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Seek foreign funds or technology? Relative impacts of different spillover modes on innovation

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Abstract
This paper identifies channels of influence of foreign linkages on innovative activity in nations and it compares the relative effects of aggregate innovation linkages, FDIs, high-tech imports, and ICT imports, on patenting across a large sample of nations. Whereas various drivers of the international innovative activity have been studied in the literature, our understanding of the contributions of different linkages to innovation deserves more attention. We ask: Are the different innovation linkages equally complementary to research inputs in fostering innovation? We find that a broader index of innovation linkages shows positive and significant spillovers on innovation. We also find some support for the positive link between FDIs and innovation; however, high-tech imports and ICT imports have opposite effects on innovation, with the former effect being negative. These spillovers are reinforced by the positive and expected impacts of R&D spending. In other results, greater venture capital investments boost innovation in most cases. The findings are somewhat sensitive across two alternative measures of patenting and there are some nonlinearities in the influence of FDIs and imports on innovation.

Keywords Patents · Innovation · R&D · FDI · High-tech imports · ICT imports · Innovation linkages

JEL Classification O31 · O33 · O38

1 Introduction

The continued global importance of technological change designed to tackle microeconomic and macroeconomic issues has researchers and policymakers keenly interested in supporting and boosting the antecedent innovations. As new challenges emerge with diseases, the environment, sustainability, space exploration, etc., new and better methods and technologies are needed.

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Whereas many initiatives, such as research subsidies, have been shown to yield dividends, the differing innovation rates across nations (and even over time for a given nation) and the inability to find solutions to some lingering problems (e.g., a cure for the common cold) have underscored the need for continued attention to the direction of research. It is in this respect that the current work attempts to add to the existing body of research. Specifically, we examine the spillovers from innovation linkages on innovation. Innovation linkages capture indirect (formal and informal) channels that impact innovation. These could be networks or other support mechanisms that complement the direct returns from R&D spending on innovation. For example, innovation linkages could emerge from the geographic concentration of firms in certain clusters, which would lower the costs of formal and informal knowledge flows that facilitate innovation (Chandrashekar and Bala Subrahmanya 2019). Effective allocation of research resources is contingent upon a correct accounting of the costs and benefits of such endeavors.

Specific avenues facilitating innovation occur via foreign interactions, including FDIs (foreign direct investments) and other imports. Spillover channels from FDIs and other imports to the innovation process might include a combination of reverse engineering, knowledge flow from labor transitions, networking and formal/informal relations between firms, and demonstration effects (Cheung and Lin 2004; Salim et al. 2017). However, the nature and strength of these spillovers can vary across nations. Thus, it is important to understand the relative influence of aggregate indicators of interactions, foreign investments, and imports on innovation.

The research questions addressed in this paper are:

- Are the different measures of innovation output equally affected by innovation linkages?
- What are the relative impacts of FDIs and different technology imports on innovation?

Whereas FDI inflows might vary substantially, including investments in established and greenfield projects, and may be initiated by the foreign investor or be in response to active solicitations by host country firms and governments (also see Coveri and Zanfei 2022). Thus, not all FDIs necessarily are technology-intensive. Related empirical investigations have generally found positive spillovers from FDIs onto innovation (Cheung and Lin 2004; Lin and Lin 2010). On the other hand, technology imports are initiated by the importer and are likely intended to fit a specific purpose or address an identified shortage.

To address these questions, data on a large sample of countries are used to identify the contributions of different innovation linkages to innovation. It is not clear a priori whether FDIs and different dimensions of technology imports (e.g., high-tech imports versus ICT (information and communications technology) imports) have similar dividends in terms of fostering innovation. One could envision scenarios where some import types, like high-tech imports, might directly replace specific products and thus make product innovation less desirable, while other imports like ICT imports might be related to production and service processes and might enhance the need for innovations. This may be partly due to the differences across industries in the manner in which specific imports interact with other inputs across industries (i.e., whether substitutes or complements (Goel 1990)). Accordingly, the distinctions between process and product inputs might be able to reveal their differing impacts on innovations and provide new insights into the channels of innovation drivers.

The measurement of science-technology linkages is challenging (e.g., Fan et al. 2017; Meyer 2006) and this research contributes to this topic. The key underlying reason is that the sources of knowledge and technology spillovers are many, ranging from spatial, formal, informal, etc., and all these vary by industry, technology, region, institutional setup, etc. Thus, it is nearly impossible for any single measure to capture the different dimensions.

This research is part of the innovation spillovers literature, which has a theoretical foundation (D'Aspremont and Jacquemin 1988; Goel 1995; Griliches 1992; Haruna and Goel 2015). A better understanding of innovation spillovers would result in a better accounting of the costs and benefits of research, both socially and privately (Antonelli 2006; Antonelli and Link 2015; de Groot et al. 2001; Döring and Schnellenbach 2006; Fischer and Varga 2003; Henderson 2007; Mowery et al. 2001; Sakakibara 2003; Singh 2005; Skare and Soriano 2021). Broadly speaking, knowledge might diffuse via trade (impersonal or unintended diffusion) or via deliberative collaborative efforts (e.g., university-industry collaborations, research joint ventures (Di Cagno et al. 2016; Kamien et al. 1992)).

Overall, different empirical studies in the literature have captured specific dimensions of research spillovers in terms of their impacts on different performance dimensions. The underlying difficulty is that the channels of spillovers are varied, with some more readily prone to measurement than others, and that the spillovers diffuse differently over time. This paper adds to this body of work by comparing the relative innovation-productivity of different innovation linkages across a large sample of nations, while also accounting for how innovation may be differently captured. An evaluation of the effectiveness of innovation linkages in promoting innovation can be useful in ascertaining the success of national or regional innovation systems (Li et al. 2021; Nelson 1993).

The empirical results show that a broader index of innovation linkages shows positive and significant spillovers on innovation, while joint ventures and university-industry collaborations fail to exert a significant influence. These spillovers are reinforced by the positive and expected impacts of R&D spending. We find some support for the positive link between FDIs and innovation; however, high-tech imports and ICT imports have opposite effects on innovation, with the former effect being negative. From a policy perspective, the findings will enable a better cost–benefit accounting of the process of innovation. At a broader level, the findings have implications for knowledge flows (Antonelli and Link 2015). In other results, greater venture capital investments boost innovation in most cases. Implications for technology policy are discussed. The layout of the rest of the paper includes the background and the model in the next section, followed by data and estimation, results, and conclusions.

2 Background and the empirical model

2.1 Background

This research can be seen as tying to the literature on the impacts of R&D and to the effects of innovation linkages, especially external linkages. To better place the research in the literature and highlight its contribution, it seems useful to provide a brief review of the related literature.[1]

Miguelez and Moreno (2018) focus on regional innovation and external linkages in Europe. A key question they ask is if the generation of new knowledge benefits from the

[1] A broader survey of the literature is in Audretsch et al. (2002).

combination of similar or dissimilar pieces of existing technologies——akin to whether there are scope economies in knowledge. They find that, at the local level, both related variety and unrelated variety influence regional innovation. An earlier study by Rothwell and Dodgson (1991) focused on firm size in this context, arguing that while small and medium-sized enterprises (SMEs) can enjoy a number of advantages in the innovation process, they can also suffer from a number of disadvantages, including the inability to establish the appropriate scientific networks. The importance of interpersonal networks in impacting knowledge diffusion was also found by Singh (2005). There is some evidence in the literature on the distinction between strong and weak spillover ties——Wang et al. (2017) provide evidence from the semiconductor industry. Finally, Love et al. (2014) examine a somewhat novel angle by studying the influence of openness to external knowledge sources on innovation output.

In addition, sources of knowledge might be embedded in the attributes of the entrepreneur. To examine this aspect, Amoroso et al. (2018) use a sample of European high-tech manufacturing firms and examine the influence of experience, age, and education of the firm's primary founder on the perceived importance of different sources of knowledge. They find variations in the impact of these features across regions and across knowledge sources. Another interesting dimension of knowledge flows, where information transmits from competitors or other applicants in innovation/funding competitions, has been considered by Fletcher et al. (2022).

A section of the literature has focused on the impacts of R&D on productivity. In this context, Coe and Helpman (1995) find that foreign R&D has beneficial effects on domestic productivity, and the estimated rates of return on R&D to be high, both in terms of domestic output and international spillovers (Engelbrecht (1997)).

Even beyond international borders, the geographic or spatial dimension of knowledge and technology spillovers is important domestically as well. The main premise is that knowledge spillovers are greater in the immediate vicinity and dissipate in more distant areas (Fischer and Varga 2003; Döring and Schnellenbach 2006; Henderson 2007). Of course, the extent of spatial spillovers is subject to the nature of the industry, the type of technology, and the institutional setup (e.g., the degree of intellectual property protection). While we do not consider the spatial aspects directly in this paper, they are indirectly accounted for via the innovation linkage variables that span different jurisdictions.

In a dynamic sense, technology spillovers have longer-term payoffs as future technologies are based on current spillovers (Antonelli 2006; Scotchmer 1991). How these spillovers depreciate over time is a key question in assessing the social returns from a given innovation (Henderson 2007).

A broader overview of these issues is provided in an informative review by Feldman (1999). She identifies four separate strains in the empirical spillovers literature: innovation production functions; the linkages between patent citations, knowledge spillovers via labor mobility; and knowledge spillovers embodied in traded goods (whereby knowledge is directly evident or possible through reverse engineering). She further notes that the spillovers are subject to knowledge agglomeration economies, the attributes of knowledge (e.g., basic or applied), and the characteristics of firms (both knowledge producers and recipients).

With respect to the FDI-innovation nexus, the empirical support in the literature is generally for the positive impacts of FDIs on innovation (Cheung and Lin 2004; Lin and Lin 2010), although some scholars fail to find a robust influence (Salim et al. 2017). Spithoven and Merlevede (2022) consider the impacts on the total factor productivity of non-R&D active firms from FDI and R&D of other firms. Another dimension of investment, via venture capital investments, has also been found to have positive innovation effects (Kortum and Lerner 2001). On the other hand, the innovation spillovers from specific import types do not seem to have been studied in much detail.

In the context of this brief literature overview, the contribution of this work lies in comparing the relative innovation-productivity of different innovation linkages across two patent measures for a large sample of nations.

2.2 The empirical model

Based on the above, we can formulate our main hypothesis:

H1 Greater innovation spillovers/linkages would lead to greater innovation, ceteris paribus.

Spillovers can be seen as boosting innovation by reducing the transaction costs of engaging in the pursuit of innovation. We consider different channels of spillovers and an evaluation of their relative impacts on innovation would interesting.

Drawing on the above discussion and to test hypothesis H1, with the unit of observation being a country and year, the general form of the estimated equation is the following (with subscripts i, j, and k, respectively, denoting, patent type, innovation linkage dimension, and technology import type)

$$\begin{aligned} \text{Patent}_{\text{i}} = \text{f}\big(&\text{R\&Dlag, Innovation linkages}_{\text{j}}, \text{FDI, Technology imports}_{\text{k}}, \\ &\text{Venture capital, GDP growth, Rule of Law, Market size}\big) \end{aligned} \tag{1}$$

i = Patent1, Patent2
j = INNlink, INNcluster
k = HighTkIMP, IctIMP
where the subscripted elements i, j, and k are described below.

The dependent variable, Patent, is an innovation output. While patents are the most readily available and frequently used measures of innovation output, patent counts are imperfect, suffering from the inability to capture unpatented or unpatentable innovations as well as the inability to qualitatively distinguish across innovations. To address this limitation, we use two alternative patenting measures. Patent1 is the number of resident patent applications per GDP filed at a given national or regional patent office, and Patent2 is the number of Patent Cooperation Treaty (PCT) applications per GDP. The Patent2 measure is of a broader scope as it makes it possible for an applicant to seek patent protection for an invention simultaneously in a number of countries by filing a single international patent application (Tables 1 and 2). One could envision cases where small, first-time inventors in a nation might apply for Patent1, while large corporations, especially multi-national corporations, might more likely file Patent2 applications. The correlation between the two innovation measures, Patent1 and Patent2, is 0.7 (Table 3), implying that they are capturing similar dimensions of innovation output.

An empirical contribution of this work lies in considering the different dimensions of innovation linkages and their spillovers on innovation (across two different measures of patenting). Innovation linkages capture different aspects of (inward) innovation spillovers, and can alternately be viewed as indirect inputs in the innovation process (Antonelli (2006)). In practice, innovation spillovers are hard to capture, and, consequently, the related theoretical

Table 1 Variable definitions and data sources

Variable	Definition	Source
Patent1	Number of resident patent applications filed at a given national or regional patent office (per billion PPP$ GDP). A resident patent application refers to an application filed with an IP office for or on behalf of the first-named applicant's country of residence	GII
Patent2	Number of Patent Cooperation Treaty (PCT) applications (per billion PPP$ GDP). A PCT application refers to an international patent application filed through the WIPO-administered Patent Cooperation Treaty (PCT). The PCT system makes it possible to seek patent protection for an invention simultaneously in a number of countries by filing a single international patent application. The origin of PCT applications is defined by the residence of the first-named applicant. Data are available only for those economies which are PCT contracting states	
R&D	Gross expenditure on R&D, % of GDP	
R&Dlag	One-year lag of R&D	
INNlink	Index of innovation linkages, including university-industry research collaboration, state of cluster development, GERD financed from abroad, joint venture/strategic alliance deals, patent families filed in two offices. Higher values, better outcomes	
INNcluster	State of cluster development, Average answer to the survey question on the role of clusters in the economy: In your country, how widespread are well-developed and deep clusters (geographic concentrations of firms, suppliers, producers of related products and services, and specialized institutions in a particular field)? Lagged one year	
FDI	Foreign direct investments (FDIs), net inflows (% of GDP, three-year average)	
HighTkIMP	High-tech imports. High-technology exports and imports contain technical products with a high intensity of R&D. Commodities belong to the following sectors: aerospace; computers & office machines; electronics; telecommunications; pharmacy; scientific instruments; electrical machinery; chemistry; non-electrical machinery; and armament; % of total trade	
IctIMP	ICT services imports. Telecommunications, computer and information services; % of total trade	
VentureCAP	Venture capital deals per investment location: Number of deals (per billion PPP$ GDP)	
GDPgrAVG	GDP per capita growth; %, 5-year average 2015–2019	WDI
RuleLAW	Rule of law index. Index reflects perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Higher values, better outcomes	
POP	Population, in million	
INFRAst	Index of infrastructure, including information and communication technologies (ICTs), general infrastructure, and ecological sustainability. Higher values, better outcomes	
ISLAND	Dummy variable (= 1) identifying an island nation; 0 otherwise	

All data are annual for the calendar year 2019 (or the year reported in GII 2020), by country, unless otherwise indicated
Although R&Dlag is used in most of the analysis, R&D is also reported here since it is used in Table 8

GII: Global Innovation Index 2020, https://www.wipo.int/global_innovation_index/en/2020/

WDI: World Development Indicators, https://datacatalog.worldbank.org/dataset/world-development-indicators

Table 2 Summary statistics

	Mean	Std. dev.	Min.	Max.
Patent1	3.525	9.16	0	72.7
Patent2	0.929	1.86	0	9.2
R&D	0.944	0.99	0	4.9
R&Dlag	0.938	0.99	0	4.6
INNlink	26.507	15.89	1.5	81.6
INNcluster	48.73	12.36	26.6	79.5
FDI	4.076	6.61	– 11.8	47.6
HighTkIMP	9.009	6.16	1.6	52.1
IctIMP	1.322	1.01	0	6.7
VentureCAP	0.111	0.21	0	1.3
GDPgrAVG	1.998	2.32	– 10.12	8.89
RuleLAW	50.528	24.21	0	100
POP	55.034	176.55	0.3	1433.8
INFRAst	41.184	12.71	16.4	64.6
ISLAND	0.15	0.35	0	1

See Table 1 for variable definitions

work (D'Aspremont and Jacquemin (1988) for a seminal theoretical study) has outpaced corresponding empirical work (see Antonelli and Link (2015) and Griliches (1992) for reviews of the literature). For instance, aspects of networking by scientists, including active and passive networking, are almost difficult to capture across nations, although such networks are crucial to research collaborations.[2]

The broader index of innovation linkages employed (INNlink) includes a number of quantitative and qualitative aspects. For instance, the components of innovation linkages include: (i) university/industry research collaboration; (ii) state of cluster development; (iii) GERD financed from abroad; (iv) joint venture/strategic alliance deals; and (v) patent families filed in at least two offices. Of these, university/industry research collaborations and state of cluster development are based on survey responses, while the rest are based on hard data (see Table 1 for details; Table 4 for a list of sample countries).[3] We also consider the state of cluster development (INNcluster) separately as a determinant of innovation in Table 5.

One would expect better/more innovation linkages to enhance innovation, although there might be differences across specific channels. In our sample, innovation linkages were the highest in Israel (index value = 81.6), and the lowest in Niger (= 1.5). The index of innovation linkages would also aid in capturing cross-sectoral, in addition to cross-national, connections that are often hard to determine (Dietzenbacher 2000). Indeed, as noted by Engelbrecht (1997) and others, some innovation occurs outside the R&D sector. A broader index would capture some of these aspects.

As a way to capture the effects of networking and formal and informal knowledge flows, we also include the state of cluster development (INNcluster). This variable is a

[2] See Goel and Grimpe (2013) for a related study of German scientists.

[3] According to an earlier issue of the Global Innovation Index (2016, p. 54) GII, "The Innovation linkages sub-pillar draws on both qualitative and quantitative data regarding business/university collaboration on R&D, the prevalence of well-developed and deep clusters, the level of gross R&D expenditure financed by abroad, and the number of deals on joint ventures and strategic alliances", (https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2016-annex1.pdf).

Table 3 Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1														
2	0.70**	1													
3	0.62**	0.84**	1												
4	0.63**	0.86**	0.99**	1											
5	0.37**	0.78**	0.82**	0.82**	1										
6	0.36**	0.60**	0.63**	0.63**	0.74**	1									
7	−0.80**	−0.00	−0.09**	−0.09**	0.16**	0.11**	1								
8	0.19**	0.12**	0.15**	0.15**	0.13**	0.30**	0.21**	1							
9	0.10**	0.43**	0.37**	0.38**	0.46**	0.28**	0.28**	−0.16**	1						
10	0.11**	0.48**	0.30**	0.30**	0.52**	0.40**	0.29**	0.07	0.33**	1					
11	0.06**	−0.07**	−0.06	−0.04	−0.02	−0.00	0.20**	0.18**	0.04	0.01	1				
12	0.32**	0.66**	0.72**	0.72**	0.78**	0.68**	0.12**	0.22**	0.47**	0.51**	0.04	1			
13	0.37**	0.04	0.09**	0.08**	−0.01	0.18**	−0.09**	0.22**	−0.08**	−0.09**	0.20**	−0.07**	1		
14	0.37**	0.58**	0.69**	0.68**	0.64**	0.62**	0.14**	0.26**	0.36**	0.36**	0.09**	0.85**	0.02	1	
15	0.03	0.10**	−0.01	0.01	0.20**	0.18**	0.24**	0.02	0.19**	0.14**	0.08**	0.24**	−0.05	0.15**	1

These pairwise correlations are based on 102 observations

**denotes statistical significance at the 5% level (or better)

1. Patent1; 2. Patent2; 3. R&D; 4. R&Dlag; 5. INNlink; 6. INNcluster; 7. FDI; 8. HighTkIMP; 9. IctIMP; 10. VentureCAP; 11. GDPgrAVG; 12. RuleLAW; 13. POP; 14. INFRAst; 15. ISLAND

Table 4 Countries included in the analysis

Albania	Costa Rica	Ireland#	Nepal	Singapore#
Algeria	Croatia	Israel	Netherlands	Slovakia
Argentina	Cote D'Ivoire	Italy	New Zealand#	Slovenia
Armenia	Cyprus#	Jamaica#	Niger	South Africa
Australia#	Czech Republic	Japan#	Nigeria	Spain
Austria	Denmark	Jordan	North Macedonia	Sri Lanka#
Azerbaijan	Dominican Republic#	Kazakhstan	Norway	Sweden
Bahrain#	Ecuador	Kenya	Oman	Switzerland
Bangladesh	Egypt	Kuwait	Pakistan	Tajikistan
Belarus	El Salvador	Kyrgyzstan	Panama	Thailand
Belgium	Estonia	Lao PDR	Paraguay	Togo
Benin	Ethiopia	Latvia	Peru	Trinidad and Tobago#
Bolivia	Finland	Lebanon	Philippines#	Tunisia
Bosnia and Herzegovina	France	Lithuania	Poland	Turkey
Botswana	Georgia	Luxembourg	Portugal	Uganda
Brazil	Germany	Madagascar#	Qatar	Ukraine
Brunei Darussalam	Ghana	Malawi	Republic of Korea	United Arab Emirates
Bulgaria	Greece	Malaysia	Republic of Moldova	United Kingdom#
Burkina Faso	Guatemala	Mali	Romania	United Republic of Tanzania
Cabo Verde#	Guinea	Malta#	Russian Federation	United States of America
Cambodia	Honduras	Mauritius#	Rwanda	Uruguay
Cameroon	Hong Kong	Mexico	Saudi Arabia	Uzbekistan
Canada	Hungary	Mongolia	Senegal	Viet Nam
Chile	Iceland#	Montenegro	Serbia	Yemen
China	India	Morocco		Zambia
Colombia	Indonesia#	Mozambique		Zimbabwe
	Iran	Myanmar		
		Namibia		

Number of countries: 131

#denotes an island nation

The number of nations included in specific models varies due to missing data

subcomponent of INNlink and it might reveal some influences on innovation that an aggregate index might mask.

With respect to the innovation linkages, it is also likely that Patent1 and Patent2 would differently capture the spillovers from the different innovation linkages. If that is the case, then that would be another contribution of this work.

Beyond broader aspects of information and technology flows, innovation might be impacted by specific channels. Among these, FDIs are a frequently cited and researched mode (Cheung and Lin 2004; Lin and Lin 2010; Salim et al. 2017). Accordingly, FDI is

Table 5 Innovation linkages and innovation: Baseline models

Dependent variable→	Patent1			Patent2		
Model→	5a.1	5a.2	5a.3	5b.1	5b.2	5b.3
R&Dlag	3.39*** (0.37)	2.39*** (0.48)	3.29*** (0.39)	0.70*** (0.07)	0.52*** (0.08)	0.70*** (0.08)
INNlink		0.06** (0.03)			0.02*** (0.01)	
INNcluster			−0.006 (0.03)			0.005 (0.01)
RuleLAW	−0.01 (0.02)	−0.02 (0.02)	−0.01 (0.02)	0.01** (0.004)	0.003 (0.004)	0.01* (0.004)
GDPgrAVG	−0.05 (0.12)	−0.04 (0.12)	−0.05 (0.13)	−0.002 (0.03)	−0.001 (0.02)	0.004 (0.03)
POP	0.006 (0.004)	0.003 (0.004)	0.007 (0.005)	0.0003 (0.0003)	0.0003 (0.0002)	0.0003 (0.0003)
VentureCAP	3.63*** (1.38)	2.47* (1.41)	3.49** (1.41)	0.99* (0.51)	0.46 (0.49)	0.91* (0.54)
N	73	73	72	69	69	68
F-value	39.0***	29.9***	31.6***	65.8***	71.3***	51.5***
R^2	0.52	0.56	0.52	0.75	0.76	0.75
VIF	1.6	2.4	1.8	1.6	2.5	1.8

See Table 1 for variable definitions. The reported estimates are based on robust regression and all models included a constant term. VIF denotes the variance inflation factor, based on related OLS regressions, to capture possible multicollinearity, with a general value under 10, generally denoting an absence of significant multicollinearity

The numbers in parentheses are standard errors, with *, ** and ***, respectively, denoting statistical significance at the 10%, 5%, 1% levels included as a regressor to see its relative impacts on the two innovation measures. As mentioned above, while FDIs have many dimensions, such investments come with know-how and facilitate interactions that can all foster innovation.

Whereas the FDI-innovation link has received attention in the literature, the role of imports has received lesser attention. We include two different imports that are likely to be relevant in the context of innovation (especially, patentable innovation). HighTkIMP is high-tech imports, comprising technical products with a high intensity of R&D (commodities in the following sectors: aerospace; computers & office machines; electronics; telecommunications; pharmacy; scientific instruments; electrical machinery; chemistry; non-electrical machinery; and armament); and IctIMP denotes ICT services imports, dealing with telecommunications, computer and information services.

One key difference between these two variables is that IctIMP likely forms an input into the production of other products and services, while HighTkIMP likely also has more direct applications in industry. In our sample, high-tech imports were nearly seven times as large as ICT imports (as a percentage of total trade; Table 1) and the correlation between HighTkIMP and IctIMP was −0.16 (Table 3).

Beyond innovation linkages that are the claimed novelty of this work, R&D input is the key input in innovation (Goel et al. 2022). Research personnel and equipment are specially designed and directed towards the generation and production of innovations. In this context, there is the issue of the time lag between research spending being incurred and when the innovation materializes (Hall et al. 1986; also see Goel and Saunoris 2016). Furthermore, there is the possibility of a bi-directional causality between the input and output of research. To address these aspects, we include a one-year lagged value of R&D (R&Dlag), which stood at about one percent of GDP in our sample.

Among the other control variables, GDP growth captures the strength of the economy and is associated with economic sentiments. In economies with high rates of economic growth, there is greater optimism, ceteris paribus, and this optimism is especially important for the pursuit of innovation. Given the year-to-year fluctuations in the GDP growth rates in many nations, we take the average 5-year GDP growth rate (per capita) from 2015 to 2019 (GDPgrAVG). The average growth in GDP per capita in our sample was around 2 percent.

Institutional quality is important in the smooth workings of the markets and in the ability of investors to protect intellectual property and reap related rewards. To this effect, we use the rule of law index (RuleLAW). Nations with a better/strengthened rule of law have better protection of property rights, workings of the legal system, and the enforcement of contracts. These are all important factors in the pursuit of innovation.[4]

Venture capital investments are directed towards new or nascent businesses and in this stage fostering innovative activity is key to gaining a foothold in many industries. The consideration of venture capital (VentureCAP) and FDIs can be seen as capturing domestic versus external capital. Further, venture capital investments are generally seed capital investments in the initial stages, especially by nascent entrepreneurs, while FDIs might be accompanied by some embedded technical know-how or process innovation (Bertschek 1995; Salim et al. 2017). Generally, there is evidence of positive spillovers from venture capital investments on innovation (Kortum and Lerner 2001).

Finally, demand-pull innovation aspects are captured by including the market size, proxied by population. Other things being the sample, a large market would make some

[4] Some studies have used a narrower index of patent protection to account for some related aspects (Goel and Saunoris 2016). Also see Goel (2020).

innovations more attractive by increasing their potential payoffs. In the following section, we discuss the data and the estimation techniques employed in our empirical analysis.

3 Data and estimation method

3.1 Data

The main source of the data for this study is the Global Innovation Index (GII) 2020, https://www.wipo.int/global_innovation_index/en/2020/). This source provides comparable data on scores of nations on various dimensions of innovation input and output.[5] These data are supplemented with data from other international sources that are routinely used in the related analyses.

Details about the variables used, including variable definitions, summary statistics, data sources are in Tables 1 and 2, and the list of nations in the sample is provided in Table 4. Note that the actual number of nations included in the different models estimated varies due to missing observations. Table 3 provides a correlation matrix between the variables used in the analysis. We turn next to a discussion of the estimation strategy.

3.2 Estimation

To address different aspects of Eq. (1) and to test the validity of our results, we employ different estimation strategies. First, Tables 5, 6, 7 report results from robust regression. A robust regression is less sensitive to outlying values compared to OLS estimation, and some large outliers exist, especially with respect to one of our dependent variables, as shown in Fig. 1. A robust regression is not radically different from an OLS regression, just that it is a form of weighted OLS that considers the influence of outlying values (and excludes them when they are large outliers (as is the case with three observations for Patent1 in Fig. 1)).[6]

The overall fit of the various models is quite good, and the variance inflation factor (VIF) shows an absence of multicollinearity across the explanatory variables.

Second, potential simultaneity issues are addressed in Table 8 through a 2SLS regression. Here, R&D is instrumented by a dummy variable identifying island nations (ISLAND) and an index of a nation's infrastructure (INFRAst). The different diagnostic tests (reported at the bottom of the table) generally support our instrument choice. The results section follows.

[5] While the GII is available for more recent years, the coverage of nations (and in some cases of the variables included) varies somewhat from year to year. We employ a cross-section analysis from the 2020 GII report, in part to maximize coverage and because the index and institutional variables in the analysis do not change much from year to year.

[6] "Robust regression can be used in any situation in which you would use least squares regression. When fitting a least squares regression, we might find some outliers or high leverage data points. We have decided that these data points are not data entry errors, neither they are from a different population than most of our data. So we have no compelling reason to exclude them from the analysis. Robust regression might be a good strategy since it is a compromise between excluding these points entirely from the analysis and including all the data points and treating all them equally in OLS regression. The idea of robust regression is to weigh the observations differently based on how well behaved these observations are. Roughly speaking, it is a form of weighted and reweighted least squares regression", https://stats.oarc.ucla.edu/r/dae/robust-regression/.

Table 6 Foreign investments, imports, and innovation

Dependent variable →	Patent1			Patent2		
Model →	6a.1	6a.2	6a.3	6b.1	6b.2	6b.3
R&Dlag	3.53*** (0.38)	3.26*** (0.36)	3.38*** (0.37)	1.00*** (0.08)	0.89*** (0.08)	0.77*** (0.07)
FDI	0.03 (0.04)			0.02** (0.01)		
HighTkIMP		−0.08** (0.04)			−0.03*** (0.01)	
IctIMP			0.52* (0.28)			0.19*** (0.06)
RuleLAW	−0.02 (0.02)	−0.01 (0.02)	−0.02 (0.02)	0.002 (0.004)	−0.0004 (0.004)	−0.002 (0.004)
GDPgrAVG	−0.09 (0.13)	0.003 (0.12)	−0.08 (0.12)	−0.03 (0.03)	0.02 (0.03)	−0.02 (0.03)
POP	0.006 (0.005)	0.008* (0.004)	0.006 (0.004)	0.0002 (0.0003)	0.0003 (0.0003)	0.0002 (0.0002)
VentureCAP	3.61** (1.44)	3.48*** (1.34)	3.45*** (1.36)	1.03* (0.61)	2.90*** (0.38)	3.27*** (0.31)
N	73	73	73	69	70	70
F-value	33.7***	35.2***	36.4***	66.2***	69.3***	106.8***
R^2	0.52	0.52	0.53	0.76	0.76	0.77
VIF	1.6	1.5	1.6	1.6	1.6	1.6

See Table 5

Table 7 Foreign investments, imports, and innovation: Nonlinear effects

Dependent variable→	Patent1			Patent2		
Model→	7a.1	7a.2	7a.3	7b.1	7b.2	7b.3
R&Dlag	3.42*** (0.38)	3.00*** (0.36)	2.76*** (0.34)	0.73*** (0.07)	0.97*** (0.08)	0.800*** (0.07)
FDI^2	0.0003 (0.001)			0.0005*** (0.0002)		
$HighTkIMP^2$		−0.001 (0.001)			−0.001* (0.0004)	
$IctIMP^2$			0.38*** (0.09)			0.07*** (0.02)
RuleLAW	−0.02 (0.02)	−0.004 (0.02)	-0.03* (0.02)	0.006* (0.004)	0.001 (0.004)	−0.003 (0.004)
GDPgrAVG	−0.06 (0.13)	−0.02 (0.12)	−0.04 (0.11)	−0.02 (0.03)	0.02 (0.03)	−0.01 (0.03)
POP	0.006 (0.005)	0.007 (0.004)	0.0003 (0.004)	0.0004 (0.0002)	0.0002 (0.0003)	0.0002 (0.0003)
VentureCAP	3.69*** (1.40)	3.86*** (1.34)	2.25* (1.22)	0.94* (0.49)	1.46** (0.60)	3.06*** (0.33)
N	73	73	72	69	69	69
F-value	31.9***	31.5***	40.8***	62.0***	59.3***	106.8***

See Table 1, for variable definitions. The reported estimates are based on robust regression and all models included a constant term. The numbers in parentheses are standard errors, with *, ** and ***, respectively, denoting statistical significance at the 10%, 5%, 1% levels

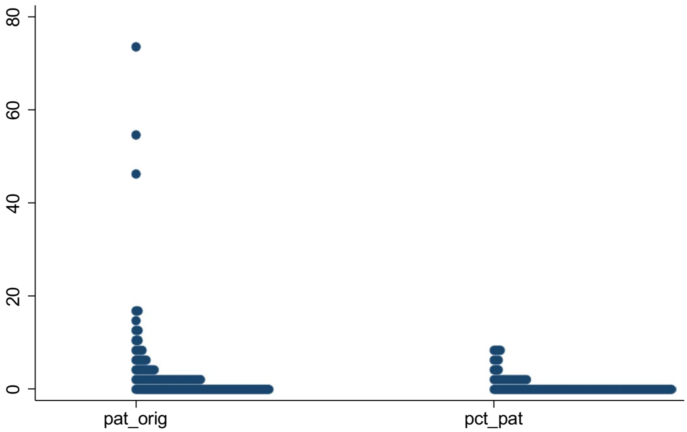

Fig. 1 Distribution of Patent1 (pat_orig) and Patent2 (pct_pat)

Table 8 Innovation linkages and innovation: 2SLS regressions

Dependent variable→	Patent1	Patent2
Model→	8.1	8.2
R&D	5.73 (3.57)	1.02** (0.52)
RuleLAW	−0.01 (0.13)	0.02 (0.02)
GDPgrAVG	0.02 (0.47)	−0.06 (0.07)
POP	0.02*** (0.01)	0.0004 (0.001)
VentureCAP	-0.65 (5.35)	2.01** (0.85)
N	76	70
F-value	6.99***	20.49***
*R*2 (centered)	0.49	0.71
Underidentification test [*p*-value]	8.6*** [0.01]	8.5** [0.02]
Weak identification test	4.4	4.3
Overidentification test [*p*-value]	2.7* [0.10]	0.89 [0.35]

See Table 1 for variable definitions. The reported estimates are based on 2SLS, with ISLAND and INFRAst used as instruments for R&D, and all models included a constant term. The underidentification test is Anderson canon. corr. LM statistic, the weak identification test is Cragg-Donald Wald F-statistic, and the overidentification test is the Sargan statistic. The numbers in parentheses are standard errors, with *, ** and ***, respectively, denoting statistical significance at the 10%, 5%, 1% levels

4 Empirical findings

4.1 Baseline models: aggregate innovation linkage spillovers

The baseline results, using robust regression, are presented in Table 5, with three models for each dependent variable, respectively.[7] The main idea behind the baseline models is to

[7] Due to the three large outliers for Patent1 shown in Fig. 1, the robust regression drops the three observations when Patent1 is the dependent variable.

identify the significant factors driving innovation across alternative aspects of patenting, and to see the effects of aggregate aspects of innovation linkages. These linkages incorporate various dimensions of knowledge flows, including formal and informal exchanges.

As expected, the effect of lagged R&D on innovation is positive and statistically significant. This finding holds across both measures of innovation——Patent1 and Patent2. Lagged R&D is the key input in the production of innovation and our results bear this out.

In terms of the magnitude of the effects, the elasticity of Patent1 with respect to R&Dlag is 0.90 (Model 5a.1), while the corresponding elasticity with respect to Patent2 in Model 5b.1 is 0.71. Thus, the productivity of R&D in generating patents (keeping in mind that not all output of research is patented or is patentable) is greater for domestic patents compared to PCT patents. This can be useful information for policymakers deciding to subsidize research based on its innovation productivity.

The story is stronger when a broader measure of innovation linkages, INNlink, is considered. In this case, the resulting coefficient is positive and statistically significant and this true for both dependent variables. The broader measure is able to capture a wider set of potential spillovers on innovation, including spillovers from and within the various channels. The findings with respect to the positive effect of INNlink on innovation can be seen as supportive of the earlier findings of Love et al. (2014) regarding the openness-innovation linkage.

Quantitatively, the elasticity of Patent1 with respect to INNlink in Model 5a.1 is 0.45, while the elasticity of Patent2 with regard to INNlink in Model 5b.1 is 0.57, implying that the spillovers from innovation linkages are of a similar order of magnitude across both measures of innovation.

Looking at the effects of innovation clusters (INNcluster), the resulting variable was statistically insignificant in the case of both patent measures.

Finally, more venture capital investments had positive spillovers on innovation——the resulting coefficient on VentureCAP being statistically significant in all cases, except one. On the other hand, the effects of GDP growth and population (POP), (the positive sign on POP is consistent with demand-pull effects), were statistically insignificant. The rule of law, tied to the protection of intellectual property, had relatively more statistical support for fostering Patent2 innovations. We turn next to a comparison of the relative innovation effects of FDIs and technology imports.

4.2 Innovation effects of FDIs and technology imports

Beyond aggregate indices of innovation linkages, it seems equally, or even more, insightful to see the effects of direct measures like FDIs and technology imports. The related results are presented in Table 6.

FDIs have positive effects across both dependent variables; however, the resulting variable is statistically significant only for Patent2 in Model 6b.1. Greater FDIs have positive spillovers on the broader measure of innovation. This makes sense since Patent2 includes patent protection in a number of countries, it is quite likely the case that FDIs investors, by applying for PCT patents, are also including/viewing patent protection in their home countries. It is possible that larger, multi-national, corporations are more likely to file for Patent2 type of patents (also see Liao and Yu (2013) for some evidence from Taiwanese firms).

Interesting contrasts appear with respect to the two types of technology imports considered.[8] Greater high-tech imports crowd-out innovation, while more ICT imports facilitate it. This difference holds across the two dimensions of innovation considered. Intuitively, the underlying rationale might be that high-tech imports, with direct application in various industries, substitute for potential innovations as nations might be seeking such imports to plug knowledge/innovation deficiencies, whereas ICT imports are more likely inputs into further production and innovation. In certain cases, however, ICT imports could crowd out process innovation, but process innovations, being easier to guard, are generally patented less frequently (Arundel and Kabla 1998).

The comparison of the relative effects of FDIs and technology imports is a key, new finding, with potential implications for policy. Lawmakers might be facilitating certain investments or imports without a recognition of their innovation spillovers. Negative innovation effects could also have longer-term effects in terms of innovation trajectories of nations and their global competitiveness.

The results for the other explanatory variables generally support earlier findings, with the consistent statistical significance of the role of venture capital investments being a noteworthy aspect. The following sections test the robustness of these findings.

4.3 Alternately addressing potential endogeneity of R&D

Since research effort or R&D is the main input in innovation production, we give further consideration to the innovation-R&D relationship. Although Tables 5 and 6 use the lagged values of R&D to address simultaneity between the input and output of innovation (see Goel et al. 2022; Henderson 2007), we also employ 2SLS estimation in Table 8 to address causality issues. To operationalize this, ISLAND and INFRAst are employed as instruments for R&D, with the two models, respectively using the two dependent variables from Tables 5 and 6. The geographic isolation of island nations provides different incentives to invest in R&D (also see Lazzeretti and Capone 2016), and the prevalence/strength of infrastructure in a nation affects R&D (via related transaction costs). The overall fit of both models is good and instrument choice is supported by the two chosen instruments. Specifically, the diagnostic statistics for the underidentification test, the weak identification test, and the overidentification test, reported at the bottom of Table 8, satisfy the usual conditions for the validity of the chosen instruments.

Regarding the main variable of interest, R&D, we find the effect of R&D to be positive in both cases. It is significant for Patent2 in Model 8.2. With respect to the other results, larger nations (POP) have greater innovation when Patent1 is the dependent variable

[8] Note that Table 3 shows a modest correlation between HighTkIMP and IctIMP, still, we include the two imports in separate models to avoid possible inherent overlaps.

We did, however, try including FDI, HighTkIMP, and IctIMP in the same model with the respective dependent variables from Table 6. All three variables maintained their signs, with HighTkIMP negative and statistically significant (at the 10% level) with Patent1 as the dependent variable, and IctIMP was positive and significant (at the 10% level) with Patent2 as the dependent variable. Additional details are available upon request.

(Model 8.1), and more venture capital deals facilitate Patent2 (Model 8.2). The other controls lack significance, which is generally supportive of earlier findings.[9]

4.4 Comparing the magnitudes of effects

It seems useful to compare the relative magnitudes of the effects of the key variables, and also highlight any differences across the two patent measures (all elasticity measures are based on the respective means). The relative magnitudes of effects can be useful to policymakers in allocating funds for different programs related to innovation generation.

The responsiveness of patenting to the R&D input (lagged one year) is somewhat greater for Patent1 compared to that for Patnet2. Specifically, the elasticity of Patent1 with respect to R&Dlag is 0.90 (Model 5a.1 in Table 5), while the corresponding elasticity of Patent2 is 0.71 (Model 5b.1). In other words, the response of resident patenting to R&D spending is greater than that of a wider patenting measure (Patent2).

Turning to the effects of technology imports in Table 6, the relative magnitudes of responses are more similar. The elasticity of Patent1 to HighTkIMP is -0.21 (Model 6a.2), while that with respect to IctIMP is positive and 0.20 (Model 6a.3). These responses are smaller than the corresponding responses of Patent2: the elasticity of Patent2 with regard to HighTkIMP is -0.29 (Model 6b.2), and with regard to IctIMP is 0.27. Thus, while we see the qualitative differences (i.e., positive versus negative effects) in the responses to technology imports within a given patent measure, there are quantitative differences across patent measures, with broader patents being more responsive.

Furthermore, the positive response of IctIMP on Patent2 is much larger than that of FDI, where the elasticity of Patent2 with respect to FDI from Model 6b.1 is 0.09.[10] This makes sense since some FDIs may be more diffused and not necessarily related to innovation, while ICT imports are likely to have more direct and indirect connections with innovation. From a policy perspective, policies based on aggregate FDI might be undercounting the impact of impacts of foreign interactions on innovation. This finding seems new in the related literature.

4.5 Extension: considering nonlinearities

The estimated relations in Table 6 between the dependent variables and the independent variables are linear. However, it is possible that there are some nonlinearities in these relations. To address this aspect, in Table 7 we report results with the quadratic terms of the key explanatory variables: FDI, HighTkIMP, and IctIMP. The consideration of nonlinear

[9] A reader might argue that FDIs and imports might also be endogenous. To address that possibility, we reran 2SLS regressions for each dependent variable, alternatively taking FDI, HighTkIMP, and IctIMP to be endogenous, and using ISLAND and INFRAst as instruments. The three focus variables maintained their signs from Table 6, while the statistical significance of the estimated coefficients was low (additional details are available upon request). One reason for the low statistical significance might be that the measures of FDIs and imports are composite, masking characteristics of individual dimensions (example: greenfield versus established FDIs, etc.). This aspect deserves greater attention in future research, subject to the availability of appropriate data.

[10] The corresponding coefficient on FDI in Model 6a.1 is statistically insignificant and thus no elasticity is reported for that case.

effects deals with the rates of change in the key explanatory variables and these can inform policy makers in projecting future trends and allocating funds.

The results show that, while the three explanatory variables of interest maintain their respective signs from Table 6, there is the presence of linearities, with some differences across patent types (or the two dependent variables).

With Patent1 as the dependent variable, the coefficient on $IctIMP^2$ is positive and statistically significant (Model 7a.3), whereas the coefficients on FDI^2 and $HighTkIMP^2$ are statistically insignificant. On the other hand, the coefficients on all three, FDI^2, $HighTkIMP^2$, and $IctIMP^2$, are statistically significant with Patent2 as the dependent variable. In fact, the coefficient on $IctIMP^2$ is positive and statistically significant in the case of both dependent variables.

Thus, relatively speaking, there is greater evidence of the presence of nonlinear relations with the broader innovation output, Patent2, as the dependent variable, and with regard to ICT imports as the explanatory variable. The concluding section follows.

5 Conclusions

Whereas various drivers of the international innovative activity have been studied in the literature, our understanding of the contributions of different innovation linkages to innovation deserves more attention (Antonelli and Link 2015; Feldman 1999; Guckenbiehl et al. 2021; Griliches 1992). This paper addresses the contributions of different innovation linkages to innovation, across two different measures of innovation. The use of multiple spillover channels also ties to addressing the payoffs from embodied and disembodied technical change (Krammer 2014). Beyond aggregate innovation indices, a comparison of the relative effects of FDIs and technology imports is a novelty of this work. The large sample of nations considered is an additional contribution of this work.

Considering three aspects of innovation linkages in terms of their impact on innovation, we find that a broader index of innovation linkages shows positive and significant spillovers on innovation. However, a narrower index dealing with the state of clusters fails to find statical support.

Focusing on the relative effects of FDIs and technology imports, we find quantitative and quantitative differences in their impacts on innovations, as well as some variations in the impacts across the alternative measures of innovation. Specifically, high-tech imports crowd-out innovation, while FDIs and ICT imports reinforce it. The positive spillovers from ICT imports are relatively more robust across alternative innovation measures. Furthermore, we found the presence of some nonlinearities in these effects (Table 7).

These results generally support hypothesis H1, with the qualification that some specific channels of spillovers might not have a significant impact. These spillovers are reinforced by the positive and expected impacts of R&D spending. In other results, greater venture capital investments boost innovation in most cases. Tying to the title of the paper, the choice between seeking foreign funds or foreign technology does not seem to be dichotomous and the two can be complementary in facilitating innovation.

Turning to the questions posed in the Introduction, we are able to provide the following answers:

- Are the different measures of innovation output equally affected by innovation linkages?

  The two measures of innovation considered seem to benefit similarly from innovation linkages. A ten percent increase in the broad index of innovation linkages (INNlink) tends to increase innovation (patent applications) by about 5-6 percent (Table 5). Thus, some channels of spillover transmissions have stronger ties to innovation than others (Wang et al. (2017)).
- What are the relative impacts of FDIs and different technology imports on innovation?

  We find differences in the impacts of FDIs and technology imports. Whereas many studies have found the presence of positive spillovers from FDIs on innovation (Cheung and Lin 2004; Lin and Lin 2010), some have found FDIs to have no direct innovation effects (Salim et al. 2017). We further find that the impacts of imports could be different, both quantitatively and qualitatively. For instance, a ten percent increase in high-tech imports (HighTkIMP) in Model 6b.2 would decrease PCT patents by about 3 percent, a similar increase in ICT imports would increase PCT patents by about a similar magnitude (Model 6b.3), while a ten percent increase in FDIs would increase such patents by only about 0.1 percent (Model 6b.1).

Some nations, especially developing nations, restrict imports for protectionism or to support infant industries. Our results suggest that such policies can have detrimental effects on innovations. Thus, policymakers should weigh the relative short-term gains from protectionist tariff revenues against longer-term adverse consequences on national technological evolution.

A number of other implications for technology policy emerge from the analysis. First, given the complementarity between R&D spending and innovating linkages, nations with resource constraints in supporting R&D directly might look to complementary channels to boost innovation. Second, sound technology policies would benefit from the use of multiple measures of innovation output, since our analysis shows that some factors driving innovation change in magnitude and significance. The broader Patent2 measure might be more relevant when regional technology policies are being framed (see Liao and Yu 2013; Yang et al. 2021). At a broader level, these findings can prove useful in the design and updates of national innovation systems (see Nelson 1993). Third, policies facilitating imports should be cognizant of their potential impacts on innovation. Some imports, like high-tech imports, can crowd out innovations. In some other cases, the innovation gains from certain imports (e.g., ICT imports) might be canceled by certain other imports (e.g., high-tech imports). Fourth, the innovation payoffs from VC investments can be undermined by certain imports, such as high-tech imports. Finally, the role of inward FDIs is complementary to domestic VC funding in that both boost innovation. Relatively speaking, VC investments are generally more forward-looking and frequently are in new (or even unproven) technologies. FDIs can also be a channel of technology spillovers (Salim et al. 2017).

In closing, we point out some limitations of this work. One, we have been unable to account for all channels of knowledge transmission. For example, the role of networking through professional conferences and associations is important (Goel and Grimpe 2013), but not captured in the measures employed. Two, the qualitative distinction across patents (e.g., design versus utility patents), and across industry/product types are likely crucial in determining the extent and the speed of spillovers (Cheung and Lin 2004). Incorporation of these aspects must await the availability of data at a finer level of detail.

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Declarations

Conflict of interest No potential competing interest was reported by the authors.

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