional units and countries (Spigel et al., 2020). The institutional setup within countries is relative homogeneous territories within there the institutional setup is similar or the same. However, at country level, it is difficult to capture agglomeration effects and knowledge spillover mechanism that are important aspects of EE.

An equally important methodological problem is related to the uniqueness of EEs. Most researchers believe that each EE is unique in terms of components, configurations, and by its own development. Consequently, policy makers should not try to replicate successful regions or countries; instead, distinctive development strategy is more appropriate (Szerb et al., 2019). As a consequence, case study is a dominant approach to describe EEs, for example, Silicon Valley (Adams, 2020), Waterloo and Calgary (Spigel, 2017), St. Louis (Motoyama & Knowlton, 2017), Turin (Colombelli et al., 2019), Zhongguancun (Han et al., 2021), Germany (Fuerlinger et al., 2015), or Poland (Brooks et al., 2019). A general problem of the case study approach is the limited comparability due to different, sometimes ad hoc, conceptual approaches. MIT's REAP (Region Entrepreneurship Acceleration Program)[2] and Babson's BEEP (Babson

College Entrepreneurship Ecosystem Project)[3] are positive examples of examining local ecosystems with the same methodology. Another possibility is to use the composite indicator (CI) technique to calculate EE scores for each territorial unit. CIs are suitable to measure multidimensional construct such as EE (Joint Research Centre-European Commission, 2008). The Global Entrepreneurship Index (Acs et al., 2014), the Regional Entrepreneurship and Development Index (Szerb et al., 2019), and the Entrepreneurial Ecosystem Index (Stam, 2018; Leendertse et al., 2021) are examples for this approach.

CI design is based on the assumption that the index components can be measured uniformly based on a benchmarking principle. At the same time, the configuration of the components is allowed to vary, representing the diversity of EEs. While it can be accepted that ecosystems cannot be replicated, useful techniques and policies to improve some components of EE could be applied carefully (Autio & Levie, 2017). Here, we provide the REDI methodology which is an appropriate tool to measure and compare country-level EEs and provide policy suggestions on how to improve the EE. Following Lichtenstein (2011) and Roundy, Bradshaw, and Brockman (Roundy et al., 2018), we claim that complexity theory, in particular CAD, is appropriate to apply to the EE concept, and REDI methodology is able to capture the most important features of CAD.

3 The Regional Entrepreneurship and Development Index: Content and Calculation[4]

The Regional Entrepreneurship and Development Index (REDI) has been constructed to capture the regionally embedded contextual features of individual entrepreneurship efforts and initiation across EU regions. REDI targets to capture the universal factors of EE in three subindices and fourteen pillars, providing a comprehensive and a comparable measure of EE across a mix of 125 NUTS1 and NUTS2 EU regions.

REDI is a multilevel comprehensive index, which reflects several aspects of the entrepreneurial context of a region. Upon constructing the index, a six-level index-building methodology was followed:

sub-indicators (1) are merged into indicators, (2) which are then reflected by variables, (3) then these construct pillars, (4) contributing to subindices (5), which finally constitute the REDI super-index (6). With respect to its content, at the subindex level we differentiate between entrepreneurial attitudes, abilities, and aspirations[5] that are then broken down to 4–5 pillars, quasi-independent building blocks of this entrepreneurship index. Szerb et al. (2017) and Szerb et al. (2019) offer a detailed description of the building methodology and computation of the REDI.

An essential question is how to capture the connection and the configuration of the components. The key idea behind REDI is that system performance is "co-produced" by its interrelated elements, according to the CAD principle. Every pillar is obtained by multiplying an individual with an associated institutional variable capturing the combined effect of individual initiations and regional institutional context.

The fourteen pillars are the most important components of REDI. REDI methodology includes two important novelties that makes possible to measure the resource optimization over the fourteen pillars. The average pillar adjustment (APA) method serves to equalize the marginal effect of each additional input over the fourteen pillars.

> The normalized pillar value averages are different, ranging from 0.36 (Finance) to 0.65 (Product innovation). We assume that these differences reflect the difficulty to reach average pillar performance in reverse order, so that it is about 1.8 times more difficult to reach average performance in Finance compared to Product innovation. This implies that for the same additional input unit we experience 1.8 times larger improvement in Product innovation than in Finance. APA corrects this distortion by equalizing pillar averages to the level of the average of the 14 pillars (0.49) and holding all the pillar values in the original [0,1] range. A potential drawback of this approach is that pillar values are only equalized over their averages, and that marginal effects are not necessarily the same if we improve non-average pillars. Monetary differences are also neglected, that is, pillar improvements are computed in natural input units as we cannot estimate the monetary value of input units. (Szerb et al., 2019, p. 1313)

A particularly important aspect of the REDI method is the penalty for bottleneck (PFB) methodology, which helps to identify constraining factors in the regional systems of entrepreneurship. A bottleneck is the worst performing element or binding constraint and is defined as a shortage or the lowest level of a particular entrepreneurial pillar as compared to the other thirteen pillars. Then, the value of each pillar is penalized as a result of linking it to the score of the pillar with the weakest performance in the region (Acs et al., 2014; Szerb et al., 2017). As a result, if the weakest pillar was raised, it would have a multiplicative effect to improve the other pillars and the whole REDI, while raising a non-bottleneck pillar would have only a minor effect. The idea here is that systems with strong weaknesses cannot fully leverage their strengths, or in other words weakly performing bottleneck pillars hold back the performance of the whole entrepreneurship ecosystem. The novelty of this method is that it portrays the entrepreneurial disparities among EU regions and provides country- and regional-level, tailor-made public policy suggestions to improve the level of entrepreneurship and optimize resource allocation over the different pillars of entrepreneurship.

The real strength of using the REDI index in our setup is that although the REDI uses one number to describe regional entrepreneurship, its detailed structure with the 14 pillars allows us to analyze different policy mixes at this level of detail. Also, building on the APA and the PFB methodology, there is not a single linear relationship between the pillars and the REDI index, but the system is able to give a sophisticated description and analysis of how different policies affect the overall entrepreneurial climate in a region and, subsequently, local and aggregate economic performance.

4 Regional Efficiency: Analysis of Composite Indicators (CIs) Based on the Benefit of the Doubt (BOD) Weighting Model

Summarizing a number of variables into a single CI entails making judgments about the importance of each variable, and the difficulty of this task increases with the number of alternatives. The REDI presented above quantifies the overall level of entrepreneurship for each European region (i) as the weighted sum of 14 pillars (v) $\left(\sum\left(w_v \times p_{iv}^*\right) = CI_i \forall w_v = 1/14\right)$. This weighting system reflects a value judgment on what is the optimal configuration of REDI constituents. This approach, based on homogeneous (across regions) and fixed (across pillars) weights, ignores region-specific heterogeneity, which may obscure policy-making processes. By construction, additional resources to improve competitive pillars (raw data) would quantitatively yield the same new CI score. Without objective guidance, managers will likely follow discretionary criteria to allocate additional resources, and the quantity improvement in entrepreneurship will be interpreted as good news. On the contrary, if policy makers are given objective, nonarbitrary information about the importance of REDI pillars, resource allocation should follow a more economically meaningful process. Quantity improvements are ensured if additional resources are deployed, but for an equal quantitative change in the CI, REDI enhancements will be qualitatively superior if policy makers target a clear set of priorities.

The REDI index has many attractive properties as well as a strong informative capacity that certify its accuracy to measure regions' entrepreneurial ecosystem. However, the homogeneous weighting scheme of this index does not allow to identify the priorities that policy makers should emphasize in order to improve resource allocation and, subsequently, their entrepreneurship level.

In light of the importance of weights for computing CIs and for identifying key indicators and policy priorities, the analysis proposed in this research evaluates the competitive level of 125 European regions from 24 countries with different entrepreneurial ecosystems, seeking to clarify how regions can implement optimal ecosystem-enhancing strategies in different contexts.

To achieve this objective, the benefit of the doubt (BOD) model is employed (e.g., Cherchye et al., 2007). Rooted in data envelopment analysis (DEA) techniques, the BOD model—originally proposed by Melyn and Moesen (1991) and further developed by, among others, Cherchye et al. (2007) and Sahoo et al. (2017)—is a special case of the input-oriented DEA model (Charnes et al., 1978) with a single constant input (Lovell & Pastor, 1999). The BOD weighting model is among the methodological approaches recommended by the OECD (2008) for computing CIs.

The model, described below, is a regionally adjusted version of the BOD model developed originally for countries (Lafuente et al., 2021). Formally, for each region (i), the BOD model considers the 14 REDI pillars $\left(p_{i,v}^{*}\right)$, and employs a set of endogenous, region-specific weights (**w**) to compute the weighted average of indicators (**y**) that maximize the CI score $\left(CI_i^{BOD}\right)$. Therefore, the BOD model generates, for each region, the optimal weighting configuration of REDI pillars by identifying the relative strengths and weaknesses of the output set. Without information about the exact weights of the outputs (**y**), the BOD weighting assigns to each region the best possible weight configuration (**w**), which leads to unveiling endogenous (region-specific) policy priorities, in terms of REDI pillars.

Table 6.1 presents summary statistics for the output set used in this study.

In terms of computational procedure, the following linear program solves the BOD weighting problem and computes, for each region (i), the optimal CI value based on the 14 REDI pillars:

$$CI_i^{BOD} = \max_{w,k} \sum_{k=1}^{K} w_{ik} y_{ik} \qquad k = 1,\ldots,K = 14 \quad i = 1,\ldots,N \tag{6.1}$$

subject to:

$$\sum_{k=1}^{K} w_{ik} y_{ik} \leq 1$$

$$w_{ik} \geq 0,\; L_k \leq \frac{w_{ik} y_{ik}}{\sum_{k=1}^{K} w_{ik} y_{ik}} \leq U_{k}.$$

Equation (6.1) computes for each region a vector of endogenous weights for the 14 outputs ($w_k = w_1, \ldots, w_{14}$) that maximizes the CI score. The CI performance value is bounded $\left(CI_i^{BOD} \leq 1\right)$: for efficient regions, $CI_i^{BOD} = 1$, while for inefficient regions, $CI_i^{BOD} < 1$ and $1 - CI_i^{BOD}$ is the

Table 6.1 REDI: Mean values for the REDI score and its pillar values

	Country	Regions	REDI	y1	y2	y3	y4	y5	y6	y7	y8	y9	y10	y11	y12	y13	y14
1	Austria	3	51.17	0.5170	0.6871	0.3784	0.5939	0.5838	0.6500	0.6409	0.4717	0.7770	0.6348	0.6307	0.2617	0.6884	0.4040
2	Belgium	3	54.93	0.5995	0.3962	0.5888	0.3745	0.4445	0.4012	0.4988	0.7456	0.7991	0.7343	0.8379	0.5721	0.8279	0.5794
3	Czech Rep.	1	38.80	0.4876	0.7072	0.1249	0.2445	0.1715	0.2498	0.4717	0.3955	0.2689	0.6607	0.6358	0.6577	0.8983	0.4743
4	Germany	16	51.99	0.5453	0.6113	0.3450	0.5586	0.6454	0.5845	0.6787	0.4208	0.7892	0.4300	0.4515	0.6478	0.7098	0.7060
5	Denmark	5	60.26	0.8834	0.4147	0.5825	0.8415	0.9913	1.0000	0.8434	1.0000	0.8652	0.8607	0.4804	0.4381	0.2188	0.8568
6	Estonia	1	45.30	0.7032	0.9808	0.6053	0.4930	0.1853	0.4407	0.5279	0.5207	0.4460	0.6034	0.6265	0.6240	0.2855	0.2046
7	Greece	4	22.90	0.2344	0.2868	0.2485	0.1238	0.0052	0.1531	0.3382	0.3815	0.3023	0.4120	0.6106	0.0841	0.2634	0.3338
8	Spain	17	33.29	0.2850	0.5572	0.3296	0.4192	0.4269	0.3620	0.5036	0.4137	0.3206	0.3181	0.4600	0.1742	0.1315	0.4263
9	Finland	4	53.63	0.8062	0.7561	0.4967	0.9714	0.7789	0.8934	0.6227	0.4563	0.4897	0.6210	0.7036	0.5361	0.2974	0.2719
10	France	8	49.36	0.4342	0.2693	0.7368	0.3904	0.5119	0.4967	0.5657	0.5494	0.7533	0.6620	0.7813	0.5527	0.5644	0.5780
11	Croatia	2	24.55	0.3370	0.4604	0.1905	0.0579	0.0079	0.0910	0.3053	0.2153	0.4410	0.2501	0.4146	0.5235	0.3703	0.4599
12	Hungary	7	20.87	0.2209	0.2085	0.1104	0.1516	0.0251	0.1871	0.3269	0.3302	0.2309	0.2470	0.2097	0.4417	0.4697	0.1467
13	Ireland	2	65.85	0.4890	0.7797	0.8386	0.6128	0.9853	0.7120	0.6630	0.8965	0.8084	0.6035	0.5741	0.7276	0.4941	0.5512
14	Italy	5	30.40	0.3100	0.2477	0.4006	0.2305	0.1998	0.1666	0.3913	0.1553	0.4038	0.9878	0.5816	0.1723	0.3702	0.4174
15	Lithuania	1	32.80	0.5128	0.2547	0.5038	0.2808	0.0401	0.2509	0.3919	0.7014	0.2305	0.3918	0.4829	0.8008	0.3483	0.3791
16	Latvia	1	36.70	0.5488	0.7581	0.4032	0.2322	0.1127	0.2483	0.3546	0.4794	0.3777	0.4063	0.2731	0.9973	0.4232	0.4229
17	Netherlands	4	57.05	0.5755	0.9398	0.3099	0.8379	0.8802	0.9446	0.6215	0.5524	0.7435	0.5932	0.4760	0.3343	0.5439	0.6262
18	Poland	6	36.65	0.4372	0.7266	0.3626	0.4715	0.3346	0.1702	0.2946	0.4044	0.1482	0.8900	0.2582	0.5708	0.5559	0.4288
19	Portugal	5	37.52	0.3138	0.4775	0.4038	0.2629	0.4861	0.4264	0.3535	0.2562	0.3659	0.4092	0.6339	0.4145	0.5009	0.3378
20	Romania	4	24.93	0.3842	0.0760	0.7159	0.1036	0.1266	0.0427	0.1937	0.2756	0.1596	0.3529	0.2442	0.9663	0.3662	0.3727
21	Sweden	8	56.20	0.9910	0.2952	0.7203	0.8631	0.8721	0.9116	0.8193	0.6138	0.7182	0.5058	0.7153	0.4192	0.4320	0.3147
22	Slovenia	2	46.50	0.3044	0.6926	0.3946	0.4480	0.4059	0.3536	0.6121	0.4599	0.5327	0.7384	0.5879	0.4669	0.6275	0.3275
23	Slovak Rep.	4	30.85	0.2858	0.2175	0.1907	0.4299	0.0703	0.1698	0.4760	0.3106	0.1545	0.6329	0.4851	0.7251	0.6880	0.5177
24	UK	12	57.53	0.5755	0.6456	0.9382	0.6442	0.7945	0.7462	0.5569	0.8046	0.8308	0.4678	0.5423	0.5690	0.4627	0.3615
	Total	125	43.54	0.4847	0.4957	0.4732	0.4852	0.5008	0.4919	0.5321	0.4906	0.5401	0.5232	0.5174	0.4734	0.4585	0.4582

For the REDI pillars: **y1**: opportunity perception, **y2**: start-up skills, **y3**: risk acceptance, **y4**: networking, **y5**: cultural support, **y6**: opportunity start-up, **y7**: technology absorption, **y8**: human capital, **y9**: competition, **y10**: product innovation, **y11**: process innovation, **y12**: high growth, **y13**: internationalization, **y14**: risk capital degree of inefficiency (i.e., the output expansion required to be fully efficient and reach the efficiency frontier). Weights are constrained to be non-negative, which makes CI_i^{BOD} a non-decreasing function of the output set ($\mathbf{y}$) (Eq. (6.1)). This constraint allows for extreme scenarios that render BOD results inaccurate (e.g., high number of artificially efficient regions). Thus, in order to account for the relative importance of all CI outputs, additional restrictions on the weights are needed. Thus, a "pie share" restriction was added: $L_k \leq \frac{w_{ik} y_{ik}}{\sum_{k=1}^{K} w_{ik} y_{ik}} \leq U_k$. This restriction is attractive because pie shares ($w_{ik}y_{ik}$) do not depend on measurement units and directly reveal the individual contribution of each pie share to the CI, while allowing for weight heterogeneity within and between regions. In Eq. (6.1), L_k (1%) and U_k (20%) are the lower and upper limit set for each pie share, respectively. Note that the endogenous weights are region-specific and the sum of the pie shares equals the CI score $\left(CI_i^{BOD}\right)$ (Eq. (6.1)). In a closely related manner, notice that Eq. (6.1) assumes that all outputs are relevant for regional entrepreneurship and territories will prioritize all ecosystem constituents.

5 Country and Regional Ranking and Grouping

The REDI scores are available for two periods, 2007–2011 and 2012–2014 (Szerb et al., 2017). In this chapter, we rely on the 2012–2014 dataset. The $REDI^{BOD}$ scores vary from 0 to a maximum of 1 (100%), where the maximum denotes those regions that use their entrepreneurial inputs the most effective ways.

Summary results of the proposed BOD model are presented in Table 6.2 (by country) and Table 6.3 (ranks by region). Overall, the findings indicate that $REDI^{BOD}$ = 0.7004 (Table 6.2), which means that the efficiency of regions' entrepreneurial ecosystem is on average 29.96% (1–0.7004). Additionally, we observe large disparities in the efficiency of regions' entrepreneurial ecosystems, which range from 0.0860 (Greece: Nisia Aigaiou, Kriti region) to the maximum value of 1 reported for ten

Table 6.2 *REDI*^{BOD} results for the analyzed European regions: BOD scores and "pie share" values

	Country			"Pie share values" ($w_{ik} y_{ik} / \sum_{k=1}^{K} w_{ik} y_{ik}$ in Eq. (6.1))													
		Regions	*REDI*^{BOD}	y1	y2	y3	y4	y5	y6	y7	y8	y9	y10	y11	y12	y13	y14
1	Austria	3	0.8109	0.0081	0.1561	0.0081	0.0081	0.0813	0.0801	0.0081	0.0332	0.0819	0.0929	0.0763	0.0081	0.1604	0.0081
2	Belgium	3	0.8838	0.0088	0.0337	0.0647	0.0088	0.0267	0.0089	0.0089	0.1768	0.1115	0.0485	0.1426	0.0722	0.1134	0.0584
3	Czech Rep.	1	0.7552	0.0082	0.1511	0.0076	0.0076	0.0075	0.0075	0.0075	0.0076	0.0076	0.1510	0.0990	0.1344	0.1510	0.0075
4	Germany	16	0.8297	0.0313	0.0624	0.0097	0.0113	0.1146	0.0302	0.0835	0.0143	0.0769	0.0192	0.0456	0.0843	0.1298	0.1166
5	Denmark	5	0.9499	0.0427	0.0095	0.0896	0.0095	0.1520	0.1349	0.0455	0.1149	0.0412	0.0955	0.0136	0.0701	0.0095	0.1215
6	Estonia	1	0.7752	0.1551	0.1551	0.1550	0.0077	0.0077	0.0078	0.0078	0.0078	0.0078	0.1550	0.0190	0.0740	0.0078	0.0078
7	Greece	4	0.2008	0.0020	0.0140	0.0237	0.0020	0.0020	0.0020	0.0020	0.0118	0.0083	0.0289	0.0402	0.0020	0.0383	0.0236
8	Spain	17	0.5382	0.0054	0.1076	0.0583	0.0378	0.0337	0.0062	0.0681	0.0370	0.0054	0.0198	0.0859	0.0110	0.0054	0.0565
9	Finland	4	0.8674	0.0667	0.1260	0.0512	0.1735	0.0744	0.1510	0.0087	0.0087	0.0087	0.0087	0.1073	0.0654	0.0087	0.0087
10	France	8	0.8114	0.0081	0.0081	0.1623	0.0081	0.0619	0.0227	0.0319	0.0213	0.0636	0.0661	0.1429	0.0599	0.0674	0.0871
11	Croatia	2	0.3256	0.0033	0.0651	0.0033	0.0033	0.0033	0.0033	0.0033	0.0033	0.0045	0.0033	0.0511	0.0651	0.0651	0.0486
12	Hungary	7	0.3401	0.0125	0.0172	0.0034	0.0034	0.0034	0.0073	0.0463	0.0554	0.0081	0.0335	0.0069	0.0680	0.0680	0.0067
13	Ireland	2	0.9469	0.0095	0.0692	0.1894	0.0094	0.1894	0.0944	0.0094	0.0943	0.0094	0.0317	0.1045	0.0480	0.0095	0.0787
14	Italy	5	0.5518	0.0055	0.0191	0.0993	0.0055	0.0055	0.0136	0.0292	0.0055	0.0251	0.1103	0.0961	0.0091	0.0445	0.0833
15	Lithuania	1	0.5804	0.0203	0.0058	0.1059	0.0058	0.0058	0.0058	0.0058	0.1161	0.0058	0.0058	0.1044	0.1161	0.0058	0.0712
16	Latvia	1	0.6437	0.1288	0.1287	0.0635	0.0064	0.0064	0.0064	0.0065	0.0064	0.0064	0.0884	0.0064	0.1287	0.0351	0.0255
17	Netherlands	4	0.9339	0.0093	0.1868	0.0093	0.1796	0.1824	0.1868	0.0093	0.0093	0.0093	0.0093	0.0093	0.0093	0.1144	0.0093
18	Poland	6	0.6821	0.0068	0.1364	0.0390	0.0696	0.0068	0.0068	0.0068	0.0232	0.0068	0.1364	0.0086	0.0539	0.1201	0.0608
19	Portugal	5	0.6203	0.0062	0.1013	0.0438	0.0062	0.0645	0.0510	0.0202	0.0062	0.0062	0.0540	0.0793	0.0299	0.1159	0.0357
20	Romania	4	0.4588	0.0502	0.0046	0.0917	0.0046	0.0046	0.0046	0.0046	0.0048	0.0046	0.0404	0.0190	0.0918	0.0746	0.0588
21	Sweden	8	0.8453	0.1453	0.0084	0.1330	0.0665	0.1429	0.1010	0.0352	0.0085	0.0322	0.0084	0.0891	0.0084	0.0580	0.0084
22	Slovenia	2	0.7503	0.0075	0.1501	0.0336	0.0309	0.0092	0.0075	0.0421	0.0075	0.0075	0.1500	0.1013	0.0465	0.1491	0.0075
23	Slovak Rep.	4	0.6036	0.0060	0.0300	0.0060	0.0669	0.0060	0.0060	0.0060	0.0060	0.0060	0.0959	0.0613	0.0971	0.1207	0.0892
24	UK	12	0.8877	0.0089	0.0781	0.1775	0.0145	0.1268	0.0748	0.0233	0.0938	0.1143	0.0332	0.0581	0.0346	0.0245	0.0254
	Overall	125	0.7004	0.0261	0.0681	0.0703	0.0321	0.0686	0.0438	0.0357	0.0362	0.0377	0.0474	0.0651	0.0473	0.0673	0.0548

For the "pie shares": **y1**: opportunity perception, **y2**: start-up skills, **y3**: risk acceptance, **y4**: networking, **y5**: cultural support, **y6**: opportunity start-up, **y7**: technology absorption, **y8**: human capital, **y9**: competition, **y10**: product innovation, **y11**: process innovation, **y12**: high growth, **y13**: internationalization, **y14**: risk capital regions: (1) Belgium: Région de Bruxelles-Capitale, (2) Denmark: Hovedstaden, (3) Denmark: Midtjylland, (4) Finland: Helsinki-Uusimaa, (5) France: Île de France, (6) Germany: Hamburg, (7) Ireland: Southern and Eastern, (8) Sweden: Stockholm, (9) UK: London, and (10) UK: South East (Table 6.3).

We also observe that countries with the most efficient ecosystems are Denmark ($REDI^{BOD}$ = 0.9499), Ireland ($REDI^{BOD}$ = 0.9469), the Netherlands ($REDI^{BOD}$ = 0.9339), and the UK ($REDI^{BOD}$ = 0.8877). On the contrary, the countries with the weakest ecosystem are Romania ($REDI^{BOD}$ = 0.4588), Hungary ($REDI^{BOD}$ = 0.3401), Croatia ($REDI^{BOD}$ = 0.3256), and Greece ($REDI^{BOD}$ = 0.2008).

Typically, the leading regions also have the highest REDI scores. Out of the top ten REDI regions, eight also lead in the $REDI^{BOD}$ ranking. Two regions with a mid-REDI score, Région de Bruxelles-Capitale (ranked 11th) and the Danish Midtjylland (ranked 24th), stepped ahead to the top-performing regions in terms of the $REDI^{BOD}$ ranking (Table 6.3).

The heterogeneity in the configuration of the efficiency level of regions' entrepreneurial ecosystem ('pie shares' values computed via Eq. (6.1)) among European regions is in line with the argument that the promotion and development of specific support policies should take into consideration the distinctive characteristics of regions' local conditions. For example, by mapping in Fig. 6.1 the drivers of the entrepreneurial ecosystem of efficient ($REDI^{BOD}$ = 1) and inefficient ($REDI^{BOD}$ = 1) regions, we notice that among the ten efficient regions the entrepreneurial ecosystem is primarily determined by prioritizing policy actions connected to the support to "high-growth SMEs," "process innovation," and "risk capital." On the other hand, the entrepreneurial ecosystem of the group of inefficient regions is mainly driven by actions that promote the "cultural support to entrepreneurship" and the "internationalization of SMEs."

We can also see for all European regions that the pillars related to "networking" and "technology absorption" are the weakest elements of the local entrepreneurial ecosystem. These results offer evidence about the need to implement specific policies that improve these pillars in order to develop a more balanced, cohesive entrepreneurial ecosystem in Europe. For further examination, we applied a K-mean cluster analysis to group the regions. For our purposes, the five-group version seems to be the most

Table 6.3 The $REDI^{BOD}$ and REDI values and the ranking of the EU regions (rank based on the $REDI^{BOD}$ scores)

Rank	Region	$REDI^{BOD}$	REDI	Rank	Region	$REDI^{BOD}$	REDI
1	Stockholm	1.0000	78.30	26	Övre Norrland	0.9190	54.80
1	Hovedstaden	1.0000	76.60	27	Scotland	0.9178	60.50
1	London	1.0000	75.50	28	South West (UK)	0.9077	62.30
1	Southern and Eastern	1.0000	71.30	29	Hessen	0.9032	58.90
1	Île de France	1.0000	70.80	30	East Midlands (UK)	0.9016	57.90
1	Helsinki-Uusimaa	1.0000	70.00	31	Ostösterreich	0.8945	56.90
1	South East (UK)	1.0000	69.60	32	Border, Midland and Western	0.8937	60.40
1	Hamburg	1.0000	69.50	33	Noord-Nederland	0.8920	55.30
1	Région de Bruxelles-Capitale	1.0000	63.20	34	Comunidad de Madrid	0.8764	51.10
1	Midtjylland	1.0000	58.20	35	Bratislavsky kraj	0.8741	44.20
11	East of England	0.9957	58.70	36	Yorkshire and The Humber	0.8718	51.80
12	Sydsverige	0.9928	65.80	37	Etelä-Suomi	0.8699	52.40
13	Saarland	0.9831	56.70	38	West Midlands (UK)	0.8577	54.00
14	West-Nederland	0.9763	63.50	39	Zahodna Slovenija	0.8521	50.00
15	Vastsverige	0.9738	59.80	40	Smaland med öarna	0.8478	45.60
16	Baden-Württemberg	0.9726	62.00	41	Region Centralny	0.8416	43.00
17	Syddanmark	0.9701	61.60	42	Schleswig-Holstein	0.8386	49.80
18	Östra Mellansverige	0.9521	59.90	43	Nordrhein-Westfalen	0.8362	54.80
18	Centre-Est (FR)	0.9521	58.50	44	Sjalland	0.8332	48.40
20	Nordjylland	0.9463	56.50	45	Région wallonne	0.8275	50.30
21	Zuid-Nederland	0.9383	57.60	46	Vlaams Gewest	0.8240	51.30
22	Berlin	0.9371	62.40	47	Norra Mellansverige	0.8231	45.50
23	Oost-Nederland	0.9291	51.80	48	Northern Ireland (UK)	0.8225	55.00
24	Bayern	0.9282	60.60	49	Sachsen	0.8183	50.50
25	Bremen	0.9222	57.10	50	Rheinland-Pfalz	0.8162	44.60

(continued)

Table 6.3 (continued)

Rank	Region	$REDI^{BOD}$	REDI	Rank	Region	$REDI^{BOD}$	REDI
51	North West (UK)	0.8150	50.40	76	Catalonia	0.6443	40.90
52	Länsi-Suomi	0.8019	48.90	77	Latvia	0.6437	36.70
53	Pohjois- ja Ita-Suomi	0.7980	43.20	78	Alentejo	0.6229	37.10
54	Niedersachsen	0.7906	50.30	79	Nord-Ovest	0.6227	33.50
55	Est (FR)	0.7896	45.50	80	Region Pólnocny	0.6098	33.70
56	Nord—Pas-de-Calais	0.7882	46.40	81	Comunidad Foral de Navarra	0.6074	36.20
57	North East (UK)	0.7866	44.30	82	Centro (IT)	0.5863	33.50
58	Méditerranée	0.7837	45.40	83	Norte	0.5843	34.30
59	Lisboa	0.7768	48.10	84	Nord-Est	0.5813	32.60
60	Wales	0.7755	50.40	85	Lithuania	0.5804	32.80
61	Estonia	0.7752	45.30	86	Region Wschodni	0.5755	31.80
62	Südösterreich	0.7732	47.60	87	Centro (PT)	0.5619	32.70
63	Westösterreich	0.7650	49.00	88	Algarve	0.5555	35.40
64	Ouest (FR)	0.7635	46.60	89	Macroregiunea trei	0.5454	29.90
65	Czech Republic	0.7552	38.80	90	Illes Balears	0.5380	34.30
66	Region Poludniowy	0.7470	40.50	91	Comunidad Valenciana	0.5230	34.90
67	Sud-Ouest (FR)	0.7114	37.60	92	Castilla y León	0.5221	34.60
68	Bassin Parisien	0.7030	44.10	93	Cantabria	0.5213	32.70
69	País Vasco	0.6910	38.80	94	Vychodné Slovensko	0.5187	26.00
70	Thüringen	0.6777	41.10	95	Brandenburg	0.5149	35.10
71	Sachsen-Anhalt	0.6747	38.20	96	Isole	0.5147	26.70
72	Region Poludniowo-Zachodni	0.6677	36.70	97	Stredné Slovensko	0.5108	26.50
73	Mecklenburg-Vorpommern	0.6612	40.20	98	Západné Slovensko	0.5106	26.70
74	Region Pólnocno-Zachodni	0.6508	34.20	99	Macroregiunea unu	0.5093	26.10
75	Vzhodna Slovenija	0.6486	43.00	100	Közép-Magyarország	0.5064	31.10

101	Principado de Asturias	0.5021	30.30
102	Aragón	0.4981	31.90
103	Andalucía	0.4958	33.20
104	Galicia	0.4843	29.50
105	La Rioja	0.4740	28.20
106	Región de Murcia	0.4739	29.30
107	Sud	0.4538	25.70
108	Canarias (ES)	0.4500	29.20
109	Extremadura	0.4334	26.10
110	Castilla-la Mancha	0.4144	24.70
111	Macroregiunea patru	0.4081	22.30
112	Macroregiunea doi	0.3722	21.40
113	Kontinentalna Hrvatska (Continental Croatia)	0.3403	25.60
114	Nyugat-Dunántúl	0.3366	21.60
115	Dél-Dunántúl	0.3286	19.80
116	Észak-Magyarország	0.3189	18.90
117	Jadranska Hrvatska (Adriatic Croatia)	0.3110	23.50
118	Észak-Alföld	0.3094	18.20
119	Közép-Dunántúl	0.3059	18.80
120	Dél-Alföld	0.2746	17.70
121	Mellersta Norrland	0.2540	39.90
122	Attiki	0.2527	28.30
123	Voreia Ellada	0.2448	22.00
124	Kentriki Ellada	0.2198	20.00
125	Nisia Aigaiou, Kriti	0.0860	21.30

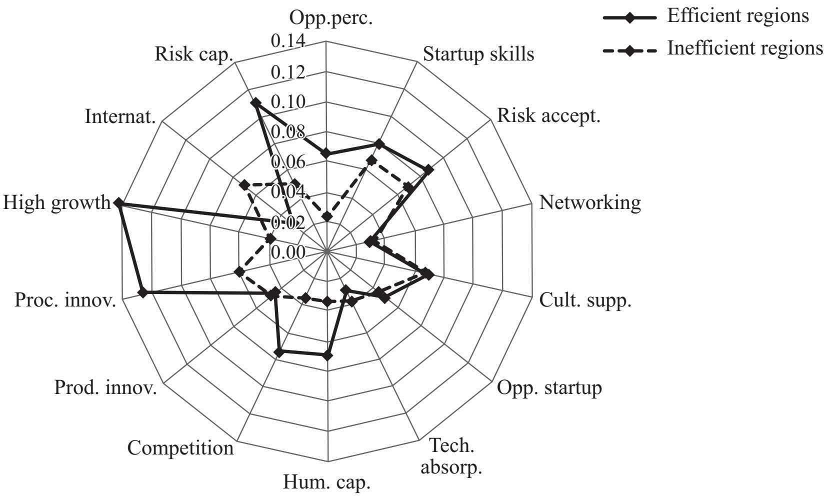

Fig. 6.1 *REDI*^{BOD} results: "Pie share" values for efficient (*REDI*^{BOD} = 1) and inefficient regions (*REDI*^{BOD} < 1) in Europe

useful where group membership numbers ranges from 14 to 33.[6] The map below pictures the 125 region clusters (Fig. 6.2).

By looking at the *REDI*^{BOD} values at cluster level, the difference between cluster 1 (mean *REDI*^{BOD} = 95.8) and cluster 2 (mean *REDI*^{BOD} = 81.3) is only 18 percent, while regions in cluster 3 (mean *REDI*^{BOD} = 63.7) are below cluster 2 results by 28 percent, a difference that is similar to that found between regions in cluster 3 and cluster 4 (mean *REDI*^{BOD} = 49.8). The differences are widening—it is around 76 percent between regions included in clusters 4 and 5 (mean *REDI*^{BOD} = 28.2).

Among regions with high-quality entrepreneurial ecosystems (high values for *REDI*^{BOD}), we find territories from Austria, Belgium, Denmark, Finland, France, Germany, Ireland, the Netherlands (all Dutch regions), Sweden, and the UK. The ten leading regions are mostly large city-regions, except the Danish Midtjylland and the UK Southern and Eastern. They are clearly ahead of the less innovative Southern and Eastern European territories.

Regions included in cluster 2 are from the same countries than regions in cluster 1, in addition to other Southern and Central European regions

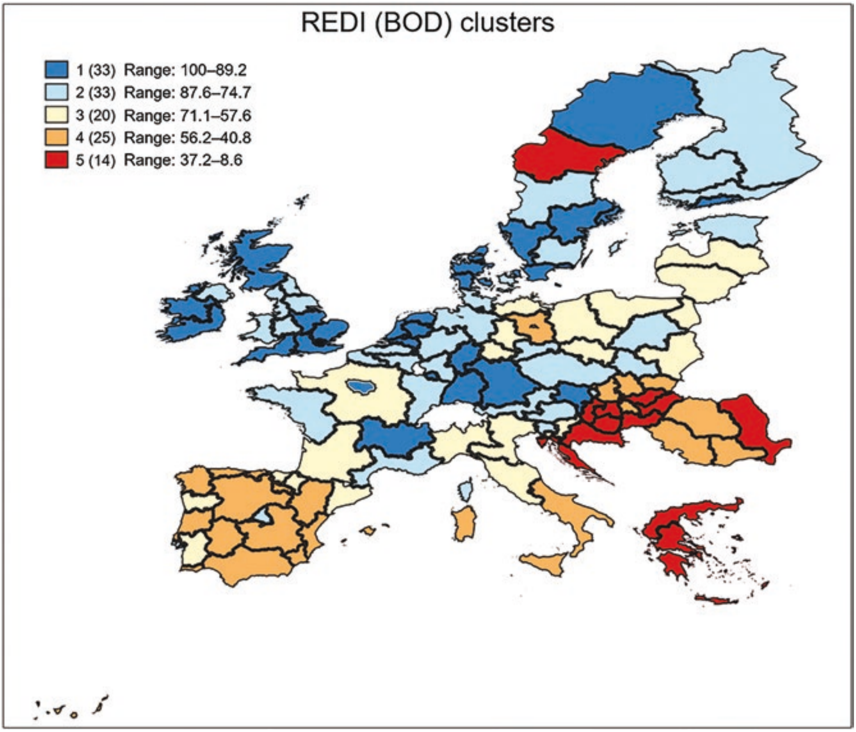

Fig. 6.2 The map of REDI (BOD) scores in five cluster categories of the 125 European Union regions

that (mostly) have a large city, like the Polish Region Centralny and Region Poludniowy, the Slovakian Bratislavsky kraj, the Slovenian Zahodna Slovenija, the Spanish Madrid. Estonia and the Czech Republic, the two developed former socialist countries, also belong to this group.

For regions in cluster 3, a greater geographic diversity was found, as this cluster includes less developed French and German regions. All of these German regions are from the former East Germany. Some Southern European regions from Italy, Spain, and Portugal are also in this cluster. Out of the Central-Eastern European countries Latvia, Lithuania, most Polish regions, and one Slovenian region (Vzhodna Slovenija) are included in this cluster.

Regions in cluster 4 are mostly located in Southern Europe (Portugal, Spain, Italy, and one Greek (Attiki) region) and former socialist countries (Romanian and Slovakian territorial units). The top-performing Hungarian region, Közép-Magyarország, is also here, together with the worst German region that is Brandenburg.

Croatian, Greek, and Hungarian regions together with one Romanian (Macroregiunea doi) and one Swedish (Mellersta Norrland) region form cluster 5. These regions lag behind other European Union regions significantly.

6 Policy Suggestions for Large City-Regions

Accurate measurement of a certain phenomenon is a necessary basic step for valid policy recommendations. Also, it should be kept in mind that $REDI^{BOD}$-based enhancement analyses cannot be done without decomposing the index into its constituents. Any region's EE efficiency depends on the level and the configuration of the fourteen REDI pillars. Regions even with the same or similar $REDI^{BOD}$ score are heterogeneous, having different strengths and weaknesses. Because of the social and economic importance of large cities across the European geography, we conducted an analysis in which we compare the prioritization strategy guiding the entrepreneurial ecosystem in regions with a large city vis-à-vis regions without a large city. Summary results are presented in Fig. 6.3.

We identified 23 large regions with a large city (i.e., a capital city or an economic booster) from 19 countries: (1) Austria: Ostösterreich, (2) Belgium: Région de Bruxelles-Capitale, (3) Denmark: Hovedstaden, (4) Germany: Bayern, Berlin, Bremen, and Hamburg, (5) Greece: Attiki, (6) Spain: Catalonia and Madrid, (7) Finland, Helsinki-Uusimaa, (8) France: Île de France, (9) Croatia: Kontinentalna Hrvatska (Continental Croatia), (10) Hungary: Közép-Magyarország, (11) Ireland: Southern and Eastern, (12) Netherlands: West-Nederland, (13) Poland: Region Centralny, (14) Portugal: Lisboa, (15) Romania: Macroregiunea trei, (16) Sweden: Stockholm, (17) Slovenia: Zahodna Slovenija, (18) Slovak Republic: Bratislavsky kraj, and (19) UK: London.

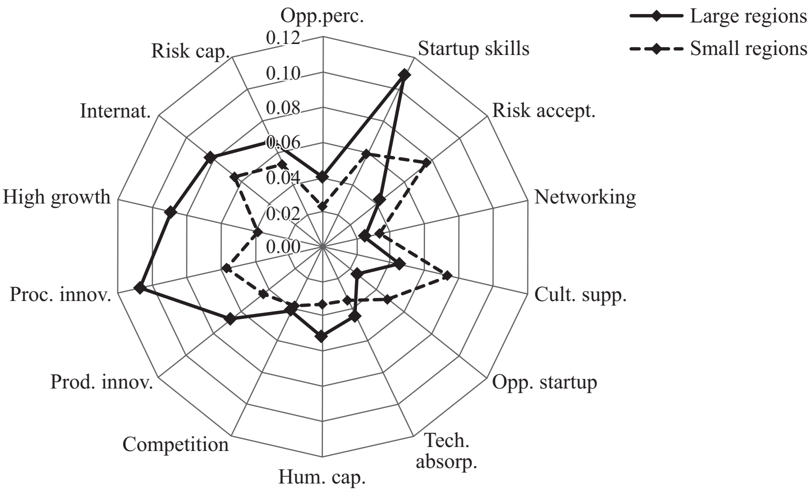

Fig. 6.3 *REDI^{BOD}* results: "Pie share" values for European regions with and without a large city

Results in Fig. 6.3 indicate that the entrepreneurial ecosystem of this group of large regions is mostly determined by a strong prioritization of the REDI pillars related to "process innovation," "start-up skills," and "high-growth SMEs," whereas the "cultural support to entrepreneurship" and "risk acceptance of entrepreneurial activities" are the key factors prioritized by the rest of regions without a large city (Fig. 6.3).

Concerning the weak points of the analyzed ecosystems, in regions with a large city, the findings indicate that policy makers should prioritize ecosystem factors related to the development of strong local networks (REDI pillar: "networking") and to facilitating to local entrepreneurs the active exploitation of new business projects (REDI pillar: "opportunity start-up") (Fig. 6.3).

Among regions without a large city, we observe that the weakest points of their entrepreneurial ecosystem that might be targeted by future policy efforts are related to assisting local entrepreneurs for identifying market opportunities (REDI pillar: "opportunity perception"), developing strong local networks (REDI pillar: "networking"), and supporting the creation of SMEs with high growth potential (REDI pillar: "high-growth").

7 Summary and Conclusion

Entrepreneurship ecosystem research has gone through a rapid expansion over the last decade. While there are numerous papers analyzing ecosystem components, the theory-based analysis of contextual effects and the governance of EEs are still rare. Here, we offer complexity theory as an appropriate approach for framing and analyzing entrepreneurship ecosystems. Along these lines, many EE scholars believe that the case study approach is a suitable method for describing and analyzing entrepreneurial ecosystems. We do not disregard a case-study approach to entrepreneurial ecosystem. Instead, we propose a different analytical view that conceives ecosystems from a bird's-eye view and tries to capture the common factors of EEs. For example, high-quality human capital is a vital ingredient of any EE, but the composition and the type of expertise vary over different locations. Similarly, risk capital is necessary to fuel start-ups and scale-ups, but its structure is not uniform over regions and countries.

An important question, frequently asked in the EE literature, is how to improve the entrepreneurship ecosystem in a way that the resulting outcome contributes to the emergence of high-growth, high-impact start-ups? EE scholars agree that ecosystem-enhancing policies should focus on smaller territorial units, preferably on city regions, and should avoid the direct replication of successful models such as the Silicon Valley. There is also an agreement that successful EE policy is tailor-made, bottom-up, considering local traditions, strengths, and weaknesses.

Nowadays, composite indicators have emerged as dominant tools to measure complex phenomena. Over years, GEI and REDI have become the leading indicators for measuring country- and regional-level entrepreneurship ecosystems, respectively. The original REDI methodology takes into account that EU regions are different with respect to the 14 ecosystem pillars. The improvement of the weakest pillar principle serves as a basis of REDI-led policy suggestions. The weakest link in the EE has a withholding effect on the other better pillars in the system. While this approach is useful to capture the systemic nature of EEs, the applied penalty function is exogenously determined.

In this chapter, we have provided an enhanced BOD-based weighting methodology to quantify the efficiency of the EE in 125 European Union regions. This improvement provides an endogenous way to identify local EE enhancing policy mix. Another advantage of the DEA method is that it does not rely on a single benchmark, but relates the REDI score of any given region to the production frontier represented by the best-performing regions, in terms of the REDI score. Therefore, regions with different input combinations can reach the maximum score. In our case, ten regions achieved the best $REDI^{BOD}$ score ($REDI^{BOD}$ = 1 or 100%), with very different configuration of the fourteen pillars. There are significant sources of heterogeneity in the EEs over the 125 regions. A five-group cluster analysis showed that the most effective EE regions are mainly regions with a large city located in Northern and Western European countries. Southern European and less developed Western European regions have lower REDI (BOD) scores. While some Central and Eastern European regions show similar EE performance than less developed Western European or Southern European ones, regions from three countries—Croatia, Greece, and Hungary—seem to be lagging behind the others.

For EE-enhanced policy recommendation, we have selected 23 large city-regions. These pillar-level policy mix suggestions are based on the most efficient use of the additional resources to improve the $REDI^{BOD}$ scores. As presented, city-region policy priorities are different as compared to other EU regions. While not presented here, we can prepare a more exact policy mix suitable for each individual region. Notice that these region-specific suggestions do not represent a perfect recipe or panacea to boost regional development but serve as a basis for identifying potential policy areas and potential resource allocations. Further research is necessary to reinforce or reformulate the recommendations emerging from the $REDI^{BOD}$ results which, in turn, offer a picture of the priorities that should guide policy actions.

Notes

1. For more variations in the definition, see Cavallo et al. (2019) or Chao and Shi (2020).
2. See https://reap.mit.edu/
3. See https://www.babson.edu/about/news-events/babson-announcements/babson-college-entrepreneurship-ecosystem-project-established/
4. This part of the paper is based on Szerb et al. (2017) that provides a full description of the applied methodology and calculation.
5. The attitude subindex aims to identify the attitude of the people toward entrepreneurship (like the level of opportunity recognition or start-up skills within the population). Abilities are principally concerned with measuring certain important characteristics of both entrepreneurs and start-ups with high growth potential (e.g. the extent to which new opportunities motivate business start-ups, the share of technology intensive and creative sectors in the region). The entrepreneurial aspiration subindex refers to the distinctive, qualitative, strategy-related nature of entrepreneurial start-up activity (i.e., the degree of innovativeness and the extent to which high growth, internationalization, and good access to finance characterize entrepreneurial businesses).
6. In fact, it is a six-group version because Nisia Aigaiou, Kriti region, was one group that we replaced to the 5th cluster manually.

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7

Measuring the Effects of Policies Targeting Entrepreneurial Ecosystems: An Application of the GMR Framework with REDI

Attila Varga, Tamás Sebestyén, Norbert Szabó, and László Szerb

1 Introduction

Recently published papers deliver increasing evidence on the positive influence of entrepreneurship on economic growth. Lafuente et al. (2016) emphasize that efficiency at the national level is largely supported by a healthy system of entrepreneurship. This finding gets further support in a cross-country study of Acs et al. (2018), which concludes that entrepreneurship triggers productivity. Prieger et al. (2016) and Lafuente et al. (2020) test the entrepreneurship-growth nexus and find that national entrepreneurial ecosystems positively and significantly influence economic growth in developing countries. In Szerb et al. (2019)

A. Varga • T. Sebestyén • N. Szabó • L. Szerb (✉)
Faculty of Business and Economics, University of Pécs, Pécs, Hungary
e-mail: vargaa@ktk.pte.hu; sebestyent@ktk.pte.hu; szabon@ktk.pte.hu; szerb.laszlo@ktk.pte.hu

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entrepreneurship ecosystem positively influences gross values added and employment growth in 125 European Union regions.

Current findings in the literature therefore suggest that policies supporting entrepreneurship should be considered in the palette of public interventions promoting economic growth such as R & D, human capital, infrastructure, or investment subsidies. Despite growing evidences, it is still unknown to what extent a given policy intervention (e.g., the support of entrepreneurial culture, increased financial support to entrepreneurs) would affect economic growth in a particular country or region and how these effects might change over time. Furthermore, the position of entrepreneurship policy among traditionally applied instruments like R & D or human capital promotion is still not clear what is. Is entrepreneurship policy a complement of or a substitute to those instruments? How would a policy combining entrepreneurship promotion and those traditional instruments affect economic growth? The relevant answers to these queries can be found only with the application of specifically constructed economic impact models.

Economic impact assessment provides important information about how policy interventions affect certain variables (like GDP, employment, or unemployment) representing the economy of a country or region. This information may inform policy design in a useful way when potential alternative interventions are weighted against each other and impact analysis also supplies relevant knowledge for ex-post policy evaluation. Economic models are commonly used instruments of impact evaluation. The QUEST (Ratto et al., 2009) and the HERMIN (Bradley, 2006) models have been the most frequently used tools of European Cohesion Policy impact assessment, whereas the REMI model (Treyz et al., 1992) is a widely applied instrument of regional policy evaluation in the United States.

These economic impact models build on the general equilibrium principle, which are powerful tools at least in two respects. First, they are able to simulate complex interactions and feedback mechanisms between many economic actors and markets through rigorously taking into account supply and demand interactions and interrelated price changes. As a result, these models help to replicate the complexity of the economic environment and to apply this complexity in the assessment of potential impacts of given interventions, while taking into account the relevant feedbacks and interrelationships that build up this complexity. Second, by setting up imaginary laboratories of actual economies, these models can be used to conduct controlled experiments, built on the ceteris paribus principle. As a result, these experiments reveal the isolated effects of modeled interventions, while ruling out the noise from these experiments that would always be present when pure empirical approaches are used to assess the impacts of implemented policies.

Nevertheless, at least two major challenges have to be solved in order to successfully estimate the growth effects of entrepreneurship policy with an economic impact model. The first is measuring the level of entrepreneurship in relation to the different interventions that aim to promote it. To date there exists only one measure of this kind, the recently developed Regional Entrepreneurship and Development Index (REDI) (Szerb et al., 2017). The other challenge is to integrate the entrepreneurship measure into an economic impact model, which is capable of estimating the productivity effects of entrepreneurship policy at the relevant spatial scale together with the effects of traditional growth-promoting policy instruments. Estimating the productivity effect is crucial since entrepreneurship is considered to be a key factor of innovation (Acs et al., 2009). Since firm-formation is dominantly affected by locally available factors (Szerb et al., 2017), sub-national regions are the relevant units of the suitable economic impact models.

This chapter builds on the most recent version of GMR-Europe, which is the first available model that estimates the economic impacts of entrepreneurship policy. The distinctive feature of this version is that it incorporates economic impact assessment of interventions targeting entrepreneurship development. GMR-Europe integrates the REDI and estimates the economic impacts of entrepreneurship policy at regional, national, and EU levels. We illustrate the capabilities of such a specifically designed economic impact model through the lens of the growth-convergence trade-off. Promoting national economic growth often comes at the cost of increasing inequalities, while promoting convergence or decreasing inequalities may hamper efficiency and aggregate growth. The aim of this chapter is to address this trade-off in the case of entrepreneurship policies and to show how the GMR framework, which integrates regional and aggregate levels of economic activity together with several feedbacks among these levels and regional units, can help policymakers in terms of quantifying and assessing the growth and convergence effects of these policies.

The chapter is structured as follows. The following section positions the REDI among the currently available measures of entrepreneurship and shortly introduces the policy optimization principle that is used in the impact assessment exercises. The third section gives a concise and non-technical outline of the GMR framework in general, one instance of which, the GMR-Europe model is used in the simulations later. The fourth section then outlines the policy simulations conducted with the GMR-Europe model and discusses the results in terms of the national growth effects and the regional disparities following from these interventions. A summary concludes the paper.

2 Entrepreneurial Ecosystems and Their Measurement

While entrepreneurship ecosystem (EE) lines of research have been evolving rapidly, the theorization and the conceptualization of EE is still in infantry phase (Stam, 2015; Acs et al., 2018; Alvedalen & Boschma, 2017; Malecki, 2018). The examination of certain phenomenon, like entrepreneurship, in terms of its context is neither new nor original (Ucbasaran et al., 2001; Zahra, 2007; Boettke & Coyne, 2009; Welter & Gartner, 2016). Same or similar individual efforts or behavior could result very different outcomes—growth, job creation, inequality depending on—at least partially—various environmental features.

As compared to the contextual approaches, EE has brought three novelties. First, EE views the different contextual factors in a holistic way and not one by one. EE components are interrelated and mutually depend on one another (Stam, 2015; Cooke, 2016; Malecki, 2018). Self-reinforcing mechanisms, forward and backward effects, supporting and hindering path dependent factors characterize the EE (Alvedalen & Boschma, 2017; Szerb et al., 2019). Second, EE separates EE components and the various entrepreneurial outputs. These entrepreneurial activity related outputs could have varying effects on the performance of EE. Out of these different activity measures, EE concentrates on the high impact, potentially high productivity startups as opposed to more general, mostly self-employment related initiations (Stam, 2015, Nicotra et al., 2018, Szerb et al., 2019). Third, EEs are geographically bounded, place-based creatures. As opposed to country level examinations, it is more appropriate to center on smaller geographic units where agglomeration economies, networking, and spillover effects play determining roles (Qian et al., 2013; Audretsch & Belitski, 2017; Szerb et al., 2019).

EE scholars maintain that the path dependent development of each EE is unique therefore neither a universal nor a copy-paste of former successful policy approaches are appropriate. Instead, each EE requires place specific, bottom-up, tailor-made policies as opposed to top-down general policy initiations (Isenberg, 2010; Acs et al., 2014; Mason & Brown, 2014).

Besides the generally agreed conceptual characteristics, there are many debated points in the EE research. There is a disagreement about the components of EE. As many researchers as many models: Isenbeg (2010) has six major categories, Mason and Brown (2014) has four, Stam (2015) has ten, Spigel (2017) has another ten just only partially overlapping with Stam. While all EE scholars agree that the entrepreneur is the central player in the system, the identification of other actors and their roles are disputed. Network analysis seems to be a promising avenue to examine the connection among the different stakeholders; however, network-based studies demand extensive data collection and is difficult to replicate (Cooke, 2016; Alvedalen & Boschma, 2017; Ter Wal et al., 2018). Some EE scholars emphasize the case study approaches; others suggest qualitative comparative analysis, agent-based modeling, and interpretivist methods as compared to more general regression-based methodologies (Isenberg, 2010; Suresh & Ramraj, 2012; Spigel, 2017; Roundy et al., 2018). There is also a disagreement about the identification of appropriate territorial unit. Most data are available for administrative units, regions, or cities, while ecosystems do not really follow artificial barriers.

Debates about the content, the connection and the combination of the components have an important consequence on how to measure EEs. Those who believe the uniqueness of EEs basically neglect the possibility to create a common measurement with generally valid factors (Isenberg, 2010; Spigel, 2017). Other approaches maintain that there are some universal features of EEs making possible to create a common measurement for all EEs. All of these approaches take into account the multidimensionality of EE and create a composite indicator.

The Kauffman Foundation's entrepreneurial ecosystem initiative focuses on four processes—density, fluidity, connectivity, and diversity—that characterize EE (Bell-Masterson & Stangler, 2015). While there were some references for future research, the initiation seems too died out after the identification of the components.

Stam developed a different model to measure the EE of the Netherlands' 12 NUTS2 regions (Stam, 2015, 2018). Stam identified framework conditions and systemic conditions that influence outputs and outcomes. Framework conditions contain formal institutions, culture, physical infrastructure, and demand. Systemic conditions contain networks, leadership, finance, talent, knowledge, and support services. For outcome, a productive entrepreneurship activity measure, entrepreneurial growth orientation is applied. The final outcome of the model is new value creation but it has not been operationalized (Autio et al., 2018).

A recent practically oriented development from the Global Entrepreneurship Network is the Global Startup Ecosystem Report (GSER) aiming to identify the drivers of startup success and of ecosystem performance. Instead of unique factors, GSER examines those elements that decentralized universality and work with all ecosystems (Startup Genome 2019). Startup Genome reports several ecosystem metrics for overall performance, sub-sectors, and ecosystem deep dive. The overall ranking is based on seven factors as Performance, Funding, Market Reach, Connectedness, Talent, Experience, and Knowledge. GSER calculated the scores for a mix of countries, regions, and cities. Besides generally applied datasets, GSER engaged in own surveys including experts and startup executives.

While it is useful to take a microscopic view of EEs and to identify local peculiarities, for more general investigations we need a wider focus, bird-eye view. These two approaches are not competitive but complements. For example, each EE requires finance (universal factor) but the combination of different financial sources like business angel money, venture capital, and crowdfunding (unique factors) could vary. The aggregate examination of the availability of finance makes possible to identify finance as a strength or the weakness of EE, and a more detailed investigation could recognize local idiosyncrasies.

2.1 The REDI

The Regional Entrepreneurship and Development Index (REDI) has been constructed to capture the regionally embedded contextual features of individual entrepreneurship efforts and initiation across EU regions. The REDI method builds on the National Systems of Entrepreneurship Theory and provides a way to profile EE in regional level (Acs et al., 2014; Szerb et al., 2017). Similar to GSER, REDI targets to capture the universal factors of EE in 3 sub-indices and 14 pillars providing a comprehensive and a comparable measure of EE across a mix of 125 NUTS1 and NUTS2 EU regions.

REDI is a multilevel comprehensive index, which reflects several aspects of the entrepreneurial context of a region. Upon constructing the index, a six-level index-building methodology was followed: sub-indicators (1) are merged into indicators (2) which are then reflected by variables (3), then these construct pillars (4), contributing to sub-indices (5) which finally constitute the REDI super-index (6). With respect to its content, at the sub-index level, we differentiate between entrepreneurial attitudes, abilities, and aspirations[1] that are then broken down to 4–5 pillars, quasi-independent building blocks of this entrepreneurship index. Szerb et al. (2017, 2019) offer a detailed description of the building methodology and computation of the REDI.

An essential question is how to capture the connection and the configuration of the components. The key idea behind REDI is that system performance is "co-produced" by its interrelated elements. Every pillar is obtained by multiplying an individual with an associated institutional variable capturing the combined effect of individual initiations and regional institutional context.

The 14 pillars are the most important components of REDI. REDI methodology includes two important novelties that makes possible to measure the resource optimization over the 14 pillars. The Average Pillar Adjustment (APA) method serves to equalize the marginal effect of each additional input over the 14 pillars. "The normalised pillar value averages are different, ranging from 0.36 (Finance) to 0.65 (Product innovation). We assume that these differences reflect the difficulty to reach average pillar performance in reverse order, so that it is about 1.8 times more difficult to reach average performance in Finance compared to Product innovation. This implies that for the same additional input unit we experience 1.8 times larger improvement in Product innovation than in Finance. APA corrects this distortion by equalising pillar averages to the level of the average of the 14 pillars (0.49) and holding all the pillar values in the original [0,1] range. A potential drawback of this approach is that pillar values are only equalised over their averages, and that marginal effects are not necessarily the same if we improve non-average pillars. Monetary differences are also neglected, that is, pillar improvements are computed in natural input units as we cannot estimate the monetary value of input units" (Szerb et al., 2019, p. 1313).

A particularly important aspect of the REDI method is the Penalty for Bottleneck (PFB) methodology, which helps in identifying constraining factors in the Regional Systems of Entrepreneurship. A bottleneck is the worst performing element or binding constraint and is defined as a shortage or the lowest level of a particular entrepreneurial pillar as compared to the other 13 pillars. Then, the value of each pillar is penalized as a result of linking it to the score of the pillar with the weakest performance in the region (Acs et al., 2014; Szerb et al., 2017). As a result, if the weakest pillar was raised, it would have a multiplicative effect to improve the other pillars and the whole REDI while raising a non-bottleneck pillar would have only a minor effect. The idea here is that systems with strong weaknesses cannot fully leverage their strengths, or, in other terms, weakly performing bottleneck pillars hold back the performance of the whole entrepreneurship ecosystem. The novelty of this method is that it portrays the entrepreneurial disparities among EU regions and provides country and regional level, tailor-made public policy suggestions to improve the level of entrepreneurship and optimize resource allocation over the different pillars of entrepreneurship.

Entrepreneurship enters the GMR-Europe model in the TFP block, through the REDI. This means that as a single variable, describing the entrepreneurial climate/ecosystem in a region, it contributes to productivity through enhancing the efficiency of human capital. As a result, an intervention positively contributing to the entrepreneurial ecosystem in a region (reflected by an increase in the REDI) positively affects regional productivity and sets in motion all the other parts of the model, which is thus able to track the effect of this policy on several variables of interest.

The real strength of using the REDI in our setup is that although the REDI uses one number to describe regional entrepreneurship, its detailed structure with the 14 pillars allows us to analyze different policy mixes at this level of detail. Also, building on the APA and the PFB methodology, there is not a single linear relationship between the pillars and the REDI, but the system is able to give a sophisticated description and analysis of how different policies affect the overall entrepreneurial climate in a region and through this mechanism their impact on local and aggregate economic performance.

2.2 Policy Optimization

As reflected by the REDI, entrepreneurship is a complex phenomenon, which emerges in the context of system-wide interactions among its different components (Acs et al., 2014). As a result, mutually interconnected policies could potentially strengthen or weaken each other, so the design of a suitable policy mix to target the intensification of regional entrepreneurial discoveries is an extremely complicated process. The GMR-Europe policy impact model, through the integration of the REDI into its setup, is particularly suitable to support policymakers in designing these policies.

Relying on the PFB analysis embedded in the REDI methodology, optimal entrepreneurship policies can be designed on a region-specific basis, taking into account the weaknesses of the local entrepreneurial ecosystem. In sum, the optimal allocation of inputs to entrepreneurship policies is attained when all the bottlenecks are alleviated in a given region. As a result, the search for an optimal policy means decreasing the retraction influence of the bottleneck pillar(s).

3 Modeling the Economic Effects of Entrepreneurial Ecosystems

While entrepreneurship ecosystems are complex systems themselves, they also contribute to and interact with their local, national, and global economic environment through many channels. Capturing these interconnections and estimating the potential contribution of evolving entrepreneurship ecosystems on the wider economic system is therefore a challenging task. Economic impact modeling tools can be useful in this respect as they are able to account for the complex interactions and feedbacks between different economic actors, sectors, and locations as well. However, connecting entrepreneurial activity into these models is not straightforward for at least two reasons. First, economic impact models build on the principle of general equilibrium to some extent at least, while entrepreneurial activity is essentially challenging this equilibrium by setting new paths for economic development. Second, entrepreneurial ecosystems affect and interact with economic systems in several channels that are difficult to take rigorously into account in their complexity.

The Geographic Macro and Regional (GMR) modeling framework was designed to handle these issues at least partially. This is a large-scale general equilibrium model suitable for the impact assessment of innovation and entrepreneurship-related policies. The model builds on the general equilibrium principle, a feature which makes it capable of tracing the complex impact mechanisms that arise from any kind of change/intervention that shape the economic landscape. It has a regional dimension, which allows it to account for agglomeration effects arising from economic activity, while its macroeconomic block ensures that aggregate conditions and policies (fiscal, monetary, trade) can also shape the effectiveness of given interventions. Finally, a detailed productivity block allows the integration of sophisticated innovation-related activities into the model.

We give a brief, non-formal description of the GMR modeling approach in this section. For a detailed and formal exposition of the model, the reader is directed to Varga et al. (2018). First, the general features of the GMR approach are exposed together with an account of its previous applications. Then, we provide a basic overview of the building blocks of the model and the intuition behind their capability of evaluating specific policy interventions. Finally, we discuss the integration of entrepreneurship policy into the model in a more extensive way.

3.1 General Features of the GMR Approach

The geographic macro and regional (GMR) modeling framework was established and has been continuously improved to better support development policy decisions by ex-ante and ex-post scenario analyses. The focus of the GMR framework is on policy instruments like R & D subsidies, human capital development, entrepreneurship policies, or the promotion of innovation-related collaboration of actors.

The GMR framework belongs to the family of general equilibrium models which are particularly suitable to estimate the complex, interdependent adjustments mechanism that take place in economies when a given policy intervention is applied. Building on the ceteris paribus principle and the laboratory setting provided by these models, we are able to experiment with different policy scenarios, disentangling their effects on several aspects of the economy from other simultaneous shocks which is problematic in case of an empirical analysis. The general equilibrium approach allows for a rigorous account of interactions between different economic mechanisms by consistently tracing the change in supply and demand conditions on various markets.

While traditional models of development policy analysis focus on the national level,[2] a novel feature of the GMR framework is that it simultaneously models distinct (sub-national) spatial units, the regions, together with different layers of economic interactions among them. This feature allows for incorporating geographic effects such as agglomeration, interregional trade, and mobility of production factors into the impact assessment exercises. Modeling geographic effects is critical as geography affects development policy effectiveness for at least four major reasons. First, interventions are applied at specific points in space and their impacts might spill over to proximate locations to a considerable extent. Second, the initial impacts can be amplified or reduced by agglomeration effects significantly. Third, labor and capital migration may further amplify or reduce these initial impacts through reshaping the spatial structure of the economy (dynamic agglomeration effects). Fourth, as a consequence of the above effects, different spatial patterns of interventions might result in significantly different growth and convergence/divergence performances at the national and regional levels.

By explicitly modeling regions and the GMR framework, it is able to capture interregional interactions such as knowledge flows over regional borders (scientific networking or spatially mediated spillovers), interregional trade, and the mobility of production factors. In addition to having a clear regional focus, the macroeconomic level is also important with respect to development policies: fiscal and monetary policy, national regulations, and external factors all shape the effects of local policy interventions. As a result of this two-level setup, the model system simulates the effects of policy interventions both at the regional and at the macroeconomic levels. With such an approach, we can compare different scenarios of interventions based on their impacts on (macro and regional) growth and interregional convergence.

The first realization of the GMR approach was the EcoRET model built for the Hungarian government for ex-ante and ex-post evaluation of the Cohesion policy (Schalk & Varga, 2004). This was followed by the GMR-Hungary model, which is currently used by the Hungarian government for Cohesion policy impact analyses (Varga, 2007). GMR-Europe was built in the IAREG FP7 project (Varga et al., 2011; Varga, 2017) and further developed in the GRINCOH FP7 project (Varga et al., 2015). The most recent version of GMR-models is GMR-Turkey (Varga et al., 2013; Varga & Baypinar, 2016) and the recently updated version of the GMR-Europe model (Varga et al., 2018).

3.2 The Logical Setup of the GMR Model

As emphasized previously, the GMR approach reflects the challenges of incorporating regional, geographic, and macroeconomic dimensions into development policy impact modeling. From the methodological point of view, this means the integration of different traditions in economics (Varga, 2006). Spatial patterns of knowledge flows and the role of agglomeration in knowledge transfers build on insights and methodologies developed in the field of the geography of innovation (e.g., Anselin et al., 1997; Varga, 2000). Interregional trade and factor mobility together with dynamic agglomeration effects is based on the tradition of the new economic geography through applying an empirical general equilibrium model (e.g., Krugman, 1991; Fujita et al., 1999). Finally, modeling policy impacts at the macroeconomic level draws on specific macroeconomic theories. These three theoretical traditions also characterize the formal setup of the GMR framework, which is structured around the mutual interaction between three model blocks, which are the Total Factor Productivity (TFP), Spatial Computable General Equilibrium (SCGE), and macroeconomic (MACRO) model blocks.

Economic models that describe economic activity at a more aggregated level (industries, economic sectors, regions, countries) extensively rely on what we call total factor productivity (TFP), that is, the overall efficiency of economic activities that convert primary production factors (labor, capital, etc.) into output. This indicator comprises many things into one number, especially about the innovative potential or ecosystem of a given economic unit (industry, regions, country) as all innovative activities contribute to a more efficient use of production resources in a broad sense. In other terms, the change in TFP reflects the innovative capabilities of the given economic unit.

The GMR framework therefore contains a productivity block (the TFP block) that opens up the black box behind this indicator and explicitly models the mechanisms that drive productivity, with special emphasis on innovation-related activities. As the GMR framework has a regional focus, total factor productivity and the mechanism that shape it (the whole TFP block) is identified at the regional level. The TFP block is

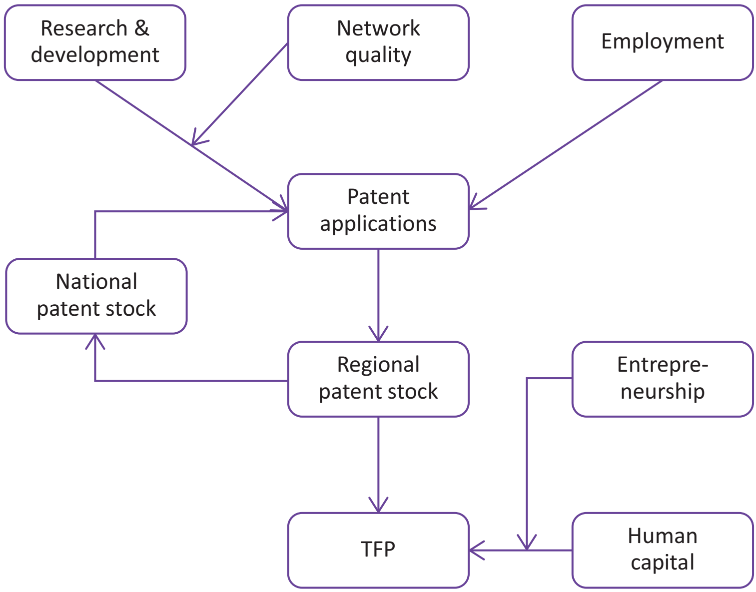

Fig. 7.1 The schematic structure of the TFP block

therefore capable of describing the local (regional) innovation ecosystem and how it affects the local (regional) productivity of economic activity. Changes in this productivity level then transfer impacts over to other parts of the model framework.

Figure 7.1 illustrates the setup of the TFP block, which is based on the knowledge production function approach of Paul Romer (Romer, 1990). New knowledge, represented by patent applications in our model setup, is produced using knowledge production factors, namely, R & D efforts and labor (employment), as well as already existing knowledge, which is represented by national patent stocks. In addition to these standard factors, we also include the role of knowledge available through interregional networks, which is assumed to affect the productivity of R & D in knowledge creation. New knowledge, that is, patent applications at the regional level then feedback into knowledge creation in a dynamic way by building up national patent stock.

TFP is primarily linked to regional knowledge levels as described before, but two factors are added to the determination of regional

TFP. First, the level of human capital in the region is supposed to affect productivity, and second, as a focal element of this chapter, we added the entrepreneurial environment (measured by the REDI) in the model which is also assumed to have a positive influence on productivity, via enhancing the contribution of human capital to TFP. Our formulation is influenced by the knowledge spillover theory of entrepreneurship (Acs et al., 2009). Entrepreneurs transfer knowledge to economic applications; therefore, a better entrepreneurial climate in a region intensifies new firm formation. A higher level of entrepreneurship in a region helps better exploiting the knowledge embodied in human capital, which eventually leads to higher total factor productivity.

The TFP block is the part of the model where most of the innovation-related policy interventions can be handled. Support to research and development activities, human capital accumulation, as well as promotion of network formation, affects variables in this model block, and the relationships in this block determine the effect of these policies on regional productivity levels. Also, policies affecting entrepreneurship are accounted for in this model block, through the REDI, which represents entrepreneurship in our model setup. A more detailed account of how entrepreneurship is handled in the model is given in Sect. 3.3.

While the TFP block accounts for the mechanisms in, and the interventions to local (regional) innovation systems, the developments in this system is transmitted to the SCGE (spatial computable general equilibrium) model block through the regional productivity levels. Changes in these local productivity levels then affect the local and interregional allocation of production resources. This reallocation drives employment and output within and outside the regions as well as prices and wages. Thus, we can trace the effect of changes and/or interventions in the innovation system on the broader economic environment. The most important feature of the SCGE block is that it takes into account interactions across regions through trade of goods and services as well as the mobility of production factors. Also, transportation costs are explicitly accounted for and (positive and negative) agglomeration effects arise as endogenous phenomena in the model.

The SCGE model block accounts for equilibrium adjustment in two time dimensions. In the short run the equilibrium nature of the model block ensures that all markets clear, given the productivity level and available quantity of production factors (labor and capital) within each region. This results in an equilibrium allocation of production and trade together with market clearing prices and wages, taking into account the exogenous transportation costs. In the long run, differing utility levels across regions (depending on consumption and population density) give rise to labor migration changing the setup of market mechanisms which mean that there is a long-run adjustment even to a one-time shock to productivity levels. Labor migration is also followed by capital migration through a mechanism in which capital stock is gradually reallocated into those regions where productivity grows at a higher rate. In the long run, this model block drives the economy to a state where interregional utility differences are eliminated.

Finally, the macroeconomic (MACRO) block of the GMR framework serves two purposes. First, this is the point, where aggregate relationships and policies can be handled (exchange rate towards the rest of the world, inflation, monetary, and fiscal policy), and second, it provides dynamics to the otherwise static SCGE block. In the latter regional productivity, labor and capital stocks are exogenous. The TFP block provides the dynamics of regional productivity levels, but in order to account for the possible employment and investment effects of the simulated policies, we need to provide dynamics for labor and capital stocks of the regions. This is done by the MACRO block, which gives an aggregate estimation of the likely employment and capital-stock impacts of the simulated policies, which are broken down to the regions in function of the regional productivity growth rates.

In line with the general equilibrium setup of the SCGE block, the MACRO block uses a dynamic stochastic general equilibrium (DSGE) model, which is a standard tool of macroeconomic analysis. In the GMR-Europe model, we use the QUEST III model developed by the European Commission for the Euro area (see Ratto et al., 2009), and re-estimated it on fresh data for the Eurozone and some additional countries relevant in the GMR setup. Using a dynamic macroeconomic model, which builds on intertemporal optimization of economic agents, we significantly improve the dynamic behavior of traditional SCGE models that

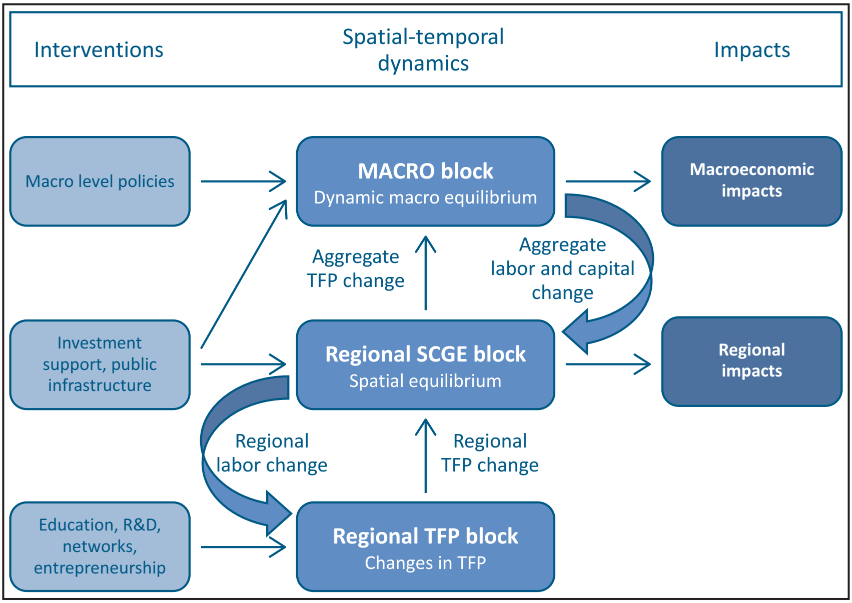

Fig. 7.2 Regional and macroeconomic impact mechanisms in the GMR-Europe model

rely on an iterative application of otherwise static equilibrium allocation mechanisms.

Figure 7.2 illustrates how the three model blocks are integrated and interact with each other to simulate the impacts of different interventions with respect to different variables of interest. First, innovation policy instruments affect model variables primarily in the TFP block. The productivity impacts induced by interventions then feed into the interregional SCGE model, which simulates the likely effect of these policies on regional-level economic variables like output, prices, labor, and capital stocks according to market equilibrium conditions across all regions. Also, some standard policy instruments like direct investment support or public infrastructure development can be handled in this model block directly.

Regional productivity impact, aggregated to the macroeconomic level, also provide the input to the MACRO block, which simulate the likely effects of these productivity impacts on aggregate-level macroeconomic variables taking into account dynamic relationships based on intertemporal optimization. The dynamics of aggregate labor and capital reallocated to the regions then drive the dynamic adjustment of the regional variables in interaction with productivity changes coming from the TFP block. In addition, regional changes in employment through the dynamic employment impacts of policies and labor migration feed back into the TFP block contributing to agglomeration effects, which results in higher productivity levels due to the concentration of economic activity.

To sum up, the model is able to trace the likely impacts of different policy interventions (entrepreneurship policies specifically) through the dynamic interaction of the three model blocks. The TFP block simulates regional productivity impacts, based on which the SCGE block generates market clearing allocation of production and consumption taking into account transportation costs and the dynamics of economic variables is driven by the MACRO block. As a result, the model traces policy impacts both at the regional and aggregate levels for various important variables.

3.3 Entrepreneurship-Related Interventions in the GMR-Europe Model

Although the GMR framework is able to simulate the likely impacts of many different interventions affecting the innovation system of specific locations, this paper focuses on its ability to integrate policies specifically designed to enhance entrepreneurship in a given region. This section discusses in more detail how these policies are reflected in the model.

Entrepreneurship enters in the TP block of the GMR framework (see Sect. 3.2), through the REDI (see Sect. 2.2). The REDI describes the quality of the entrepreneurial ecosystem in a given location (region), and it is assumed to contribute to overall productivity through enhancing the efficiency of human capital there. As a result, an intervention that positively contributes to the entrepreneurial ecosystem in a region (reflected by an increase in the REDI) positively affects regional productivity and sets in motion all the other parts of the GMR model. Changes in the different variables that the model supplies at different levels (regional, aggregate output, employment, price levels) then trace the effect of these interventions on the local and broader economic environment.

The real strength of using the REDI in our setup is that although the REDI uses one number to describe regional entrepreneurship, its detailed structure with the 14 pillars allows us to analyze different policy mixes at this level of detail. In other terms, the structure of the REDI with its PFB principle can be regarded as a further model block that is integrated into the GMR framework. The REDI accounts for the complex interactions of various factors affecting the entrepreneurship ecosystem of a location, the TFP block integrates this into the mechanisms of the wider regional innovation system providing an effect on local productivity which then affect the local and broader economic systems that is traced by the SCGE and MACRO blocks of the framework.

As reflected by the REDI, entrepreneurship is a complex phenomenon, which emerges in the context of system-wide interactions among its different components (Acs et al., 2014). As a result, mutually interconnected policies could potentially strengthen or weaken each other, so the design of a suitable policy mix to target the intensification of regional entrepreneurial discoveries is an extremely complicated process. The GMR framework, through the integration of the REDI into its setup, is particularly suitable to support policymakers in designing these policies.

Relying on the PFB analysis embedded in the REDI methodology, optimal entrepreneurship policies can be designed on a region-specific basis, taking into account the weaknesses of the local entrepreneurial context. In sum, the optimal allocation of inputs to entrepreneurship policies is attained when all the bottlenecks are alleviated in a given region. As a result, the search for an optimal policy means decreasing the retraction influence of the bottleneck pillar(s).

4 Growth or Convergence? The Economic Impact of Alternative Regional Entrepreneurship Policies

Understanding the possible economic impacts of different entrepreneurship development strategies is crucial for policymakers. Changes in the REDI indicate the effects of these strategies or policies on the regional entrepreneurship ecosystem, but understanding the economic development paths that these changes can bring requires a broader, more general analysis of economic circumstances and processes. As exposed in the previous section, the GMR framework incorporates several interrelated mechanisms through which changes in the REDI evolve into regional, national, and in the case of the GMR-Europe model also EU-level economic effects. This section is devoted to the analysis of policy simulations that illustrate the ability of the GMR framework in estimating the likely impacts of policies targeting entrepreneurship.

The economic impacts of entrepreneurship development policies are determined by a number of important factors in the GMR framework. First, the initial level of REDI is crucial in terms of economic growth since a relative increase in REDI implies a higher absolute change in entrepreneurially more developed regions. This translates into a more intensive change in productivity in these more advanced regions. Second, the level of human capital in a region also plays a crucial role in the determination of how effectively entrepreneurship can influence productivity: a higher level of human capital leverages investments into the entrepreneurial ecosystem. Third, trends of human capital development enhance the efficiency of entrepreneurship in the long run as well by increasing productivity even when entrepreneurship supports are exhausted. Fourth, the interaction between changing employment and capital stocks also play a crucial role in generating economic impacts. These impacts result from, and feedback into regional productivity and spillover to the local and wider economy through changing prices and the spatial reallocation of resources. Fifth, diverse regional paths for economic growth induce migration which can be a further source of growth in some places while resulting in a leakage of resources at others. Sixth, changes in interregional trade play further significant role in the development of regional economies. The relative size and direction of all those forces will eventually determine economic growth of regions and nations.

In this section, we track the economic impact mechanisms of different interventions targeting entrepreneurship development through the lens of a well-known policy problem. What are the costs of an entrepreneurship policy that targets national growth in terms of regional divergence? Alternatively, what are the costs of an entrepreneurship policy targeting regional convergence in terms of loss in aggregate economic growth? In addition, do policymakers have to face country-specific differences in this trade-off?

We explore the growth and convergence effects of entrepreneurship policies using the REDI and the GMR-Europe economic impact assessment model (a specific instance of the GMR model family). Following the Penalty for Bottleneck method (described in Sect. 2), we set up three scenarios for three selected countries in the EU: Germany (representing Western Europe), Hungary (a country from Central Europe), and Italy (a Southern European country). The first scenario reflects a situation where additional resources (efforts) are optimally allocated in a way that this allocation brings uniformly a 10% increase in REDI in all regions. In other terms, we have the PFB logic behind this optimal allocation, which requires the allocation of additional resources to that pillar of the entrepreneurial ecosystem in a region that creates a bottleneck. When this bottleneck is eliminated, resources are put to the next pillar which steps in as a new bottleneck, and others. This method is followed until the REDI in the given region increases by 10%. This is called the *uniform* solution or scenario. In the second case, called *policy optimization* each country starts with the amount of additional resources that was calculated and allocated in the uniform solution. This pool of resources are then reallocated among the country's regions and REDI pillars in order to maximize the country average of the REDI. The third scenario starts again from the uniform solution, but the pool of national resources are reallocated to the poorest regions of the given country, until the resources are exhausted. This is labeled as *poor regions* solution. Poorest regions are those, where the REDI scores are the lowest in the country. Once these different scenarios are implemented, the GMR-Europe model is applied to trace their economic impacts at the regional, national, and EU levels. With regard to the trade-off mentioned before, we contrast the results of the scenarios in terms of the gross value added (GVA) as a measure of economic output at the three levels with the GINI coefficient accounting for the level of cohesion. The GINI coefficient was calculated on the basis of regional gross value added impacts of the different scenarios.

4.1 Uniform Solution: Even Improvement of Entrepreneurship

In this basic scenario, we uniformly increased the value of the REDI in each region by 10%. The additional efforts required to reach this goal were distributed according to the PFB method at the regional level. Optimization results show significantly different patterns for each country (Fig. 7.3). In general, the uniform solution for Germany concentrates resources extremely on three pillars: risk perception, human capital, product innovation, and partially to two other—process innovation and technology absorption. However, we must note that in some cases lower value pillars were highly important for some regions (e.g., globalization in Bremen and financing in Mecklenburg-Vorpommern). Furthermore, the allocation of additional efforts in Germany is the most evenly distributed compared to the other three countries. It means that REDI can be

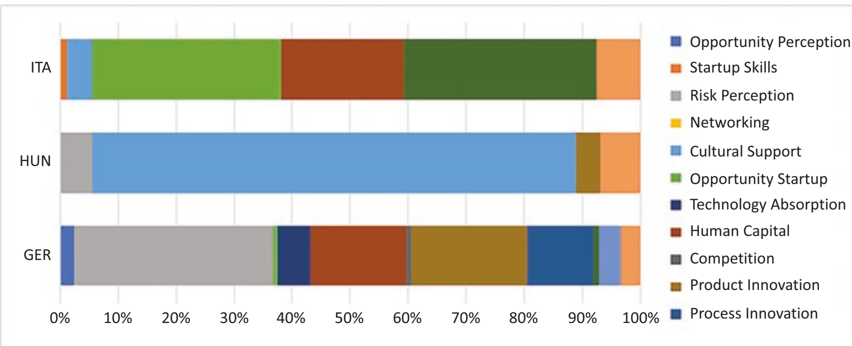

Fig. 7.3 The distribution of additional efforts in REDI among the 14 pillars at the country level in case of uniform solution

increased by the simultaneous development of numerous pillars, and practically there are no extremely weakly performing pillars in Germany.

In less developed countries, such as Hungary, the distribution of additional efforts shows a more concentrated structure. On average, 83% of additional efforts were allocated to cultural support, which was responsible for the majority of REDI growth. Apart from that, financing and risk perception played a modest role in the optimization. In a regional perspective, the concentration can be even stronger: the REDI in Budapest increased exclusively as a result of the cultural support pillar.

Italy is found between Hungary and Germany in terms of the resource allocation structure: less concentrated than Hungary, but also less balanced than Germany. Additional resources were mainly concentrated here in opportunity startup, high growth, and human capital. In addition, financing gained relatively large improvement of REDI in Northeast and Central Italy. The amount of resources required to increase REDI by 10% is different in each country (and region): 4.354 units in Germany, 1.798 in Italy, 0.764 in Hungary.

As it was discussed previously, the REDI scores are imputed into the TFP block of the GMR-Europe model, resulting in changes to the local productivity levels, then spilling over to economic activity locally, nationally and EU-wide. The results of the allocation process described above manifest in regional REDI changes. These changes were distributed over five years between 2014 and 2018 in every scenario. This policy shock period represents the first five years of the previous EU Cohesion Policy. Estimated impacts of policy interventions then span from 2015 to 2031. Impacts are measured in terms of percentage deviation from the no-intervention (baseline) scenario.

Figure 7.4 shows the spatial distribution of the REDI changes (left hand panel) and that of the short-run (first year) economic impact of the uniform solution. These impacts depend on several regional factors, most importantly the initial level of entrepreneurship and human capital. Based on that, in Germany, Berlin and southern German regions both with high initial REDI and human capital stocks are expected to increase the most in terms of value added. However, in other areas where the distribution of human capital and REDI does not show the same pattern the potential change of value added is not self-evident. Following a similar

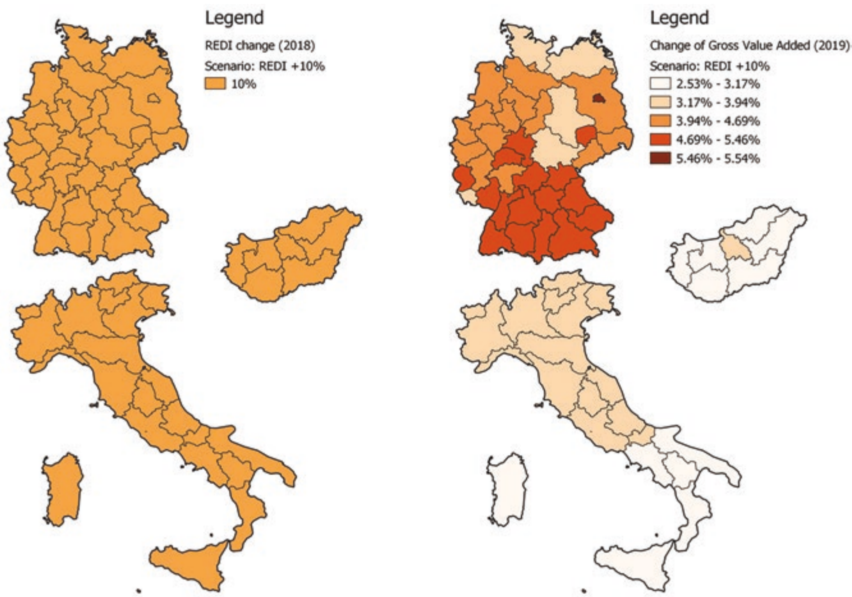

Fig. 7.4 Spatial distribution of REDI shocks (left-hand panel) and their impacts on gross value added (right-hand panel) in the case of the uniform solution scenario in 2019

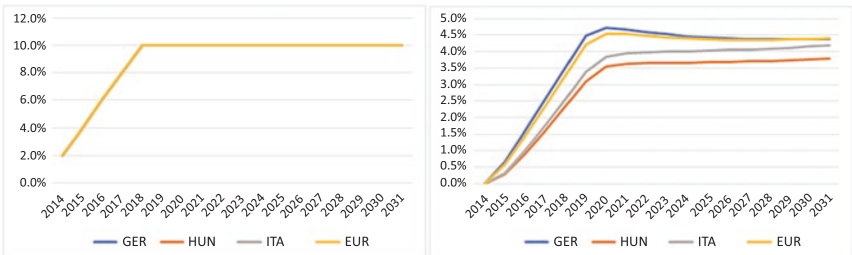

Fig. 7.5 The national impact on national average REDI (left-hand panel) and value added (right-hand panel) in case of uniform solution

logic in Hungary, the highest growth is expected in Budapest. Similarly, in Italy human capital and entrepreneurship is concentrated in the northern part of the country; thus the shock will have a more significant value added effect in those areas.

Figure 7.5 depicts the country-level dynamic effects of regional REDI shocks. Temporal paths of regional human capital significantly influence the dynamic impacts of entrepreneurship on regional GVA. Furthermore, this effect is augmented by migration and interregional trade in the long run. The effect of REDI on TFP is lagged in time by one period; thus initial REDI shocks in 2014 will have productivity and economic impacts one year later. This also means that the five-year period of REDI interventions expires in 2018 while direct economic impacts continue after this year.

The level of human capital influences the immediate economic impacts of the uniform solution; this is why Germany gains the most economic growth in 2015 and Hungary benefits the least. After 2018, in spite of the regional REDI scores remaining the same, there are further changes in the long-run paths of national value added. In addition to the differences influenced by temporal paths of human capital, migration, and interregional trade, we have to highlight the role of investment here. In 2020, we observe a further increase of value added, explained by increasing productivity affecting incomes and investment decisions, which will have positive impacts on regional investment volumes. Thus, through investment, REDI has another effect that remains in the impact mechanisms even when the REDI improvement is released. In the long run, the German growth path converges to the European average from above, while Italy and Hungary converge to the European average from below. Again, Italy converges faster since it has higher human capital stock and it increases at a higher rate during the simulation, affecting the REDI impact directly and the long-term productivity growth as well.

4.2 Policy Optimization Solution: Targeting National Growth

The second scenario reflects the economic impacts of country level optimization of the REDI. This means that the same amount of additional resources are used, but allocated in a way that generates the highest country-level (average) growth in REDI. By doing so, we expect that country-level economic growth can be further promoted.

As a result, in Germany the country-level average REDI score was increased by 10.63%. The inner structure of pillars changed slightly, but the five most important pillars almost kept their share of efforts. In Germany, growth was achieved by concentrating more efforts in product innovation and technology absorption and partially in high growth pillars in general. On the other hand, this means that less effort was allocated to human capital, risk perception, and opportunity startup pillars (in order of significance). Regionally, efforts have been reallocated in favor of relatively efficient regions (Brandenburg, Rheinland-Pfalz, and Sachsen-Anhalt) in terms of human capital and/or entrepreneurship at the expense of lower amount of allocated resources in Niedersachsen and Thüringen.

The second largest increase in country-level average REDI (10.40%) can be achieved in Hungary by allocating even more efforts to cultural support, risk perception, and slightly to networking, at the expense of financing and product innovation pillars. Interestingly Budapest seems to be an exception, since in this region efforts have been reallocated from cultural support in favor of risk perception. The regional distribution of efforts was mainly reallocated to the most developed parts of the country: the capital and slightly to Western Hungary. Finally, in Italy the increase of country-level average REDI (10.19%) resulted in higher concentration of efforts in Opportunity startup and Human capital pillars, while reducing efforts mainly in the Cultural Support pillar (Fig. 7.6). In this

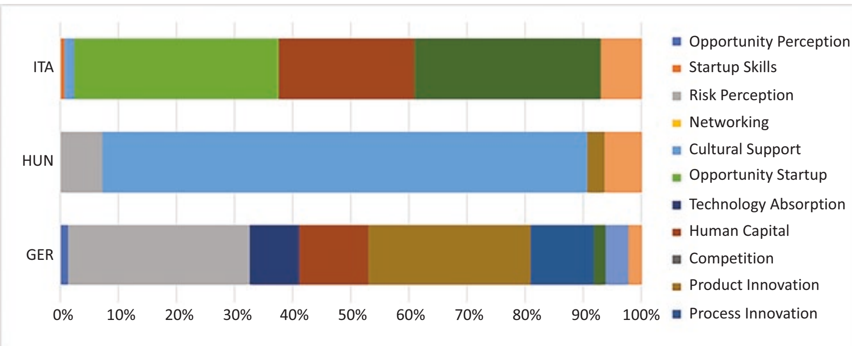

Fig. 7.6 The distribution of additional efforts in REDI among the 14 pillars at the country level in case of policy optimization

case, however efforts were mainly reallocated in favor of the southern underdeveloped regions.

In this scenario, the relative change of REDI will be different in every region as a consequence of country optimization which makes the analysis even more difficult. Now we have to account for the initial size of REDI, its change and the level of human capital stock in the region because the combination of these three factors will determine the regional TFP changes. Finally, the change of gross value added is mainly driven by the changes of TFP, and in the long run other factors may play a role (e.g., migration, trade, investment).

The regional impacts on gross value added are depicted in Fig. 7.7. There are strong country-specific characteristics in the spatial pattern of value added growth. In Germany and Hungary policy optimization

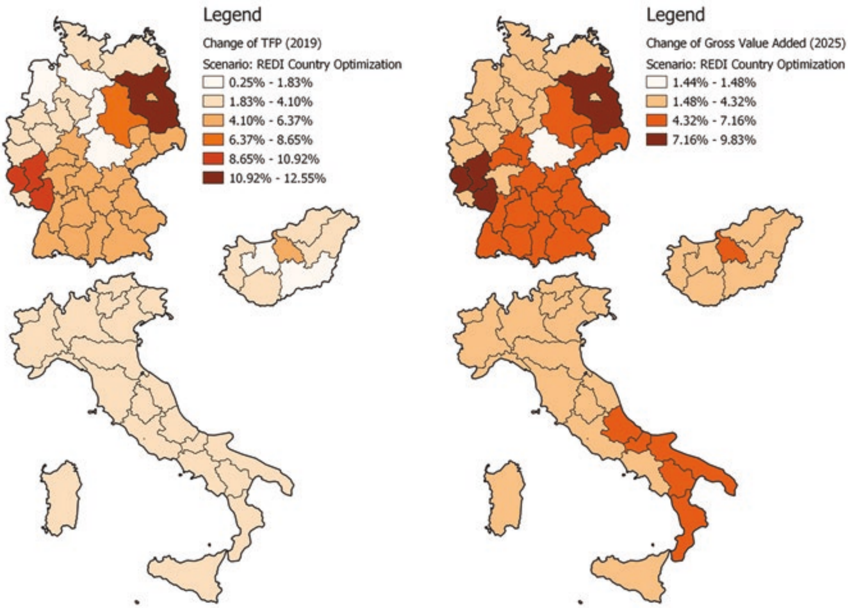

Fig. 7.7 The spatial distribution of REDI shocks (left-hand panel) and their impacts on gross value added (right-hand panel) in case of the policy optimization scenario

coincides with developed regions with high level of human capital, which amplified the total change of value added in the short run. In Italy, however, the largest national REDI growth occurred by allocating resources to poor southern regions with low levels of human capital. Compared to the uniform solution in 2019, both Germany (+0.02%) and Hungary (+0.50%) reached higher value added over the simulation period by focusing resources on highly efficient regions. Italy on the other hand reaches lower value added (−0.10%) since resources were concentrated in lagging regions, which serves as another proof of the tensions between economic growth and regional convergence.

There is a slow convergence to EU average in the long run even in the case of Italy (Fig. 7.8). We must note that in Germany the growth path slightly goes below that of the uniform solution from 2025. The reason for that can be found in the interrelation of employment and investment effects described above, which slightly drives down EU average growth after the interventions are released and then turns it around. This cyclic behavior is overcompensated by the high growth rate of Hungarian and Italian human capital, but in Germany the slow growth of human capital was not enough to compensate this impact. This also highlights the fact that changing entrepreneurship is not a sufficient predictor of economic growth, but the broader regional economic environment has to be taken into account.

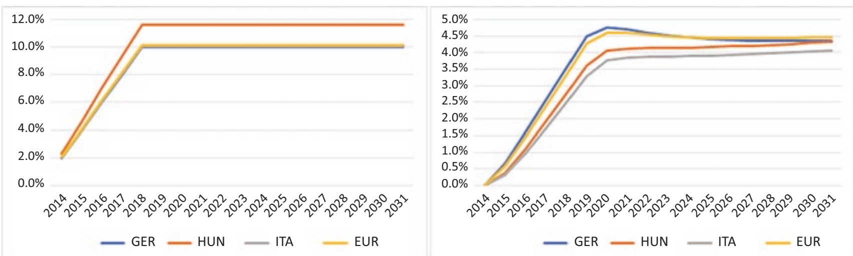

Fig. 7.8 The national impact on national average REDI (left-hand panel) and value added (right-hand panel) in case of the policy optimization scenario

4.3 Poor Regions Solution: Targeting Underdeveloped Regions

In this scenario, we turn our attention towards poor regions in each country and we assess the extent of possible economic growth that can be achieved by concentrating more efforts in those regions. The additional effort required by the uniform solution is allocated to regions that are considered the poorest in each country. Practically, it results in decreasing regional differences in terms of REDI scores since higher REDI score regions receive no additional efforts, while poorer regions can utilize all the resources. Figure 7.9 indicates the result of optimization in terms of the 14 pillars.

Broad diversification characterizes the results of this solution in Germany: originally large pillars (e.g. risk perception, human capital) were decreased in favor of many smaller pillars. Strengthening cultural support in Hungarian poor regions does not result in the highest REDI growth. On the contrary, efforts in cultural support were decreased by the PFB method mainly in favor of risk perception and networking pillars. Apart from Southern Transdanubia, all regions diversified in Hungary in favor of the above-mentioned pillars, while in Southern Transdanubia cultural support was further supported by the optimization. Some of the largest pillars were weakened in Italy (high growth, human capital), but

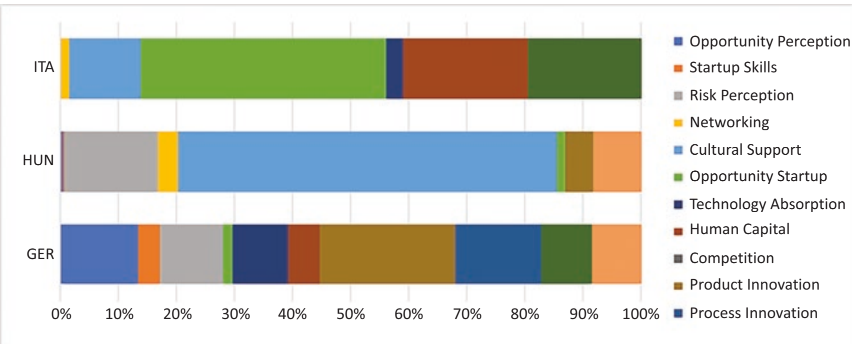

Fig. 7.9 The distribution of additional efforts in REDI among the 14 pillars at the country level in case of poor regions scenario

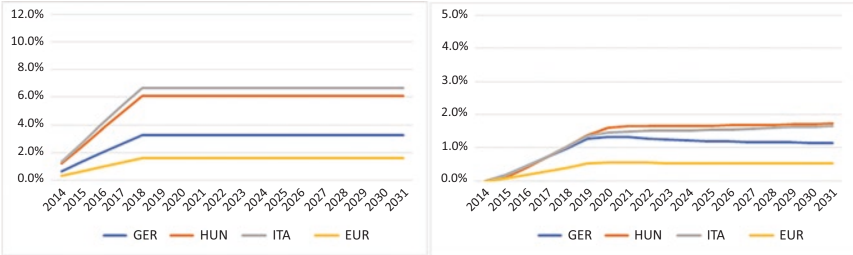

Fig. 7.10 The national impact of national average REDI (left-hand panel) and value added (right-hand panel) in case of poor regions scenario

another important pillar (opportunity startup) was significantly improved. Still the largest improvement occurred in Cultural support, which was not significant nationally in the previous scenarios. These results underline again the important connection between human capital, cultural support, entrepreneurship, and economic growth in underdeveloped areas.

Figure 7.10 indicates the change of REDI averages in the three countries, which is now clearly lower than in the other two scenarios. It can also be observed that Italy and Hungary benefited the most of this intervention in terms of REDI change and Germany is lagging behind. Thus, it seems that entrepreneurship development in poorer regions may be more successful in less developed countries.

In this scenario, national average values do not show us a clear picture of the economic impact mechanism. Since intervention takes place in poor regions (Fig. 7.11), local human capital promotes economic growth dominantly, which is much lower than the national average; thus economic impacts are expected to be modest. In addition, the relative size of relevant human capital in poor regions between countries can differ significantly. In case of Italy, for example, it can be seen that the general level of human capital is much larger than in Hungary although when only less developed regions are considered, this relation is reversed. In terms of human capital, the southern regions of Italy are less developed than Hungarian poor regions, while the national value is much higher thanks to the highly developed northern dynamic regions. German poor regions seem to be significantly more developed than regions in the other two

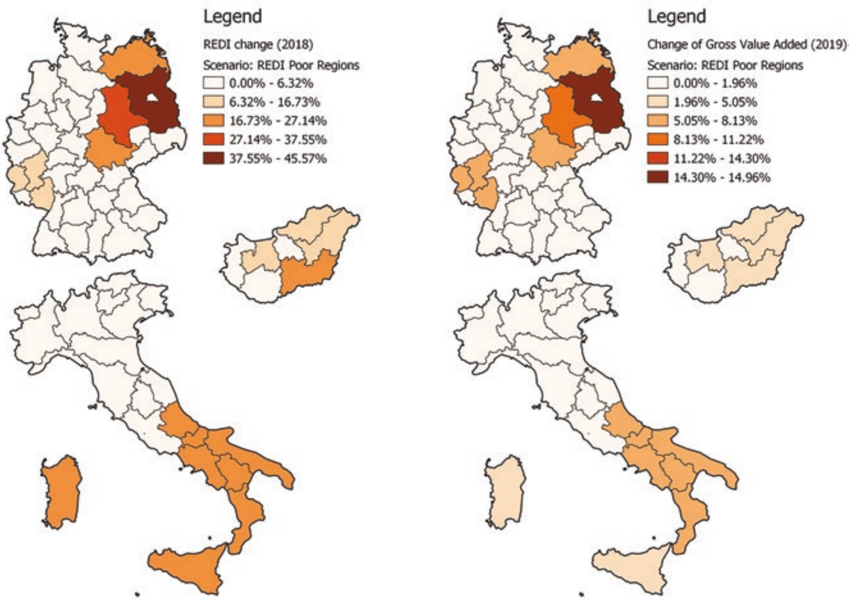

Fig. 7.11 The spatial distribution of REDI shocks (left-hand panel) and their impacts on gross value added (right-hand panel) in case of the poor regions scenario

countries. Thus, the immediate economic effects are resulting from a combination of REDI change and the level of local human capital. Based on that, short-run immediate economic growth appears to be the largest in Germany and Italy, and then in Hungary. With time, however economic impacts are dominantly influenced by the change of human capital stock in poor regions. As a consequence, the initial low Hungarian economic impact soon overtakes all the other countries and, with the high growth rate of human capital, Italy follows Hungary.

4.4 The Cost of Growth: Convergence Effects

A key question in our analysis is how the regional distribution of growth is impacted in these scenarios, that is, what is the trade-off between aggregate growth and convergence. This was already reflected by the results

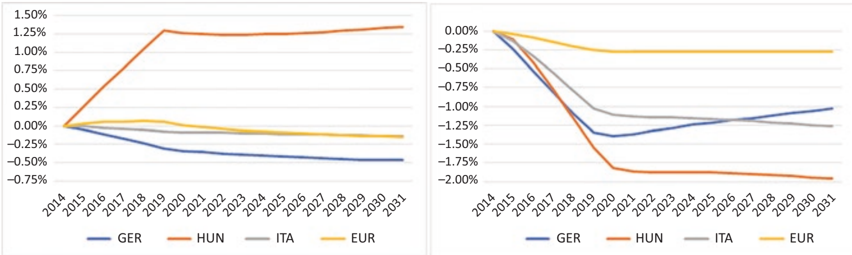

Fig. 7.12 The impact on convergence: policy optimization (left-hand panel) and poor regions (right-hand panel)

discussed so far, but a more direct insight can be given using GINI coefficients calculated on the basis of regional gross value added. Figure 7.12 shows the impact (as compared to the baseline, no-intervention scenario) of the growth-targeting policy optimization solution (left-hand panel) and that of the convergence-targeting poor regions solution (right-hand panel).

The results suggest that in the case when policy optimization targets regions where economic activities are highly concentrated (such as in Hungary), convergence costs of growth can be significant, whereas in Germany and Italy, the GINI coefficient even decreases a little bit (indicating slight convergence), in spite of the resources targeting the most developed regions. This result draws attention to spillover mechanisms through which entrepreneurship development in developed regions can affect less developed regions through various economic feedback mechanisms that the GMR framework is able to account for. Considering the other option when entrepreneurship policy targets less-developed regions, we observe a similar pattern. Naturally, the policy leads to convergence (decreasing GINI coefficients) in this case, but there are differences among countries. Hungary observes the strongest convergence effect, which is the consequence of the high concentration of economic activities in Budapest, the capital region. In this scenario, significant amounts of resources are reallocated from the core to the periphery, which positively affects the patterns of inequality. The convergence effects in case of Germany and Italy are modest relative to Hungary, but still significant.

4.5 Lessons Learned from the Simulations

The results of our simulations extend our knowledge on the efficiency of entrepreneurship policies in the growth-convergence axis in two dimensions.

First, with respect to the growth focused, policy optimization scenario, we learned that country optimization of entrepreneurship policy becomes successful to promote growth if high REDI change occurs in regions where large human capital stock is paired with high entrepreneurship levels. Considering the factors that influence the dynamic impacts (human capital growth, interregional trade, migration, the interplay between employment and capital accumulation), the combination of all those components results in further boost in economic performance. Otherwise, the lack of one or more of those components can overcompensate the total effect of policy interventions, as it happens in the case of Italy. However, promoting growth by country optimization does not necessarily imply the emergence of costs in terms of convergence. While the Hungarian experience supports the generally expected growth-convergence trade-off (with a 1.25% cost in terms of increasing inequality) in Germany and Italy, a slight convergence is materialized.

Second, regarding the convergence-oriented policy, we experienced that a focus on entrepreneurship support in underdeveloped regions more efficiently promotes growth in generally less developed countries (Hungary and Italy). This happens partially because the same rate of growth of REDI costs less "efforts" in those countries and partially because in the long run, these regions are characterized by higher growth rates of human capital, which enables them to capitalize more on the same change of REDI than lagging regions of a more developed country. We observed increasing convergence in the three countries, which is in accordance with expectations. However, there are country-specific differences in this respect as well: the effect is the highest in Hungary followed by Germany and Italy. The growth cost of the convergence policy is around 2.5% with some variation across the countries.

5 Summary

Economic impact assessment of entrepreneurship policies has been hindered by two major challenges: the measurement of the impacts on entrepreneurship and the estimation of economic effects in the context of a policy impact model. With REDI and the novel developments of the GMR-Europe model, the possibility of estimating the economic effects of entrepreneurship policy emerged recently. In this chapter, we outlined the structure of the GMR-Europe model and discussed simulations to illustrate the capability of the GMR-Europe model to tackle entrepreneurship policies in a detailed way. The simulations were carried out in the context of the growth vs. convergence trade-off, by pointing out the strength of the regional-level impact modeling framework in targeting the issue to such a detailed level.

Differences in regional and national economic impacts are related to a multitude of factors, most importantly to the initial level of the REDI, the level and the dynamic change of human capital in the region, migration patterns of factors of production and changes in interregional trade initiated with the policy. The relative size and direction of all those forces will eventually determine economic growth of regions and nations.

Three impact scenarios were discussed, one with an even allocation of entrepreneurship-development across regions, one targeting national growth rates, and one targeting less developed regions. From these exercises, a few important conclusions can be drawn. First, successful high-growth entrepreneurship development requires the allocation of additional support to regions characterized by both high initial level of entrepreneurship (REDI) and skilled workforce. Second, promoting entrepreneurship in underdeveloped regions can successfully decrease regional inequalities, and increase convergence, but this surely comes at the cost of lower levels of national economic growth. However, there are significant differences between countries with respect to the relative loss of growth that is associated with the same increase in convergence. The paper also points out the capability of the GMR-Europe model in quantifying these effects. Third, there is no clear "best practice" recipe for entrepreneurship development. Countries/regions with different levels of economic and entrepreneurial performance can be developed by focusing additional support on different sources (pillars) of entrepreneurship, as indicated by the REDI. Fourth, it needs to be clearly determined whether regional convergence or economic growth is the main objective function of policy interventions. Areas with high potential for entrepreneurship development do not necessarily coincide with areas with high potential for economic growth. Policymakers should treat economic and entrepreneurial development together to find an optimal balance between the two targets to come up with the best solution. As our study highlights, economic impact assessment models as the GMR-Europe model can successfully support such complex decision problems.

Notes

1. The attitude sub-index aims to identify the attitude of the people towards entrepreneurship (like the level of opportunity recognition or start-up skills within the population). Abilities are principally concerned with measuring certain important characteristics of both entrepreneurs and start-ups with high growth potential (e.g., the extent to which new opportunities motivate business startups, the share of technology intensive and creative sectors in the region). The entrepreneurial aspiration sub-index refers to the distinctive, qualitative, strategy-related nature of entrepreneurial start-up activity (i.e., the degree of innovativeness and the extent to which high growth, internationalization, and good access to finance characterize entrepreneurial businesses).
2. These models either follow the tradition of macroeconometric modeling (like the HERMIN model—ESRI, 2002), the tradition of macro CGE modeling (like the ECOMOD model, Bayar, 2007) or the most recently developed DSGE approach (QUEST III—Ratto et al., 2009).

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8

Digital Inequality and the Signature of Digital Technologies and the Digital Ecosystem: Analysis of Deviations in the Rank-Size Rule of Internet Access Data

Esteban Lafuente, Zoltán J. Ács, and László Szerb

1 Introduction

Digital inequality cannot be overlooked. The world has become a more digitally dependent place, mostly as a result of the rapid penetration of Internet and information and communications technologies (ICTs) in

E. Lafuente (✉)
Business School, Costa Rica Institute of Technology (ITCR), Cartago, Costa Rica
e-mail: elafuente@itcr.ac.cr

Z. J. Ács
George Mason University, Arlington, VA, USA
e-mail: zacs@gmu.edu

L. Szerb
Faculty of Business and Economics, University of Pécs, Pécs, Hungary
e-mail: szerb.laszlo@ktk.pte.hu

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the day-to-day routines of governments, organizations, and the people (United Nations, 2020; Acs, et al., 2021). But, digital integration is not occurring evenly. The increased digitization of societies has given rise to a new form of inequality—namely, digital inequality—that is spreading across the globe. Digital inequality is currently affecting millions of people, being the poorest the most negatively affected as reflected by United Nations (2020): 20% of people have access to the Internet in developing countries (87% in developed countries). Various factors are at play in digital inequalities. Besides the obvious economic differences within and between countries, geopolitics also spurs the digital divide. The rivalry between China—whose recently developed tech industry is propelling the country's digital prosperity—and the United States is fueling a digital polarization that has materialized in restrictions on access to 'hard tech' components and the mutual banning of digital platforms (US Department of Commerce, 2020; *The Economist*, 2021a).

Also, by altering societies' functioning, the Covid-19 pandemic is leaving a legacy of increased digital inequality (e.g., Nguyen et al., 2021; O'Sullivan et al., 2021). For people living on the wrong side of the digital divide, the damages of being unable to connect to the Internet are profound, in terms of access to information, e-commerce, remote education, remote work, remote healthcare, and digital banking services. As the data flow, they reveal that with the pandemic both developed and developing countries have fallen short in equipping citizens and businesses with the means to carry out their daily activities (e.g., United Nations, 2020; Tranos & Ioannides, 2020; Nguyen et al., 2021).

All these problems threaten digital integration. Digital infrastructures are not the only medicine to combat inequality. Recently, various voices invoke the digital ecosystem supporting the networks of ecosystem actors as an essential ingredient to trigger the societal benefits of ICTs and, consequently, help reduce digital inequality (Acs, et al., 2021; O'Sullivan et al., 2021).

In articulating this discussion, we carry out a simple empirical exercise to support our arguments. We briefly anticipate that, unlike other studies on power laws in social phenomena including WWW and Internet connections (e.g., Albert et al., 1999; Faloutsos et al., 1999; Gabaix, 2009; Arshad et al., 2018), we adopt a lens of power law ($y(x) \propto Cx^{-k}$) in which deviations in the rank-size rule of the Internet access data for 107 countries are at the center of the analysis. We report estimates of the effects of digital technologies on rank deviations in Internet access. In the second stage, we describe countries' digital ecosystem using the digital platform economy index proposed by Acs, et al. (2021).

The logic of the study approach is straightforward. As in Cristelli et al. (2012) and Bettencourt and Zünd (2020), we interpret the rank deviation in Internet access as a quantitative proxy-indicator of the degree of digital integration (estimations in Appendix 1 illustrate this intuition). In other words, as in any human-made system, empirical discrepancies in the Internet access distribution can be understood as the result of complex processes mediated by different stakeholders. Instead of proposing a canonical power law study we argue that, in contexts characterized by incomplete data and substantial socio-economic differences, rank deviations in Internet access acquire the meaning of valuable information that can be connected to the digital prioritization strategy and economic reality of the studied countries.

Despite the utter simplicity of our analysis, the implication of our study is clear: by correlating rank deviations in Internet access data with digital technologies and the digital ecosystem, we are in a better position to describe the degree of global digital integration and identify potential actions that countries might adopt if the objective to reduce digital inequality is the desired goal.

2 Methods

We follow a two-step approach to analyze the links between digital inequality, digital technologies, and the digital ecosystem on a sample of 107 countries during 2015–2019. First, we rely on a standard power law function of the form $\ln(\mathit{rank})_i = \ln \alpha - \beta \ln \mathit{Internet\ users}_i$, where α is a constant and β is the power exponent, to represent the rank-size rule for the Internet access data. Parameters (α, β) are estimated by OLS using STATA© software. Appendix 2 gives full details on the construction of the study variables (Table 8.4), offers the data used in the empirical exercise (Tables 8.5 and 8.6), and presents descriptive statistics for the variables (Table 8.7).

Figure 8.1 shows the log-log plot of the rank-size relationship for the Internet access data for 2015 and 2019. The comparison between the observed ranks in 2015 (r_{2015}) and 2019 (r_{2019}) allows us to calculate, for each country (i), the rank deviation[7]: $DiffRank = r_{2015} - r_{2019}$. By definition the *DiffRank* variable does not vary continuously; therefore, for enhanced estimation accuracy we use a normalized form of this variable: $normDiffRank_i = (DiffRank_i + N)/(2 \times N)$. The relatively good fit of estimations in Fig. 8.1 suggests that the proposed rank-size relationship characterizes the heterogeneity in the distribution of the Internet access data. Thus, the rank deviation variable can be considered a convenient proxy measure of digital dispersion.

We employ OLS models to examine how digital inequality (*normDiffRank*) is affected by digital technologies (i.e., broadband subscriptions

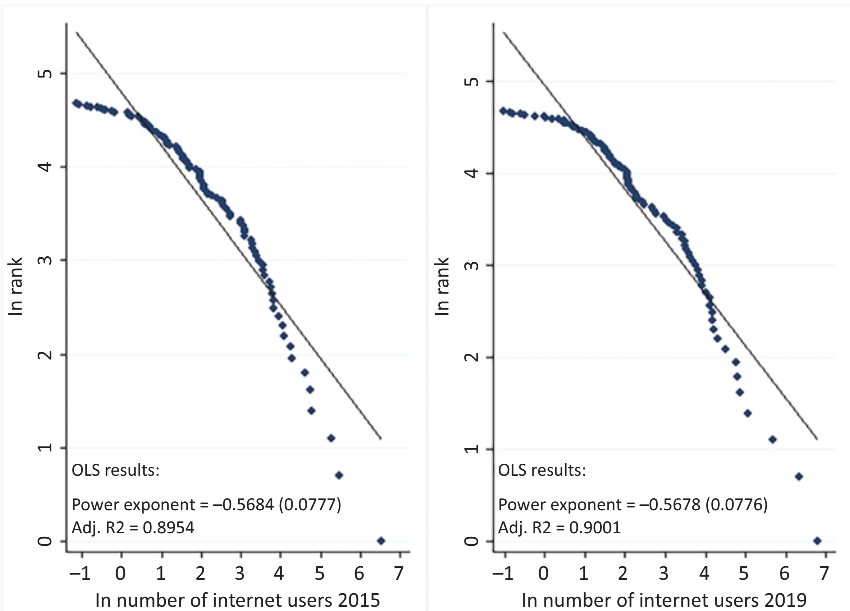

Fig. 8.1 Log-log plot of the number of internet users for 2015 and 2019 (N–107 countries). We followed Gabaix and Ibragimov (2011) to compute the standard error (SE) of the power law exponent $\left(\mathrm{SE} = \sqrt{2/N} \times \beta\right)$. For the two power law exponents the p-value < 0.001 (two-tailed)

and bandwidth capacity). We interpret rank deviations as signals of the degree of digital dispersion or inequality (Cristelli et al., 2012; Tranos & Ioannides, 2020). That is, a positive coefficient would indicate an impact on *normDiffRank* towards the decrease of digital dispersion, that is, towards a greater degree of integration in the number of Internet users. In the second stage, we offer a descriptive comparison between the Internet access data and countries' digital ecosystem. Acs, et al. (2021) offer a detailed description of the digital platform economy index.

3 Results

3.1 Digital Technologies and Digital Integration

We begin by analyzing the relationship between digital technologies and rank deviations. The estimated effects on digital inequality (*normDiffRank*) are reported in Panels A (variables in levels) and B (variables as variation between 2015 and 2019) in Table 8.1.

We observe that, instead of merely having more digital technologies (Model 1 in Table 8.1), investing in digital infrastructures that facilitate the access to the Internet for citizens and local businesses—which materializes in, among other things, a greater number of broadband subscriptions (Tranos & Ioannides, 2020; Nguyen et al., 2021)—is positively correlated with rank deviations of Internet users (Model 2 in Table 8.1). That is, the increased usage of broadband Internet results in national digital systems which are more uniform and integrated, and are characterized by a greater number of Internet users.

Therefore, an increase (decrease) in the adoption of broadband technologies is associated with high (low) levels of "digital catch-up" or digital integration (inequality). Additional analyses using as dependent variable the change in Internet users during 2015–2019 are presented in Models 3 and 4 in Table 8.1. The findings corroborate that variations in broadband subscriptions are positively correlated with changes in the number of Internet users.

Table 8.1 Regression results (OLS)

	Dependent variable: normalized difference in ranks (*normDiffRank*)		Dependent variable: variation (%) in the number of Internet users (*VarIntUsers*)	
	Model 1	Model 2	Model 3	Model 4
Broadband subscriptions per Internet user (BS) in 2015 (%)	–0.0002 (1.23)		–0.0034 (1.44)	
Bandwidth (bits/s) per Internet user (BW) in 2015 (ln)	–0.0020 (0.70)		–0.0543 (1.35)	
Variation in BS (2015–2019)		0.0052*** (4.51)		0.0532* (1.99)
Variation in BW (2015–2019)		–0.0005 (1.22)		–0.0034 (0.53)
Total population in 2015 (ln)	0.0010 (0.92)	0.0015 (1.42)	0.0304 (1.18)	0.0379 (1.43)
GDP per capita in 2015 (ln)	–0.0129*** (3.68)	–0.0125** (2.83)	–0.1433** (3.14)	–0.1771** (3.27)
Trade in 2015 (%)	0.0051 (1.28)	0.0031 (0.94)	0.0876 (1.79)	0.0450 (1.18)
OECD dummy	–0.0018 (0.38)	–0.0062 (1.52)	–0.1074 (1.70)	–0.1641** (2.92)
Constant	0.6468*** (13.46)	0.6191*** (14.27)	2.3081*** (3.69)***	2.0136*** (3.75)
F test	7.18***	19.21***	13.07***	14.78***
Adjusted R2	0.3388	0.4305	0.4168	0.4369
RMSE	0.0213	0.0198	0.2985	0.2933
VIF (min-max)	2.21 (1.41–3.10)	1.50 (1.08–2.19)	2.21 (1.41–3.10)	1.50 (1.08–2.19)
Observations	107	107	107	107

Full details on the construction of the dependent variable (*normDiffRank*) as well as the set of independent variables are presented in Appendix 2 (Table 8.4). Notice that the digital platform economy index (DPE) and its sub-indicators are not included in the OLS models due to collinearity issues (i.e., the digital technology variables are included in the construction of the DPE) (see Acs, et al. (2021) for a detailed description of the DPE). Absolute *t*-statistics based on robust (heteroskedastic) standard errors clustered by country are presented in parentheses

* = *p*-value < 0.05, ** = *p*-value < 0.01, and *** = *p*-value < 0.001 (two-tailed)

3.2 The Role of the Digital Ecosystem

As with any human-made system, to synthesize and map all the relations that exist between the different actors of the digital ecosystem is a challenging task. This obviously implies that, despite its methodological validity and analytical usefulness, quantitative work based on correlations might mask other relevant factors explaining digital inequalities. We thus include in the analysis the digital platform economy index (DPE) for 2019, developed by Acs, et al. (2021) using multiple data from 2015 to 2018, to describe the main properties of countries' digital ecosystem.

This way, we take the digital inequality discussion to a more qualitative level, and add to this brief debate potentially valuable clues on how the digital ecosystem can help reduce digital inequalities. Results are presented in Fig. 8.2. We complement the analysis by using Epanechnikov kernel density estimates to evaluate differences in the DPE sub-indicators between outperforming countries that improved their rank between 2015 and 2019 (*DiffRank* > 0) and underperforming countries that worsened their rank during the same period (*DiffRank* < 0) (full results are shown in Table 8.8 of Appendix 3).

Overall, two main results emerge from the inspection of the data summarized in Fig. 8.2. First, the good news, at the global scale poor countries are catching up, and the reported 'digital catch-up' between 2015 and 2019 is especially evident among less developed countries in Africa, Asia, and Latin America, in terms of GDP per capita (Fig. 8.2). This result is consistent with our OLS estimations (Table 8.1), and is further corroborated by the analysis presented in Appendix 3: outperforming countries (*DiffRank* > 0) show a significantly weaker digital ecosystem (DPE) than underperforming countries (*DiffRank* < 0) (Fig. 8.2 and Table 8.8).

For example, African nations report the greatest growth in both Internet usage (44.57%) and broadband subscriptions (144.65%), and only three countries—that is, Mauritius, Uganda, and Zimbabwe—report a negative rank deviation (*DiffRank* < 0). Similarly, 17 out of the 29 Asian countries report positive rank deviations (*DiffRank* > 0), and Internet usage rates grew more intensively in less developed countries

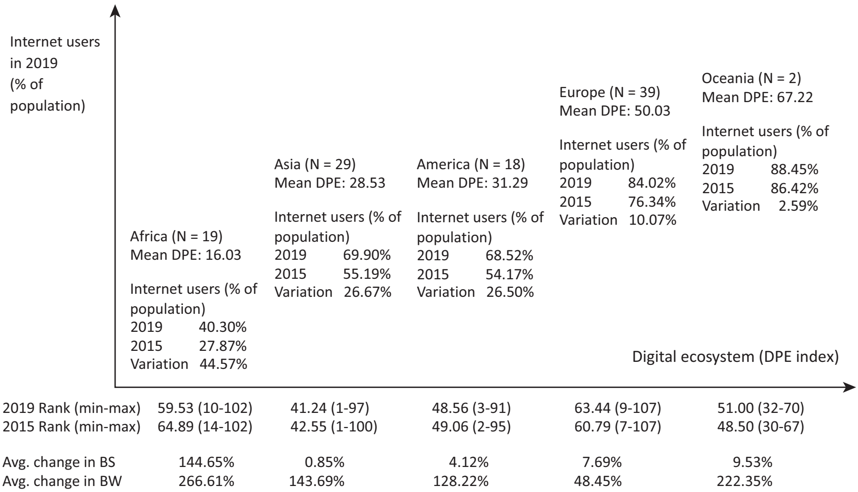

Fig. 8.2 Digital integration, digital technologies, and the digital ecosystem (DPE). Note: DPE = digital platform economy index (Acs, et al., 2021), BS = broadband subscriptions (% of total population), BW = international bandwidth capacity (bits/s) per Internet user. For each continent, *N* refers to the sample size

(39.40%) (e.g., Bangladesh, India, Mongolia, Pakistan, and Sri Lanka) than in developed nations with *DiffRank* < 0 (8.32%) (e.g., Japan, Korea, and Singapore). In China, a popular case with *DiffRank* > 0, 64.57% of the population has Internet access in 2019 (50.30% in 2015) and broadband subscriptions grew 23.94%. In Latin America, 10 out of the 16 nations show *DiffRank* > 0 and their rate of Internet users grew 48.71% during 2015–2019 (23.55% for underperforming countries with *DiffRank* < 0). These results are higher than those reported for Canada (growth in Internet users = 12.92%) and the United States (growth in Internet users = 22.80%).

Second, the bad news, severe digital inequalities still prevail and this is especially visible when comparing Africa viz-à-viz other geographies. Although African countries show the highest improvement in rank values (5 points) and Internet usage rates (44.57%), only 40.30% of Africans have access to the Internet in 2019, a result that is sensitively lower than that found for the rest of continents (Fig. 8.2). Also, a comparison of the

OLS estimations in Appendix 1 suggests that the pace of global digital integration is slowing down over the last decade.

The wealthy world is also, to a certain extent, exposed to digital inequalities. Rank deviations are mostly small and negative among global economic locomotives, which can be attributed to their development level and associated large investments in digital technologies (e.g., $DiffRank_{USA} = -1$, $DiffRank_{Germany} = -2$, $DiffRank_{Japan} = -2$, and $DiffRank_{UK} = -4$). The greater growth in Internet users of China and India further contribute to explain these results. The case of Europe is also worth mentioning: 29 out of the 39 European states show a negative rank deviation ($\overline{DiffRank}_{Europe} = -2.64$, ranging from −7 to 1) (for details, see Table 8.5 in Appendix 2). Despite the evident "digital catch-up" process, for ten European countries, mostly Eastern European (including four EU member states), it was found a relatively low rate of Internet users that is comparable to Europe's result for 2015: 64.03% in 2015 and 76.18% in 2019.

4 Discussion and Concluding Remarks

We started this study with the motivation of analyzing digital inequalities, in terms of access to the Internet. In the context of complex human-made systems—such as the case analyzed in this work—where rank-size rules hold approximately due to substantial differences in the socio-economic dynamics of the studied system, our approach based on rank deviations in the distribution of Internet access data offers a way to produce valuable information that helps identify temporal trends and unveil policies with the potential to trigger structural changes in the digital system.

Digital integration is a complex process characterized by investments in digital technologies and the structure of the digital ecosystem. The proliferation of digital technologies is promoting a "digital catch-up" that supports digital inclusion (O'Sullivan et al., 2021), and this "digital catch-up" process is stronger in underdeveloped countries (see Appendix 3). But, descriptive evidence signals that the pace of digital integration is slowing down (see Appendix 1), and that poor countries have a fragile digital ecosystem. Additional tests show that governance (e.g., regulation, cyber protection, and data privacy) and platforms' activity (e.g., social media and online payments) are decisive pillars of digital integration (see Appendix 4). Echoing recent work in the economic field (e.g., Brynjolfsson et al., 2019; Goldfarb & Tucker, 2019), we speculate that this result emphasizes the role of platforms as "matchmakers." By providing structures that reduce search costs of products and services, platforms trigger economic- and information-based exchanges between people and businesses (Goldfarb & Tucker, 2019; Acs, et al., 2021).

In closing, digital inequalities still prevail around the globe, and much has to be done for fully realizing the positive externalities of the digitalization of societies (e.g., decrease in the rural-urban divide, and increases in business productivity and consumer surplus) (e.g., Kolko, 2012; Brynjolfsson et al., 2019; Goldfarb & Tucker, 2019). In parallel, various tensions between governments and between digital platforms and governments increase the risk of inequality. Notable examples of such tensions include the digital polarization caused by geopolitical rivalries, and the enactment of regulations guided by the increased interest of policymakers for controlling the key input of the digital production function, namely the data (*The Economist*, 2021b; *The Guardian*, 2021).

Digital ecosystems are not checklists that can be altered in the short run. Furthermore, the inherent differences across countries support the notion that policy isomorphism is a suboptimal strategy. In this sense, the just digital framework (e.g., O'Sullivan et al., 2021) and the digital platform economy index (Acs, et al., 2021) are examples of tools that can equip policymakers with reliable information for promoting more informed, tailor-made reforms. Policies targeting the governance umbrella and the activity of platforms are especially relevant if the set goals are to prevent digital exclusion and its manifestations in the post-Covid pandemic period, and eradicate digital inequality in the long term.

Appendix

Appendix 1: Power law exponent for the number of Internet users (selected years: 2000, 2005, 2010, and 2015)

This material presents the results of the power law estimations for the distribution of the number of internet users for the years 2000, 2005, 2010, and 2015. Figure 8.3 shows the log-log plots for the analyzed data, while full OLS regression results are presented in Table 8.2. Finally, the data used in this analysis, available at the World Bank databases (URL: https://data.worldbank.org/indicator), is presented in Table 8.3.

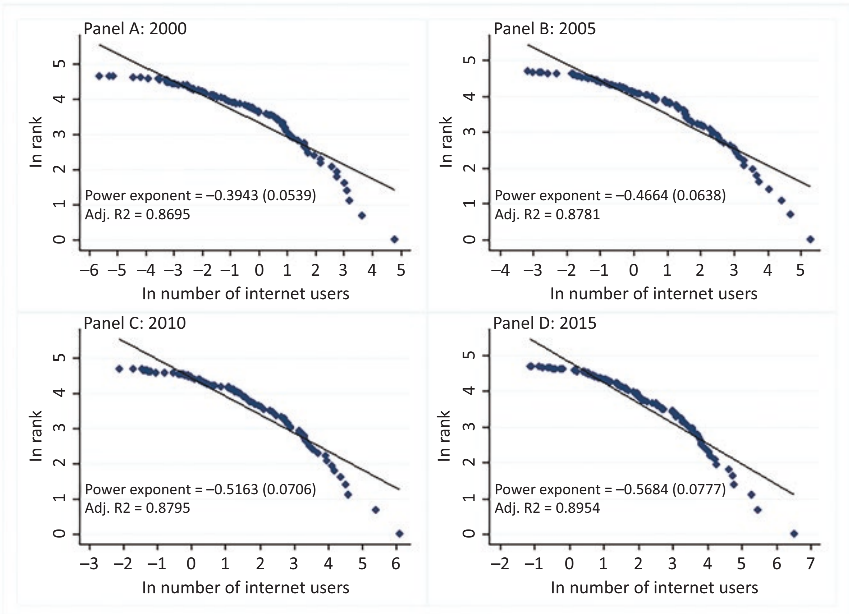

Fig. 8.3 Log-log plots of the number of internet users for the years 2000, 2005, 2010, and 2015. We followed Gabaix and Ibragimov (2011) to compute the standard error (SE) of the power law exponent $\left(\mathrm{SE} = \sqrt{2/N} \times \beta\right)$. For all power exponents the *p*-value < 0.001 (two-tailed)

Table 8.2 OLS models: results for the power law analysis of the number of Internet users

Year	Power exponent	Constant	Adj. R2	F-test	RMSE	Obs.
2000	–0.3943 (0.0539)***	3.3251 (0.0483)***	0.8695	213.02***	0.3360	105
2005	–0.4664 (0.0638)***	3.9544 (0.0288)***	0.8781	239.61***	0.3250	107
2010	–0.5163 (0.0706)***	4.4265 (0.0479)***	0.8795	241.46***	0.3232	107
2015	–0.5684 (0.0777)***	4.8045 (0.0663)***	0.8954	267.56***	0.3011	107

For the year 2000 data for Serbia and Montenegro is not available because these countries formed the State of Serbia and Montenegro. The standard error (SE) of the power law exponent is computed based on the method proposed by Gabaix and Ibragimov (2011) $\left(\mathrm{SE} = \sqrt{2/N} \times \beta\right)$
*** = p-value < 0.001 (two-tailed)

Table 8.3 Data for the number of internet users (millions of people) for selected years (2000, 2005, 2010, and 2015)

	Country	Year 2000	Year 2005	Year 2010	Year 2015
1	Albania	0.0035	0.1820	1.3109	1.6391
2	Algeria	0.1526	1.9373	4.4972	15.1761
3	Argentina	2.5952	6.8921	18.3548	29.3483
4	Armenia	0.0399	0.1566	0.7193	1.7290
5	Australia	8.9552	12.8487	16.7441	20.1389
6	Austria	2.7023	4.7721	6.2868	7.2547
7	Azerbaijan	0.0119	0.6739	4.1650	7.4300
8	Bahrain	0.0409	0.1894	0.6825	1.2824
9	Bangladesh	0.0907	0.3360	5.4603	12.9693
10	Belgium	3.0171	5.8492	8.1717	9.5890
11	Benin	0.0155	0.1015	0.2879	1.1903
12	Bosnia and Herzegovina	0.0406	0.8030	1.5841	1.8038
13	Botswana	0.0477	0.0587	0.1192	0.7913
14	Brazil	5.0177	39.1290	79.5576	119.2642
15	Bulgaria	0.4388	1.5295	3.4190	4.0668
16	Cambodia	0.0057	0.0421	0.1803	2.7939
17	Cameroon	0.0391	0.2487	0.8747	4.2636
18	Canada	15.7418	23.1059	27.3059	32.1326
19	Chile	2.5468	5.0450	7.6781	13.7698
20	China	22.4235	111.1194	458.8328	689.7237
21	Colombia	0.8748	4.6943	16.5063	26.5664
22	Costa Rica	0.2298	0.9458	1.6707	2.8972

(*continued*)

Table 8.3 (continued)

	Country	Year 2000	Year 2005	Year 2010	Year 2015
23	Croatia	0.2969	1.4284	2.4291	2.9360
24	Cyprus	0.1439	0.3372	0.5896	0.8326
25	Czech Republic	1.0030	3.6015	7.2085	7.9801
26	Denmark	2.0917	4.4840	4.9219	5.4749
27	Dominican Republic	0.3138	1.0447	3.0443	5.5743
28	Ecuador	0.1854	0.8288	4.3577	7.9342
29	Egypt	0.1854	0.8288	4.3577	7.9342
30	El Salvador	0.0693	0.2542	0.9832	1.6953
31	Estonia	0.3992	0.8325	0.9866	1.1629
32	Finland	1.9281	3.9073	4.6602	4.7355
33	France	8.7153	27.0850	50.2533	51.9117
34	Georgia	0.0198	0.2372	1.0186	1.7721
35	Germany	24.8413	56.6647	67.0571	71.5491
36	Greece	0.9875	2.6370	4.9379	7.2321
37	Guatemala	0.0826	0.7381	1.4973	4.4843
38	Honduras	0.0791	0.4848	0.9224	2.4696
39	Hungary	0.7147	3.9309	6.5000	7.1691
40	Iceland	0.1251	0.2582	0.2970	0.3249
41	India	5.5738	27.4058	92.5711	195.2127
42	Indonesia	1.9577	8.1510	26.4083	57.0064
43	Iran	0.6130	5.6507	11.7282	35.5844
44	Ireland	0.6792	1.7309	3.1853	3.9259
45	Israel	1.3128	1.7460	5.1459	6.4822
46	Italy	13.1598	20.2893	31.8201	35.3098
47	Jamaica	0.0827	0.3507	0.7777	1.2206
48	Japan	38.0412	85.5071	100.1635	115.7721
49	Jordan	0.1344	0.7457	1.9751	5.5705
50	Kazakhstan	0.0995	0.4486	5.1577	12.4256
51	Kenya	0.1017	1.1361	3.0262	7.9420
52	Korea, Rep.	21.0126	35.4157	41.4768	45.8605
53	Kuwait	0.1377	0.5886	1.8370	2.9918
54	Latvia	0.1496	1.0298	1.4351	1.5662
55	Lithuania	0.2249	1.2034	1.9240	2.0735
56	Luxembourg	0.0999	0.3256	0.4594	0.5490
57	Macedonia	0.0582	0.1683	0.2971	0.4672
58	Malaysia	4.9600	12.4931	15.8811	21.5118
59	Mali	0.0156	0.0648	0.3010	1.8014
60	Malta	0.0512	0.1665	0.2611	0.3381
61	Mauritius	0.0864	0.1864	0.3542	0.6331
62	Mexico	5.0255	18.2435	35.4259	69.9845
63	Moldova	0.0375	0.4225	0.9243	1.9558
64	Mongolia	0.0301	0.2021	0.2774	0.6746

(*continued*)

Table 8.3 (continued)

	Country	Year 2000	Year 2005	Year 2010	Year 2015
65	Montenegro	0.0000	0.1665	0.2323	0.4238
66	Morocco	0.1998	4.5941	16.8186	19.7860
67	Namibia	0.0295	0.0777	0.2458	0.5946
68	Netherlands	7.0047	13.2191	15.0735	15.5380
69	New Zealand	1.8278	2.5928	3.5006	4.0665
70	Nigeria	0.0784	4.9285	18.2279	44.3787
71	Norway	2.3353	3.7906	4.5661	5.0231
72	Oman	0.0798	0.1678	1.0897	3.1378
73	Pakistan	0.9778	10.1510	14.3540	21.9370
74	Panama	0.1986	0.3824	1.4607	2.0321
75	Paraguay	0.0398	0.4605	1.2371	3.3254
76	Peru	0.8140	4.7651	10.0929	12.4481
77	Philippines	1.5460	4.6596	23.4917	45.9509
78	Poland	2.7873	14.8120	23.7083	25.8296
79	Portugal	1.6907	3.6751	5.6355	7.1090
80	Qatar	0.0288	0.2140	1.2809	2.3832
81	Romania	0.8110	4.5837	8.0846	11.0498
82	Russia	2.8986	21.8531	61.4253	101.0108
83	Rwanda	0.0050	0.0492	0.8031	2.0464
84	Saudi Arabia	0.4568	3.0259	11.2428	22.0807
85	Senegal	0.0396	0.5308	1.0143	3.1635
86	Serbia	0.0000	1.9569	2.9822	4.6345
87	Singapore	1.4500	2.6021	3.6045	4.3734
88	Slovakia	0.5080	2.9653	4.0819	4.2108
89	Slovenia	0.3005	0.9364	1.4340	1.5084
90	South Africa	2.4051	3.5856	12.2921	28.7561
91	Spain	5.5274	20.9011	30.6476	36.5473
92	Sri Lanka	0.1216	0.3503	1.0131	2.5374
93	Sweden	4.0535	7.6598	8.4403	8.8791
94	Switzerland	3.3838	5.2134	6.5651	7.2454
95	Tanzania	0.0393	0.4230	1.2860	5.1483
96	Thailand	2.3223	9.8294	15.0517	27.0159
97	Tunisia	0.2671	0.9758	3.9138	5.1987
98	Turkey	2.3789	10.4979	28.8006	42.2056
99	Uganda	0.0387	0.4823	3.6320	15.0952
100	Ukraine	0.3522	1.7663	10.6879	22.0734
101	United Arab Emirates	0.7404	1.8353	5.8140	8.3829
102	United Kingdom	15.7960	42.2808	53.3514	59.9071
103	United States	121.5532	200.8569	221.7566	239.1244
104	Uruguay	0.3499	0.6673	1.5587	2.2032
105	Vietnam	0.2032	10.6802	26.9621	41.7047
106	Zambia	0.0199	0.3381	1.3606	2.1120
107	Zimbabwe	0.0477	0.2898	0.8127	3.1418

Appendix 2: Data for the empirical analysis

This material describes the variables employed in the empirical exercise of the study (Table 8.4). We also include the data used in our analyses (Tables 8.5 and 8.6) and the descriptive statistics for the selected variables (Table 8.7).

Appendix 3: Kernel density plots for the digital platform economy (DPE) index and its sub-indicators

Table 8.8 in this material presents the results of the statistic tests (*t*-test, Mann-Whitney U test, and Kolmogorov-Smirnov test of equality of distributions) evaluating differences in the DPE indicator and its four sub-indicators, namely: digital multisided platforms, digital technology entrepreneurs, digital governance, and digital citizenship. In the table, the comparison of the values for the digital ecosystem proxy variables distinguish between outperforming countries that improved their rank between 2015 and 2019 (*DiffRank* > 0) and underperforming countries whose rank value worsened between 2015 and 2019 (*DiffRank* < 0).

Appendix 4: OLS regression results

This material presents the results of the OLS models relating the digital platform economy (DPE) index to the digital integration variable (normalized difference in ranks: *normDiffRank*) and the variation (%) in the number of Internet users.

Table 8.4 Description of the study variables

Variable	Code	Description	Source
Internet users in 2019 (million people)	*IntUsers*	Internet users are individuals who have used the Internet (from any location) in the last three months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV, and so on.	World Bank: https://data.worldbank.org/indicator
Difference in ranks	*DiffRank*	This variable is the difference in ranks (Internet users). The variable is calculated as $DiffRank = r_i^{2015} - r_i^{2019}$, where r_i^{2015} and r_i^{2019} are the observed ranks of country *i* for 2015 and 2019, respectively.	Authors' elaboration
Normalized difference in ranks	*normDiffRank*	The variable *DiffRank* is the difference between two count variables (observed ranks). For estimation accuracy, we normalized *DiffRank* in order to employ in the OLS models a continuous dependent variable that ranges between 0 and 1. The normalized form of *DiffRank*—that is, *normDiffRank*—is calculated as follows: $(DiffRank_i + N)/(2 \times N)$	Authors' elaboration
Variation (%) in the number of Internet users	*VarIntUsers*	The variable *VarIntUsers* is the percent variation in the number of Internet users between 2015 and 2019.	Authors' elaboration

Bandwidth (bits/s) per Internet user in 2015 (ln)	*BW*	International bandwidth is the total used capacity of international bandwidth (Mbit/s). It is measured as the sum of used capacity of all Internet exchanges (locations where Internet traffic is exchanged) offering international bandwidth. International bandwidth (bit/s) per Internet user is calculated by converting to bits per second and dividing by the total number of Internet users.	International Telecommunication Union (ITU): https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx
Broadband subscriptions per Internet user in 2015 (%)	*BS*	Broadband subscriptions are residential and business fixed subscriptions to access to the public Internet (a TCP/IP connection); at downstream speeds equal to; or greater than; 256 kbit/s. This includes cable modem; DSL; fiber-to-the-home/building; other fixed-broadband subscriptions; satellite broadband and terrestrial wireless broadband. The variable *BS* is calculated by dividing broadband subscriptions by the total number of Internet users.	International Telecommunication Union (ITU): https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx
Total population in 2015 (ln)	*TotPop*	Total population is the sum of all country residents regardless of legal status or citizenship.	World Bank: https://data.worldbank.org/indicator
GDP per capita in 2015(ln)	*GDPcap*	Gross Domestic Product (GDP) per capita based on purchasing power parity (PPP) at constant 2017 international dollars.	World Bank: https://data.worldbank.org/indicator
Trade relative to GDP in 2015 (%)	*Trade*	The variable is computed by dividing Total Trade (the sum of exports and imports of goods and services) by GDP.	World Bank: https://data.worldbank.org/indicator

(*continued*)

Table 8.4 (continued)

Variable	Code	Description	Source
OECD country (dummy)	*OECD*	Dummy variable taking the value of one for OECD member states, and zero otherwise.	Organisation for Economic Co-operation and Development (OECD) https://www.oecd.org/about/
Digital Platform Economy (DPE) Index	*DPE*	The Digital Platform Economy (DPE) Index results from integrating 12 pillars grouped in four sub-indicators (platforms, technology entrepreneurs, digital infrastructures, and digital users) associated with two separate but related ecosystem literatures, namely: digital ecosystem and entrepreneurial ecosystem. The DPE works under the assumption that for technology to be successfully introduced both the digital ecosystem and the entrepreneurial ecosystem need to be developed simultaneously. Acs, et al. (2021) offer a detailed description of the variables and data used to build the four sub-indicators that form the DPE as well as the DPE computation method.	Global Entrepreneurship and Development Institute (GEDI) https://thegedi.org/ See Acs, et al. (2021) for details on the data, variables, and methodology employed to construct the DPE.

Table 8.5 Data

	Country	*IntUsers*	*DiffRank*	*normDiffRank*	*VarIntUsers*	*BW*	*BS*	*TotPop*	*GDPcap*	*Trade*	*OECD*
1	Albania	1.96	–2	0.4907	0.1951	10.9849	14.8171	1.0580	9.3825	71.80	0
2	Algeria	24.76	2	0.5093	0.6311	10.3355	14.9534	3.6821	9.3671	59.70	0
3	Argentina	33.39	–3	0.4860	0.1376	10.4676	23.3602	3.7643	10.0831	22.49	0
4	Armenia	1.97	–3	0.4860	0.1387	11.1325	16.5595	1.0735	9.3344	71.68	0
5	Australia	21.95	–2	0.4907	0.0899	10.2282	33.9045	3.1704	10.7714	41.49	1
6	Austria	7.79	–7	0.4673	0.0745	10.8081	33.8471	2.1567	10.8742	102.43	1
7	Azerbaijan	8.13	–2	0.4907	0.0942	10.4657	25.5647	2.2669	9.6060	72.60	0
8	Bahrain	1.64	–3	0.4860	0.2813	11.3923	19.7321	0.3162	10.7813	154.93	0
9	Bangladesh	21.03	3	0.5140	0.6214	9.6525	37.7272	5.0515	8.2161	42.09	0
10	Belgium	10.37	–1	0.4953	0.0813	11.6759	42.9767	2.4225	10.8087	154.19	1
11	Benin	3.42	19	0.5888	1.6739	7.5297	6.1549	2.3586	7.9882	56.76	0
12	Bosnia and Herzegovina	2.31	–2	0.4907	0.2833	11.1854	35.2019	1.2324	9.4439	89.34	0
13	Botswana	1.41	1	0.5047	0.7748	9.0036	4.6564	0.7517	9.7240	105.93	0
14	Brazil	155.99	0	0.5000	0.3080	10.0638	21.3664	5.3204	9.6197	26.95	0
15	Bulgaria	4.74	–3	0.4860	0.1646	11.9281	39.7007	1.9710	9.8843	126.98	0
16	Cambodia	5.90	15	0.5701	1.0947	9.8506	2.9888	2.7422	8.1737	127.86	0
17	Cameroon	8.67	18	0.5841	1.0552	7.4457	0.4796	3.1484	8.1486	49.87	0
18	Canada	36.28	–3	0.4860	0.1292	11.0298	40.8164	3.5752	10.7692	66.16	1
19	Chile	15.60	–1	0.4953	0.1329	11.5958	19.7492	2.8887	10.1040	58.97	1
20	China	902.49	0	0.5000	0.3085	8.7805	40.1677	7.2235	9.4487	39.46	0
21	Colombia	32.72	–2	0.4907	0.2315	11.6036	20.7998	3.8612	9.5536	38.36	1
22	Costa Rica	4.10	0	0.5000	0.4138	11.062	19.2827	1.5785	9.8254	60.75	1
23	Croatia	3.21	–7	0.4673	0.0918	10.9562	33.5903	1.4359	10.1090	92.54	0
24	Cyprus	1.03	–2	0.4907	0.2410	10.9311	31.304	0.1493	10.1334	137.59	0
25	Czech Republic	8.63	–4	0.4813	0.0815	10.9348	36.9248	2.3558	10.4959	155.18	1

(*continued*)

Table 8.5 (continued)

	Country	*IntUsers*	*DiffRank*	*normDiffRank*	*VarIntUsers*	*BW*	*BS*	*TotPop*	*GDPcap*	*Trade*	*OECD*
26	Denmark	5.70	–6	0.4720	0.0420	11.1855	43.9268	1.7376	10.8760	104.05	1
27	Dominican Republic	8.14	6	0.5280	0.4314	10.3254	12.3084	2.3304	9.6375	52.17	0
28	Ecuador	9.39	1	0.5047	0.1841	10.6863	18.749	2.7858	9.3840	45.24	0
29	Egypt	9.39	1	0.5047	0.1841	9.1946	18.749	2.7858	9.3840	45.24	0
30	El Salvador	3.26	10	0.5467	0.8876	11.0542	20.8224	1.8445	9.0049	76.56	0
31	Estonia	1.20	–2	0.4907	0.0345	11.5771	33.5591	0.2741	10.3440	150.94	1
32	Finland	4.95	–7	0.4673	0.0443	11.1959	36.5302	1.7010	10.7144	71.38	1
33	France	56.05	–4	0.4813	0.0798	10.7734	51.7552	4.1979	10.6770	61.75	1
34	Georgia	2.56	1	0.5047	0.4463	11.5428	35.8694	1.3151	9.4419	98.77	0
35	Germany	73.23	–2	0.4907	0.0235	10.659	42.918	4.4029	10.8405	86.25	1
36	Greece	8.11	0	0.5000	0.1217	11.2593	47.5521	2.3815	10.2488	65.37	1
37	Guatemala	7.37	5	0.5234	0.6451	10.0527	10.2545	2.7452	9.0022	49.89	0
38	Honduras	3.13	–5	0.4766	0.2672	9.7102	7.9924	2.2097	8.5723	107.26	0
39	Hungary	7.85	–2	0.4907	0.0948	10.8445	37.9236	2.2868	10.2219	167.24	1
40	Iceland	0.36	0	0.5000	0.1250	12.8541	38.3045	–1.1062	10.8520	95.82	1
41	India	560.23	1	0.5047	1.7599	9.1879	8.6791	7.1779	8.6065	41.92	0
42	Indonesia	129.06	5	0.5234	1.2638	10.1888	6.9869	5.5544	9.2252	41.94	0
43	Iran	64.48	6	0.5280	0.8123	9.0325	18.5718	4.3630	9.4492	39.02	0
44	Ireland	4.29	–5	0.4766	0.0916	11.2377	33.3547	1.5480	11.1783	215.16	1
45	Israel	7.86	1	0.5047	0.2130	10.9168	33.5227	2.1259	10.5352	59.83	1
46	Italy	45.45	0	0.5000	0.2872	10.2539	42.1984	4.1064	10.6028	56.42	1
47	Jamaica	2.01	4	0.5187	0.6475	10.4816	18.7519	1.0616	9.1560	76.12	0
48	Japan	117.09	–2	0.4907	0.0114	9.9809	33.5768	4.8453	10.5936	35.43	1
49	Jordan	6.75	–3	0.4860	0.2118	9.9178	5.5601	2.2264	9.2248	95.36	0
50	Kazakhstan	15.16	1	0.5047	0.2196	11.1324	18.5183	2.8646	10.0978	53.05	0
51	Kenya	11.86	5	0.5234	0.4937	11.5862	1.7012	3.8687	8.2493	44.18	0
52	Korea, Rep.	49.72	–4	0.4813	0.0842	10.7315	43.6637	3.9321	10.5669	79.13	1

53	Kuwait	4.19	−1	0.4953	0.4013	11.0589	1.8384	1.3443	10.9121	98.70	0
54	Latvia	1.65	−3	0.4860	0.0510	11.6419	32.1478	0.6818	10.1895	122.28	1
55	Lithuania	2.28	−7	0.4673	0.1004	11.8645	40.1886	1.0664	10.3336	138.55	1
56	Luxembourg	0.60	0	0.5000	0.0909	15.7553	35.576	−0.5628	11.6123	408.36	1
57	Macedonia	0.55	0	0.5000	0.1702	11.5959	36.372	−0.5073	9.6207	113.70	0
58	Malaysia	26.90	−1	0.4953	0.2506	10.4501	14.2424	3.4102	10.1181	131.37	0
59	Mali	5.11	22	0.6028	1.9389	7.4506	0.1942	2.8587	7.6684	63.64	0
60	Malta	0.43	0	0.5000	0.2447	12.6724	48.2766	−0.8095	10.5871	299.47	0
61	Mauritius	0.78	−1	0.4953	0.2381	10.4264	31.1818	0.2332	9.8983	105.01	0
62	Mexico	89.39	0	0.5000	0.2774	10.3287	21.0871	4.8029	9.8662	71.09	1
63	Moldova	2.03	−5	0.4766	0.0357	11.6856	27.3231	1.0419	9.2458	89.33	0
64	Mongolia	1.65	4	0.5187	1.1227	10.0094	30.8379	1.0981	9.3077	90.29	0
65	Montenegro	0.46	0	0.5000	0.0952	11.4721	26.5197	−0.4745	9.8127	102.69	0
66	Morocco	27.13	2	0.5093	0.3709	9.7949	5.7997	3.5457	8.8867	77.20	0
67	Namibia	1.01	1	0.5047	0.7019	8.8181	11.8403	0.8394	9.2626	97.24	0
68	Netherlands	16.18	−3	0.4860	0.0412	11.6029	45.2381	2.8297	10.8776	157.82	1
69	New Zealand	4.52	−3	0.4860	0.1106	11.0568	35.6789	1.5281	10.6234	54.82	1
70	Nigeria	67.52	4	0.5187	0.5114	7.0068	0.2156	5.1993	8.6152	21.33	0
71	Norway	5.24	−5	0.4766	0.0438	11.2211	40.8205	1.6465	11.0507	69.86	1
72	Oman	4.49	0	0.5000	0.4299	10.9812	7.4331	1.4510	10.3140	91.32	0
73	Pakistan	36.97	6	0.5280	0.6651	9.8191	8.1743	5.2954	8.3613	27.65	0
74	Panama	2.70	−2	0.4907	0.3300	11.0507	15.5588	1.3784	10.2555	99.94	0
75	Paraguay	4.83	1	0.5047	0.4505	9.7304	6.4695	1.9004	9.3785	66.94	0
76	Peru	19.49	3	0.5140	0.5655	10.3749	16.0624	3.4168	9.4018	45.16	0
77	Philippines	50.69	−4	0.4813	0.1032	11.6869	6.3111	4.6261	8.8956	59.14	0
78	Poland	30.54	−3	0.4860	0.1823	10.0519	28.1287	3.6372	10.2327	95.43	1
79	Portugal	7.75	−4	0.4813	0.0900	10.7743	44.1999	2.3378	10.3456	80.49	1
80	Qatar	2.82	−6	0.4720	0.1849	11.0908	9.9773	0.9422	11.4717	93.71	0
81	Romania	14.27	1	0.5047	0.2914	10.7244	38.572	2.9865	10.0807	83.59	0

(continued)

Table 8.5 (continued)

	Country	*IntUsers*	*DiffRank*	*normDiffRank*	*VarIntUsers*	*BW*	*BS*	*TotPop*	*GDPcap*	*Trade*	*OECD*
82	Russia	119.34	0	0.5000	0.1815	10.2239	26.6125	4.9705	10.1619	49.36	0
83	Rwanda	3.28	4	0.5187	0.5000	8.7304	1.0323	2.4309	7.5439	45.23	0
84	Saudi Arabia	32.80	1	0.5047	0.4855	11.3336	28.6928	3.4569	10.7980	71.12	0
85	Senegal	6.44	11	0.5514	1.0280	8.9947	3.1803	2.6795	7.9951	58.11	0
86	Serbia	5.38	–2	0.4907	0.1620	10.1439	28.487	1.9594	9.6536	97.40	0
87	Singapore	5.07	–3	0.4860	0.1602	13.5535	33.983	1.7111	11.3979	329.47	0
88	Slovakia	4.52	–6	0.4720	0.0736	10.632	30.2514	1.6908	10.2643	180.95	1
89	Slovenia	1.74	–1	0.4953	0.1523	11.5682	37.7235	0.7244	10.4282	146.30	1
90	South Africa	39.94	1	0.5047	0.3787	9.6357	4.901	4.0143	9.4603	61.62	0
91	Spain	42.76	–3	0.4860	0.1699	10.0257	37.0559	3.8383	10.5288	64.21	1
92	Sri Lanka	6.32	17	0.5794	1.4882	10.6094	24.6679	3.0431	9.3835	49.56	0
93	Sweden	9.71	–1	0.4953	0.0935	11.0004	39.3762	2.2823	10.8382	83.72	1
94	Switzerland	7.99	–2	0.4907	0.1021	11.1985	51.0749	2.1141	11.0922	113.12	1
95	Tanzania	11.60	18	0.5841	1.2624	7.7114	2.0589	3.9412	7.7343	40.76	0
96	Thailand	46.41	5	0.5234	0.7176	10.8962	23.0568	4.2300	9.6979	124.84	0
97	Tunisia	7.80	3	0.5140	0.5000	10.2633	11.0408	2.4141	9.2601	91.01	0
98	Turkey	61.72	1	0.5047	0.4622	10.9622	22.5197	4.3635	10.1643	51.09	0
99	Uganda	3.21	–7	0.4673	0.1494	7.2442	0.5348	3.6435	7.6276	37.85	0
100	Ukraine	31.13	0	0.5000	0.4105	11.1899	22.5557	3.8101	9.2745	107.81	0
101	United Arab Emirates	9.69	–1	0.4953	0.1763	12.1504	14.7257	2.2260	11.0855	175.22	0
102	United Kingdom	61.83	–4	0.4813	0.0320	12.8024	41.1689	4.1762	10.7109	56.00	1
103	United States	293.63	–1	0.4953	0.2280	11.5161	42.7443	5.7706	10.9763	27.76	1
104	Uruguay	2.89	–4	0.4813	0.3036	11.206	40.8927	1.2273	9.9419	45.33	0
105	Vietnam	66.23	5	0.5234	0.5882	10.6024	18.3615	4.5291	8.7700	178.77	0
106	Zambia	3.39	3	0.5140	0.6166	6.3969	1.1075	2.7650	8.1443	79.87	0
107	Zimbabwe	3.68	–5	0.4766	0.1720	8.5169	5.2195	2.6257	7.9924	56.75	0

Table 8.6 Digital platform economy (DPE): Data for the DPE and its sub-indicators

	Country	DPE	Multisided platforms	Technology entrepreneurs	Digital infrastructures	Digital user citizenship
1	Albania	20.52	21.47	19.09	21.35	20.15
2	Algeria	12.47	10.31	15.56	11.13	12.89
3	Argentina	30.35	28.44	27.99	31.81	33.15
4	Armenia	25.00	25.40	30.80	24.35	19.44
5	Australia	69.28	69.24	56.89	73.74	77.27
6	Austria	56.99	50.02	56.57	63.74	57.61
7	Azerbaijan	23.91	17.14	26.14	25.28	27.05
8	Bahrain	27.63	33.33	30.40	34.18	12.59
9	Bangladesh	11.18	10.87	13.78	10.44	9.64
10	Belgium	62.48	64.85	59.49	65.79	59.77
11	Benin	9.54	9.47	10.48	5.02	13.17
12	Bosnia and Herzegovina	21.50	21.31	16.62	29.41	18.66
13	Botswana	19.44	15.85	18.39	21.65	21.86
14	Brazil	31.24	36.35	31.17	29.51	27.94
15	Bulgaria	35.01	34.75	34.84	36.85	33.60
16	Cambodia	9.81	10.42	12.17	5.45	11.20
17	Cameroon	10.82	9.52	10.13	8.34	15.29
18	Canada	78.17	78.83	77.13	75.37	81.34
19	Chile	38.38	41.30	36.85	36.70	38.66
20	China	28.05	29.88	34.80	19.15	28.38
21	Colombia	28.01	26.00	27.05	31.50	27.47
22	Costa Rica	34.25	30.67	35.03	35.28	36.02
23	Croatia	34.73	33.94	28.96	41.38	34.66
24	Cyprus	44.26	43.48	46.35	50.12	37.09
25	Czech Republic	48.86	45.82	43.12	51.64	54.87
26	Denmark	71.05	73.30	64.32	78.20	68.39

(*continued*)

Table 8.6 (continued)

	Country	DPE	Multisided platforms	Technology entrepreneurs	Digital infrastructures	Digital user citizenship
27	Dominican Republic	19.41	16.11	15.99	30.94	14.61
28	Ecuador	21.30	18.66	20.02	22.22	24.30
29	Egypt	19.50	16.94	23.12	20.37	17.58
30	El Salvador	16.43	17.41	16.76	15.46	16.09
31	Estonia	59.91	57.42	55.12	63.10	64.01
32	Finland	68.87	67.09	66.05	71.50	70.86
33	France	63.51	60.26	65.34	63.52	64.94
34	Georgia	26.43	25.15	22.16	26.22	32.18
35	Germany	64.32	56.26	63.10	67.61	70.30
36	Greece	35.93	31.73	38.84	37.71	35.44
37	Guatemala	14.70	15.02	16.68	10.66	16.44
38	Honduras	13.73	13.92	15.16	10.84	15.01
39	Hungary	38.34	37.98	37.75	41.77	35.87
40	Iceland	62.57	65.56	65.34	70.66	48.74
41	India	23.81	20.76	31.66	19.76	23.06
42	Indonesia	23.20	24.74	29.62	18.56	19.88
43	Iran	19.52	28.79	22.10	10.63	16.54
44	Ireland	65.99	65.29	69.49	66.00	63.20
45	Israel	56.13	66.88	60.89	48.24	48.52
46	Italy	46.09	46.07	47.30	40.74	50.26
47	Jamaica	19.71	22.40	17.51	18.24	20.71
48	Japan	56.78	44.20	53.74	60.99	68.18
49	Jordan	25.11	23.72	31.52	22.73	22.47
50	Kazakhstan	23.53	20.18	21.42	28.25	24.27
51	Kenya	17.45	16.57	19.76	16.01	17.45
52	Korea, Rep.	56.30	59.51	53.18	57.90	54.59
53	Kuwait	21.73	27.82	25.55	19.63	13.92

54	Latvia	42.79	44.60	37.95	46.67	41.95
55	Lithuania	44.26	46.20	38.31	47.07	45.47
56	Luxembourg	65.55	60.25	62.88	73.59	65.48
57	Macedonia	24.52	31.21	17.32	26.73	22.81
58	Malaysia	42.01	44.03	40.45	42.02	41.55
59	Mali	10.22	5.83	13.84	6.45	14.76
60	Malta	53.25	59.34	55.07	55.28	43.29
61	Mauritius	31.86	28.51	29.56	35.93	33.44
62	Mexico	29.36	26.32	28.06	31.51	31.53
63	Moldova	24.34	20.95	22.05	26.83	27.53
64	Mongolia	17.28	21.87	19.85	7.54	19.86
65	Montenegro	28.40	26.69	31.75	28.56	26.58
66	Morocco	24.34	25.63	19.95	29.97	21.80
67	Namibia	17.46	19.48	20.29	6.25	23.82
68	Netherlands	82.19	86.26	78.65	89.49	74.35
69	New Zealand	65.15	70.31	54.86	69.43	66.00
70	Nigeria	13.67	11.97	18.46	11.63	12.62
71	Norway	74.13	73.46	63.68	84.40	74.98
72	Oman	28.73	29.25	20.53	33.33	31.80
73	Pakistan	13.97	13.32	17.45	12.82	12.28
74	Panama	27.93	23.68	30.19	29.55	28.28
75	Paraguay	15.61	13.33	16.44	15.02	17.66
76	Peru	23.60	20.37	25.30	24.28	24.46
77	Philippines	24.35	24.83	27.33	22.49	22.75
78	Poland	40.48	40.58	36.58	42.44	42.33
79	Portugal	50.70	50.45	50.72	50.99	50.65
80	Qatar	40.64	46.85	36.98	42.31	36.42
81	Romania	32.89	29.83	30.65	35.37	35.70
82	Russia	32.57	37.94	36.28	24.82	31.26

(continued)

Table 8.6 (continued)

	Country	DPE	Multisided platforms	Technology entrepreneurs	Digital infrastructures	Digital user citizenship
83	Rwanda	11.85	7.62	18.96	7.34	13.49
84	Saudi Arabia	29.23	30.91	35.13	28.13	22.76
85	Senegal	14.27	9.70	14.72	13.79	18.89
86	Serbia	27.47	28.78	24.67	27.74	28.70
87	Singapore	55.61	58.48	61.16	55.13	47.66
88	Slovakia	40.39	38.76	35.31	43.51	43.98
89	Slovenia	45.00	42.72	42.26	49.19	45.84
90	South Africa	26.41	25.29	28.11	28.53	23.71
91	Spain	53.32	52.50	53.73	53.97	53.06
92	Sri Lanka	18.23	23.35	23.72	9.13	16.72
93	Sweden	76.59	79.47	74.32	78.32	74.24
94	Switzerland	76.08	69.35	84.84	75.50	74.63
95	Tanzania	9.78	9.53	9.46	7.24	12.88
96	Thailand	27.18	32.16	29.19	22.09	25.28
97	Tunisia	21.05	20.17	22.63	19.24	22.15
98	Turkey	32.20	35.40	32.67	33.22	27.50
99	Uganda	11.01	8.30	16.89	7.32	11.52
100	Ukraine	29.24	30.31	36.60	23.10	26.93
101	United Arab Emirates	43.05	50.52	45.18	43.15	33.35
102	United Kingdom	82.41	84.77	81.27	80.11	83.51
103	United States	84.84	87.41	92.22	80.73	79.00
104	Uruguay	36.21	32.36	30.70	29.84	51.94
105	Vietnam	20.32	29.81	21.18	12.29	18.00
106	Zambia	13.39	10.97	14.03	12.19	16.39
107	Zimbabwe	10.01	8.66	12.40	6.91	12.06

Table 8.7 Descriptive statistics for the study variables (N = 107 countries)

Variable (description in Table 8.2)	Mean	Standard deviation
Number of Internet users (million people) in 2019	36.03	106.79
Rank difference	0.38	5.60
Normalized rank difference	0.50	0.03
Bandwidth (bits/s) per Internet user in 2015 (ln)	10.56	1.34
Broadband subscriptions per Internet user in 2015 (%)	24.28	14.53
Total population (ln)	2.61	1.63
GDP per capita (ln)	9.79	0.96
Trade divided by GDP (%)	89.92	59.46
OECD (dummy)	0.35	0.48
Digital Platform Economy (DPE) index	35.33	20.13
Digital multisided platforms	35.36	20.62
Digital technology entrepreneurs	35.44	19.26
Digital infrastructures	35.50	22.17
Digital user citizenship	35.08	20.05

Table 8.8 Mean comparisons

	DPE	Multisided platforms	Technology entrepreneurs	Infrastructures	User citizenship
Panel A: Descriptive statistics					
DiffRank < 0 (N = 54)	45.99	45.65	44.83	47.74	45.75
DiffRank > 0 (N = 53)	24.47	24.87	25.87	23.02	24.21
Overall (N = 107)	35.33	35.36	35.44	35.50	35.08
Panel B: Comparison tests					
t-test	6.522***	6.014***	5.829***	6.927***	6.568***
Mann-Whitney U test	5.717***	5.296***	5.268***	5.957***	5.439***
Kolmogorov-Smirnov test	0.572***	0.553***	0.493***	0.572***	0.571***

All results reported in the table are statistically significant at 0.001 (two-tailed p-value < 0.001)

Table 8.9 Regression results (OLS)

	Dependent variable: normalized difference in ranks (*normDiffRank*)		Dependent variable: variation (%) in the number of Internet users (*VarIntUsers*)	
	Model 1	Model 2	Model 3	Model 4
Digital platform economy (DPE) index	–0.0001 (0.79)		–0.0028 (1.25)	
Multisided platforms		0.0007* (2.10)		0.0079 (1.58)
Technology entrepreneurs		–0.00001 (0.03)		0.0036 (0.67)
Infrastructures		–0.0007 (1.76)		–0.0170** (3.00)
User citizenship		–0.00004 (0.13)		0.0026 (0.72)
Total population in 2015 (ln)	0.0013 (1.24)	0.0005 (0.40)	0.0382 (1.52)	0.0177 (0.65)
GDP per capita in 2015 (ln)	–0.0143* (2.49)	–0.0142* (2.49)	–0.1808* (2.35)	–0.1640* (2.17)
Trade in 2015 (%)	0.0040 (1.21)	0.0033 (0.83)	0.0572 (1.55)	0.0467 (1.04)
OECD dummy	–0.0008 (0.19)	0.0024 (0.54)	–0.0824 (1.53)	–0.0326 (0.58)
Constant	0.6397*** (11.92)	0.6411*** (11.93)	2.1176** (3.00)	2.0022** (2.88)
F test	9.89***	6.73***	16.64***	12.23***
Adjusted R2	0.3368	0.3453	0.4005	0.4308
RMSE	0.0213	0.0212	0.3026	0.2949
VIF (min-max)	2.98 (1.42–5.54)	10.83 (1.64–21.79)	2.98 (1.42–5.54)	10.83 (1.64–21.79)
Observations	107	107	107	107

Full details on the construction of the dependent variable (*normDiffRank*) as well as the set of independent variables are presented in Appendix 2 (Table 8.4). Notice that the digital platform economy index (DPE) and its sub-indicators are not included in the OLS models due to collinearity issues (i.e., the digital technology variables are included in the construction of the DPE) (see Acs et al. (2021) for a detailed description of the DPE). Absolute *t*-statistics based on robust (heteroskedastic) standard errors clustered by country are presented in parentheses

* = *p*-value < 0.05, ** = *p*-value < 0.01, and *** = *p*-value < 0.001 (two-tailed)

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9

A Tale of Two Cities: How Arlington Won and Baltimore Lost in Battle for Amazon's HQ2

Abraham Song and Keith Waters

1 Amazon HQ2 Race

The 2017 Amazon announced its plans to build a second headquarters in North America by investing $5 billion and creating 50,000 high-paying jobs. The announcement was met with great enthusiasm by 238 city and state government officials, who submitted competitive bids. Amazon's public search drew a lot of attention and was politically controversial. Some economic developers saw it as a once-in-a-generation opportunity, while others criticized the trillion-dollar company for pitting resource-strapped states against each other for subsidies. When Top 20 finalists

A. Song (✉)
Graduate School of Education and Psychology, Pepperdine University, Los Angeles, CA, USA
e-mail: abraham.song@pepperdine.edu

K. Waters
School of Complex Adaptive Systems, Arizona State University, Tempe, AZ, USA
e-mail: keith.waters@asu.edu

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were announced, the search process drew even more criticism for selecting on major metropolitan cities and leaving out mid-tier cities, especially in the heartland of America and many industrial cities like Cleveland, Detroit, and St. Louis. Eventually, Amazon split the HQ between Arlington, Virginia, and Long Island, New York. But because of a backlash by civil activists in Long Island, Amazon had to settle on just Arlington.

Amazon HQ2 search process offers a valuable case study to better understanding what economic development should and should not look like in the twenty first century. Because of its highly publicized nature, a lot of data and information is documented; numerous studies and analyses are useful for understanding the evolution in firm strategy (from the firm's perspective) and place-based policy (from the policymakers' perspective).

The old model of economic development that emphasized branding, marketing, and business attraction needs to be drastically reimagined to better reflect the changing economic landscape and the market needs. The old model of economic development was based on the industrial age and optimizes on cost minimization. In today's knowledge economy, however, business attraction is becoming increasingly costly and tax incentives difficult to justify. At one point in time, place-based policies were synonymous to "smokestack chasing." Generous tax subsidies targeted manufacturing plants because they generated many jobs (also middle-class jobs under unions) at once like no other business. However, over the years, the manufacturing sector has become leaner and does not create as many jobs or the high-paying jobs. Tax incentives chasing distribution centers and data centers are becoming increasingly difficult to justify on cost basis (Greenstein & Fang, 2020).

Amazon HQ2 race, however, demonstrated that many city and local governments still base their economic development strategies on the old model. Maryland, for example, offered as much as $8 billion in tax and other incentives. The winning state, Virginia, offered just a fraction of that, about $1 billion, but more importantly the package differed qualitatively. Virginia's winning bid put talent pipeline at its front and center. This bid offers to economic developers a new model of economic development that moves away from the industrial age thinking and adapts to digital age.

The US economy is principally a network of some 400 metropolitan economies. Each metropolitan economy is organized around unique set of industry specializations and regional comparative advantages. While national policies and regulatory frameworks set conditions for economic growth and access to opportunity, it is ultimately up to the state and local actors and institutions to address the unique market failures and economic opportunities.

One lesson that ought to be learned from the Amazon HQ2 competition is that the innovation sectors prize the ability to produce talent workforce. Highly educated workforce is today's most valuable resource. Enrico Moretti, Economics professor at UC Berkeley, argues that "In the twentieth century, competition was about accumulating physical capital. Today it is about attracting the best human capital."

The goal of economic development should be to put a region on a path to a higher growth by improving the productivity of firms and people in a manner that increases the region's prosperity (Liu, 2016). This approach prioritizes the innovation, skills, infrastructure of existing industries over business attraction from other localities and departs from inefficient tax giveaways (Bartik, 2019).

The structural changes to the economy are reflected in the list of most valuable US companies.[1] In 1917 and for the majority of the twentieth century, the most valuable companies were large industrial firms like US Steel, American Telephone & Telegraph, Standard Oil of N.J., Bethlehem Steel., and Armour & Co. In 2017, the most valuable companies were technology firms like Apple, Alphabet, Microsoft, Amazon, and Facebook. These are digital platform businesses whose primary asset is the knowledge workers (Acs et al., 2021).

Today, the best and the brightest college and graduate school degree holders are not evenly distributed across the country. Rather, they are clustered in a few major metropolitan areas like San Francisco, San Diego, New York City, and Boston. Over the past decade or two, the clustering of this knowledge workers has only accelerated. Today, there's just a handful of cities boast high-tech industries and an agglomeration of talent. The reason for this phenomenon is widely documented in empirical evidence; there are significant advantages and benefits to agglomeration effects. Knowledge is the density of people and talent. Innovative ideas and technological breakthroughs occur through knowledge recombinations and spreads through knowledge spillovers. Locating in these "Brain hubs" dramatically increases the human capacity for innovation and, hence, wealth creation. For this reason, both employers and employees, small and large firms, concentrate to "Brain hubs." Even though the cost of doing business in these metros is higher than in other locations, employers are willing to pay premium to access talented workforce.

In the United States, there is a persistent labor shortage; every state suffers from an under supply of talent. A large part of the problem is that technological advancements are occurring at a faster pace than the education system is able to adapt. Today, 90% of occupations in the United States have rapidly digitalized and over two-thirds of the jobs require some kind of interaction with computers. There is a need for retooling and reskilling of existing workforces because technology is evolving so quickly. Many employers, like Google, are offering employee apprenticeship programs to address labor shortages. Many non-traditional educational systems, such as coding academies, are making their way into the marketplace, but these programs are not scalable. Traditional providers need make sure that their curriculums and programs provide the training and education that fill the skills gaps of the market.

It is time for economic development policies to adapt to the dynamics of the knowledge economy. The policy emphasis should be put on talent pipeline and devise long-term strategies on for developing human capital as a homegrown asset. This emphasis on talent workforce extends beyond merely STEM workforce with bachelor's degrees. It is about revamping the K-14 education system and building a robust industry-university partnership that generates knowledge spillovers. It is about building a sustainable transit hub with emphasis on walkability and diversity—the type of places where talent workforces want to live and work.

2 A Tale of Two Cities: The Story

The New York Times identified top 25 candidate cities that met Amazon's selection criteria, and picked Denver over Boston and Washington, D.C. for its lifestyle and affordability, supply of tech talent, and a startup scene.[2] In fact, the article emphasized the already growing presence of big tech companies, including I.B.M, Google, Twitter, and that Amazon would benefit as well.

Moody's Analytics applied data analytics to the criteria and determined that Austin, Texas, was the best candidate for the HQ2, closely followed by Atlanta and Philadelphia (See Table 9.1).[3] Around the same time, but more privately, Apple's corporate expansion plans were also under way. Incidentally, Apple picked Austin, Texas to build their new $1 billion campus.

When the top 20 finalists were announced, three of them were located in the Washington metropolitan area, namely, the District of Columbia; Montgomery County, Maryland; and, Northern Virginia. Maryland's initial bid was centered on Baltimore, Maryland, a logistical and transportation hub of the mid-Atlantic coast. The decision to front Baltimore was telling about its policymakers' stubborn attachment to the old model of economic development. If Amazon was to choose the HQ2 based on tax incentives, Maryland outbid everyone else. However, Amazon showed little interest in the Baltimore site (Port Covington and Old Goucher), but showed interest in Montgomery County (White Flint).[4] So was the state's bid quickly pivoted to White Flint in Montgomery County, but the strategy remained unchanged. Compete on the cost basis. Maryland's nearly $8.5 billion in tax incentives, the largest of its kind in the nation, was an audacious attempt to outcompete others.

Northern Virginia charted a different course in pursuing Amazon HQ2. Virginia's state-and-local team architected a novel, talent pipeline-based proposal.[5] Stephen Moret, President and CEO of the Virginia Economic Development Partnership, recognized this early on in regard to Amazon's HQ2 location: "If they make this decision on costs or on incentives, we're dead."[6] Despite the many advantages of a dense

Table 9.1 Analysis of cities by five major categories based on Amazon HQ2 criteria

Metro	Population (thousand)	Business Environment	Human Capital	Cost	Quality of Life	Transportation	Geography	Average Score	Rank
Austin-Round Rock, TX	2056	4.6	3.3	1.9	3.5	2.2	2.2	3.08	1
Atlanta-Sandy Springs-Roswell, GA	5790	3.6	4.3	3.3	2.5	1.7	2.7	3.08	2
Philadelphia, PA	2131	3.1	4.1	3.1	2.2	2.9	4.3	3.07	3
Rochester, NY	1079	1.8	3.3	4.2	3.1	2.6	3.0	3.01	4
Pittsburgh, PA	2342	2.9	3.7	3.5	2.1	2.8	4.0	2.99	5
New York-Jersey City-White Plains, NY-NJ	14,399	3.3	4.5	0.6	3.8	2.7	3.7	2.97	6
Miami-Miami Beach-Kendall, FL	2713	3.6	3.2	2.4	3.2	2.2	3.0	2.94	7
Seattle-Bellevue-Everett, WA	2938	4.2	2.9	0.8	3.8	2.9	0.8	2.93	8
Portland-Vancouver-Hillsboro, OR-WA	2425	3.7	2.2	2.1	3.6	2.9	1.0	2.91	9
Boston, MA	1995	3.9	4.2	0.8	2.9	2.7	3.5	2.90	10
Washington-Arlington-Alexandria, DC-VA-MD-WV	4841	2.3	4.4	0.6	3.1	2.4	3.3	2.59	38
Baltimore-Columbia-Towson, MD	2799	2.5	3.8	1.3	2.5	2.1	3.7	2.42	47

Source: Moody's Analytics

Note: Five major categories are rated on an ordinal scale of 0 to 5 (0 being poor and 5 being good) public-transit or a business-friendly government, Virginia has disadvantages of high living or labor costs (see Table 9.1).

To craft the incentive package, Moret drew on the ideas of that Enrico Moretti, the economics professor at University of California at Berkeley, laid out in his book, *The New Geography of Jobs*. Innovation in the high-tech sector depends not only on the skilled workforce but an entire ecosystem (Li et al., 2022). For example, a biotech laboratory does not exist in isolation but takes advantage of agglomerative advantages in research centers, universities, and other complementary entities. For this reason, a select few cities have grown into high-tech hubs, attracting both companies and workforce. This realization helped Moret to put a tech talent pipeline as the centerpiece of Virginia's pitch to Amazon HQ2. Moret claimed that Virginia was the only place in the nation to put education centerpiece of the bid.

Moret's conviction about talent turned out to be exactly what Amazon was looking for. What matters most to regions seeking to build a high-tech economy is talent. HQ2 location decision was about talent, talent, talent.[7] Even Amazon's decision to split the HQ2 location between New York City and Washington metro area was telling of its motives. They chose nation's largest two labor markets with the deepest pool of tech workers (Table 9.2). In part, these rankings mirror city size, as New York City and Los Angeles metros are two of the largest in the United States. It is also unsurprising to find that San Francisco ranks high. The San Francisco Bay Area and the Silicon Valley is best captured by two metro areas (San Francisco and San Jose), who together account for about 287,000 tech workers. Remarkable is the abundance of tech talent in the Washington metro area. Washington metro's emergence as a tech talent hub was long in the works. Part of the credit goes to the expansion of the federal government and the series of policy choices made by its regional leaders, but also to the economic development community driven by the market forces.

In 1960, Baltimore's population hovered around 940,000, the sixth largest in the country. By 1980, after two decades later, with the industrial sector waning, the city's population was still 150,000 people larger than Washington. But since then, the fortunes have turned. Washington transformed into a major metropolitan center propelled by the growth of

Table 9.2 Tech Talent across major US metropolitan areas

Metro area	Tech workers	Ranking
New York, NY	320,694	1
Washington, D.C.	263,258	2
Los Angeles, CA	173,007	3
San Francisco, CA	169,232	4
Chicago, IL	160,051	5
Dallas-Fort Worth, TX	152,382	6
Seattle, WA	141,003	7
Boston, MA	126,706	8
Atlanta, GA	120,418	9
San Jose, CA	117,587	10
Philadelphia, PA	112,016	11
Houston, TX	91,899	12
Minneapolis-St. Paul, MN	88,400	13
Denver, CO	76,968	14
Baltimore, MD	74,247	15
Austin, TX	66,678	16
Phoenix, AZ	65,214	17
San Diego, CA	61,938	18
Detroit, MI	60,811	19
Miami, FL	59,220	20

Source: American Community Survey (2017)
Note: Tech workers are workers employed in computer and mathematical occupations. Shaded in yellow are two locations that ultimately won the race

the federal government, government contracting, lobbying, and homeland security spending. Washington's population grew precipitously from 570,000 in 2000 to over 700,000; Baltimore's population decline continued to below 600,000.

While Washington became home to a dozen Fortune 500 companies, Baltimore was left with zero following a series of mergers and departures. Baltimore's economic development policies still reflect the industrial era; its tax incentives target the manufacturing, trade, and transport sectors (see Table 9.3). In 2015, Baltimore offered $45 million to Amazon to build a distribution center. It offered another $7.1 million in Cecil County/North East in 2017 and $16.2 million in Dunalk in 2018. In 2017, Baltimore participated in the Amazon HQ2 race but did not even make to the Top 20 finalist. The city had lost its competitiveness on talent

Table 9.3 Tax subsidies granted to Amazon in Virginia and Maryland

Subsidy year	City and/or county	State	Subsidy amount	Activity
2020	Chesapeake	Virginia	$250,000 state grant and undisclosed subsidies from the Port of Virginia	Distribution center
2020	Suffolk	Virginia	$500,000 state grant and undisclosed subsidies from the Port of Virginia	Distribution center
2019	Arlington County	Virginia	$51,000,000 (local subsidy only; TOT grant and TIF estimates)	Offices (HQ2)
2018	Dundalk	Maryland	$16,200,000	Distribution center
2019	Arlington County	Virginia	$750,000,000 (state subsidy only)	Offices (HQ2)
2017	Cecil County/ North East	Maryland	$7,100,000	Distribution center
2017	Clear Brook	Virginia	Secret	Distribution center
2015	Baltimore	Maryland	$45,125,000	Distribution center
2015	Warrenton	Virginia	$2,700,000	Distribution center
2014	Not available	Virginia	$2,331,839	Distribution center
2014	Not available	Virginia	$863,460	Distribution center
2014	Not available	Virginia	$500,000	Distribution center
2012	Chesterfield County	Virginia	$1,000,000	Distribution center
2012	Dinwiddie County	Virginia	$2,500,000	Distribution center
2012	Not available	Virginia	$850,000	Distribution center

Source: Good Jobs First, Subsidy Tracker

to other metro areas. As if to make a final blow, Amazon decided to locate to a nearby Arlington, Virginia, pledging to invest $2.5 billion and creating more than 250,000 high-salaried jobs in computer science and related fields.

Virginia also has offered Amazon subsides for distribution centers, but they are substantially smaller in amount because the Commonwealth's tax subsidies are not targeted to the industrial sector. Virginia's $550 million in tax breaks and $195 million transportation improvements also are several magnitudes smaller compared to other bids. Virginia's bulk of tax subsidies were geared for revamping the tech pipeline. Specifically, it allocated $1.1-billion into the Tech Talent Investment Program, pledging to double the number of bachelor's and master's degrees in computer science and related fields conferred each year in Virginia, as well as create a new Virginia Tech Innovation Campus. The proposal promised to increase tech education from kindergarten through 12th grade, expand university offerings to produce 17,500 new bachelor's degrees in computer science and related fields and a tech campus that would produce as many master's degrees.

There are several lessons to be learned from the Amazon HQ2 experience:

First, incentives are only a part of the story. In the knowledge economy, the use of tax subsidies should no longer focus on minimizing cost for firm relocations but rather on maximizing value for the region through public investments in infrastructure and human capital.

Tax subsidies, along with tax rates, are often viewed as state and local government's only policy lever of lowering costs for businesses. But corporate location decisions are rarely made solely on cost factors. If incentives were the sole driving factor, Amazon would have accepted the largest bid from Maryland ($8.5 billion). Low cost is certainly a factor, but in the knowledge economy, high priority is given to the qualitative environment. A select urban centers have become a magnet to skilled workforce and knowledge hubs. And, companies are willing to take price-premiums for access to talent and technology. Another important factor is risk minimization (e.g., budget, delivery schedule, ability to operate in short- and long-term horizon) from a location standpoint. Ideally, a company would pick a location of lowest cost, best quality, and lowest risk.

Second, incentives should be well targeted. If taxation is broad-based (applies uniformly to all firms), incentives are a narrow-base (applies only to eligible firms) fiscal policy for recipient firms. In theory, firm-specific incentives can attract marginal firms at lower cost than a corporate tax cut for all firms. Well-targeted incentives (e.g., pick the "right winners") may achieve the desired economic objectives of taxes at a fraction of the cost. However, poorly targeted incentives pose serious risks of creating unintended "disincentives" that can potentially distort the market competition and firm behavior. For example, incentives can complicate the tax system by narrowing the tax base or driving up tax rates for ineligible firms, and thereby distorting the market and failing to generate economic growth. But effective targeting of incentives has proven to be an elusive task. There are uncertainty problems (e.g., which firms are and which are not productive firms is difficult to predict) and information asymmetry problems (e.g., firms that opt into tax subsidies could always find ways to circumvent the legal provisions). Moreover, it may not be sound policy for every state and local government to chase after the tech sector; a region's economic development should leverage its comparative advantages. Because of these challenges, tax subsidies that prove to be most effective are those that are not necessarily firm-specific but a public investment in the talent pipeline and the infrastructure, such as customized job training subsidies and other forms of subsidies that directly invest in a regions' human capital.

3 A Tale of Two Cities: The Analysis

In this section, we use the Quarterly Census of Employment and Wages (QCEW) produced by the Bureau of Labor Statistics (BLS) to visualize and analyze how the tale of two cities diverged overtime. Over the last two decades, in part due to strategic planning and in part due to market forces, the regional comparative advantages of two metropolitan statistical areas (MSA), Washington metro and Baltimore metro areas, have changed dramatically. In general, there has been a nation-wide structural transformation within cities from predominantly manufacturing to predominantly services sector-based economies. Both Washington metro and Baltimore have been on this migration path, but one has outpaced the other. In the knowledge economy, winners take all. Whoever that is able to attract talent will attract technology firms; whoever is able to attract technology firms will attract talent. As with many issues viewed from a complexity perspective, the lead of winning regions often becomes entrenched. Here, the Washington metro emerged as a magnet for talent, which has created a virtuous cycle of innovation and economic growth entrenched over more than 20 years, while Baltimore has been unable to claim its competitive ground in the knowledge economy.

To measure the industrial structures of DC and Baltimore, we take a complexity perspective that envisions the economy as an ecology that is constantly changing and adapting through the network of interactions of parts of the economy (Arthur, 2021). Within regional economics, two main strands of complexity economics have developed, relatedness measures examine the correspondence between economic activity and location while complexity metrics use information on the geographic of economic activity to measure the sophistication of the activities (Hidalgo, 2021). Relatedness measures use the correspondence of economic activity, gained by location information, to build abstract "spaces" that describe the linkages between the activities. Spaces of economic activity that have been examined include technology and research space (Kogler et al., 2013; Boschma et al., 2015; Guevara et al., 2016), occupation space (Muneepeerakul et al., 2013; Shutters et al., 2015, 2016), and skills space (Alabdulkareem et al., 2018; Shutters & Waters, 2020).

Here we map the industry space by examining the colocation of specialized industries. We begin by calculating MSA level location quotient (LQ) for each industry.[8] Following Shutters and Waters (2020), the location quotient is defined as:

$$LQ_{i,m} = \frac{\left(e_{i,m} / \sum_i e_{i,m} \right)}{\left(\sum_m e_{i,m} / \sum_m \sum_i e_{i,m} \right)}, \tag{9.1}$$

where e is employment, i indexes the industry, and m indexes MSAs. LQs are the industry's share of regional employment over the industry's share of employment in all MSAs. Following Muneepeerakul et al. (2013), we then create a presence-absence matrix.

Industries are deemed present if $LQ_{i,m} \geq 1$ and absent if $LQ_{i,m} < 1$. We refer to present industries as *specialized industries*, as employment accounts for a higher proportion of total employment in the region of interest than in all regions collectively. The higher share of local employment, therefore, indicates a *revealed comparative advantage*. Having created the presence absence matrix, we again follow Muneepeerakul et al. (2013) and calculate a co-occurrence measure, x, between two industries i and j. Formally:

$$x_{i,j} = \frac{P\left[LQ_{i,m} \geq 1,\ LQ_{j,m} \geq 1\right]}{P\left[LQ_{i,m'} \geq 1\right]P\left[LQ_{j,m''} \geq 1\right]} - 1, \tag{9.2}$$

where m, m' and m'' are randomly selected MSAs. The numerator is the probability that two industries, i and j, both appear as specialized in randomly selected MSAs. The denominator is the probability that i and j would appear in the same MSA at random. Co-occurrence, $x_{i,j}$, measures how often industries are observed to appear specialized in the same cities compared to what would be expected at random given their independent occurrences. One is subtracted off to balance the measure around zero. Values of $x_{i,j}$ greater than zero indicate the two industries are specialized in the same MSAs more often than would be anticipated at random while values less than zero indicate that the two industries appear together less frequently than would be anticipated at random.

To make this more concrete, the top industry pairs are shown in Table 9.4. The two industries that co-occur in MSAs more frequently than any others are “Rail Transportation” (NAICS 4821) and “Tobacco

Table 9.4 Top three Industry Pairs by $x_{i,j}$

$x_{i,j}$ Rank	Industry 1	Industry 2	$x_{i,j}$
1	Rail Transportation (4821)	Tobacco Manufacturing (3122)	76.6
2	Leather and Hide Tanning and Finishing (3161)	Apparel Knitting Mills (3151)	63.7
3	Rail Transportation (4821)	Motor Vehicle Manufacturing (3361)	54.4

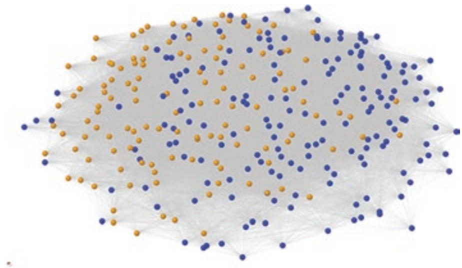


Fig. 9.1 Industry Louvain Communities, 2020. (Note: Nodes in the network are comprised of industries, while the edges connecting nodes are the co-occurrence values, *x*. The larger community (Blue) is comprised of a much larger share of industry in NAICS 31–33, 44, and 45, which we term the Manufacturing Trade, and Transport (MTT) community. The Service community is shown in gold. The Network is visualized in Pajek using the Kamada-Kawai layout)

Manufacturing" (NAICS 3122). Also appearing far more frequently together than would be expected at random are "Leather and Hide Tanning and Finishing" and "Apparel Knitting Mills" as well as "Rail Transportation" and "Motor Vehicle Manufacturing."

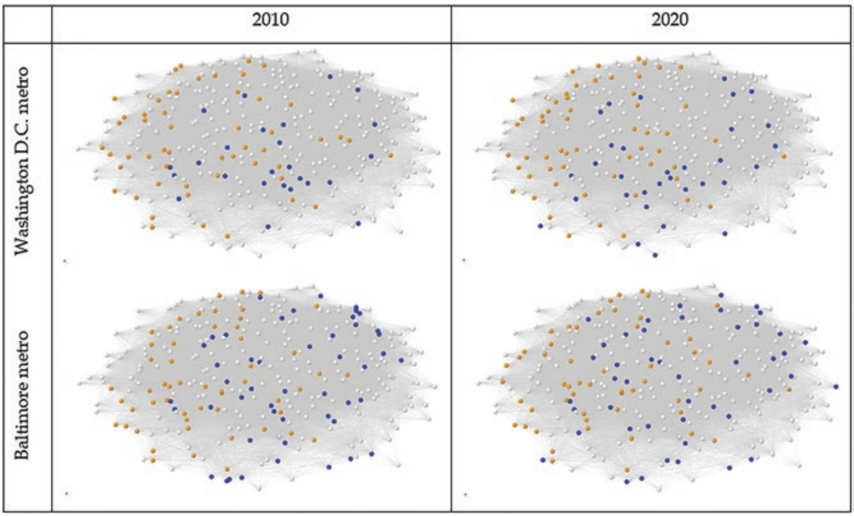
Finally, we create a network from the resulting $x_{i,j}$ values. In the network, nodes represent industries, and the edges represent the co-occurrence values, $x_{i,j}$. Edges in the network are non-directed and the nodes have no weights. The network is created and analyzed using the Python library NetworkX and visualized using the network software Pajek.

The national co-occurrence network (created using $LQ_{i,m} \geq 1$) is shown in Fig. 9.1.[9,10] Within this national network, the Louvain Community (LVC) detection algorithm is used to find communities.[11] The LVC algorithm works iteratively to optimize the density of connections within communities and minimize connections between communities. Using data between 1990 and 2020, we identify two communities.

- We call the first community the "Manufacturing, Trade, and Transportation" (MTT) with 2-Digit NAICS code of 31–33 (Manufacturing), 42 (Wholesale Trade), 44–45 (Retail Trade), and 48–49 (Transportation and Warehousing).[12] This is broadly a community of industrial sectors.[13]

- We call the second community the "Services" community, which is comprised primarily of the remainder of 2-digit NAICS codes.[14] In 2020, there were 126 4-digit industries in the Services community, of which 80 (63%) were in these 2-digit industrial codes. Example industries include Aquaculture (1125), Postal Service (4911), Satellite Telecommunications (5174), Securities and Commodity Exchanges (5232), Investigation and Security Services (5616), and Business Schools and Computer and Management Training (6114).

Finally, we locate Baltimore and DC withing the LVCs found in the national co-occurrence network by identifying which 2020 LVCs the respective MSAs specialty industries (LQ's > 1) fall in. That is, the specialized industries for DC and Baltimore for 2010 and 2020 are highlighted in the 2020 national co-occurrence network (Fig. 9.2).[15] We hold the co-occurrence network constant for 2020 to more clearly highlight shifts within the network.



Source: QCEW, 2010, 2020

Fig. 9.2 DC and Baltimore Locations in the National Industry Co-Location Network: 2010 and 2020

Table 9.5 Share of Specialty Industries by Louvain Communities: 2000 to 2020

Louvain Community	DC Specialty Industries			Baltimore Specialty Industries		
	2000	2010	2020	2000	2010	2020
Services	65% *(53)*	68% *(54)*	64% *(58)*	46% *(52)*	52% *(54)*	54% *(55)*
MTT	35% *(29)*	33% *(26)*	36% *(33)*	54% *(61)*	48% *(49)*	46% *(47)*
Total	100% *(82)*	100% *(80)*	100% *(91)*	100% *(113)*	100% *(103)*	100% *(102)*

Notes: Percentages may not equal 100% due to rounding. Number of specialty industries noted in italicized parentheses. Specialty industries for DC and Baltimore for each year are identified within the 2020 national co-occurrence network. NAICS changes are not cross-walked, with results in some industries from 2000 and 2010 being excluded. Holding the national co-occurrence network and subsequent LVCs constant is preferred over including all industries

Locating the specialty industries in the national co-occurrence network reveals that DC had a much stronger presence in the Services community from 2000 to 2020, while Baltimore only had a majority of specialty industries in the Services community beginning in 2010 (Table 9.5). DC had 64% of specialty industries in the Services community in 2020. While down only slightly from 2000 and 2010, DC increased the number of specialty industries in the Services community from 2000 to 2010 and again from 2010 to 2020. The decline in the share was driven by a large increase in the number of specialty industries in the MTT community. In comparison, while Baltimore increased its share of specialty industries in the services industry from 46% in 2000 to 52% in 2010 and 54% in 2020, the increased shares were primarily driven by declines in the number of specialty industries in the MTT community.

Overall, the DC MSA had a stronger presence in the Services community which only increased. Furthermore, the DC MSA increased the number of specialty industries in the MTT community from 2010. Meanwhile, Baltimore had a relatively flat number of specialty industries in the Service community and a declining number of specialty industries in the MTT community. The overall presence of DC in the service community and decline of Baltimore in the MTT highlight the strength of the DC MSA from 2000 to 2020, particularly with regard to white-collar activities sought after in the new service-focused economy.

4 Conclusion

Economic development strategies of the old, industrial era have become outdated and ineffective in today's knowledge economy dominated by technology firms. The key shift is from manufacturing to service, from cost minimization to value maximization paradigms. Amazon HQ2 race served as a great lesson for what technology firms value: talent. Virginia demonstrated a good understanding of this market need and its economic development strategy, reflected in its bid that prioritized the talent pipeline. Washington metro area is well-poised for continued innovativeness and economic prosperity because of its investments in homegrown assets, whether public infrastructure or the investments in human capital. Once, the federal government served as the anchor, creating a seedbed of knowledge and knowledge transfer that had rippling effect on the entrepreneurial and innovation ecosystem. With Amazon's arrival as well as the new Virginia Tech campus, the anchor shifts from government to the private sector. Amazon's presence will also serve to attract even more talent from outside as well as other corporations and workers. We have demonstrated using network analysis how the tale of two cities has played out.

Appendix

Table 9.6 Share of Specialty Industry-Pair Connections by Louvain Communities: 1990 to 2020

	DC			Baltimore		
Year	Within Service	Within MTT	MTT × Service	Within Service	Within MTT	MTT × Service
1990	38%	14%	48%	20%	30%	50%
2000	42%	12%	46%	21%	29%	50%
2010	46%	10%	44%	27%	22%	50%
2020	40%	13%	47%	29%	21%	50%

As an alternate examination of Table 9.4, Table 9.6 shows all pairs of industries that are both specialized in each MSA. For example, in 2020 the DC MSA specialized in NAICS 5413, Architectural, Engineering, and Related Services, (LQ = 1.93) and NAICS 5417, Scientific Research and Development Services, (LQ = 3.77), both industries are in the Service community. DC also specializes in NAICS 3271, Clay Product and Refractory Manufacturing, which is in the MTT community. Thus, there is one link within the Service community and two links between the Service and MTT community for these three NAICS. If one industry is specialized and the other is not, the pair is not included. In 2020, Baltimore and DC had 5151 and 4095 specialty pairs, respectively.[16]

Table 9.6 shows the portion of *within and between* community pairs. DC increased the share of within Service community pairs from 38% in 1990 to 46% in 2001, before slipping somewhat in 2020. Baltimore also increased the share of within Service community pairs, from 20% in 1990 to 29% in 2020. In 2000, DC had a 21 percentage point advantage over Baltimore. However, DC's advantage narrowed to 19 percentage points in 2010 and 12 percentage points in 2020.

Notes

1. https://www.visualcapitalist.com/most-valuable-companies-100-years/
2. https://www.nytimes.com/interactive/2017/09/09/upshot/where-should-amazon-new-headquarters-be.html
3. https://www.economy.com/economicview/analysis/298321/Where-Amazons-Next-Headquarters-Should-Go
4. http://www.natemjensen.com/wp-content/uploads/2018/02/baltimore-amazon-hq2-proposal.pdf
5. https://issuu.com/teamsubjectmatter/docs/nova_r1_proposal_full_doc_single_pa
6. https://www.washingtonian.com/2019/06/16/the-real-story-of-how-virginia-won-amazon-hq2/
7. https://www.brookings.edu/blog/the-avenue/2018/11/13/for-amazon-hq2-location-decision-was-about-talent-talent-talent/
8. We use employment data from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages. We use 4-digit NAICS codes. NAICS data are used unaltered. While NAICS updates the classifications on occasion, we do not control for changes. We use Metropolitan Statistical Areas as the geography of analysis, with no alterations to control for changes among years. Thus, each year is calculated independently.
9. Negative values are dropped as they indicate a repulsion between two industries.
10. Networks are visualized with the Kamada–Kawai algorithm that works to both minimize edge crossings and output evenly spaced nodes (Cheong & Si, 2016; De Nooy et al., 2018).
11. LVC communities have higher co-occurrence values between industries within the community than with industries outside the community. For the entire period analyzed (1990 to 2020), the same resolution parameter of 0.8 is used to find communities. This parameter was chosen to reveal 2 communities for the entire period.
12. Exceptions were the years 1995, 2001, 2004, 2005, and 2018. These years, the community with the highest share of MTT industries was identified as the MTT community.

13. In 2020, the larger community, which we refer to as MTT community, had 178 industries. Of the 178 total industries in the MTT community, 111 (62.4%) were accounted for by MTT industries
14. In the Service community, only 46 of the 126 industries (36.5%) were MTT. Despite the identification of two communities, community modularity, which ranges from 0 to 1, was just 0.12 in 2020. This indicates that the internal cohesion of the communities is relatively weak.
15. While the specialized industries of the two MSAs are located in different portions of the network, given the low modularity, the differing locations are subtle. While the two communities are found in all years, the definitions and $x_{i,j}$ values vary annually. It may be the case that if occupation or skills networks were used, the variation would be smaller, as such communities have been found to be more distinct (Alabdulkareem et al., 2018; Shutters & Waters, 2020).
16. This is the combination of all industry specialties.

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10

Measuring the Modern Entrepreneur: An Evaluation of Elon Musk

Camilla Bosanquet

1 Introduction

In his 400-page book on multibillionaire Elon Musk, biographer Ashlee Vance uses the word "entrepreneur" just 15 times. On only four of these occasions does Vance describe Musk as one. In *Time* Magazine's article covering Elon Musk as their 2021 Person of the Year, the then-CEO of Tesla, SpaceX, and Neuralink is not once referred to as an entrepreneur.[1] Elon Musk's official Tesla mini bio does not claim that he is an entrepreneur, favoring instead terms like "founder" and "leader."[2] Yet typing the Boolean search phrase "Elon Musk AND entrepreneur" into any search engine yields millions of results. Case in point, Google assures us that there are nearly, by its estimation, 21.6 million such results available across the World Wide Web.[3]

C. Bosanquet (✉)
Schar School of Policy and Government, George Mason University, Arlington, VA, USA
e-mail: cbosanqu@gmu.edu

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What is to be made of this? Ask the person on the street if Elon Musk is an entrepreneur and the response will most likely be in the affirmative. The editors and contributing authors over at *entrepreneur.com* routinely celebrate Musk as an entrepreneur.[4] But is this descriptor accurate? Does Elon Musk technically qualify to be characterized as an *entrepreneur*, per se?

This chapter qualitatively considers whether Elon Musk should be characterized as an entrepreneur. It does so by contemplating the qualities of an entrepreneur; the aggregation of such standards subsequently enables our evaluation of Musk. Further analysis compares Elon Musk with two of his predecessors, Henry Ford and Kiichiro Toyoda, while taking into account the histories of Tesla Motors, Ford Motor Company, and Toyota Motor Corporation. Several accusations against Elon Musk are also weighed, especially those which theoretically challenge the characterization of Musk as an innovator, founder, and entrepreneur.

The exercise of profiling entrepreneurs and determining whether Musk is one among them is neither a philosophical nor an esoteric one. Creative, productive, innovative entrepreneurs are important to society. They matter because their contributions have the potential to benefit individuals, communities, societies, and the world. Entrepreneurial successes can improve the economy and boost the health and well-being of those residing within the localities, countries, and regions in which such activity occurs, whether directly (via employment) or indirectly (via philanthropy). Lessons learned from evaluating entrepreneurs and entrepreneurism can facilitate the thoughtful design of public policies aimed at influencing innovative entrepreneurship.

Identifying those who are entrepreneurs versus those who are not, as well as what counts as innovation versus what does not, has a practical purpose in policymaking. Taking stock of who, in particular, contemporaneously qualifies as an entrepreneur can facilitate dialogue with such persons and enable the study of their ventures. By understanding the goals of modern entrepreneurs, as well as the objectives of their businesses, public officials will be better informed when weighing issues of public and private interests. Therefore, identifying and engaging with entrepreneurs can empower legislators and bureaucrats in their work to optimize the positive economic outcomes that can result from entrepreneurial action.

2 The Entrepreneur

What are the fundamental qualities of an entrepreneur? Interestingly, many tend to equate the entrepreneur with the small business owner or those who are self-employed. Economists who study entrepreneurism, however, tend to be more conservative in their assessments regarding who, exactly, actually qualifies as an entrepreneur. In *Good Capitalism, Bad Capitalism, and the Economics of Growth and Prosperity*, William Baumol, Robert Litan, and Carl Schramm survey the findings of several prominent economists concerning what the entrepreneur does,[5] for example,

- "the entrepreneur upsets and disorganizes," per Jean-Baptiste Say;
- the entrepreneur engages in "creative destruction," per Joseph Schumpeter; and
- "entrepreneurs innovate," thereby creating "dynamic disequilibrium," per Peter Drucker.

Baumol, Litan, and Schramm also provide their own interpretation of the entrepreneur as "any entity, new or existing, that *provides a new product or service* or that *develops and uses new methods* to produce or deliver existing goods and services at lower cost."[6]

Other scholars have elaborated upon and expanded such ideas. Ronald Coase and Ning Wang, for example, assert that "Entrepreneurship involves *undertaking new business initiatives*, such as setting up a new firm, creating a new market, inventing a new product, experimenting a new way of marketing, retailing, or organizing the production line, *and bearing the related risks*."[7] Zoltan Acs, Saul Estrin, Tomasz Mickiewicz, and László Szerb argue that entrepreneurs "act as the agents who, by commercializing innovations, *provide the transmission mechanism transferring advances in knowledge into economic growth*."[8] Ross Levine and Yona Rubinstein emphasize that "productivity-enhancing" entrepreneurs "perform activities demanding comparatively *strong nonroutine cognitive skills*, such as (i) creativity, analytical flexibility, and generalized problem solving and (ii) complex interpersonal communications associated with persuading and managing."[9]

Scholarship on entrepreneurism today frequently references Joseph Schumpeter, celebrated for his work on economic development and capitalism (see Schumpeter, 2021). Importantly, Schumpeter is credited as having introduced the concepts of the "entrepreneur" as an economic actor and "creative destruction" as the means by which entrepreneurs pursue their ends. Coase and Wang, in fact, describe entrepreneurship itself as "a critical *Schumpeterian* force" that, in keeping with Schumpeter's views, serves "as a vital source of endogenous change within the economy."[10] William Baumol has cautioned, however, against simply conflating entrepreneurship with creativity and/or ingenuity irrespective of outcomes. Instead, Baumol differentiates "unproductive" and "productive" forms of entrepreneurship, explaining that the latter actually leads to positive economic growth.[11]

By combining the aforementioned, we get the sense that the entrepreneur is, fundamentally, creative, innovative, and risk-accepting. He or she also demonstrates intelligence, analytical thinking, problem-solving ability, and skill in "complex interpersonal communications."[12] Ideally, the entrepreneur successfully commercializes innovations, while also capably leading, managing, and persuading others. Crucially, entrepreneurial activity tends to upset equilibria, disorganize systems, and replace the old with the new; entrepreneurs understand this and often (but not always) purposefully seek to accomplish these outcomes.

In their empirical review of the literature, Joern Block, Christian Fisch, and Mirjam van Praag list a number of entrepreneurial characteristics that scholars have identified as being common. Entrepreneurs, they explain, typically are self-confident, educated, networked, and technically proficient.[13] Moreover, they are capable of identifying innovative opportunities.[14] Esteban Lafuente, Zoltan J. Acs, Mark Sanders, and László Szerb discuss how such capability contributes positively to an economy by improving the efficiency of markets.[15] They attribute to the economist Israel M. Kirzner the development of the idea that some entrepreneurs "discover and exploit failures in the market pricing mechanisms by reacting to others' competitive actions."[16] Lafuente et al. elaborate that Kirznerian entrepreneurs do not necessarily create "new opportunities that may shift the country's production function," but rather "primarily [focus] on the identification and exploitation of existing business opportunities under given technology restrictions."[17]

While Esteban et al. describe the "two dominant approaches dealing with the role of entrepreneurship on national performance,"[18] Block et al. assert that the "fundamental question within entrepreneurial research [involves] the distinction between imitative and innovative entrepreneurs."[19] Aforementioned, Baumol et al. adhere to the Shumpeterian model, describing "imitative" entrepreneurship as "replicative," while urging us to consider entrepreneurism through the lens of innovation. The authors argue that "if economic growth is the object of interest, then it is the innovative entrepreneur who matters."[20] Moreover, Baumol's own perspective is that the descriptor of "entrepreneur" ought only to apply when such individual engages in *productive* work, that is, that which leads to positive economic benefit, rather than that which is *unproductive*, for example, rent-seeking activities, multiple and frivolous lawsuits, and illicit activity.[21] We will consider the *innovative* and *productive* entrepreneur herein. Our preliminary understanding of common characteristics of the entrepreneur appears in Table 10.1.

Innovative entrepreneurship benefits from both creativity and knowledge spillover, the latter concept neatly articulated by Audretsch and Feldman in 1996.[22] This is to say, both creativity and knowledge spillover *enable* the entrepreneur to innovate. As they relate to entrepreneurship, each of these concepts is important in its own right: innovation,

Table 10.1 Common characteristics of an entrepreneur

Possesses the following qualities:	Demonstrates capability to:
• analytical	• commercialize innovation(s)
• communicative	• identify opportunities
• creative	• lead others (e.g., founder/co-founder)
• educated[a]	• manage (e.g., firms, materials, finances)
• innovative	• network
• intelligent	• problem-solve
• productive	• understand technical information
• risk-accepting	
• self-confident	

Common characteristics, yet not *comprehensive*. Additional qualities may well exist, for example, initiative, focus, and determination

[a]Formally, autodidactically and/or via apprenticeship

creativity, and knowledge spillover. By innovation, we simply mean the creation of something new; as Schumpeter explained, "something new" can include a notable improvement over an existing good, an altogether new good, a new method, the creation of a new market, the securing of a new source of supply or input, and a novel organization of an industry.[23] Paraphrasing Keith Simonton, Richard Florida explains that creativity is "the act of bringing something useful, that works, and is non-obvious into the world."[24] Florida further describes creativity as being "pervasive and ongoing: it drives the incremental improvements in products and processes that keep them viable…[m]oreover, technological and economic creativity are nurtured by and interact with artistic and cultural creativity."[25] Frustratingly, such descriptions of the terms "innovative" and "creative" appear to reference each other. Perhaps a helpful way of differentiating the two might be to define creativity in terms of one's ability to generate new ideas, full stop. Innovation, on the other hand, refers to one's ability to translate or transform such creative ideas into something observable, for example, an innovative new product, process, organization, or method of management. Creativity does not necessarily lead to innovation, but innovation is almost always creative.

3 Elon Musk—An Entrepreneur?

By the end of 2002, Elon Musk had already sold two companies—Zip2 (for $307 million, reportedly netting Musk $22 million[26]) and PayPal (for $1.5 billion)—and had started a third, the Space Exploration Technologies Company (i.e., SpaceX) (Musk, 2009).[27] He was, at the time, just 31 years old. The now multi-billionaire once described his early successes with a degree of nonchalance, sharing that when "the internet came along…I wanted a piece of the action. It's a common story [as other firms had already been] started by people [like me] who dropped out of their graduate programs" (Musk, 2007).[28] The graduate program to which he referred was not one into which he had yet matriculated but was instead simply an alleged offer to join the Stanford University Physics Department as a doctoral student. At least he did not downplay his early upbringing and education, sharing that he "grew up in a technical household," having had an engineer for a father, taken high school coursework in physics, and drawn inspiration from reading "Richard Feynman's lectures and books."[29] Musk went on to study both physics and business at the University of Pennsylvania, crediting his study of physics as having developed his internal "mental framework for problem solving."[30] By any standard measure, Elon Musk met the objective criteria of having been an educated, intelligent, and analytical person as early as his days as a student at Penn.

Broadly considering Musk's contributions and accomplishments in making successes of Zip2, PayPal, Tesla, Solar City,[31] and SpaceX, one might hastily infer that Musk possesses all of the characteristics and capabilities of an entrepreneur, per Table 10.1. For the sake of this case study, however, we will reserve such judgments pending an analysis of Musk in his role *as the founder and CEO of Tesla*, exclusive of his prior business ventures and his recent takeover of Twitter. In what ways was Musk *creative and innovative* with his electric vehicle company? In what other ways did Musk behave like an entrepreneur in building Tesla? If our analysis demonstrates that Musk's work with Tesla was not entirely—or perhaps not at all—entrepreneurial, what might such findings mean, for example, would they undermine our generally accepted perceptions of Musk as an entrepreneur and beliefs in his accomplishments as entrepreneurial?

The way that Ashlee Vance tells the story in *Elon Musk: Tesla, SpaceX, and the Quest for a Fantastic Future*, Musk invented neither the electric automobile nor the Tesla electric vehicle. It seems absurd to have to say this, but the success of Tesla vehicles in the past decade seems to have obscured these facts. Moreover, Musk did not conceive of, invent, create, or incorporate Tesla Motors. The *original* co-founders of Tesla Motors were Martin Eberhard and Marc Tarpenning.[32] Within a few months, they were joined by Ian Wright; together, they went out and sought venture capital but were repeatedly rejected.[33] After many more months of searching for investors, Eberhard received a tip that Musk was potentially interested in investing in electric vehicles.[34] Once Musk carefully studied the financial model of Tesla Motors and met with the company's founders, he bought into the firm for $6.5 million, thereby gaining its largest ownership share.[35] Musk then brought in another inventor with whom he was already familiar, J.B. Straubel. Having met Straubel only a few months earlier, Musk was aware that Straubel had already made strides in adapting lithium ion battery technologies to electric vehicle use.[36] Eberhard and Tarpenning had envisioned that lithium ion batteries would power Tesla Motors vehicles; Musk simply made the match between the firm's founders and Straubel, who subsequently joined Tesla.[37]

At this point it is worth pausing to consider who truly qualifies as the company's founders. According to the firm's website, "Tesla was founded in [July] 2003 *by a group of engineers*…."[38] Technically speaking, these persons would have been Eberhard and Tarpenning, who were subsequently joined by Wright after three months' time. Per Fred Lambert of *Electrek*, Musk would not provide his $6.5 million to Tesla Motors until February 2004, during a $7.5 million "series A" investment round, and Straubel would not join the firm until May 2004.[39] Tesla's website, however, paints a different picture, asserting twice in the first two sentences of Musk's online bio that "Elon Musk co-founded and leads Tesla" and that he is "the co-founder and CEO of Tesla."[40] This is not a trivial discrepancy. Either Musk founded the firm, or he did not. He technically did not. Musk's attorneys and public relations team, however, might well argue that he was "in on the ground floor," that is, well within an initial "founding" period. From this perspective, Musk would have had an early and instrumental role in the development of Tesla Motors as a company. This supposed distinction, then, begs the question: was Musk *creative and innovative* in his role as CEO of Tesla Motors? Or was he simply a particularly good CEO and businessman?

We must, of course, reflect upon the fact that, in the beginning, Musk was an angel investor. His exceptionally large, early investment resulted in his garnering the title of "chairman"—but chairman of what? He was chairman of the board of a company that was just starting out and did not yet have its prototype built. The team building the prototype did not include Musk. Within a year, in January 2005, Musk would invest another $9 million in Tesla Motors during a $13 million "series B" investment round.[41] By his biographer's account, Musk "would visit [Tesla Motors] now and again from Los Angeles," but he was not physically present when the founders and their early employees stood up their first workshop, assembled their office furniture, purchased their machine tools, worked through the night on research and development, tested the early battery pack prototypes, or dealt with flammability issues that urgently required re-engineering the batteries.[42] One must remember that, by this point in his life, Musk was already a *billionaire*. He was not hands-on during the early days of Tesla, nor was that his role. He was also completely preoccupied with SpaceX.[43] What Musk did for Tesla Motors during those early years, besides providing a large share of the initial funding, was to offer suggestions concerning Tesla's *design*, that is, the *look* of the first model's exterior and interior, as feedback to a dedicated team of designers.[44]

Musk continued to invest, adding another $12 million during a $40 million investment round in May 2006.[45] At this point, Musk had invested $27.5 million of the $60.5 million that had facilitated Tesla Motors building their prototype—the EP1 Roadster. Once the vehicle was revealed to the public, *The New York Times* interviewed Eberhard and profiled Tesla Motors. Musk had not been mentioned in the article and was reportedly furious about the omission.[46] Yet, even in mid-May 2006, Musk was "merely" the majority shareholder and board chairman. He would not become the Tesla Motors CEO until late in 2008, after reportedly forcing out Eberhard (Tesla's co-founder and the first CEO) and sinking even more of his own personal fortune into the firm.[47]

4 A Tale of Two Predecessors

It might be instructive, at this seeming impasse in evaluating Musk's fitness to be characterized as an entrepreneur, to consider two of his predecessors in the automobile industry. Discussions of important automobile company founders sometimes, if not often, become conversations about Ford and Toyota. Perhaps, by paying close attention to the accomplishments and characteristics of Henry Ford and Kiichiro Toyoda, we might discover instructive parallels between their lives and that of Elon Musk. We also might wish to determine whether—and to what degree—criticism of Musk as innovator, founder, and leader might also apply to Ford and/or Toyoda.

We might well start with Henry Ford, a high school dropout and a farmer by birth—were we to convey only a cursory account of his early life.[48] In actuality, Ford was mechanically minded, a tinkerer who left his country classroom to work consecutive jobs in a machine shop, at a dry-dock, with Westinghouse, and in an electric utility.[49] He was an engineer by all accounts. Ford first built a "quadricycle" automotive vehicle in 1896,[50] no doubt having been inspired by the successes of Germany's Gottlieb Daimler and Karl Benz in 1885, then France's Armand Peugeot, followed by many other American creators from 1893 forward.[51] In other words, Henry Ford *did not invent the automobile*, just as Elon Musk did not invent the electric vehicle. Henry Ford did, however, found his own automobile company in 1903—eponymously naming it the Ford Motor Company.[52]

Ford is credited with the implementation of something incredibly innovative and productive—unlike anything that had been employed in automobile manufacturing to date—the standardized production line.[53] Mass production, Ford argued, would facilitate the manufacture of an affordable car. A large and ready market would buy such affordable cars, ensuring the mass proliferation and profitability of the Ford automobile. As Ford himself once put it, "Standardization, instead of making for sameness, has introduced unheard-of variety into our life. It is surprising that this has not been generally perceived."[54] Ford was right, and by "the early 1920s, the Ford Motor Company was producing more than 60 percent of all motor vehicles made in the United States, and about half made in the entire world."[55] Also notable? Henry Ford won universal acclaim in his having "introduced the five-dollar [work]day… [reduced] the workday from nine and ten hours to eight… [and] pioneered [a reduction of] the workweek from six days to five."[56] By 1919, 16 years after the company's inception, Ford had become a billionaire, purchased all of the public shares of the company, and gained full (private) control over his firm.[57]

The Toyota Motor Company story starts a bit differently than that of the Ford Motor Company. The Toyota Motor Company was conceived within a corner of the Toyoda Automatic Loom Works factory, the Toyoda Group then already a considerable Japanese powerhouse built by the "King of Inventors" and Imperial Order of Merit awardee Sakichi

Toyoda.[58] After Sakichi's son, Kiichiro Toyoda, expressed a sincere desire to pursue automaking, Sakichi offered his blessing and the requisite funding for Kiichiro to commence the venture.[59] Kiichiro was no dilettante, having both earned a formal degree from Tokyo Imperial University in mechanical engineering and already worked for the Toyoda Group.[60] After a 1929 visit to automobile parts makers and assembly factories in both Great Britain and the United States, Kiichiro started his own research and development in the aforementioned factory corner.[61]

Acknowledging Kiichiro's privileged start and his assumption of far less personal risk in launching the Toyota Motor Corporation (TMC) than his father, Sakichi Toyoda, had once assumed in launching the Toyoda Automatic Loom Works, was Kiichiro entrepreneurial? After all, he did not invent a new product. His trip to Britain and America in 1929 enabled his study of contemporary automobile production. He had benefited from closely reading Henry Ford's *My Life and Work*.[62] In fact, his early vehicles "borrow[ed] liberally from foreign models."[63] Likewise, he imported (versus created) necessary machining tools—as well as a "high-grade castings…molding machine."[64] He built a production line, produced a car, switched to the manufacture of trucks (in accordance with the needs of the Japanese government at that time), and then built factories in Kariya and Koromo.[65] From commencing research in 1930 until his automobile department was officially transformed in 1937 into an independent firm, Kiichiro had remained under protection of the Toyoda Automatic Loom Works.[66] Even upon the creation of TMC, Kiichiro was only named the firm's Vice President—a position that he would hold for four years before promoting to President.

This critique might be heavy-handed. Kiichiro, after all, doggedly pursued his goal of manufacturing *Japanese* automobiles—not unlike his own father had once doggedly pursued perfecting and then manufacturing *Japanese* commercial/industrial looms. Kiichiro did so in the face of the reluctance of Japanese *zaibatsu* to tackle auto production and despite the fact that three other Japanese manufacturers were already attempting the project.[67] Kiichiro fought for funding despite the misgivings of his brother in law, Risaburo Toyoda, who had assumed leadership of the Loom Works in accordance with Japan's hereditary customs.[68] Furthermore, Kiichiro exhibited particularly entrepreneurial competencies in getting an early jump on Nissan, the only other major domestic automobile manufacturer, in the engineering and production of military trucks. Immediately after Kiichiro exhibited his new trucks, Japan's "Ministry of Commerce and Industry announced that it had selected Toyoda Automatic Loom Works as one of the licensed automakers" to receive production authorization.[69] In other words, Kiichiro had identified an emerging opportunity and exploited it. Kiichiro was, in sum, indefatigably and productively entrepreneurial, if not for new inventions, then in his sheer determination to succeed in the automobile industry.

5 Ford, Toyoda, and Musk—Comparatively Considered

Henry Ford, Kiichiro Toyoda, and Elon Musk all demonstrated their resolve to commercialize a particular kind of innovation of their times, the automobile. None of the men invented the vehicle, yet the product at the heart of their work generated "creatively destructive" Schumpeterian effects all the same. Ford's standardized, mass-produced, assembly-line automobiles enabled, for the first time, small business owners and common households to purchase a vehicle for their own economic ends. Toyoda's domestic production of cars, trucks, and buses facilitated a major market disruption whereby Japanese-manufactured vehicles wholly replaced imported foreign autos in less than a five-year span. Musk's initial and substantial contribution of capital to Tesla Motors for the independent manufacture of electric vehicles proved the *sine qua non* of a major, industry-wide disruption that forced the well-established corporate automakers to play catch up for many years.

All three men identified the opportunities at hand: Ford, to capture the market for automobiles through mass manufacture; Toyoda, to capture a domestic market; and Musk, to capture a niche market in sustainably powered electric vehicles with a goal of growing the sector over time. Pursuing their projects necessarily required that Ford, Toyoda, and Musk understand the technical details that would bring their vision to life. In the cases of Ford and Toyoda, both men were engineers by informal or formal education. Musk, having been formally educated in physics and business, was scientifically minded. Moreover, by virtue of his past work with Zip2 and PayPal, along with his contemporaneous work with SpaceX, had the added advantage of prior experience in leading and managing teams in the production of highly marketable products.

Also a requirement of their pursuits was a capacity for problem solving, which each was made to exercise in spades. Beyond their individual contributions to the engineering and design of their vehicles, that is, solving *engineering* problems, each man had to address problematic externalities efficiently and creatively. Ford's introductions of the five-dollar day, the eight-hour workday, and the five-day workweek,[70] for example, may well have represented practicality, rather than altruism. From Ford's perspective, he was quite concerned "with reducing the unacceptable turnover in his plants than with any other impulse."[71] Toyoda was made to navigate the precarious events of "the war years" and their aftermath, problem-solving his way through the restrictive demands of the Japanese government for wartime production; the essential in-house development of steel works, machine works, and aircraft companies; and the rebuilding of the Toyoda group both during and after the Allied Occupation.[72]

Elon Musk's involvement with and role in Tesla Motors appears to have expanded over time. In a relatively recent interview, Musk admitted to not initially wanting to assume the role of Tesla CEO, or CEO of any electric-car start-up, for that matter. According to Musk's recollections of that period in time, he was already incredibly busy with the demands of SpaceX and hoped that Tesla Motors would provide him with an opportunity to "have [his] cake and eat it too," sharing that "I thought that maybe I could allocate 20 to 30 hours a week and just work on product engineering."[73] After a reported leadership crisis during the timeframe when Tesla Motors launched its first vehicle, Musk took over as CEO. He has since explained that, in his opinion, "it was too hard to find a qualified CEO since Tesla was not a typical gas vehicle company and had the culture of a start-up."[74] Musk therefore decided to make an even greater investment in Tesla and step in to lead the firm. From that point forward, Musk is credited with having brought vehicle production costs down, taken the company public, expanded production to six different models of electric vehicles, started production in a newly built Tesla factory in Shanghai, and more—all of which, arguably, required substantial hands-on and problem-solving.

Throughout their automaking adventures, Ford, Toyoda, and Musk were all beneficiaries of knowledge spillovers related to the products themselves, as well as each of their firms' organization and management. In their discussion of "The knowledge spillover theory of entrepreneurship," Zolan Acs et al. (2009, p. 16) argue that "start-ups with access to entrepreneurial talent and intra-temporal spillovers from the *stock* of knowledge are more likely to engage in radical innovation leading to new industries or replacing existing products." This is an important point that becomes evident in all three cases. It is not impossible to think of Ford, Toyota, and Tesla as having benefited from the earlier examples of, for example, Josiah Wedgwood (mass production), Sakichi Toyoda (building a better product for domestic use and consumption), and August Thyssen (demanding departmental results, rather than merely activity, and also reinvesting profits in diversification for growth). Understandably, the concept of "knowledge spillover" can be employed to strengthen arguments having to do with investing in entrepreneurism to the end that doing so will facilitate economic growth. While it may be the case that third-party businesses clustered around the principal firm do benefit from such spillover,[75] it has also been found that "the start-up serves as the mechanism through which knowledge spills over from sources that produced it (such as a university or research laboratory in an incumbent firm) to a new organizational form where it is actually commercialized."[76] All of this is to say that the Ford, Toyota, and Tesla automobile companies all benefited from others' knowledge spillovers inasmuch as they, themselves, contributed to knowledge spillover.

In further considering each firm's entrepreneurial qualities, it is worth evaluating how the marketing strategies of each company conformed to (or strayed from) from what McCraw and Tedlow have called "The Three Phases of Marketing." The authors introduce this "characteristic sequence of mass marketing of products to consumers" in an analysis of the Ford Motor Company, but one or more of the elements arguably have bearing upon our analyses of the Toyota Motor Company and Tesla Motors, too (McCraw & Tedlow, 1997, p. 268). These three phases encompass: (1)

market fragmentation, (2) the definition and unification of the market "by a superior brand or product," and (3) market segmentation (McCraw & Tedlow, 1997, pp. 268–269). Key for entrepreneurship, generally, and for Ford, Toyota, and Tesla, specifically, is the second phase. Ford, Toyoda, and Musk were able to disrupt and capture markets by virtue of their innovative practices designed to deliver relatively "high-volume production, low margins, low prices, and national (and perhaps international) mass distribution" (McCraw & Tedlow, 1997, p. 269). Ford did this remarkably well. Toyoda followed suit. Musk capitalized upon *relatively* high-volume production and *relatively* low prices by being a first mover in the all-electric vehicle space.

6 The Importance of Entrepreneurship

What might get lost in discussions of the definition of entrepreneurship, as well as the qualities and capabilities of entrepreneurs, is an explanation as to *why entrepreneurism matters*. To this end, Thomas McCraw provides a compelling case for what technological innovation can do for societies.[77] He frames his explanation in the context of the human condition prior to the eighteenth century so that we might understand how technological advances, creativity, and entrepreneurship facilitate the betterment of conditions for all of humankind. Once individuals were able to break from past traditions (i.e., agrarian existence in which most of the population was beholden to entitled landlords) and see that they could forge new paths as merchants, traders, manufacturers, builders, and so on, life for entire populations underwent substantial change. McCraw further explains that this transformation changed mindsets. People were no longer trapped, as he describes it, in the economics of competing for part of "a pie of fixed size," but were instead able to build wealth in a way that facilitates growth across the society.[78]

Zoltan Acs, Abraham Song, László Szerb, David Audretsch, and Éva Komlósi, in their article "The Evolution of the Global Digital Platform Economy: 1971–2021," subsequently provide us with a more comprehensive overview, while deepening our understanding of just how important entrepreneurism has been over three centuries. Acs et al. (2021, p. 4) therein trace the "evolution of markets, hierarchies, and networks" from local and national markets to a globalized world, from the factory and the corporation to the digital platform, and from coal and oil to wind and solar. They assert the Schumpeterian perspective, that is, that *innovation* drives economic growth (facilitating returns to the society, writ large), and explain how new firms, or entrepreneurial "start-ups," are the entities to drive such innovation.[79]

Interestingly, the entrepreneur innovates to meet consumer demands for what *does not yet exist*.[80] This is important insofar as it advances our lives—entrepreneurial innovations can ease our suffering, prolong our lives, make our mental efforts (e.g., in the workplace) more efficient, make our physical efforts (e.g., manual labor) safer and less stressful, enhance our leisure activities, facilitate more productive learning, reduce/eliminate environmental and climatological damage wrought by past technologies, and much more. In sum, *constructive and productive* entrepreneurial innovation can make our lives better. Moreover, the economic gains from the development of new technologies can enrich us as both individuals and societies.

The value of the contributions made by Henry Ford, Kiichiro Toyoda, and Elon Musk to the automaking industry transcended their particular field. Ford famously testified that he simply wanted to "do as much [good] as possible for everybody concerned" (McCraw & Tedlow, 1997, p. 277). Toyoda doggedly pressed for his vision of domestic mass production of passenger cars for the Japanese people.[81] Musk has famously pushed for the development of clean energy solutions and advancement of technologies to facilitate human space exploration and the colonization of Mars. Musk's motivations have been shared publicly and, in his view, constitute nothing more than the preservation of humankind.

Interestingly, some of the most successful entrepreneurs have contributed to their communities, countries, and the world via philanthropic endeavors. Philanthropic giving could be viewed as a second-order benefit of entrepreneurism insofar as founders and firms generously distribute part or all of their accumulated of wealth following the commercialization of their innovative ideas. Philip Auerswald and Zoltan Acs (2009, p. 9) emphatically argue that only "through giving—in particular, through the organized large-scale action of philanthropic foundations—is the imbalance inherent in capitalist growth corrected to create a self-sustaining process of wealth creation, social innovation and opportunity." This assertion is considered in greater detail within the Zoltan Acs and Ronnie Phillips reflection on "Entrepreneurship and Philanthropy in American Capitalism" (Acs & Phillips, 2002), and within *Why Philanthropy Matters*, by Zoltan Acs (2017). These authors argue that we restore our obligations to each other through philanthropy. "Philanthropy," Acs and Phillips explain, "remains part of an implicit social contract stipulating that wealth, beyond a certain point, should revert to society" (Acs & Phillips, 2002, p. 189). While philanthropy is not an *obligation*, per se, it does seem to be embraced by many Americans—particularly the ultra-wealthy who establish foundations and/or sign on to the Giving Pledge, an effort established by Warren Buffett, Melinda French Gates, and Bill Gates (Acs, 2017, pp. 205–225).

McCraw and Tedlow list a handful of philanthropic initiatives carried out by Henry Ford within his own lifetime, for example, Ford built a museum, preserved American frontier buildings, restored an historic American inn dating to the colonial era, and sponsored the preservation of folk music and folk dancing (McCraw & Tedlow, 1997, pp. 266–297). For his part, Elon Musk has been credited with creating a nonprofit (i.e., the XPrize Foundation) to oversee the management of a "$100 million carbon renewal prize," donating $20 million for public education in "a Texas county" and $10 million for the rehabilitation of a downtown area in "a Texas town," as well as a issuing a promise to make "major disbursements" in the next two decades (Onwuka, 2022).[82] This signal of intent to give away wealth at some point in the future echoes Musk having signed the Giving Pledge a decade ago, announced via press release from The Giving Pledge Foundation on April 19, 2012.[83] Notably, neither Musk's giving intent letter nor an excerpt from the same were made available to the public.

Musk is, however, on record for having donated $55 million to St. Jude's Children's Research Hospital.[84] Musk has also, according to Eliza Haverstock of Forbes.com, donated to "the Mercatus Center, a libertarian think tank at George Mason University in northern Virginia that aims to advance free-market ideas, [which received] $1 million from Musk."[85] The Forbes piece additionally reported on a February 2022

Securities and Exchange Commission filing that Musk disclosed having donated $5.7 billion of Tesla shares to charity in November 2021.[86] Yet where exactly that charitable funding went reportedly remains a mystery, with Heverstock speculating that it might have been transferred to "a donor-advised fund…which behaves like a philanthropic bank account [where] the money can sit…for years without ever going to an operating non-profit group."[87]

7 Entrepreneurs, Comparatively Assessed

Throughout, we have contemplated whether Elon Musk "qualifies" to be characterized as an entrepreneur. We have explored certain standards by which some scholars would have us measure the entrepreneur and have considered the case studies of two asynchronous would-be automotive companies and their founders. What work remains is to compare Elon Musk, on the basis of his involvement with Tesla Motors, against Henry Ford and Kiichiro Toyoda.

Table 10.2 captures the totality of what has been discussed herein. Should we equate *creativity* with *invention*, none of the men "invented" the automobile in any of their respective iterations. This category is, therefore, left blank in the table. However, it is apparent that each man was *innovative* in their identification and exploitation of opportunities, the commercialization of their firm's innovations, and the management of each company. Moreover, their accomplishments were constructively disruptive, that is, Schumpeterian, within the automotive industry. While Musk was not technically the founder of Tesla Motors, he did give it life as the original angel investor, guide the early team as the company's chairman, and then officially lead the firm through and beyond several crises as Tesla's eventual CEO.

Elon Musk has been philanthropic according to his own ends and preferences, but this is not globally embraced as an *essential* quality of the entrepreneur. By the comparative analysis of these three businessmen, albeit according to qualitative and anecdotal evidence, a clear picture of Elon Musk as an *entrepreneur* does appear to emerge from historical, biographical, and media accounts of the multi-billionaire.

While not an analysis of Elon Musk's involvement in Tesla Motors, per se, Steven Muegge and Ewan Reid (2019) evaluate Musk by employing "the *emancipation perspective on entrepreneurship* (Rindova et al., 2009) as a theoretical lens to identify, describe, and interpret examples of seeking autonomy, authoring, and making declarations—the three core elements of entrepreneuring emancipation." While Rindova's views (cited by Muegge and Reid) on "authoring" and "making declarations" appear consistent with what leadership and management qualities might already be expected of inspired founders, the notion of entrepreneurs intuiting a need "to break free of or break up perceived constraints"[88] is somewhat compelling, and perhaps ought to be added to a future revision of Table 10.2. This quality of *intuition* or *perception*, or simply the desire of entrepreneurs to emancipate themselves from the *de rigueur* of societal

Table 10.2 Cross-comparison of Ford, Toyoda, and Musk

Quality or capability	Henry Ford	Kiichiro Toyoda	Elon Musk
Analytical	✓	✓	✓
Communicative	✓	[a]	✓
Creative			
Dedicated/driven	✓	✓	✓
Educated/knowledgeable	✓	✓	✓
Focused	✓	✓	✓
Innovative	✓	✓	✓
Intelligent	✓	✓	✓
Philanthropic	✓	[a]	✓
Productive	✓	✓	✓
Risk-accepting	✓		✓
Self-confident	✓	✓	✓
Self-starter/takes initiative	✓	✓	✓
Commercializes innovations	✓	✓	✓
Identifies opportunities	✓	✓	✓
Leads others	✓	✓	✓
Manages the firm	✓	✓	✓
Networks		✓	✓
Problem-solves	✓	✓	✓
Understands technical details	✓	✓	✓

[a]In the case of Toyoda, it is unclear as to whether he possessed the "*complex* interpersonal communications [skills] associated with persuading and managing," per Levine and Rubenstein's qualification. Philanthropic giving unknown

and/or governmental expectations and requirements, equally applies to Ford, Toyoda, and Musk.

Moreover, this quality appears consistent with the aforementioned Kirznerian perspective on entrepreneurship (Lafuente et al., 2020). Each man, considered herein, in turn and in their own time, appears to have struck out in the direction of not merely *improving* the automobile but, in the Shumpeterian fashion, upending the market entirely. An emancipatory motivation looks a lot like a desire for independence and control; Ford and Musk both exemplify this, while Kiichiro Toyoda seems to have also demonstrated this quality—albeit in a muted, more culturally consistent, way.

8 Concluding Thoughts

One "pulse test" for ascertaining the public's perception of Elon Musk as an entrepreneur, beyond merely noting quantities of particular search engine results, is to establish "Ngram" counts of Google Books mentions. Oftentimes used to estimate the historical appearance (or expiration) of some particular word or concept, for example, *knickerbocker* or *gingerbread*, Ngram counts are sometimes useful in identifying instances of dependencies between people, things, concepts, adjectives, and the like. For our purposes, looking at counts of the appearances of the names of our three entrepreneurs and their three firms[89] gives us a sense of the global consciousness of Henry Ford, Kiichiro Toyoda, and Elon Musk, as well as the Ford, Toyota, and Tesla automobile companies, during particular points in the twentieth and twenty-first centuries. Moreover, linking adjectives like "founder" or "entrepreneur" with Ford, Toyoda, and Musk—or the word "vehicle" with Ford, Toyota, and Tesla, for that matter—provides us with a non-scientific snapshot of the incidences of such concepts showing up in published books, rather than across the wild and worldwide web.

The results of such an effort are somewhat informative, if not simply amusing. Henry Ford and his Ford Motor company appear prominently over time. Kiichiro Toyoda is hardly known by comparison, although mentions of Toyota skyrocket in the mid-1990s. Elon Musk and Tesla Motors are understandably latecomers to the party, with mentions for each not taking off until 2014 or so. Despite such recency, however, Musk has overtaken Ford in fame as a "founder" and "entrepreneur," for what this observation may be worth. To be fair, however, Ford was not referenced by the term "entrepreneur" in his heyday.

As stated at the start, from a policy perspective, identifying *who* qualifies as an entrepreneur enables us to consider *what* qualifies as entrepreneurship (and vice versa). Comprehending innovation has a practical purpose in policymaking, particularly given the ramifications of policymaking on the economy. Engaging with contemporary entrepreneurs can facilitate the development of an understanding of their professional goals and the objectives of their businesses, important when weighing matters of public and private interest. In sum, the pursuit of positive economic outcomes requires conversations between private entrepreneurs and public representatives, both legislators and bureaucrats.

Identifying Elon Musk as a contemporary entrepreneur—despite controversies surrounding his personality, behaviors, choices, actions, projects, investments, and tweets[90]—is of enormous importance to policymakers, particularly in the United States. Elon Musk is the wealthiest man on Earth today. How his many businesses are regulated and taxed, how he as a citizen is taxed, and how the US government engages in public-private partnerships with his companies—are all of great concern to political elites and ordinary citizens alike. In an era of "too big to fail," political polarization, disinformation and free speech concerns, privatized space exploration, income and wealth inequalities, and mounting tensions between the United States and China—Elon Musk exists at center stage, for better or worse, and must be understood by presidents, policymakers and bureaucrats, each in the context of their own unique public responsibilities.

Notes

1. Molly Ball, Jeffrey Kluger, and Alejandro de la Garza, "Time 2021 Person of the Year: Elon Musk," *Time*, December 13, 2021, https://time.com/person-of-the-year-2021-elon-musk/.

2. Tesla, "Elon Musk," November 15, 2022, https://www.tesla.com/elon-musk. Musk's online bio opens simply with the assertion that "Elon Musk co-founded and leads Tesla, SpaceX, Neuralink and The Boring Company." This bio had not been updated to reflect Musk's acquisition of Twitter on October 27, 2022. The summary did, however, note prior affiliations, sharing that "Previously, Elon co-founded and sold PayPal, the world's leading Internet payment system, and Zip2, one of the first internet maps and directions services." The word *entrepreneur* is noticeably absent from Musk's 559-word online bio on the *Tesla.com* official website.
3. Search performed on November 15, 2022.
4. Musk-as-entrepreneur seems a *fait supposé*. Notably, *entrepreneur.com* authors who hype Musk *qua entrepreneur* often attach flattering qualifiers, e.g., Randy Garn's "genius, visionary, futurist" entrepreneur (May 2021), Jessica Thomas's "billionaire" entrepreneur (Sep. 2020), Manish Dudharejia's "the most successful" entrepreneur (Nov. 2017), Carolyn Sun's "serial" entrepreneur (Sep. 2016), et al. Further, *entrepreneur.com* offers readers the opportunity to "[be inspired and learn] from the likes of Elon Musk" in its 'Celebrity Entrepreneurs' section, https://www.entrepreneur.com/living/celebrity-entrepreneurs.
5. William J. Baumol, Robert E. Litan, and Carl J. Schramm, "Entrepreneurship and Growth: A Missing Piece of the Puzzle," in *Good Capitalism, Bad Capitalism, and the Economics of Growth and Prosperity*, New Haven: Yale University Press, 2007, p. 3. http://ebookcentral.proquest.com/lib/gmu/detail.action?docID=3420392.
6. Ibid.
7. Siri Terjesen and Ning Wang, "Coase on Entrepreneurship," *Small Business Economics* 40, no. 2 (February 2013), p. 179. https://doi.org/10.1007/s11187-012-9468-2. Coase and Wang effectively echo Schumpeter's own perspective on economic development *qua* phenomena. See also Joseph A Schumpeter, *The Theory of Economic Development*, translated by Redvers Opie, Routledge Classics, New York: Routledge, 2021, p. 55. Schumpeter argues that "development…is defined by the carrying out of new combinations." He elaborates upon such new combinations, i.e., Schumpeter lists the following specific examples: (1) "the introduction of a new good" or an existing good of "new quality;" (2) "the introduction of a new method of production;" (3) "the opening of a new market;" (4) the conquest of a new source of supply; and (5) "the

new organization of any industry," e.g., "the creation of a monopoly… or the breaking up of a monopoly position."

8. Zoltan J. Acs, Saul Estrin, Tomasz Mickiewicz, and László Szerb, "Entrepreneurship, Institutional Economics, and Economic Growth: An Ecosystem Perspective," *Small Business Economics* 51, no. 2 (August 2018), p. 502. https://doi.org/10.1007/s11187-018-0013-9.
9. Ross Levine and Yona Rubinstein, "Smart and Illicit: Who Becomes an Entrepreneur and Do They Earn More?" *The Quarterly Journal of Economics* 132, no. 2 (May 1, 2017): p.965. https://doi.org/10.1093/qje/qjw044.
10. Terjesen and Wang (2013), p. 174.
11. William J. Baumol, "Entrepreneurship: Productive, Unproductive, and Destructive," *Journal of Political Economy* 98, no. 5, Part 1 (October 1990): p. 897. https://doi.org/10.1086/261712.
12. Levine and Rubinstein (2017), p. 965.
13. Joern H. Block, Christian O. Fisch, and Mirjam van Praag, "The Schumpeterian Entrepreneur: A Review of the Empirical Evidence on the Antecedents, Behaviour and Consequences of Innovative Entrepreneurship," *Industry and Innovation* 24, no. 1 (January 2017): p. 71. https://doi.org/10.1080/13662716.2016.1216397.
14. Ibid.
15. Esteban Lafuente, Zoltan J. Acs, Mark Sanders, and László Szerb. "The Global Technology Frontier: Productivity Growth and the Relevance of Kirznerian and Schumpeterian Entrepreneurship." *Small Business Economics* 55, no. 1 (June 2020): p. 155. https://doi.org/10.1007/s11187-019-00140-1.
16. Ibid.
17. Ibid.
18. Ibid.
19. Block et al. (2017), p. 71.
20. Baumol et al. (2007), p. 3.
21. Baumol (1990), p. 915.
22. See David B. Audretsch and Maryann P. Feldman. "R & D Spillovers and the Geography of Innovation and Production." *The American Economic Review* 86, no. 3 (June 1996): 630–640. https://www.jstor.org/stable/2118216.
23. Joseph A Schumpeter, *The Theory of Economic Development*, translated by Redvers Opie, Routledge Classics, New York: Routledge, 2021, p. 55.

24. Richard L. Florida, *The Rise of the Creative Class: Revisited*, 2019 edition, New York, NY: Basic Books, 2019, p. 6.
25. Ibid.
26. Ashlee Vance, *Elon Musk: Tesla, SpaceX, and the Quest for a Fantastic Future*, First edition, New York, NY: HarperCollins Publishers, 2015, p. 14.
27. Elon Musk, "Risky Business." *IEEE Spectrum* 46, no. 6 (June 2009): p. 40. https://doi.org/10.1109/MSPEC.2009.4977610.
28. Elon Musk, "Once a Physicist: Elon Musk," as interviewed in *Physics World* 20, no. 3 (March 2007), p. 50. https://doi.org/10.1088/2058-7058/20/3/39.
29. Ibid.
30. Ibid.
31. Solar City was founded by Elon Musk's cousins. He funded their venture and advised them on their start-up. SpaceX later acquired Solar City despite the objections of shareholders. In May 2022, SpaceX and Musk won a lawsuit brought by those shareholders who objected to the acquisition. See Isobel Asher Hamilton, "How Elon Musk Transformed His Cousins' Solar Panel Company into Tesla Energy, Which Has Faced Lawsuits from Angry Shareholders and Consumers," Business Insider, April 29, 2022. https://www.businessinsider.com/solarcity-tesla-energy-beleaguered-history-elon-musk-2021-7.
32. Vance (2015), p. 150.
33. Ibid.
34. Ibid., p. 153.
35. Ibid., pp. 153–154.
36. Ibid., pp. 148–149.
37. Ibid., p. 150 and 154.
38. Tesla, "About," May 15, 2022, https://www.tesla.com/about.
39. Fred Lambert, "Elon Musk Says JB Straubel Should Have Been Tesla's Only Other Cofounder, Dredging up the Past," Electrek, April 14, 2022. https://electrek.co/2022/04/14/elon-musk-starting-tesla-not-just-jb-straubel-worst-business-decision/.
40. Tesla, "Elon Musk," November 15, 2022, https://www.tesla.com/elon-musk.
41. Vance (2015), p. 157.
42. Ibid., pp. 156–158.
43. For a timeline of SpaceX, visit https://abcnews.go.com/Technology/timeline-spacexs-trek/story?id=16224465.

44. Vance (2015), p. 160.
45. Ibid.
46. Ibid., p. 161.
47. Taylor Locke, "Elon Musk: 'I Really Didn't Want to Be CEO of Tesla'—Here's How He Says It Happened," CNBC, January 30, 2020. https://www.cnbc.com/2020/01/30/elon-musk-i-really-didnt-want-to-be-ceo-of-tesla.html.
48. Thomas K. McCraw and Richard S. Tedlow, "Henry Ford, Alfred Sloan, and the Three Phases of Marketing," in *Creating Modern Capitalism: How Entrepreneurs, Companies, and Countries Triumphed in Three Industrial Revolutions*, edited by Thomas K. McCraw, Cambridge, Massachusetts: Harvard University Press, 1997, p. 272.
49. Ibid.
50. Ibid.
51. Ibid., pp. 267–268.
52. Ibid., p. 272.
53. Ibid., p. 273; Ford also innovated "the moving assembly line, which became fully operational by 1914," p. 274.
54. Ibid.
55. Ibid., p. 274.
56. Ibid., p. 275.
57. Ibid., p. 276.
58. Jeffrey R. Bernstein and Thomas K. McCraw, "Toyoda Automatic Looms and Toyota Automobiles," in *Creating Modern Capitalism: How Entrepreneurs, Companies, and Countries Triumphed in Three Industrial Revolutions*. Cambridge, Massachusetts: Harvard University Press, 1997, pp. 406–408.
59. Ibid., p. 407.
60. Ibid., pp. 407–408.
61. Ibid.
62. Ibid., p. 408.
63. Ibid.
64. Ibid.
65. Ibid., p. 410.
66. Ibid.
67. Ibid., p. 407.
68. Ibid., p. 408 and p. 403, respectively.
69. Ibid., p. 410.

70. McCraw and Tedlow (1997), p. 275.
71. Ibid.
72. Bernstein (1997), pp. 411–413.
73. Locke (2020).
74. Ibid.
75. Ibid., p. 17. As Acs et al. (2009) explain, "entrepreneurship contributes to economic growth by acting as a conduit through which knowledge created by incumbent forms spills over to agents who endogenously create new firms."
76. Ibid., p. 18.
77. McCraw, Thomas K. "Introduction." In *Creating Modern Capitalism: How Entrepreneurs, Companies, and Countries Triumphed in Three Industrial Revolutions*, edited by Thomas K. McCraw, 1–16. Cambridge, Massachusetts: Harvard University Press, 1997.
78. Ibid. See also Holcombe (1998) and Kirzner (1976) under references. Holcombe (1998) explains that "incorporating entrepreneurship into the framework of economic growth…[shows] the nature of increasing returns to scale," on p. 60.
79. Ibid., p. 7.
80. Acs, Z., "Economics, Entrepreneurship, and Public Policy," lecture on January 20, 2022, George Mason University.
81. Notably, despite the research and design start as early as 1930, Kiichiro Toyoda would not see this particular dream bloom until 1947. See Bernstein (1997), pp. 413–414.
82. Patrice Onwuka, "Elon Musk's Philanthropy and Donor Privacy," *Philanthropy Roundtable* (blog), March 24, 2022. https://www.philanthropyroundtable.org/elon-musks-philanthropy-and-donor-privacy/.
83. Giving Pledge, "Press Release—The Giving Pledge," April 19, 2012. https://givingpledge.org/pressrelease?date=04.19.2012.
84. Eliza Haverstock, "Here's Where Elon Musk's $5.7 Billion Gift Likely Went," Forbes, February 15, 2022. https://www.forbes.com/sites/elizahaverstock/2022/02/15/elon-musk-reports-donating-57-billion-to-charity-but-there-is-no-trace-of-that-gift-yet/.
85. Ibid. According to Haverstock, "The Mercatus donation was intended for 'Covid-19 scientific research,' per the Musk Foundation's tax filing."
86. Ibid.
87. Ibid.
88. Steven Muegge and Ewan Reid (2019), p. 19.

89. Ngram counts reflect mentions within the extensive digitized Google Books collection, specifically.
90. Much remains to be determined regarding Elon Musk's leadership of, control over, and decision making concerning his most recent acquisition, Twitter.

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11

How to Tame the Beast? Toward a 'Regulation Revolution' in the Digital Platform Economy

Márton Sulyok

1 Introduction

The literal 'IT-debate' of the century revolves around answering the question: *how to tame the beast*. This refers to tackling the manifold regulatory pressures brought about by innovation in information and communication technology and all the 'creative destruction' that comes with it as an essential fact of capitalism.[1] In spite of this, the 'who,' 'why,' 'when,' and 'how' of regulation regarding digital platforms at the foundations of the 'digital platform economy' are questions gaining more and more emphasis in public discourse.

This contribution to the book is intentionally the odd one out, as it does not deal with economic issues and indicators regarding the digital economy.

M. Sulyok (✉)
Mathias Corvinus Collegium (MCC), Budapest, Hungary

Institute of Public Law, University of Szeged, Szeged, Hungary
e-mail: sulyok.marton@mcc.hu

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The author was asked to rely on these as a broad frame of reference and address certain legal and regulatory issues that arise in a platform context.

The chapter therefore obviously does not intend to provide an in-depth legal analysis of these questions, but only serves to cautiously counterpoint some of those 'natural drives' that nourish a digital platform ecosystem and incentivize technological and digital evolution, pushing the proverbial 'final frontier' of law (understood as the means to create order) further and further, and testing the limits of states and their role as primary regulators as well as their essential state functions.

Coming to speak of these essential state functions, it is in and of itself a question among legal scholars, regulators, and economists, when and to what extent can and should states (or international organizations) intervene and regulate the market to try and set limits to a variety of possible rights violations that affect the right to life, the right to privacy, the rights of the child, the rights of consumers, or the freedom of expression—just to mention a few. These different rights issues separate the legal debates into different domains of consumer protection, competition and antitrust law, privacy and data protection, content regulation and participatory democracy, which all require the careful consideration of many underlying issues of economic policy choices in different legal systems.

As states and their 'subjects' operating 'in sovereign territory' breach the digital barrier through technological evolution, reimagined concepts of said sovereignty start to emerge in the digital sphere. More and more actors with a huge economic footprint appear in the life of states with many ways and means to affect the 'analog context' of traditional sovereignty, that is, the life of the population and decision-making relevant to their social relations and the exercise of their fundamental rights.

As formulated in the subtitle of the chapter, this seems to bring about a 'Regulation Revolution,' that is, a tendency of increasing regulatory intervention and policymaking on big data, on 'the big five,' automated or algorithmic decision-making, and so on to the dismay of many of these private economic actors.

It has always been a long-standing question within the legal community whether law has primacy over politics and policy or vice versa. In this current context, the question should rather be whether the (digital platform) economy has primacy over law, policy choices, and ensuing regulation, or it should be the other way around.

Section 2 analyzes and explains concepts of digitization, digitalization, and automation in the context of platform economy and points to issues that give rise to regulatory choices across the board. Fusing this into the introduction of the effect of automation on individual autonomy and the potential dangers that it represents from the point of view of the operation of platforms, under 1.1 I will point out a variety of regulatory and rights issues for consideration. Section 3 takes a longer look at the status quo of pertinent regulation from a European perspective mentioning the different challenges and the ways in which they are currently addressed on a broad spectrum from the household use of AI to justifications for the use of autonomous weapons systems. Section 4 will take a broader look on the changing role of states in regulating disruptive technologies, the fault-lines on traditional concepts of sovereignty and subsidiarity that appear through technological development, and the different regulatory approaches states may prefer in tackling some of these issues. In the context of 'regulation revolutions' trying to 'tame the beast' of 'creative destruction' caused by digital innovation, the chapter will briefly reflect on some essential state functions and their scope in terms of regulating the effects of disruptive technologies.

2 Digit(al)ization and Automation: From Disambiguation to Regulation?

The *digital* or *fourth industrial revolution* (a term supposedly coined in a 2011 German government document[2]) made services created by, based on, and using automation become part of our everyday lives. For nearly 15 years now, we have been living in a world of *ubiquitous computing*,[3] where *the Internet of Things (IoT)* is our everyday reality, bringing with it many atypical and archetypal threats.

Through merging several preexisting concepts, Hungarian economist Ferenc Gyüre defines the era of digitalization as "*an IT, economic, social phenomenon with new technological innovations, with the help and as a consequence of which the complete digitalization and automation of basic production, service processes and social relations can be observed, [and] the* *result is a fast, all-reacting, global, automatic system*."[4] The pandemic of 2020 has accelerated the digitalization process in almost all countries,[5] with clear benefits for companies as a key to their survival and long-term sustainable, profitable operations.[6] In general, more and more digital services are entering the market.[7]

On the negative side, there are currently only 55 professions that can be automated at any level, which would replace 12% of jobs in Hungary, that is, 513,000 employees.[8] This of course implies the loss of jobs for many people with lower skills.[9] For the labor market in the legal profession, this phenomenon particularly affects the less experienced as well, as law firms and corporate legal departments can use AI in legal administration, basic legal research and drafting assignments and legal compliance projects to work more accurately and quickly. (The emergence of Chat-GPT, already graduating law school in the US and passing the bar exam has further added to these concerns.)[10] McKinsey's relevant 2018 analysis cited no more than 1 million jobs that could be affected by automation in Hungary (where the author is from).[11]

In late 2021, Bloomberg analyst and publicist Andreas Kluth pointed to a sociologically significant danger in an article on industrial automation in the present context. He alluded to this dystopic perspective as "the crisis of masculinity."[12] Increasing robotization (i.e., automation) in many 'blue collar' sectors—he argued—will make it unnecessary to employ the 'breadwinners' (mainly men) of the past, which could lead to tensions and a crisis of their own masculinity. The most far-reaching legal consequences of this 'identity crisis' could be, for example, a turn to crime or even an increase in domestic violence.

Of course, there have been similar crises in the past and threats to the labor market and the economy may be interpreted in many different ways, as I tried to illustrate with referencing some survey data. However, perhaps nothing of such a scale had happened so far in our modern world than what is suggested by the possibilities to substitute human resources in the labor market and in many sectors of the economy. If Kluth is right, and this 'identity crisis' takes on social proportions, it will ultimately be humans who become the 'weaker sex' in relation to robots. This paints a strange picture of our brave new world of digital economy. Obviously, however, digitalization (encompassing all sorts of automation) can now be said to be an essential part of the future of humankind.

In the following, I aim to present different legal and ensuing regulatory issues in the context of the digital or platform economy. Aware that the law cannot always keep pace with and thus is challenged by technological development, I would like to review some effective solutions to these challenges to ponder the possibilities for regulating seemingly uncontrollable (but certainly unstoppable) technical and technological development.

In the EU, there are a number of national efforts to promote digitalization through investment, innovation, but also regulation.[13] In Belgium, for example, several digitization strategies were published in 2018 and the *Digital Belgium* program was launched in 2015.[14] In Hungary, the National Digitalization Strategy 2021–2030 is currently being implemented, with the objective of increasing the efficiency of back-office processes in public administration through automation.[15]

This above term 'automation' automatically carries a lot of negative connotations. Mick Chisnall links the emergence of *automated information gathering systems* directly to the idea of digital slavery[16] to which individuals fall victim through their data, while others, for example, LSE's Leslie Willcocks in his book titled *Robotic Process and Cognitive Automation: The Next Phase*, write that the role of automation in job creation is largely neglected as a positive factor.[17]

As these examples show, many people define digitization and automation as separate concepts, so the need for disambiguation presents itself. In addition, the term *automation is* often used in English terminology in a way that is fundamentally and often separate from the term *digitalization - digitization.*

(i) *Digitization* means the conversion of analogue to digital; while
(ii) *Digitalization* refers to the use of digital technologies and digitized data in the development of various processes. According to SAP Insights, a search frequency study conducted between 2004 and 2020 found that the two terms now appear at almost the same density in Google Trends reports, but have different meanings (as noted above).[18]

(iii) Although the author's native language (Hungarian) does not distinguish between *automation* and *automatization* (it uses the term *automatizáció* for both), the meaning of the two original English words is slightly different—if one recognizes that such a linguistic difference between them even exists.

a. By *automation*, we mean the activity of replacing human power with machines or artificial intelligence (AI).
b. *Automatization* is a much less used variant of this term, used only in connection with activities with which we are familiar.[19] The second term is therefore the automation of a higher order activity, although some linguistic sources argue that *automatization is a* term that does not exist in the most relevant linguistic corpus, and that it is *automation* that should be used correctly (and exclusively).

Ad (iii), the archetypal concept of automation can be defined from an industrial perspective as *"the replacement with computers and machines to that of human thinking" or "as the use of set technologies and automatic control devices that results the automatic operation and control of industrial processes without significant human intervention and achieving superior performance than manual control."*[20] Since the concept also includes the reduction of the need for human labor as an objective, it is questionable in what context the reduction of jobs, previously invoked as a negative, should be interpreted in the light of the objectives that push for automation. *(I forego any further discussion of this issue herein, given its not explicitly legal or regulatory nature.)*

Automation undoubtedly increases productivity; it is cost-effective and widely used in many sectors. One of the main applications is robotics. Industrial robots are defined by ISO 8373 (and accepted by the IFR, the International Federation of Robotics as well) as "*automatically controlled, reprogrammable, multi-purpose manipulators that can be programmed in 3 or more axes.*"[21]

Automation, however, is not only present in the above-mentioned area. 'Siri' (developed by Apple), the voice of 'whom' almost all of us are familiar with, can also be used to automate our homes, but such an investment into our comfort can also pose atypical dangers, not just archetypal ones. In the Home app on iOS, Siri can automatically turn off lights when the app user leaves the home, turn them on when motion is detected, or run a scenario when opening the front door.[22] Amazon's own virtual assistant, 'Alexa,' is also capable of automated decision-making around the house.[23]

Of course, these are just two apps that make our everyday lives easier through automation. We should not forget, however, that despite 'all the blessings of liberty'—to borrow a phrase from the preamble of the US constitution—there are also many downsides we and our posterity needs to face due to the fact that these omni-present and almost omni-potent systems have become so integral in our lives.

One such archetypal danger by now is that we started humanizing these tools and technologies by giving them actual human (usually female) names and often rely on them as our 'digital slaves' and helpers in many chores. Some robotic vacuum cleaners (RVCs) are sold with a deliberately chosen human name by the manufacturer (e.g., Trifo's RVC machine Lucy[24]). In one specific case, the DR4GHE project aimed to turn an RVC device into a digital *cleaner to companion* for certain household functions, building on acceptance of the device by the users and enhancing its AI capabilities.[25]

In the context of more atypical dangers, it made the global news not so long ago that the 'home assistant' Alexa unreservedly suggested a minor asking about a pastime that she should complete an internet challenge (*penny challenge*) involving the use of electricity and thus a significant risk to human life.[26] Amazon has of course averted the problem, but it is still an excellent illustration of the as yet un-archetypal dangers inherent in similar automated data collection, management, and processing systems.

To be fair, however, every coin has two sides and there are some, like Orly Lobel, who do not voice concerns about technological development and see it as a force that brings equality and bridges the digital divide. In her book, *The Equality Machine—Harnessing Digital Technology for a Brighter, More Inclusive Future* (Public Affairs, 2022),[27] Lobel, a renowned tech policy and IT law scholar, proposes many defenses for technology in legal terms as well, focusing on anti-discrimination, education, free speech, and even climate change.

According to Kaminski, it was actually Lobel that coined the term "platform economy" and that she believes that it represents the "third generation of the Internet." Despite Kaminski describing Lobel's stance on platforms as "largely optimistic," she also voiced an important regulatory issue already in 2017, as follows: "*What makes the platform economy legally disruptive is that these companies tend not to fit neatly into existing legal categories in regulated areas.*"[28]

Indeed, one of the largest global compilations of contemporary ideas and patterns of platform regulation in terms of social media governance (published last year by Nomos) introduces the term 'platform' as a powerful metaphor with which legal problems may arise because they "*can be seized, hijacked and controlled or they can be virtual common carriers. Often it appears as a locus that is neutral and necessary for commerce in the commodity for which the platform accommodates trade. 'Platform' has become a weighted term, an opportunity for a wide variety of distinct approaches to regulation to be articulated, legislated and implemented*"[29]—writes Monroe E. Price, the namesake of the world renowned media law moot court competition in the foreword to Perspectives on Platform Regulation.

Price then adds that the appeal of the platform-concept is the categorical distinction it establishes between production and distribution of content, which opens up the playing field for a variety of regulatory choices necessary "*to allow zones of immunity from liability, said to be critical in the development of social media and the Internet. Distinguishing the platform from its users has had complex implications for regulation of ownership in successive iterations of media and society*."[30] Regulatory choices are indeed wide open, as many legal problems persist amid negotiations on the correct paths forward.

2.1 Automation, Autonomy, and Resulting Rights and Regulatory Issues

Beyond such problems and salves, going back to the basics, it is also in our own self-interest to be aware of the extent to which our privacy and personal data is exposed to digitalization and automation. Mick Chisnall, quoted above, refers to this with his dystopian image of 'digital slavery,' when he talks about the many concerns that these systems raise about the diminishing of individual and community autonomy.[31] *"As a primary tool to improve their performance, they collect, aggregate and utilise data, for example in order to optimise their ranking, target-ing and recommending systems."*[32] Autonomy, in relation to data protection and privacy,[33] is seen as the legal category of informational self-determination—the right to determine to whom our data is disclosed and who can access it.[34]

In general, at least in European legal and regulatory thinking, any data is subject to protection that attaches to the person, whose data is at the heart of a legal issue; therefore we refer to it as 'personal data' when we talk about fundamental rights. Privacy is a corollary to this fundamental right, while originally mostly tied to physical space surrounding the person. The online environment changed both concepts to a point where now both need to be protected not only through legal but more and more technological means as well. Chisnall, cited above, takes issue with the link between privacy and data protection, arguing that the vast majority of online breaches are not privacy issues, but a chain of offenses and crimes committed with personal data.[35]

There are national constitutions, like the Hungarian Fundamental Law,[36] that reflect on this link and provide for their protections under the same heading (including certain other layers of privacy—like the family home, correspondence into this grouping), while other national constitutions, like that of the United States, don't even contain the word privacy, but judicial practice has provided extensive protections for the private sphere in many different contexts, over the years. Internationally, the same patterns exist with the difference that regional international law in Europe (ECHR) subsumes protections for personal data under Article 8,[37] protecting private and family life, while the fundamental rights instrument of the EU (the Charter of Fundamental Rights) protects privacy and personal data under separate provisions.[38] In accordance with the unitary regulatory concept of the EU's GDPR (General Data Protection Regulation),[39] 'personal data' became an umbrella term as "any information relating to the data subject" (i.e., an identified or identifiable person).

As a special category of personal data, legal regulation encompasses sensitive data as well, meaning all data falling within the sensitive (protected) categories of personal data, such as revealing racial or ethnic origin, political opinions, religious or philosophical beliefs, trade-union membership, genetic data, biometric data for the purpose of uniquely identifying natural persons, health data, and personal data concerning the sex life or sexual orientation of natural persons (which are normally protected characteristics in any country that provides for the statutory protection of these, at least in the wider European legal thinking). Further problems arise in terms of the broad approach to the concept, if we consider that our geographic location may be considered personal data in terms of automated decision-making on blocking access to certain services.[40]

Nowadays, various forms of automation operate with, and can be based on, extensive use of personal data. Initially, in the early 1980s, the focus was on protecting data against automated processing. The so-called Convention 108, adopted in 1981, was dedicated by the Council of Europe to the rules on the protection of individuals with regard to *automatic processing* of personal data. Now that automated processing is the new norm, data protection must be surrounded by other means, not only legal ones. But the set of legal problems is not changing, it is just evolving.

For example, *profiling*[41] is not only a problem in the work of law enforcement agencies on an ethnic basis, but it also happens with intelligent robots. Robots need to be able to understand the different behaviors and needs of people, and profiling is a basic tool for this. Using this, a robot can also generate information about people's personality, characteristics, behavior, interests, or identity.[42] Such an algorithm cannot only make life easier, but in some cases it can also save our lives, for example, by transmitting our medical history to the hospital, easily revealing our vulnerabilities.[43] What we can conclude is that automation (here specifically as automated data processing and decision-making) leads to profiling in many cases. With regard to the data protection risks of profiling and how they are addressed, the EU GDPR sets further limits, namely, that it gives the data subject (to whom the data relates) the right not to be subject to a decision based solely on automated processing (including profiling) "which produces legal effects concerning him or her or similarly significantly affects him or her."[44]

AI is in and of itself an ADM (*Automated Decision-Making*) process in the sense that it processes data in a fully automated way, without any human intervention affecting the final result.[45] Examples of such automated AI-based systems are Google's search engine optimization tools or Instagram's content recommendation tools. All of these create a 'taste profile' of the user and recommend content based on that profile. (Businesses have the option to ask Facebook to set up automatic ad placements, as "*the system learns over time what is likely to perform best, and makes improvements and suggestions*"[46] This way social media and communication platforms also use profiling.)

"*With the help of algorithms […] finding the right person for the right content can be perfected, and thereby the attention of users can be exploited in a much more effective way than by traditional commercial media. The format of some platforms leads to shorter communications, which may also be less sophisticated in analysis*."[47] As a result of such instances of (taste or other) profiling, our emotional drives and state become wide open to tailoring to a certain preference that is not necessarily dictated by the individual's well-being.[48] In summary: all our data channels into automation, as our Facebook page also uses our personal data collected from our search history, private conversations, and other activities (often extrapolated from this additional data) to decide what ads to send us, how to shape our further searches, further perfecting (but in reality narrowing) said 'taste profile.' As Lilla Kiss puts it, "*Machines are able to draw conclusions based on users' shared or hidden information. Knowing the users helps the algorithms find what triggers their further consumption of the contents of the platform.*"[49] Unfortunately, profiling is part of this process, but the relevant provisions of the GDPR seek to prioritize data protection concerns, at least in the European Union.

Already in 2014, the European Commission estimated that the value of the personal data of half a billion EU citizens is expected to reach €1000 billion per year by 2020.[50] It is not without reason that we hear more and more often that data is "the oil of the 21st century."[51] As the most valuable social resource, our personal data has monetary value, and we have entered the phase of "commodification." If we consider personal data as a commodity then we regard it as the object of commerce, which entails a regulatory mindset or approach completely different from the one described herein, but I will return to this issue in more detail in the conclusions of the chapter.

3 The State of AffAIrs and RemAIning Challenges—A European Point of View

A constantly expanding legal framework provides some of the answers to the societal issues raised by AI. Unfortunately, legal regulation is lagging behind technological advances, but legal frameworks that protect our personal data and address societal issues are constantly expanding to help us exploit the potential of AI in a more secure way.[52] In the following, we will look at existing and planned regulation at both national and international level. In the latter category, the focus is on relevant EU legislation.

The legal framework for AI in the European Union is currently in its very early stages. As mentioned above, the GDPR also contains provisions that play an important role in bringing this issue within the legal framework. The draft EU Regulation on Artificial Intelligence was published in April 2021,[53] and is currently under review. The draft includes three categories of AI: (i) prohibited practices, and (ii) high- and (iii) low-risk AI systems.

The European Data Protection Board (EDPB) and the European Data Protection Supervisor (EDPS) have adopted a joint opinion on the proposed Regulation, stressing the need to align the concept of 'risk to fundamental rights' with the EU data protection framework. Andrea Jelinek, President of the EDPB, and Wojciech Wiewiórowski, European Data Protection Supervisor, agreed that the introduction of remote biometric identification in publicly accessible places means the end of anonymity in these places. Applications such as live facial recognition enable intrusions into fundamental rights and freedoms to such an extent that they could call into question the very essence of these rights and freedoms.[54] The new plan,[55] coordinated with Member States, aims to promote security and fundamental rights. The new rules on machinery products[56] also aim to improve safety rules.[57] Under the new regime, there is an unacceptable risk from AI systems that clearly compromise people's safety, livelihood, and rights. These include AI systems or applications that enable social credit[58] or manipulate human behavior to circumvent the free will of users.[59] High risk AI systems will be subject to specific regulations. These are systems used in critical infrastructures,[60] justice and law enforcement,[61] essential private and public services (utilities), migration management,[62] education or training,[63] security devices for products,[64] or employment, management of workers, and access to self-employment.[65] The EU also introduced ethical guidelines on trustworthy AI in 2019.[66]

Within the existing regulatory framework, we should also separately mention the 2018 strategy,[67] the coordinated plan for AI of the same year,[68] and the 2019 guidelines of the Expert Group on Artificial Intelligence.[69] In 2020, the Commission published a White Paper on the subject,[70] which was accompanied by the "*Report on safety and liability aspects of AI, IoT and robotics*."[71]

Looking at the interface between automation and privacy (regarding data collection and protection), there are many challenges for future legislators and executives as well as judiciaries. Cooper and Yun, for instance, approach from the point of view of competition law and look at how data collection transforms privacy into a key dimension of competition and antitrust regulation in the United States. However, they argue that—contrary to popular belief in the US and elsewhere as well—"*there appears to be little systematic relationship between* [giant/dominant platforms'] *market power and low levels of privacy* [protection]."[72]

Based on the data collected, automation also brings with it the possibility of ADM, and in this context increased scrutiny is necessary monitoring compliance with relevant rules.[73] Profiling and ADM are also used in the banking, financial, tax, and healthcare sectors. Here again, tailored to the European context, decision-making based solely on automated processing is only allowed if the data subject has given his or her explicit consent or if the decision is necessary in the context of a contract or the intention to enter into a contract.[74]

In addition to these areas, there is also a growing need for ADM in courts.[75] Whether AI mechanisms can potentially replace judicial discretion[76] in the future is going to be the burning question for the next 10–15 years, and judiciary regulators already have data available to them on the use AI tools, for example, in the context of examining patterns of international judicial decisions.[77]

András Osztovits, a judge of the Civil Chamber of the Hungarian Kúria (Supreme Court) argued that if we let smart technology in the courtroom, it will take over some of the human decision-making. The most important area of adjudication is the decision itself, which must be kept in human hands, even accounting for human fallibility. However, he also mentioned that research has already been carried out in Argentina to make an app available to judges that suggested a decision based on previous case law. This proposal was accepted by all the judges who took part in the testing.[78]

The app Prometea[79] could become an applicable tool in the Argentine legal system, setting a good example for judicial systems around the world. Its biggest advantage is time efficiency: while in the days of paper and digital bureaucracy, it took 174 working days to make 1000 decisions on housing rights, with Prometea it takes 45 days. The initiative is also proving to be effective in terms of accuracy, with prediction rates for cases of 96% accuracy in less than 20 seconds. Other results include reducing the time taken for the selection of urgent cases by the Constitutional Court of Colombia, which receives thousands of petitions a day, to 2 minutes from 96 days, and correcting 6000 administrative entries in the Buenos Aires City Registry Office in 2 months instead of 8 months.[80]

Naturally, judicial applications of ADM raise a number of ethical questions. Perhaps the most important is whether there is a threshold beyond which the judiciary cannot allow decisions to be taken through automated means. This also brings about the following question: What will be the fate of fairness and the essential human element (the 'internal conviction' of the judge) in adjudication overshadowed by the need to increase efficiency?

Since our current global context is unfortunately shaped by the prolonging Russian-Ukrainian war, another important area needs to be very briefly addressed, in which ADM will pose problems for regulators. Technology enables a number of unprecedented forms of warfare, for example, payload attacks by hacker groups—as non-state actors—against so-called critical infrastructures.[81] Some of these have already been addressed by public international law, as it will be seen below.

However, the cornerstones of the theory of 'mechanized warfare,' as it is known in international military law, have undergone many changes since the emergence of the inter-war literature that gave rise to the theory. The excellent summary by Hungarian scholar, Ödön Harka reflects on Fuller's idea that the essence of warfare is to put an army in a position to conduct combat operations with the most economical use of their forces.[82] Rapid advances in technology and military and defense innovation obviously serve this purpose (e.g., with the advent of UAV capabilities). Moving away from the original notion of 'mechanization' to the next stage of 'mechanized (even automated) war,' the current debate revolves around the justification for the use of and the limitations of *autonomous weapon systems* (AWS).[83]

Although governments, politicians, experts, and even some arms manufacturers are raising their voices against the creation of fully automated robots, the only legal obstacle to the development of this process currently is the need to comply with the principles of the Law of War, in particular the principles of discrimination and proportionality.[84] According to this provision, civilians and combatants shall, even in cases not covered by the relevant international rules, be protected and subject to the general principles of international law deriving from established custom, the laws of humanity, and the requirements of the conscience of mankind.[85] The use of robotic weapons is also prohibited because they cannot weigh the value of human life or make decisions accounting for the fundamental value of human dignity.[86]

Diplomatic dialogue on this issue has been taking place since 2014 at the United Nations in Geneva, within the institutional framework of the *Convention on Certain Conventional Weapons (*CCW).[87] In 2018, an international forum of experts representing around 80 states met to draft legislation on the phenomenon.[88] The CCW has established the *Group of Governmental Experts* (GGE) on Lethal *Autonomous Weapons Systems* (LAWS), which will be the main institutional forum for the annual international discussion on the issue of autonomy of weapons systems from 2020.[89]

While non-profit groups and advocacy organizations have for some time been calling for a ban on the development of these weapons,[90] their main aim is to push for national legislation to guarantee meaningful human control of AWS capabilities using 'military AI.'[91] However, as these technologies are certainly part of our future, the primary task of law and regulators is to ensure that their development and use are safe[92] and comply with protections for the right to life and human dignity. Further questions that remain include:

(i) Defining the role of *human-machine interaction* and *meaningful human control* in relation to the use *of force* as essential elements of any future regulation, and
(ii) Examining whether AWSs can meet the requirements of humanitarian law. [93]

4 Justifications for a 'Regulation Revolution' to 'Tame the Beast': Conclusion?

After the introduction of the manifold challenges that international and supranational organizations, states and public and private regulators need to face and tackle in light of the 'creative destruction' of the digital economy, we need to briefly reflect on the possible justifications for 'Taming the Beast' and a 'Regulation Revolution' (in the face of many archetypal and atypical dangers) as suggested by two references to the title of this Section.

In the areas presented, regulation is not only urgent, but also essential. Regardless of the level, at which these regulatory problems arise, the issue central to current debates is who shall be the primary (or exclusive) regulator over technology. In addition to the erosion of the concepts of state and sovereignty in the multilevel international framework, a twofold problem presents itself.

(i) Firstly, technology also creates fault-lines on the traditional concept of sovereignty, and the inquiry into who is or can be sovereign surpasses the conventional contexts of public law, expanding into technology and economy. Digital states may as well appear, to which the online existence and metaverse presence of Liberland[94] can be the best example. Can such a 'state' act as a regulator that only has an online footprint, but according to that it has ministries, conducts international relations, and has citizens as well?[95]

(ii) Secondly, nation states are no longer the sole subjects of sovereignty inquiries. Therefore, their initial role as the primary regulator is brought into question. In addition to international organizations (IOs), private regulators such as TMNCs enter the arena and carve out important terrain for themselves to introduce private regulation for all of those processes that arise in the context of their internal operations.

Both of these two problems revolve around the same question: who shall have digital sovereignty, who is the digital sovereign? Primarily talking about TMNCs and IOs, Hungarian state and legal theory scholar Péter Szigeti argued already in 2014 that these are composed of institutional and ideological elements that erode national economies, challenging sovereignty and thus redefining points of contact between citizens.[96]

We may add that this also leads to changing notions of subsidiarity, which is a key issue in defining the point of origin of any regulation. What I understand under this is that certain actors of the digital economy, such as social media or online commercial platforms (and the companies behind them) might feel themselves—in the spirit of subsidiarity—closest to the community in their daily operations. Consequently, creating their own solutions and rules to solve problems that arise in this online community becomes their natural drive. This obviously may clash with traditional notions of subsidiarity in local and state contexts and this is how public and private regulation may end up challenging each other, creating some of the most basic debates in our new world order.

Already in 1991, David Held mentioned the following factors as key to this new world order:[97]

- Governments have less and less possibilities to enforce efficient regulation,
- Their influence over citizens decreases (*Cf. references to changing notions of subsidiarity*),
- Traditional state tasks are more and more realized through international cooperation *(NB especially in the context of third generation human rights and their digital contexts)*,
- Quicker integration and the growing number of IOs make international law more relevant in regulating the conduct of national actors and internal social and legal relations.

In this context, I suggest that academic and public discourse should turn to the issue of "essential state functions," a notion that is explicitly mentioned in TEU Article 4(2) in the context of European integration and is usually tied to debates on constitutional identity.

The EU Treaty remains silent on the range of these functions tied to inherent political and constitutional structures of the Member States, but mentions national security and maintaining law and order. What has been said above regarding the war and critical infrastructures clearly evidences that states have a primordial responsibility to regulate disruptive technologies as they pose risks to the above, for example, in terms of cybersecurity.[98]

Every integration (federal or otherwise) has its own special debates about the division of regulatory competences based in national sovereignty. It is not my purpose to paint an in-depth picture of current European debates, but one key issue is the terrain where these state regulatory functions interact with such competences of international organizations. There are domains where these functions and rules need to coexist and blend into each other.

In the context of the digital economy, this has been referred by Columbia Law's Anu Bradford to as the "Brussels Effect" (on how the EU rules the world),[99] clearly alluding to the regulatory approach of the EU regarding the Digital Services Act (DSA) and the Digital Markets Act (DMA), in terms of which the European regulator engaged in conditioning operators to accept regulation from a very early stage, through prolonged key negotiations such as the ones arising regarding the acceptance of the GDPR by Facebook or the broader EU-US Privacy Shield debate. With every integration comes regulatory competition as well, and digitalization only exacerbates this dynamic.

The role of the state obviously does transform in these processes. Vagelis Papakonstantinou goes as far as to suggest that states themselves could be regarded as platforms with applying all relevant platform regulation exigencies to their daily operations as well. In his view a 'platform-state' is an "*intermediary in an information flow from its citizens […] to everybody else. Its role would be twofold: First, it would store information and, second, it would make them available to anyone interested. […] Both roles are critical to our lives.*"[100] In this context, Papakonstantinou also talks about a necessity to transfer the results of 'platformization' from the market to the political philosophy, and that the current logics of the European regulators are market-based. In his words, the "*platform economy […] imposed a protective regulatory approach whereby the market needs to remain contestable. Equating the state to a market would carry grave consequences to this understanding.*"[101]

One also may argue that state roles and functions should turn toward oversight and control/cooperation in rules enforcement from endless top-down production of rules. In this view, this is just as natural as the transformation of the human function in the workplace from engagement solely in production to the oversight and control of the results of automated processes. This paves the way for the appearance of cooperative models of co-regulation between public and private regulators. It is important to underline, however, that private regulators should not dominate public regulators and to avoid this, states should be awake to the basic truth of "*you snooze, you lose*." Through dialogue, they should find ways to reconcile 'technology-sensitive regulation' with 'regulation-sensitive technology.'

The role of the state needs to change also because the preexisting logics of the economy change as well. While in the past regulating property and ownership were key factors to leading a successful business venture and to access the market, at present regulation is necessary to facilitate access to shared resources on regulated markets (e.g., Airbnb, Uber/Lyft).

The role of the state and the focus of regulation also changes because new rights issues emerge as pre-existing rights paradigms shift. For instance, 10 years ago the biggest issue of workplace privacy was how much private life can employees establish at their workplace or with the equipment provided by the employer. Since the pandemic, the main questions of regulation revolve around the permissible extent of penetration of the employer into the private life of the employee in the context of distance work and home office.

The question then arises: How should governments as national regulators respond to these challenges? One possible and plausible answer to this might be that creating policy cycles and regulatory mechanisms adaptive to change in technology and circumstances (crises, war, etc.) is a key factor for any effective response. This also requires the transformation of regulatory thinking about technology, which was undoubtedly made easier due to the public interest tied to the mitigation of lasting damage brought about by the pandemic.

Regulatory frameworks should contain adequate technological safeguards for near-essential utilities and critical infrastructures connecting us to others, to the market, to the government, but regulators should not be blind to potentially egregious rights violations despite the obvious economic benefits (time, cost, and resource efficiency).

The dynamics of the social contract changed in the information society and the citizens are inclined to claim more and more rights instead of relinquishing them in order to get some of them back. These 'new rights claims' simultaneously permeate both public and private 'regulatory universes' and impulses to respond to these might be stronger in the private sphere, which traditionally reacts quicker and better to such stimuli or incentives. This is due to the above-mentioned issue of the changing notion of subsidiarity, which leads back to the debate about sovereignty in the digital context.

Digital economy platforms feel themselves closest to the online community with many points of constant interaction between them and their perceived role in serving the public interest is carried out by creating previously state-issued rules in the form of soft law to mitigate security or public health concerns in the 'public forum' they occupy online. In these new public spaces 'organized technology' also may represent problems beyond the 'private surveillance' of users and creating opportunities for increased breaches of confidence online. All of these instances essentially affect state actors in view of their traditional functions of regulation and the hard law that originates with them (guided by the state's primary prerogative to regulate social relations). Therefore, cooperation between these two sides is essential because excluding the state as a regulator would clearly violate established principles of rule of law and due process.

On the other hand, public regulators, led by the motivation to protect their citizens from the harms of the online environment establish rules that amount to the creation of 'surveillance states' or 'surveillance economies,' which bring about regulatory issues with separation or fusion of powers, checks and balances, and transparency that again tie back to rule of law and due process.

Perhaps the biggest difference in justifications for regulation (or lack thereof) in the context of digital economy is the regulatory approach taken to address rights issues that arise in the context of privacy and data protection and the protection of the individuals' rights in general.

(i) European regulation is governed by an approach I now call 'dignity-oriented,' focusing on shielding the individuals and their human dignity from harm to the broadest possible extent. In this effort, regulators create many additional layers of protection for the different layers of the persons and their personality (privacy, personal data, correspondence, self-determination).[102] To those who believe in alternative approaches, this might seem as unnecessary overregulation (or labeled as regulatory overreach) complicating and hindering economic development. To be fair, based on some lessons learned from the GDPR,[103] we can even give credit to some of these critiques. However, at the outset, these solutions really only serve to limit the abuse of these core rights, driven by economic instinct, relying on the trade-off that people make enabling them to use the benefits of technology on a societal level, seemingly free of charge.

(ii) The alternative approach that I call upon here is the 'liberty-oriented' one, mostly characteristic to the United States, in which digital economy platforms are shielded to the greatest possible extent from regulation (perceived as harm), thereby facilitating the exercise of democratic freedoms. Under this logic it is said that it is harmful to the society at large if we allow boundless surveillance. Consequently,

> the platforms (from regulation) required to exercise democratic rights like freedom of speech need to be protected. Outside of this context, however, this approach tends to regard personal data as goods in the spirit of commodification and focuses on a much more transaction-centered regulation governed by a free-market logic also protecting the free flow of information.

Regardless of the different regulatory reflexes that might be induced in different legal systems based on a mixture of the above considerations, transatlantic debates revolve around the same key words: sovereignty, subsidiarity, essential state functions and regulation—all these shape public discourse to help reinforce the global positions of the respective actors. This became first clear to me when I studied the 2020 Report of the so-called Berkowitz Commission on Unalienable Rights.[104] In essence, the basic debates on constitutionalism, sovereignty, and fundamental rights that occupy the minds of constitutional scholars on both sides of the Atlantic are basically the same. These include exploring:

(i) the vital role of national sovereignty in ensuring human rights;
(ii) the issue of subsidiarity;
(iii) ways to preserve and reinforce global positions and role as a regulator.[105]

The competition for regulatory dominance involves concurrence in legal competitiveness as well, which is certainly of key importance in trying to meet the exigencies of the digital economy. Legal competitiveness also translates into competition between states and as the 2022 DESI Index by the OECD suggests, Hungary is 22nd in the EU27 region in terms of the development of digital economy, before Slovakia, Poland, Greece, Bulgaria, and Romania. Faced with these numbers I have asked myself the question whether this was the reason why two of the herein enumerated countries (Hungary and Poland) have initially been the most vocal in trying to dominate the private regulators behind social media platforms in terms of regulatory scruples regarding online freedom of speech.

Legal as well as technological innovation is key in bridging the digital divide and to successfully fulfill regulatory tasks in this realm, states have to adopt a paternalistic approach to technology respecting the applicable legal constraints and addressing justified fears of rights violations. The overarching context of 'digitalization' provides a valid excuse for outbreaks of 'regulation revolutions,' irrespective of the level we focus on in the structures of multilevel governance. The reason for this is because every actor with 'skin in the game' knows that digitalization and the continued evolution of the digital economy through innovation is unavoidable.

To sum up, let me paraphrase President Ronald Reagan, who is said to have said that the "*[g]overnment's view of the economy could be summed up in a few short phrases: 'If it moves, tax it. If it keeps moving, regulate it. If it stops moving, subsidize it.*'" The famous phrase attributed to him describes how the government should approach economic regulation, but how does it apply to the digital economy and its current 'ecosystem'?

We are obviously aware that the digital economy moves, and issues of taxation are already resolved (even if sometimes are debated).[106] It will presumably not stop moving any time soon, so we do not need to address the issue of subsidies. However, we should see that it keeps moving at a pace faster than ever before; therefore we do need to regulate it with as many tools as possible to ensure the future fate of all of the above-mentioned legal issues that have been described in this chapter. The debate over the best possible regulatory choices in many different domains however is far from over.

Notes

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13. European digitalization efforts in 2020 are summarized from the perspective of the functioning of several public subsystems in the article by László Trócsányi - Gábor Lovászy László (szerk.): Európai körkép (Ludovika, Budapest, 2020). In particular, see the chapters on the Czech Republic, Denmark, Estonia, France, Germany, Holland, Croatia, Ireland, Ireland, Latvia, Lithuania, Luxembourg, Malta, Germany, Austria, Portugal, Romania, Spain, Sweden, Slovenia, and Sweden.
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15. https://2015-2019.kormany.hu/download/f/58/d1000/NDS.pdf pp. 78. (On p. 21., the Strategy also mentions the impact on the labor market, which we have mentioned as a negative, as a problem to be expected from 2030.)
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35. See Chisnall 2020. https://blogs.lse.ac.uk/businessreview/2020/03/04/are-we-becoming-digital-slaves-why-online-privacy-is-a-misnomer/.
36. Article VI of the Fundamental Law of Hungary in its current form can be read at: https://hunconcourt.hu/uploads/sites/3/2021/01/thefundamentallawofhungary_20201223_fin.pdf.
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Household Social Robots, University of Szeged, Faculty of Law and Political Sciences—Innovariant, Szeged, 2021.

44. GDPR Article 22 (1).
45. For more on the ADM problem, see. Gültekin Várkonyi 2021. pp. 95–99.
46. https://www.facebook.com/business/help/223852498347426?id=2393014447396453.
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58. For more on the subject, see, for example, the Konrad Adenauer Stiftung's analysis on the subject, Chris Fei Shen: Social Credit System in China (online) https://www.kas.de/documents/288143/4843367/panorama_digital_asia_v3a_Shen.pdf/a55cefce-8e97-32d6-63a4-2e4cc47c0513.
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60. See, for example, Phil Laplante, Ben Amaba: Artificial Intelligence in Critical Infrastructure Systems. In: Computer. Published by the IEEE Computer Society. 24 September 2021. Available at: https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9548022.
61. Opinions are divided on the use of the VeriPol 'automatic lie detection' AI system introduced by the Spanish authorities. See, for example, https://algorithmwatch.org/en/spain-police-veripol/ or https://www.bestpractice.ai/studies/spanish_national_police_identifies_false_robbery_reports_with_over_80_accuracy_using_machine_learning_and_natural_language_processing.
62. See, for example, the ideas for the development of the EU-LISA (European Union Agency for the Operational Management of Large-

Scale IT Systems in the Area of Freedom, Security and Justice) system, see, for example, https://www.eulisa.europa.eu/Publications/Reports/AI%20in%20the%20OM%20of%20Large-scale%20IT%20Systems.pdf.

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12

The Ecology of Innovation: The Evolution of a Research Paradigm

Hilton L. Root

1 Introduction

Policymakers all over the world have embraced the Entrepreneurial Ecosystem (EE) concept in their policy documents (Brown & Mason, 2017; Brown & Mawson, 2019). They are drawing from a rich literature in applied economics.[1] The study of entrepreneurship began with a focus on the entrepreneur; it advanced to consider the ecosystem of which the individual actor is a part; Lundvall (1992) took it to the level of national systems of innovation, Porter (1998) to regional clusters, and Cooke et al. (1997) to regional innovation systems.[2] So far essential local conditions have been identified at the city, regional, and national level. Ecological metaphors were proposed by Moore (1993) and were popularized by Isenberg (2010). Entrepreneurship at the national level is about the ecosystem. The emergence of entrepreneurial ecosystems as a research

H. L. Root (✉)
Schar School of Policy and Government, George Mason University, Arlington, VA, USA
e-mail: hroot2@gmu.edu

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field of its own has been surveyed by (Acs et al., 2017), whereas Lafuente et al. (2020), Cao and Shi (2021), and Wurth et al. (2022) have studied the connections between ecosystems and territorial outcomes. The entrepreneurial ecosystem has been used to understand the rise of technology-led entrepreneurship in the digital economy (Acs et al., 2021; Lafuente et al., 2022). Yet, the study of the entrepreneurial ecosystem is still young. The journey has only just begun and has much further to go. The ecosystem approach needs to be grounded in a broader theoretical framework, or meta-theory, that can embody culture more broadly.

The purpose of this chapter is to demonstrate how complex system analytics can enhance entrepreneurship scholarship and policy. It will suggest ways to think about the relationship between the decisions and strategies of agents and the structure of the environment in which choices are made. The chapter will aim to understand the relationship of system variables at their macroscopic scale, in the hope of defining global properties that are independent of the details at the microscopic scale. The end result will be a literature that is richer in insights about the informal constraints, such as social norms, beliefs and ideologies, and the cognitive processes and cultural elements that underpin them, leading to a meta-theory that integrates a community's culture, and its historical specificity with its system of innovation.

The plan of the chapter follows. Section 2 briefly describes the development of entrepreneurial ecosystems as a research field from an evolutionary perspective. Section 3 discusses the role of complex systems for building models that explain entrepreneurship as well as the links among agents and cultural elements that emanate from the system's internal dynamics. Section 4 presents complex adaptive systems (CAS) as a purposeful theoretical framework with the potential to enhance our understanding of the evolutionary algorithms that underpin EE models. Section 5 concludes.

2 Evolution and Entrepreneurial Ecosystems

The study of entrepreneurship and innovation more generally has two distinctive strands. I want to find common ground between them. One body of literature offers narratives that present innumerable sociological, historical variables as they affect individual innovators, but the lack of clear boundaries between the variables makes it difficult to establish causal relationships (Isaacson, 2014). The neoclassical perspective seeks to overcome these obstacles to the creation of cumulative knowledge. In this approach operability is obtained by extreme reductionisms. Aggregate outcomes are obtained by making strongly unrealistic assumptions: Atomized individuals that operate without a social or historical context, follow narrowly, rational scripts, and respond to exogenous variables according to detailed axioms. This enables deductive accounts of relationships in which precise hypothesis can be subject to rigorous statistical tests. Many advances are made possible with this approach. There are also many reasons why this approach has limited validity as a problem-solving tool.

Whereas the original focus was individuals or firms, the ecosystem approach brought researchers into contact with structures that defined the local economic and social context. To increase the scope of entrepreneurship scholarship beyond the initial concern with the characteristics and behaviors of individuals or firms, researchers were encouraged to take the perspective of economic development policymakers and ask entrepreneurs directly what they need and then meet these needs with available public resources (Feld, 2012). Acs et al. (2014) provide criterion to measure structures of entrepreneurship at the national level. Stam and van de Ven (2021) offer an alternative approach that conceptualizes EEs through two sets of elements: resource endowments (including physical infrastructure, demand, intermediaries, talent, knowledge, leadership, and finance) and institutional arrangements, including formal institutions, culture, and networks. Both authors concentrate upon discovering the microscopic rules or instructions that may lead to simple policy interventions. But superficial categorization of the entrepreneurial environment results and the policy proposition underlying this work is that changing the instructions—the codes embodied in technology or financial processes—are sufficient to bring about change in the system. What they ignore is that for instructions to modify behaviors cultural intermediaries that can drive cultural evolution are required.

Ecosystems are evolutionary constructs, yet this expansion of EE was conducted without there being an underlying notion of what is evolutionary about these systems. In biology only populations evolve. Early economists like Alfred Marshall viewed the economy as an evolutionary process in which agents adapted to environmental changes that are generated by their own interactions. Since there was no way to measure frequency dependent selection or mutation nor were there structural populations from which to study population genetics among actors in the economy, the Darwinian modeling of the replication of natural systems was eschewed by economists. The original work by Richard Nelson and Sidney Winters (1982, 2002) and Nelson (2005) introduced evolutionary considerations into economic analysis without an analogue to genes in biological replication. They adapted Darwinian logic to the problem of innovation in the production of manufactured objects. Their work on technology describes the co-evolution of technologies and institutions that lead to innovations, as companies respond to environmental changes. In their conception when the business environment changes and profitability diminishes, innovative companies respond by updating their knowledge to amend their routines and launch new technologies. The fitness of any one firm is not constant but depends upon the fitness of others in its population set. Selection emerges whenever two or more firms reproduce at different rates. This enables one firm to enhance its fitness strategy by reproducing new products faster than its rival. This effort at evolutionary theorizing in economics generalizes from Darwinian assumptions at the both the individual and multilevel. But Nelson and Winter address variation, replication, selection, and propagation superficially and often only capture one stage of the feedback process. They did not address the question of why much of the radical innovation that we observe, such as the development of digital platforms, arises via new firms that enter the market and challenge the technology and business models of incumbents. How disruptive innovation arises is essentially a political economy question, an area that EE has been averse to tackle. In addition, the evolutionary algorithms Nelson and Winter describe do not take into account changes in the socio-economic context that transform values and behavioral norms.

The EE literature has met the challenge of definition and measurement by developing indices of entrepreneurship that trace the evolution of the variables through the simple and local interactions between a designated and confined list of constitutive elements. The list of variables represents regional knowledge production and how place-based innovation can spread and catalyze innovation. But there is more to account for. Entrepreneurs derive autonomy on the basis of relationships outside of their community. They also transmit new ideas from their community of origin to those outside by relying on linkages to hub-based connectivity within the system. Within the larger ecology sub-systems must be allowed to proliferate as incubators for new ideas and products. No one can know a-priori which sub-systems will be critical to new ventures. What we do know is that sub-systems must have connectivity to system level hubs to disseminate local innovations widely (Root, 2023). To trace such linkages will require more integration of network models into the analytical tool kit.

The literature has identified the sources of the entrepreneurial ecosystems to local conditions at the local, regional, and national level, but what we need are network analyses of how these different levels and sub-systems are linked, and how those linkages allow innovations that occur locally to have transformative effects at the system level. This will also raise the question concerning the resilience and stability properties of the system (Root, 2020, pp. 79–111).

3 The Coevolution of Agency and Structure in Entrepreneurial Ecosystems

The ecosystem approach to innovation makes it possible to construct models in which structure plays a leading role. This represents a significant departure from pure neoclassical approaches in which agency is constrained by equilibrium.[3]

To encompass the full range of evolutionary forces at play in entrepreneurial ecosystems, we need an evolutionary theory of agency that reflects sociocultural factors in decision making. We are not there yet. The agency/structure relationship in typical EE models are grounded in notions of individual behavior that reflect fully rational, deductive decision making aimed at maximizing utility. These unrealistic notions of agent behavior are used to build political economy arguments based on path dependency that give rise to exogenous coordination problems.

Innovation is the end result of a process of cumulative causation that depends upon social feedback. The entrepreneur is a product of the system of innovation. To understand the entrepreneur's role, which may vary from society to society, researchers must develop an evolutionary theory of agency that traces decision-making to its sociocultural roots. This means going beyond neoclassical economics to identify the factors that make it more difficult to solve those dilemmas of collective action that prevent or enable entrepreneurial sprits to flourish in a community. EE scholars have effectively applied the approach of institutionalists but are less successful at identifying the co-evolution between norms and formal institutions.

The definition of entrepreneurship must not include its consequences, we must be able to distinguish consequences from the factors that contribute to it. Isenberg, for example, defines the characteristics of EE in terms of their consequences—appropriate finance, quality human capital, venture-friendly markets, and institutional supports (Isenberg, 2011, p. 1). Social capital is a useful idea once distinguished from its consequences. However, an economy's competitiveness cannot be explained by arguments such as "a society being rich in social capital that is committed to public goods performs well." The statement is a tautology; social trust cannot be both a cause and a consequence. What we ideally want to know are the evolutionary dynamics that produced these properties in the first place.

By adopting a complex systems perspective, we can conceive of the relationship of agency and structure systemically, in terms of the emerging properties of the collective networked behavior of the whole, which encompasses hierarchical relationships of authority, as well as the norms, beliefs, and ideologies, that legitimate those hierarchies. This will enable an explanation of entrepreneurship that identifies the links, among agents and cultural elements as emergent properties emanating from a system's internal dynamics.

What the current EE models do not achieve is an understanding of how cultural evolution exerts an influence on the moral precepts, beliefs, and norms that induce and limit agent behaviors. To understand differences in the dynamism of entrepreneurial incentives, we need models in which strategic behavior and the formation of expectations can be identified with some process of learning. The diffusion of precepts or conventions that enable cooperation often depend upon a shared cosmology or collectively adhered to paradigms about how the world operates. This further entrenches normative restrictions on agent preferences, and is essential information for understanding why entrepreneurial motivations are more prevalent in one environment than another.

To understand the conditions, impulses, incentives, and behaviors that give rise to creative entropy, we will need models in which the mechanics of interaction between micro and macroscopic layers of the entrepreneurial ecosystem can be understood. To date synergy exists between the computational modelers and economists working on global value chains (Balland et al., 2022; Hausmann et al., 2014). But their concept of economic complexity does not directly address the incentives for innovation either at the community or the individual level and provide little insight into the social context in which behavior is embedded. This will be aided by computationally enabled models that are in the experimental stage, but in which there has been considerable progress during the last twenty years (Axtell & Farmer, 2022). The next step is to capture the complexity that arises not from variables themselves but from the mutual interactions of the variables over time. We want to know the patterns that form from their interactions, and to observe the complexity that arises from the higher-level patterns that arise globally.

An analogy of complexity is the game of pool. Armed with a good understanding of Newton's laws of motion, one can reasonably calculate how a cue ball should be hit if there were two other pool balls on the table. Especially if we can assume a perfectly flat table. But now consider that the number of balls on the table increases and the table is on a ship during a storm. Now knowing the exact distances between the balls is no longer sufficient, and the rules of physics governing any pair of colliding balls no longer suffices. The ocean upon which the entrepreneurial pool table is sitting comprises the psychological and ultimately neurological process that shape human cognition. The dimensions to consider are cognitive, affective, and social; individuals learn and modify their behavior in relationship to other individuals. The available set of communication mechanisms are all socially constructed and reflect deep variations in original conditions among population groups. These variations exist at national and regional levels but also within subsets of national populations.

4 The Entrepreneurial Ecosystem as a Complex Adaptive System (CAS)

The EE approach arose as a hybrid blend of disciplines, a similarity that it shares with the study of ecology in natural systems.[4] As relatively new fields of inquiry, both enjoyed freedom to explore a wide range of disciplinary domains. Most research in ecology is strongly grounded in the study of complex adaptive systems. In the scientific sense complexity is a property of systems comprising many interdependent parts, arising when the behavior of the whole emerges from the interactions of its components. A change in one part of the system affects other parts until the system acquires new properties that its individual components did not possess.

Shifts in trade and in geopolitical influence have created new networks and brought about an interconnectedness of the world's many social and economic systems that exist at different stages of development. These networks are not only interconnected, they are constantly reacting to the behaviors, or anticipated behaviors, of other networks that are also repositioning themselves as the landscape they share is altered. Together they shape the larger system, creating rules and identities at the macro level that differ from those at the micro levels.

Interdependence among connected but diverse parts is a characteristic that distinguishes complex from merely complicated systems. In a complex system, the removal of a single part will change the behaviors of remaining components; in a merely complicated system, such as a clock, an internal combustion engine or a nuclear reactor, the removal of one part will not cause a change in the remaining parts, although the system itself may cease to function. Complex systems may be organized hierarchically, but they can also self-organize without design, making it impossible to predict the behaviors of numerous components in constantly shifting environments and organization formations. What happens in one component may affect seemingly unrelated components, so distinguishing cause and effect is not easy (Root, 2013).

Here is how the complex system approach can enhance the evolutionary algorithms that underpin EE models:

1. The *replicator* dynamics of EE usually refer to domain specific routines and habits, such as business plans, product designs, corporate cultures, and formal institutions. The rules of social replication include punishment, language, copying, written registers, judicial laws, and institutionalization. A vision that is communicated hierarchically and inculcated by top-down instructions is how organizations such as firms or political parties transfer domain-specific knowledge, culture, and operational designs to ensure their acceptance among the rank and file. The replicator dynamics of CAS refer to modes of collective cooperation made possible by prototypical norms, beliefs, ideologies, expressed via social paradigms, ethical constructs, symbolic group attachments, or collective norms such as forbearance of cousin marriages by the community, something common in some cultures but not in others. Since no individual can unilaterally modify the topology that they are in, the social and hierarchical relationships, norms, beliefs, and ideologies of a collective or social network are essential inputs to entrepreneurial incentives.
2. The *variation* that EE concerns itself with are essentially alternative ideas or product or procedural innovations that are domain specific. CAS, as noted, concerns itself with social paradigms such as ethical codes or ideology. The selection mechanism in the EE approach is either social approval, peer pressure, market competition, or the preferences of leadership cliques. CAS views selection as cultural adaptation or inertia, expressed in system-level templates of stability or resilience. It seeks to understand evolutionary mechanisms that are not strictly Darwinian, encompassing topics such as group selection, where replication occurs at multiple levels and in which agents are creatively constructing the environment they inhabit. Embracing

CAS scholars of entrepreneurship can further integrate their efforts with scholarship seeking to elaborate evolutionary theories about why humans cooperate. As science progresses future research will probe into neurophysiological domains to better grasp the functioning of the brain. Step-ups will occur according to the extent that progress is made in studies of experimental economics and cognitive psychology.

3. EE typically focuses on tangible physical products, work behaviors in firms, and political or civic activities more generally and the codification of organizational designs, technologies, goods and services, constitutions, rules and bylaws. CAS seeks to encompass social governance, probing religious and symbolic representation, including cultural devolution and practices, ritualistic behavior, and shared meta-visions that elaborate a vision of the core drivers of societal evolution within a given historical community. An example is how local communities are supplanted by imagined communities that allow strangers to share a common identity beyond kinship, or that allow products designed for one set of consumers to find broader markets.
4. Although EE emphasizes the interaction of elements and networks that produce cultural values, the system components and the environment of adaptation tends to be narrow. EE places most of its emphasis on micro behaviors in markets and social networks of leadership, finance, talent, knowledge, and support services. The structural and ideational supports that enables those behaviors to be carried out receives fleeting notice. A fully developed CAS would deal with social governance, and would confront the cumulative causation that makes social feedback complex, and the broader historical legacies of societies that link behavior, norms, and beliefs to prior events. In this regard, cultural evolution and history are highly relevant to the question of what supports the emergence of entrepreneurship in one society and not in another.

Cultural anthropologist Joseph Henrich (2020) and evolutionary economist Jonathan Schulz (2022) have emphasized Christianity's role in forging cultural commonalities across western European populations by promulgating rights outside of kinship and banning cousin marriages. In the urban communes of pre-modern Europe, Christianity allowed deeper forms of cooperation and provided a basis for social cohesion. The forces unleashed via literacy, or religious conversion attained evolutionary influence over individual psychology, and this helped to foster a sense of identity, a shared cosmology, and a shared criteria for social status. Following a similar logic, during the nineteenth century the bolstered apparatus of Western European states enabled national identities to emerge. These were constructed identities. Today markets create consumer tribes that transcend national boundaries.

5. The menu of behavioral mechanisms at the disposal of entrepreneurs will vary according to social context. However, the topic of diffusion, propagation and policy advocacy is treated by EE in terms of best practices, articulated in off-the-shelf, developmental advisory services. Such approaches are weak at identifying what will motivate individuals to modify their underlying behaviors as the result of the same environmental change. One of the reasons this approach performs poorly in different cultural milieus is that actors deliberate on the basis of conditional reasoning, their motivations are multidimensional; optimization according to an egocentric utility function is just one. By contrast, in CAS diffusion occurs through symbolism that resonates at the community level. Ultimately, CAS has potential to be a metatheory for gauging how the environment shapes agents' behavior and how collective behavior of the agents affects the configuration of structure. In the end it is the system that acts as a breeder of innovations and entrepreneurs, of which only a fraction will survive.

5 Conclusion

An entrepreneurial ecosystem is largely understood to include local, social, institutional, and cultural processes that support firm formation and growth (Acs et al., 2014; Lafuente et al., 2020; Wurth et al., 2022). Yet there is still much to learn about the evolutionary dynamics of entrepreneurial ecosystem, if we are to provide a better answer to enduring policy dilemma of animating local innovation systems to contribute to the innovation engine that drives global growth. Innovation systems are heterogeneous across economies and within sectors and regions of national economies, their structure, their timing and cultural mechanisms vary in terms of their ability to support entrepreneurial ventures, especially those that will alter the status quo. Success in overcoming local constraints is rarely continuous, but episodic. Entrepreneurship arise unexpectedly and fortuitously in one sector of an economy or region of the world, with no prior indication of their timing, and without notice to then suddenly dry up and move on. Once having adapted CAS into the analysis, we will be able to embark on a journey that promises further advances into unraveling this mystery of why some ecosystems are more likely to encourage discovery, creativity, and resilience.

Notes

1. Between 1970 and 2017 215 papers on entrepreneurial ecosystems were reported by Scopus and 116 by the Web of Science (Malecki, 2018).
2. The original focus was the "Schumpeterian" entrepreneur.
3. Conventional neoclassical approaches analyze social phenomena in terms of the actions of atomized actors. Individual incentives are seen to be what guides behavior. In theories that are purely structural, behavior is determined according to social norms. Introducing a time element introduces an intermediate position between methodological individualism and methodological collectivism.
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Glossary

BOD Benefit of the Doubt
CAS Complex Adaptive System
DEA Data Envelopment Analysis
DEE Digital Entrepreneurial Ecosystem Framework
DEI Digital Entrepreneurship Index
DPE Digital Platform Ecosystem
EE Entrepreneurial Ecosystem
FIRES Financial and Institutional Reform to build and Entrepreneurial Society
GEDI Global Entrepreneurship and Development Institute
GEI Global Entrepreneurship Index
GEM Global Entrepreneurship Monitor
GEN Global Entrepreneurship Network
GERA Global Entrepreneurship Research Association
GSER Global Startup Ecosystem Report
GMR Geographic Macro and Regional Modeling Framework
KSTE Knowledge Spillover Theory of Entrepreneurship
NSE National Systems of Entrepreneurship
NUTS Nomenclature of Territorial Units for Statistics
PFB Penalty for Bottleneck

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REDI Regional Entrepreneurship and Development Index
RSE Regional Systems of Entrepreneurship
TEA Total Entrepreneurial Activity
TFP Total Factor Productivity

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[1] Note: Page numbers followed by 'n' refer to notes.

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