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Dmitry Ivanov
Alexandre Dolgui
Boris Sokolov *Editors*

Handbook of Ripple Effects in the Supply Chain

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Dmitry Ivanov · Alexandre Dolgui ·
Boris Sokolov
Editors

Handbook of Ripple Effects in the Supply Chain

Springer

Editors
Dmitry Ivanov
Department of Business and Economics
Berlin School of Economics and Law
Berlin, Germany

Alexandre Dolgui
Department of Automation, Production
and Computer Sciences
IMT Atlantique, LS2N - CNRS UMR
Nantes, France

Boris Sokolov
SPIIRAS
St. Petersburg, Russia

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Preface

Purpose and Content of the Book

This handbook comprises recent developments in a new research field of the ripple effects in supply chains (SC). The chapters of this handbook are written by leading experts in SC risk management and resilience. For the first time, the chapters present a multiple-faceted view of the ripple effect in SCs, while considering organization, optimization, and informatics perspectives. The ripple effect occurs when an SC disruption cascades downstream, rather than remaining localized, and impacts the performance of the SC. The ripple effect considers structural network dynamics in the SC that is initiated by a severe disruption (or a series of disruptions) and describes the propagation of this disruption downstream the SC in terms of switching off some nodes and arcs in the network, e.g., due to material shortage. The impacts of the ripple effect might include lower revenues, delivery delays, loss of market share and reputation, or decreases in stock returns—the costs of these negative impacts can be devastating.

This book offers an introduction to the ripple effect in the supply chain for larger audience. The book delineates major features of the ripple effect and methodologies to mitigate the supply chain disruptions and recover in case of severe disruptions. The book reviews recent quantitative literature that tackled the ripple effect and gives a comprehensive vision of the state of the art and perspectives. The methodologies comprise mathematical optimization, simulation, control theoretic, and complexity and reliability research. The book observes the reasons and mitigation strategies for the ripple effect in the supply chain and presents the ripple effect control framework that is comprised of redundancy, flexibility, and resilience. Even though a variety of valuable insights has been developed in the said area in recent years, some crucial research avenues have been identified for the near future.

The book is expected to furnish fresh insights for supply chain management and engineering regarding the following questions:

- In what circumstance does one failure cause other failures?
- Which structures of the supply chain are especially prone to the ripple effect?
- What are the typical ripple effect scenarios and what is the most efficient way to respond to them?

Given these reflections, numerous ways to apply quantitative analysis to ripple effect modelling arise. Several research gaps might be addressed by the ability to dynamically change parameters during experiments and to observe how these changes impact performance in real time, e.g., considering:

- disruption propagation in the supply chain;
- dynamic recovery policies;
- gradual capacity degradation and recovery;
- multiple performance impact dimensions including financial, customer and operational performance.

Distinctive Features

- It considers ripple effect in the supply chain from interdisciplinary perspective.
- It offers an introduction to the ripple effect mitigation and recovery policies in the framework of disruption risk management in the supply chains for larger audience.
- It integrates management and engineering perspectives on disruption risk management in the supply chain.
- It presents innovative optimization and simulation models for real-life management problems.
- It considers examples from both industrial and service supply chains.
- It reveals decision-making recommendations for tackling disruption risks in the supply chain in proactive and reactive domains.

Target Audience

Management and engineering graduate and Ph.D. students, supply chain and operations management professionals, industrial engineers, operations and supply chain risk researchers.

Berlin, Germany — Dmitry Ivanov
Nantes, France — Alexandre Dolgui
St. Petersburg, Russia — Boris Sokolov

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The author gratefully acknowledges all those who have helped bring this book to publication. First and foremost, we have greatly benefited from the wealth of a vast array of published materials on the subject of supply chain risk management and associated topics. We would also like to thank the authors of each of the chapters. The content of this book has benefited immensely from their valuable insights, comments, and the suggestions of many reviewers. With regards to manuscript preparation, we thank Ms. Meghan Stewart for a thorough proofreading of the manuscript, as well as Ms. Tamara Erdenberger for her technical assistance. Finally, we wish to thank the editors, Neil Levine and Dr. Camille Price, and the entire Springer production team for their assistance and guidance in the successful completion of this book. Last, but not least—we thank our families for their enormous support during the writing and development of this book.

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About the Editors

Prof. Dr. habil. Dr. Dmitry Ivanov is Professor of Supply Chain Management at Berlin School of Economics and Law (HWR Berlin), Deputy Director and Executive Board Member of Institute for Logistics, and Director of master program in Global Supply Chain and Operations Management at HWR Berlin since 2011. He is leading working groups, tracks, and sessions on Supply Chain Risk Management and Resilience in global research communities. He is a recipient of many prestigious Best Paper awards. He edits the *International Journal of Integrated Supply Management*. His publication list includes around 300 publications, including 65 research papers in prestigious academic journals and leading books *Global Supply Chain and Operations Management* and *Structural Dynamics and Resilience in Supply Chain Risk Management*.

He has been *teaching* classes for more than 20 years in operations management, production and supply management, supply chain management, logistics, management information systems, and strategic management at undergraduate, master's, Ph.D., and executive M.B.A. levels at different universities worldwide in English, German, and Russian. He has given guest lectures, presented scholarly papers and has been a Visiting Professor at numerous universities in Asia, Europe, and North America. He has been involved with collaborative educational projects with many universities worldwide. He is leading anyLogistix educational virtual lab and published handbooks on using AnyLogic and anyLogistix software in management education.

His *research* explores supply chain structural dynamics and control, with an emphasis on supply chain risk analytics, global supply chain design with disruption consideration, scheduling in Industry 4.0 systems, and digital supply chain. He is co-author of structural dynamics control methods for supply chain management. He applies mathematical programming, simulation, control and fuzzy theoretic methods. Based upon triangle "process-model-technology", he investigates the dynamics of complex networks in production, logistics, and supply chains. Most of his courses and research focuses on the interface of supply chain management, operations research, industrial engineering, and information technology.

His *academic* background includes industrial engineering, operations research, and applied control theory. He studied industrial engineering and production management in St. Petersburg and Chemnitz and graduated with distinction. He gained his Ph.D. (Dr.rer.pol.), Doctor of Science (Sc.D.), and Habilitation degrees in 2006 (TU Chemnitz), 2008 (FINEC St. Petersburg), and 2011 (TU Chemnitz), respectively. In 2005, he was awarded the German Chancellor Scholarship.

Prior to becoming an *academic*, he was mainly engaged in *industry and consulting*, especially for process optimization in manufacturing and logistics and ERP systems. His practical expertise includes numerous projects on the application of operations research and process optimization methods for operations design, logistics, scheduling, and supply chain optimization. Prior to joining the Berlin School of Economics and Law, he was Professor and Acting Chair of Operations Management at University of Hamburg.

Professor Ivanov's research has been published in various academic journals, including *Annals of Operations Research*, *Annual Reviews in Control*, *Computers and Industrial Engineering*, *European Journal of Operational Research*, *IEEE Transactions on Engineering Management*, *International Journal of Information Management*, *International Journal of Integrated Supply Management*, *International Journal of Production Research*, *International Journal of Production Economics*, *International Journal of Technology Management*, *International Journal of Systems Science*, *International Transactions in Operational Research*, *Journal of Scheduling, Omega, Transportation Research: Part E*, etc.

He has been Guest Editor of special issues in different journals, including *Annals of Operations Research*, *International Journal of Production Economics*, *International Journal of Production Research*, *International Transactions in Operations Research*, *International Journal of Information Management* and the *International Journal of Integrated Supply Management*. He co-edits *International Journal of Integrated Supply Management*. He is an Associate Editor and Editorial Board Member of the *International Journal of Production Research* and *International Journal of Systems Science* and Editorial Board member of several international and national journals, e.g., the *International Journal of Systems Science: Operations and Logistics* and the *International Journal of Inventory Research*.

He is Chairman of IFAC TC 5.2 "Manufacturing Modelling for Management and Control" and Co-Chairman of the IFAC TC 5.2 Working group "Supply Network Engineering". He has been member of numerous associations, including INFORMS, POMS, CSCMP, VHB, and GOR.

He regularly presents his research at scientific and industry events and welcomes new collaborations. He has been Chairman of IFAC MIM 2019 conference, advisory board member and IPC member of many international conferences, where he has organized numerous tracks and sessions (including IFAC MIM, INCOM, EURO, INFORMS, IFORS, OR, IFAC World Congress, and IFIP PRO-VE).
e-mail: divanov@hwr-berlin.de; https://blog.hwr-berlin.de/ivanov.

Prof. Dr. habil. Alexandre Dolgui is a Distinguished Professor (Full Professor of Exceptional Class in France) and the Head of Automation, Production, and Computer Sciences Department at the IMT Atlantique (former Ecole des Mines de Nantes), France. His research focuses on manufacturing line design, production planning and supply chain optimization. His research is mainly based on exact mathematical programming methods and their intelligent coupling with heuristics and metaheuristics algorithms.

He is the co-author of 5 books, the co-editor of 16 books for conference proceedings, the author of 225 refereed journal papers, 27 editorials, and 28 book chapters, as well as the author of over 400 papers written for conference proceedings. He is the Editor-in-Chief of the *International Journal of Production Research*, an Area Editor of *Computers & Industrial Engineering*, and an Associate Editor of *Journal Européen des Systèmes Automatisés*. He is also past Associate Editor of *International Journal of Systems Science* (2005–2008), *IEEE Transactions on Industrial Informatics* (2006–2009), and *Omega-the International Journal of Management Science* (2009–2012), as well as having been the consulting Editor of the *International Journal of Systems Science* (2009–).

He is a member of editorial boards for 25 other journals, including the *International Journal of Production Economics*, *International Journal of Manufacturing Technology & Management*, *International Journal of Simulation & Process Modelling*, *International Journal of Engineering Management & Economics*, *Journal of Decision Systems*, *Journal of Mathematical Modelling & Algorithms*, *Journal of Operations and Logistics*, *Journal of Industrial Engineering and Management & Production Engineering Review*, *Decision Making in Manufacturing and Service*, *Risk and Decision Analysis*, etc. He is also a fellow of the European Academy for Industrial Management, a member of the board of the International Foundation for Production Research, Vice-Chair of IFAC TC 5.2 Manufacturing Modelling for Management and Control, a member of IFIP WG 5.7 Advances in Production Management Systems, IEEE System Council Analytics, and Risk Technical Committee, and Guest Editor of special issues of European Journal of Operational Research, International Journal of Production Research, International Journal of Production Economics, Omega-the International Journal of Management Science, Journal of Intelligent Manufacturing, Journal of Mathematical Modeling and Algorithms and Annual Reviews in Control. He was General Scientific Chair of the 12th IFAC symposium INCOM'06, Chairman of International Program Committee of SCM'02, MOSIM'04, INCOM'09, INCOM'12, IESM'13, MIM'13, INCOM'15, IESM'17, GSC'18 and MIM'19, and Chairman of Steering committee of MIM'16. He was also Chairman of the Organizing Committee of the International Conference MOSIM'01 and ROADEF'2011. In the last 10 years, he was a member of the Program Committees of over 200 International Conferences, etc. He has been responsible for the French national CNRS working group on Design of Production Systems (with about 336 individual members) and the regional project on Design and Management of Reconfigurable Manufacturing Systems. e-mail: alexandre.dolgui@imt-atlantique.fr

Prof. Dr. Eng. Boris Sokolov born in 1951, is Head of Laboratory of Information Technologies in System Analysis and Modeling at Saint Petersburg Institute of Informatics and Automation of the Russian Academy of Sciences (SPIIRAS). From 2006 to 2017, he was Deputy Director for research of SPIIRAS. In 2008, he became an honored scientist in Russia. He is a Laureate of the Prize of the Government of the Russian Federation in the field of science and technology (2013).

He received his M.Sc., Ph.D., Dr. Sc. Eng., and Prof. in 1974, 1983, 1993 and 1994, respectively. He is a founder of a new scientific direction in the field of automating the management processes of complex technical objects (CTO) associated with complex analysis and management of processes in critical applications.

The research interests of Prof. B. Sokolov are as follows: basic and applied research in integrated modeling, simulation and mathematical methods in scientific research, optimal control theory and mathematical models and methods of decision-making support in complex technical-organizational systems under uncertainties and with multi-criteria, implementations of RFID technology and mobile IT in supply chain management processes. Over the past years, Prof. Sokolov intensively developed an original applied theory of structural dynamics management. The reliability and validity of his conclusions and developments have been confirmed both internationally and within Russia by numerous publications, implementations, and testing.

The results of the research, conducted by him personally and his students, have been widely and diversely implemented both in scientific organizations and enterprises. Professor Sokolov and representatives of his scientific school have developed analytical methods, methods, algorithms, and techniques for integrated automated planning and control of their structural dynamics, which are resolved with minimal resources.

From 1999 to the present, he worked on a number of projects funded by the Russian Academy of Sciences, the Russian Foundation for Basic Research, the Russian Science Foundation, the Applied Problems Section of the Presidium of the Russian Academy of Sciences, and international organizations (EORD, CRDF).

Professor Sokolov has been actively teaching since 1982. Since 1999, he has been a Professor of St. Petersburg SUAI. He developed several original courses of lectures on the integrated modeling of the management processes of the structural dynamics of complex objects in various subject areas. He has supervised 10 candidates of technical sciences (Ph.D.) and 4 doctors of technical sciences (Dr. Habil.). Professor Sokolov is a member of the academic council of SPIIRAS and two dissertation councils, and has repeatedly been a member of the program committees at prestigious Russian and international conferences. He is a member of the Editorial Board of the International Journal of Integrated Supply Management, the Advisory Committee of the International Journal of Instrumentation, the International Journal of Information Technology, the Astronautics Federation, and the Academy of Navigation and Motion Control.

He is (co)-author of 7 monographs and books on system analysis, decision support systems, supply chain management and systems and control theory, and of more than 570 scientific works published in various academic journals, including the European

Journal of Operational Research, the International Journal of Manufacturing Technology and Management, the International Journal of Production Research, the Journal of Computer and Systems Sciences International, Differential Equations, Automation and Remote Control, and Annual Reviews in Control.

The works of Prof. Sokolov on this book were supported by the Russian Foundation for Basic Research (grants 16-29-09482-ofi-i, 17-11-01254, 17-29-07073-ofi-i, 18-07-01272, 19-08-00989), grant 074-U01 (ITMO University), state order of the Ministry of Education and Science of the Russian Federation №2.3135.2017/4.6, state research 0073–2018–0003, International project ERASMUS +, Capacity building in higher education, № 73751-EPP-1-2016-1-DE-EPPKA2-CBHE-JP, Innovative teaching and learning strategies in open modelling and simulation environment for student-centered engineering education'.
e-mail: sokol@iias.spb.su

Introduction

Chapters in this Book

The Chapter "Ripple Effect in the Supply Chain: Definitions, Frameworks and Future Research Perspectives" by Dmitry Ivanov, Alexandre Dolgui, and Boris Sokolov begins the book. This chapter aims to delineate both major features of the ripple effect and methodologies for mitigating SC disruptions and recovering from severe disruptions. It presents an overview of the causes of the ripple effects and mitigation strategies. A framework for ripple effect control, comprised of redundancy, flexibility, and resilience, is developed. In addition, though a variety of valuable insights has been garnered in recent years, new research avenues and ripple effect taxonomies are identified for the near future. Special focus is directed toward SC risk analytics and the ripple effect in SCs.

Next, in the Chapter "A Multi-portfolio Approach to Integrated Risk-Averse Planning in Supply Chains under Disruption Risks", Tadeusz Sawik suggests a methodical approach to time- and space-integrated decision-making. In the context of SC disruptions, the portfolio is defined as the allocation of demand for parts among suppliers or the allocation of demand for products among production facilities. A disruptive event is assumed to impact both primary suppliers of parts and the firm primary assembly plant. Considering the integration of mitigation and recovery decisions over time and space, the author shows that the primary portfolios to be implemented before a disruptive event are optimized simultaneously via recovery portfolios for the aftermath period as well as the portfolios of both parts suppliers and product manufacturers in different geographic regions. Risk-averse solutions are obtained through conditional cost-at-risk and conditional service-at-risk measures. The findings indicate that when the objective is to optimize service level with no regard to costs, both supply and demand portfolios are more diversified. The author concludes that the proposed multi-portfolio approach enables time- and space-integrated decision-making that may help to better mitigate the impact of disruption propagation on SC performance, i.e., the ripple effect.

Virginia L. M. Spiegler, Mohamed M. Naim, and Junyi Lin focus their Chapter on "The Rippling Effect of Non-linearities". Using control theoretic tools, they show that nonlinearities can lead to unexpected dynamic behaviors in the SC that could then either trigger disruptions or make the response and recovery process more difficult. This chapter is particularly relevant for researchers wanting to learn more about the different types of nonlinearities that can be found in the SC, the existing analytical methods for dealing with each type of nonlinearity, and the potential direction of future research based on current knowledge in this field.

Jennifer Blackhurst and Kevin Scheibe devote their Chapter "Systemic Risk and the Ripple Effect in the Supply Chain" on the concept of systemic risk coupled with the impact of the ripple effect in the SC. They describe the dimensions of systemic risks as part of the nature of disruption, SC structure and dependence, and managerial decision-making. Moreover, the authors discuss interrelations between the ripple and bullwhip effects. The authors conclude that because disruptions frequently ripple through a system, a systemic risk perspective is crucial for understanding not only the nature of the disruption but also the effects of the structure of the SC and the consequences of choices made by decision makers.

In their Chapter "Leadership for Mitigating Ripple Effects in Supply Chain Disruptions: A Paradoxical Role", Iana Shaheen, Arash Azadegan, Robert Hooker, and Lorenzo Lucianetti analyze how leaders' adaptive decision-making (ADM) affects the extent of operational performance damage caused by different forms of SC disruptions. SC disruptions often sever multiple value-generating streams, creating a ripple effect across organizations. Reestablishing production links in a web of interorganizational exchanges requires careful examination of what is at stake for purchasing and supply managers. Using paradox and leadership theories, they offer hypotheses related to unexpected, complicated, and enduring SC disruptions. By empirically testing the hypotheses using secondary (financial) and primary (managerial assessment) data from a cross-section of 251 manufacturing firms, they show a concave curvilinear relationship between leader's ADM and operational damage from SC disruptions, suggesting that moderate levels of ADM are optimal. Higher ADM is particularly effective for diminishing ripple effects in the face of infrequent disruptions. On the other hand, low ADM is more effective in the face of unexpected and complicated disruptions.

In their Chapter "A Model of an Integrated Analytics Decision Support System for Situational Proactive Control of Recovery Processes in Service-Modularized Supply Chain", Dmitry Ivanov and Boris Sokolov consider the challenge recovery process, a disruptive event, planning of the recovery control policy, and implementation of this policy in the SC. These events are distributed in time and subject to SC structural and parametrical dynamics. In other words, environment, SC structure and the SC's operational parameters may change in the period between the planning of the recovery control policy and its implementation. As such, situational proactive control with combined use of simulation optimization and analytics is proposed to improve processes of transition between a disrupted and a restored SC state. Implementation of situational proactive control can reduce investments in robustness and increase resilience by obviating time traps in problems of transition process control. This chapter presents a decision support system model for situational proactive control of SC recovery processes based on a combination of optimization and analytics techniques. More specifically, three dynamic models are developed and integrated with each other, i.e., a model of SC material flow control, a model of SC recovery control, and a model of SC recovery control adjustment. The given models are developed within a cyber-physical SC framework based on an approach of service modularization.

In their Chapter "Bullwhip Effect of Multiple Products with Interdependent Product Demands", Srinivasan Raghunathan, Christopher S. Tang, and Xiaohang Yue present a study that extends current theory to provide insights for a firm that manufactures multiple products in a single product category with interdependent demand streams. This study finds that interdependency between demand streams plays a critical role in determining the existence and magnitude of the bullwhip effect. More importantly, the authors show that interdependency impacts whether the firm should manage ordering and inventory decisions at the category level or at the product level, and whether the bullwhip effect measure computed at the category level is informative or not.

The Chapter "Performance Impact Analysis of Disruption Propagations in the Supply Chain" by Dmitry Ivanov, Alexander Pavlov, and Boris Sokolov develops a method for quantifying the ripple effect in the SC with consideration of recovery policy. The performance impact index developed is then used to compare sales (revenue) in different SC designs to measure the estimated annual magnitude of the ripple effect. First, optimal SC recovery for two disruption scenarios is computed. Second, the performance impacts of disruptions for six proactive SC designs are assessed. Finally, the performance impact indexes of different SC designs are compared and conclusions are drawn about the ripple effect in these SC designs along with recommendations for the selection of a proactive strategy. The performance impact index developed can be used to assess how different markets are exposed to the ripple effect and how different SC designs can be compared according to their resilience to severe disruptions.

In their Chapter "Ripple Effect Analysis of a Two-Stage Supply Chain Using Probabilistic Graphical Model", Seyedmohsen Hosseini and MD Sarder develop a new methodology to control and monitor the ripple effect in SCs by analyzing the ripple effect in a two-stage SC. This probabilistic graphical model is capable of capturing disruption propagation that can transfer from upstream suppliers to downstream end customer in the SC.

Dmitry Ivanov's Chapter "Entropy-Based Analysis and Quantification of Supply Chain Recoverability" addresses the problem of designing resilient SCs at the semantic network level. The entropy method is used to show the interrelations between SC design and recoverability. Easy-to-compute quantitative measures are proposed to estimate SC recoverability. For the first time, an entropy-based SC analysis is brought into correspondence with consideration of SC structural recoverability and flexibility downstream in the SC. Exact and heuristic computation algorithms are suggested and illustrated. This approach and recoverability measure can be applied in selecting a resilient SC design according to potential recoverability.

In their Chapter "New Measures of Vulnerability within Supply Networks: A Comparison of Industries", James P. Minas, N.C. Simpson, and Ta-Wei (Daniel) Kao point out that one distinct element of SC risk is the potential for detrimental material to propagate through the SC undetected, eventually exposing unsuspecting consumers to defective products. Based on methods inspired by epidemiology, new measures for quantifying this risk are proposed. The authors apply these measures to real-life supply networks from eight industries to compare their relative levels of risk across a 17-year time horizon. The results indicate that while aggregate SC risk has increased over time, both the level and sources of risk differ markedly by industry.

Dmitry Ivanov and Maxim Rozhkov study capacity disruption and recovery policy impacts on SC performance in their Chapter "Disruption Tails and Revival Policies in the Supply Chain". A discrete-event simulation methodology is used for analysis with real company data and real disruptions. Two novel findings are presented. First, disruption-driven changes in SC behavior may result in backlog and delayed orders, the accumulation of which in the post-disruption period we call "disruption tails". The transition of these residues into the post-disruption period causes post-disruption SC instability, resulting in further delivery delays and non-recovery of SC performance. Second, a smooth transition from a contingency policy through a special "revival policy" to the normal operation mode enables partial mitigation of the negative effects of the disruption tails. These results suggest three managerial insights. First, contingency policies need to be applied during the disruption period to avoid disruption tails. Second, recovery policies need to be extended toward integrated consideration of both the disruption and the post-disruption periods. Third, revival policies need to be developed for the transition from the contingency to the disruption-free operation mode. A revival policy is intended to mitigate the negative impact of the disruption tails and stabilize SC control policies and performance. The experimental results suggest a revival policy should be included in an SC resilience framework if performance cannot be recovered fully after capacity recovery.

In their Chapter "Managing Disruptions and the Ripple Effect in Digital Supply Chains: Empirical Case Studies", Ajay Das, Simone Gottlieb, and Dmitry Ivanov analyze the impact of accelerating digitalization on SC risk management. Digital technologies, such as big data analytics, Industry 4.0 applications, additive manufacturing, blockchain, advanced tracking and tracing technologies, and enterprise resource planning software systems are considered. Empirical evidence on the interrelations between digital technologies and the risk of SC disruptions, as well as the influence of the one on the other, are analyzed based on the findings from the multiple case studies. These findings are comprised of the insights and managerial recommendations of experts from multiple industries. The empirical analysis is guided by hypotheses and a conceptual framework based on extant theory.

Rameshwar Dubey devotes his Chapter "Resilience and Agility: The Crucial Properties of Humanitarian Supply Chain" to theorizing and testing the impact of agility and resilience on humanitarian supply chain performance. Supply chain agility and resilience are explained based on the existing literature and further tested the theory using confirmatory factor analysis. The multivariate statistical analyses suggest that supply chain agility is an important property of pre-disaster performance, and supply chain resilience is an important property of the post-disaster performance.

The chapter "Digital Supply Chain Twins: Managing the Ripple Effect Resilience, and Disruption Risks by Data-Driven Optimization, Simulation, and Visibility" is written by Dmitry Ivanov, Alexandre Dolgui, Ajay Das, and Boris Sokolov. The impact of digital technology, Industry 4.0, blockchain, and data analytics on the ripple effect and disruption risk management in SCs is studied in this chapter. This chapter does not pretend to be encyclopedic, but rather seeks to advance the knowledge we have to further research on the relationship between digitalization and SC disruptions risks based on recent literature and case studies. It then presents an SC risk analytics framework and explains the concept of digital SC twins. It analyzes perspectives and future transformations that can be expected in the transition towards cyber-physical SCs. It shows how digital technologies and smart operations can help to integrate resilience and lean thinking into a *resileanness* framework for a "Low-Certainty-Need" (LCN) SC.

Ripple Effect in the Supply Chain: Definitions, Frameworks and Future Research Perspectives

Dmitry Ivanov, Alexandre Dolgui and Boris Sokolov

Abstract This chapter aims at delineating major features of the ripple effect and methodologies to mitigate the supply chain disruptions and recover in case of severe disruptions. It observes the reasons and mitigation strategies for the ripple effect in the supply chain and presents the ripple effect control framework that is comprised of redundancy, flexibility and resilience. Even though a variety of valuable insights has been developed in the given area in recent years, new research avenues and ripple effect taxonomies are identified for the near future. Two special directions are highlighted. The first direction is the supply chain risk analytics for disruption risks and the data-driven ripple effect control in supply chains. The second direction is the concept of low-certainty-need (LCN) supply chains.

1 Ripple Effect in the Supply Chain: Basic Definitions

1.1 Supply Chain Risks and Ripple Effect

Disruptions are considered high-impact-low-frequency events (e.g. fire or tsunami) in the supply chain (SC) that change the SCs structural design and significantly impact performance. The propagation of a disruption through an SC and its associated impact is called the *ripple effect*. A ripple effect is distinct from the well-known bullwhip

D. Ivanov (✉)
Berlin School of Economics and Law, Department of Business and Economics, 10825 Berlin, Germany
e-mail: divanov@hwr-berlin.de

A. Dolgui
IMT Atlantique, LS2N, CNRS, La Chantrerie, 4, rue Alfred Kastler, 44300 Nantes, France
e-mail: alexandre.dolgui@imt-atlantique.fr

B. Sokolov
Saint Petersburg Institute for Informatics and Automation of the RAS (SPIIRAS), V.O. 14 line 39, 199178 St. Petersburg, Russia
e-mail: sokol@iias.spb.su

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effect. It manifests when the impact of an SC disruption cannot be localized or being contained to one part of the SC and cascades downstream, resulting in a high-impact effect on SC performance (Dolgui et al. 2018). The ripple effect considers structural network dynamics in the SC while bullwhip effect characterizes the oscillations in operational parameters. The ripple effect is initiated by a severe disruption and describes the propagation of this disruption downstream the SC, e.g. in terms of propagation of the demand fulfilment downscaling as a result of a severe disruption. In more severe cases, the ripple effect can be manifested in temporary switching off some nodes and arcs in the network, e.g. due to material shortage. The bullwhip effect, on the contrary, is launched by a small operational deviation and is expected to be amplified in the upstream direction.

While the reasons for bullwhip effect have been extensively studied over the past two decades, the ripple effect is quite a new phenomenon and analysis its impacts deserve more research attention. These impacts might include lower revenues, delivery delays, loss of market share and reputation and stock return decreases—the cost of all of which could be devastating.

Consider an example. On 17 October 2016 as a result of an incorrect maintenance operation on a pipeline at BASF facility in Ludwigshafen (Germany), there was an explosion and subsequent fires at North Harbor, a terminal for the supply of raw materials such as naphtha, methanol and compressed liquefied gases. More than 2.6 million tons of goods are handled there each year and an average of seven ships a day moor at its docks. Two steam crackers, the starting point for producing basic chemicals, needed to be stopped because they could no longer be supplied, and 22 were only partially working. The two steam crackers could have been restarted two days later, but only in May 2017 was the concept for reconstruction released whereby the reconstruction should be completed by September 2017. Restricted production output, a daily revenue decrease of 10–15% as compared to the previous year during the disruption period, impact on the basic chemicals division (about 21% of sales), delivery delays, limited access to key raw materials, exhausted product inventories and a forecasted impact on 6% of BASFs annual earnings were some of the consequences of this incident (Dolgui et al. 2018, and references within). Logistics was temporarily shifted from ships and pipelines to trucks and trains. BASF was in close contact with its customers to keep them informed about the current availability of products to minimize the impact on customer deliveries. Because of BASF integrated “Verbundsystem” (networking system), comprised of various plants and delivery systems for feedstocks, the incident had an impact along the global SC. This high and long-term impact is the so-called ripple effect (Ivanov et al. 2014a, b).

BASF built a resilient SC, which is why the economic consequences of the aforementioned incident were considerably smaller than expected. BASF took process safety and risk prevention measures that included globally valid guidelines and requirements for buildings, etc. and practical security trainings for employees and support staff. Along with process safety and risk prevention measures, BASF has global emergency response management. This management consists of the integration of worldwide group companies, joint ventures, partners, suppliers and customers. Emergency phones and an integrated network of control centres (e.g. internal/external

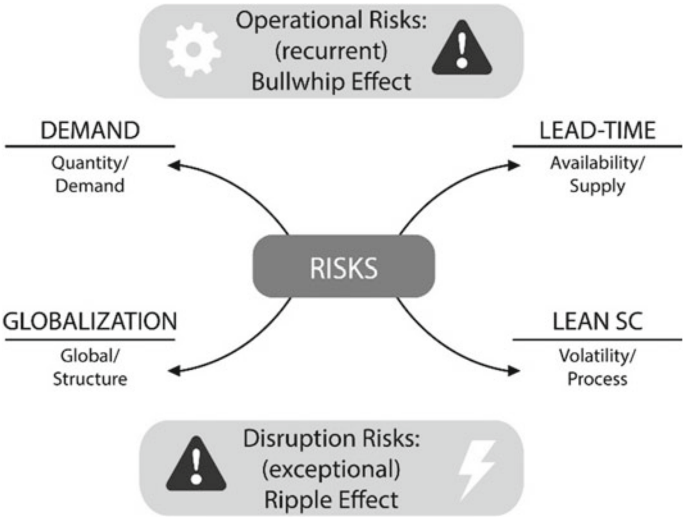

Fig. 1 Supply chain operational and disruption risks (Ivanov 2018b)

fire departments and rescue service) also enable this global emergency response management to work even more closely together. BASF was prepared for the incident in October 2016, but there is still long-term impact.

The BASF example shows the importance of SC risk management and the threats that severe disruptions may influence the SC performance. *Risk management* in the SC became one of the most important topics in research and practice over the last decade. A number of books (Handfield and McCormack 2008; Kouvelis et al. 2012; Waters 2011; Gurnani et al. 2012; Heckmann 2016; Mistree et al. 2017; Khojasteh 2017; Ivanov 2018b; Sawik 2018) and literature review papers (Klibi et al. 2010; Simangunsong et al. 2012; Ho et al. 2015; Fahimnia et al. 2015; Snyder et al. 2016; Dolgui et al. 2018) provide insightful overviews and introductions to different aspects of this exciting field.

Recent literature introduced different classifications of SC risks (Chopra and Sodhi 2004; Tang and Musa 2011; Ho et al. 2015; Quang and Hara 2018; Macdonald et al. 2018) (see Fig. 1).

Risks of demand and supply uncertainty are related to random uncertainty and business-as-usual situation. Such risks are also known as *recurrent* or *operational risks. SC* managers achieved significant improvements at managing global SCs and mitigating recurrent SC risks through improved planning and execution (Chopra and Sodhi 2014).

From 2000 thru 2018, SC disruptions (e.g. because of both natural and man-made disasters, such as on 11 March 2011 in Japan, floods in Thailand in 2011, fire in the Phillips Semiconductor plant in New Mexico, etc.) occurred in greater frequency and intensity, and thus with greater consequences (Chopra and Sodhi 2014; Simchi-Levi et al. 2014). Hendricks and Singhal (2005) quantified the negative

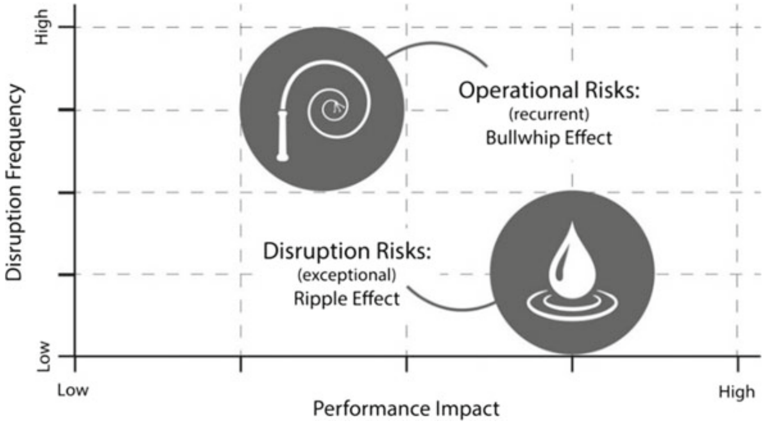

Fig. 2 Operational and disruption risks in supply chains (Ivanov et al. 2019)

effects of SC disruption through empirical analysis and found 33–40% lower stock returns relative to their benchmarks over a 3-year time period that started one year before and ended two years after a disruption.

1.2 Disruption Risks and the Ripple Effect

Disruption risks represent a new challenge for SC managers who face the *ripple effect* (Liberatore et al. 2012; Ivanov et al. 2014a, b; Levner and Ptuskin 2018; Ivanov 2018a; Dolgui et al. 2018; Ivanov and Dolgui 2018; Ivanov et al. 2018; Ivanov et al. 2019; Ivanov and Rozhkov 2017; Hosseini et al. 2019) subject to *structural disruptions* in the SC, unlike the *parametrical deviations* in the bullwhip effect (Fig. 2).

In the last two decades, considerable advancements have been achieved in research regarding the mitigation of inventory and production shortages and response to demand fluctuations. In particular, the *bullwhip effect* in the SC has been extensively considered in this domain subject to *randomness uncertainty* with the help of stochastic and simulation models.

The differences between the bullwhip effect and ripple effect are presented in Table 1 (Dolgui et al. 2018, 2019).

The Bullwhip effect considers weekly/daily demand and lead-time fluctuations as primary drivers of the changes in the supply chain which occur at the parametric level and can be eliminated in a short-term perspective. In recent years, the research community has started to investigate severe supply chain disruptions with long-term impacts that can be caused, for example, by natural disasters, political conflicts, terrorism, maritime piracy, economic crises, destroying of information systems, or transport infrastructure failures. We refer to these severe natural and man-made disasters as the ripple effect in the supply chain where changes in the supply chain

Table 1 Ripple effect and bullwhip effect (Dolgui et al. 2018)

Feature	Ripple effect	Bullwhip effect
What uncertainty?	Hazard, deep uncertainty	Random uncertainty
What risks?	Disruption, exceptional risks (e.g. a plant explosion)	Operational, recurrent risks (e.g. demand fluctuation)
What can be disturbed?	Structures and critical performance (such as supplier unavailability or revenue)	Operational parameters such as lead time and inventory
How are deviations prevented?	Proactive redundancy and flexibility	Information coordination
What happens after the disturbance?	Short-term stabilization and middle- and long-term recovery; high coordination efforts and investments	Short-term coordination to balance demand and supply
What is performance impact?	Output performance can decrease, such as in annual revenues or profits	Current performance can decrease such as in daily or weekly stock out/overage costs

occur at the structural level and recovery may take mid- and long-term periods of time with significant impact on output performance such as annual revenues. In this setting, supply chain disruption management can be considered a critical capability which helps to create cost-efficient supply chain protection and implement appropriate actions to recover supply chain disruptions and performance.

Most studies on supply chain disruption consider how changes to some variables are rippling through the rest of the supply chain and impacting performance. Studies by Ivanov et al. (2014a, b) and Dolgui et al. (2018) suggest considering this situation as *the ripple effect in the supply chain*, as an analogy to computer science, where the ripple effect determines the disruption-based scope of changes in the system.

The *ripple effect* in the supply chain occurs if a disruption cannot be localized and cascades downstream impacting supply chain performance such as sales, stock return, service level and costs (Ivanov et al. 2014a, 2015; Dolgui et al. 2018; Ivanov 2018a). The methodical elaborations on the evaluation and understanding of low-frequency-high-impact disruptions are therefore vital for understanding and further development of network-based supply concepts (Tomlin 2006; Liberatore et al. 2012; Sawik 2016).

Details of empirical or quantitative methodologies differ across the works on supply chain disruption management, but most share a basic set of attributes:

- a disruption (or a set of disruptions)
- impact of the disruption on operational and strategic economic performance
- stabilization and recovery policies.

Within this set of attributes, most studies on supply chain disruption consider how changes to some variables are rippling through the rest of the supply chain and

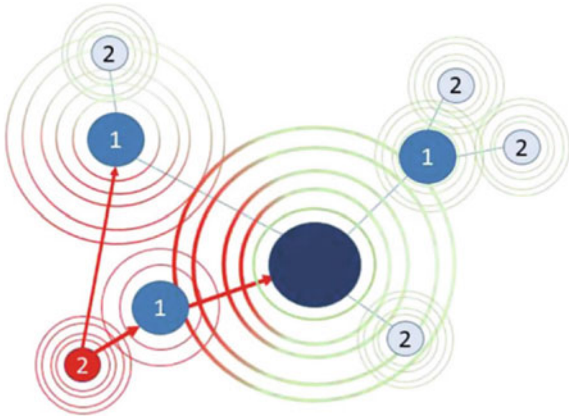

Fig. 3 Disruption propagation in the supply chain (Ivanov et al. 2019)

impacting performance. We suggest considering this situation, *the ripple effect in the supply chain*, as an analogy to computer science, where the ripple effect determines the disruption-based scope of changes in the system.

The ripple effect is a phenomenon of disruption propagations in the supply chain and their impact on output supply chain performance (e.g. sales, on time delivery and total profit). It may have more serious consequences than just short-term performance decrease. It can result in market share losses (e.g. Toyota lost its market leader position after tsunami in 2011 and needed to redesign supply chain coordination mechanism). The ripple effect is also known as "domino effect" or "snowball effect". The reasons for ripple effect are not difficult to find. With increasing supply chain complexity and consequent pressure on speed and efficiency, an ever-increasing number of industries come to be distributed worldwide and concentrated in industrial districts. In addition, globalized supply chains depend heavily on permanent transportation infrastructure availability.

The ripple effect describes disruption propagation in the supply chain, impact of a disruption on supply chain performance and disruption-based scope of changes in supply chain structures and parameters.

Following a disruption, its effect ripples through the supply chain. The missing capacities or inventory at the disrupted facility may cause missing materials and production decrease at the next stages in the supply chain. Should the supply chain remain in the disruption model longer than some critical period of time (i.e. *time-to-survive* (Simchi-Levi et al. 2015)), critical performance indicators such as sales or stock returns may be affected.

Ripple effects are not an infrequent occurrence. In many examples, supply chain disruptions go beyond the disrupted stage; i.e. the original disruption causes disruption propagation in the supply chain, at times still higher consequences are caused (Fig. 3).

The studies by Liberatore et al. (2012), Ivanov et al. (2014a, b, 2016, 2017b), Han and Shin (2016), Sokolov et al. (2016), Mizgier (2017), Schmitt et al. (2017), Ivanov

Table 2 Ripple effect reasons and countermeasures (based on Dolgui et al. 2018)

Reason	SCM impact	Ripple effect impact	Countermeasures
Leanness	Single sourcing	In the non-disrupted scenario, it is irrational to avoid lean practices. At the same time, a capacity disruption may result in the ripple effect and performance decrease. Recommendation to use capacity buffers or a backup facility as additional capacity reserves	Multiple/dual sourcing/backup suppliers
	Low inventory		Risk mitigation inventory
	Inflexible capacity		Postponement
Complexity	Globalization	Without a coordinated contingency policy, disruption recovery and performance impact estimation can be very long lasting and expensive. Coordinated control algorithms are needed to monitor SC behaviour, identify disruptions and adjust order allocation rules using a coordinated contingency policy	Geographical sourcing diversification
	Decentralization		Global SC contingency plans
	Multistage SCs		Supplier segmentation according to disruption risks

(2017, 2018b), Levner and Ptuskin (2018), Dolgui et al. (2018), Pavlov et al. (2018), Scheibe and Blackhurst (2018), Akkermans and van Wassenhove (2018) extensively analysed SC ripple effect, its reasons and efficient countermeasures. These findings are summarized in Table 2.

First, literature provides evidence that disruption duration and propagation impact SC performance. Second, proactive strategies such as backup facilities and inventory have positive impacts concerning both performance and prevention of disruption propagation. Third, the speed of recovery plays an important role in mitigating the performance impact of disruptions. Fourth, an increase in SC resilience implies significant cost increases in the SC.

1.3 Ripple Effect and Supply Chain Structural Dynamics

Ripple effect causes structural changes in the SC. The main supply chain features are the multiple structure design and changeability of structural parameters because of objective and subjective factors at different stages of the supply chain life cycle. In other words, supply chain *structural dynamics* is constantly encountered in practice

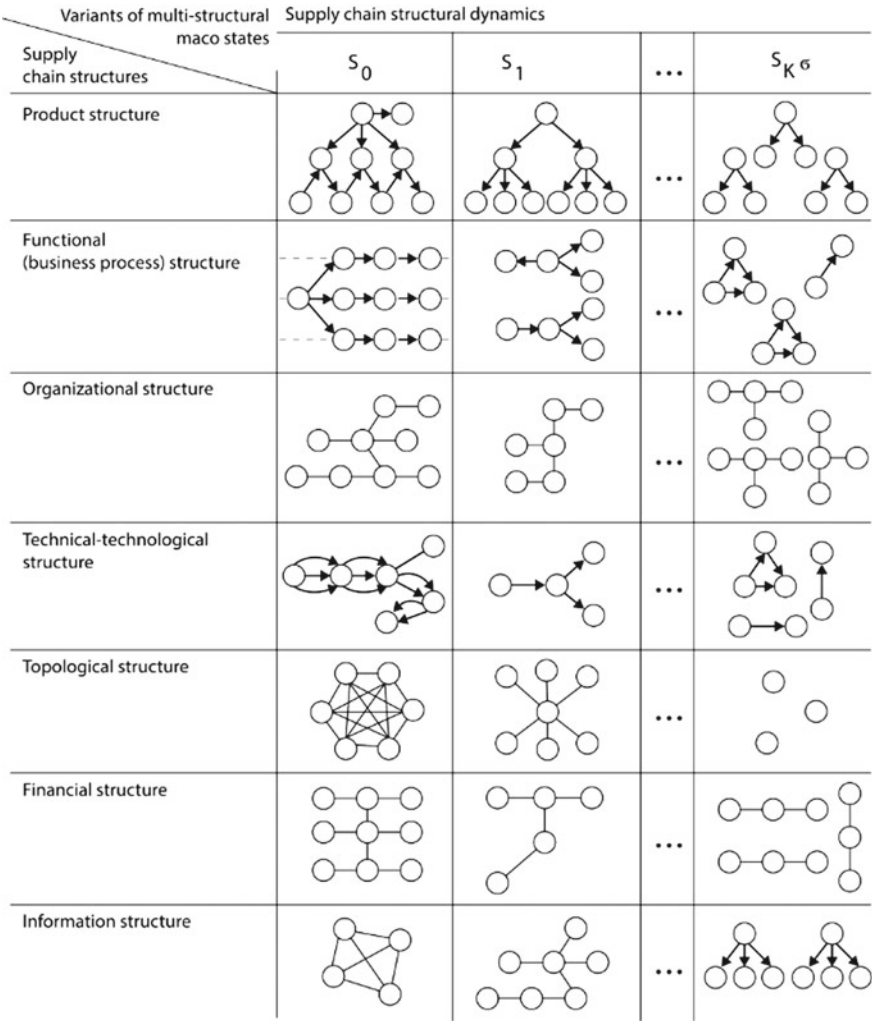

Fig. 4 Supply chain multi-structural composition and structural dynamics (based on Ivanov et al. 2010)

(Ivanov and Sokolov 2010; Ivanov et al. 2010). Figure 4 depicts major structures and their changes in dynamics. The composition of different structures at different point in time results in supply chain multi-structural macrostates *S*. Multi-structural macrostates describe supply chain design evolution over time due to planned (controllable) and uncertain factors.

The multi-dimensional dynamic space along with coordinated and distributed decision-making guides us in understanding modern supply chains as *multi-structural dynamic systems* (Ivanov et al. 2010).

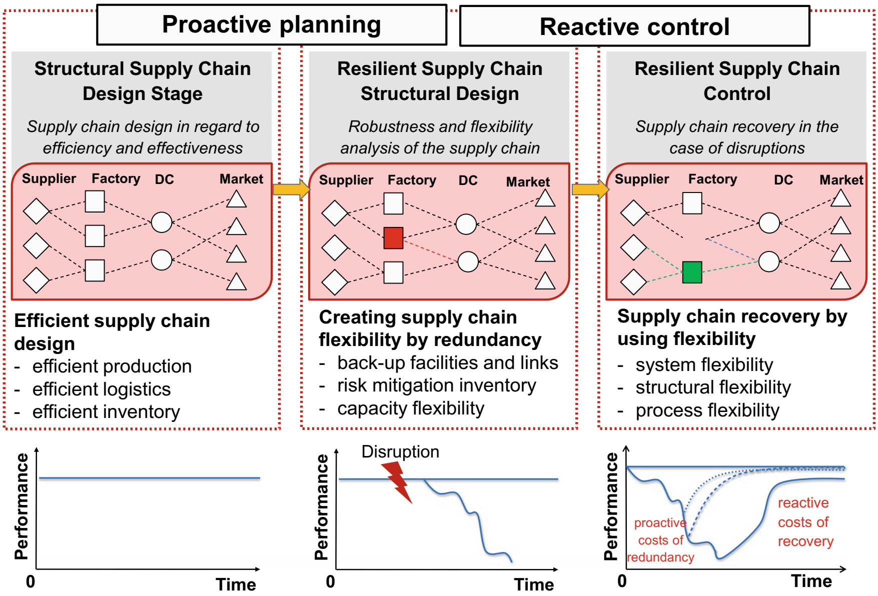

Fig. 5 Supply chain structural dynamics control (Ivanov 2018b)

1.4 Supply Chain Performance, Resilience and Ripple Effect Control

One of the main objectives of supply chain management is to increase total supply chain performance, which is basically referred to as supply chain effectiveness (i.e. sales and service level) and efficiency (supply chain costs). At the same time, the achievement of planned performance can involve the impact of disruptions in a real-time execution environment. Supply chain execution is subject to uncertainty at the planning stage and disruption at the execution stage. Cost efficiency comes with a huge hidden expense should a major disruption (i.e. a more severe impact than a routine disturbance) occur. This requires supply chain protection against and efficient reaction to disturbances and disruptions. Therefore, supply chains need to be planned to be *stable, robust and resilient* enough to (1) maintain their basic properties and ensure execution; and (2) be able to adapt their behaviour in the case of disturbances in order to achieve planned performance using recovery actions.

Decisions in supply chain structural dynamics control can be roughly classified into proactive and reactive stages (Fig. 5).

Resilient supply chain design extends traditional supply chain design approaches with regard to the incorporation of redundancies such as backup facilities, inventory and capacity flexibility. These redundancies create, at the proactive planning stage, some flexibility that can be used at the reactive control stage in the case of disruptions

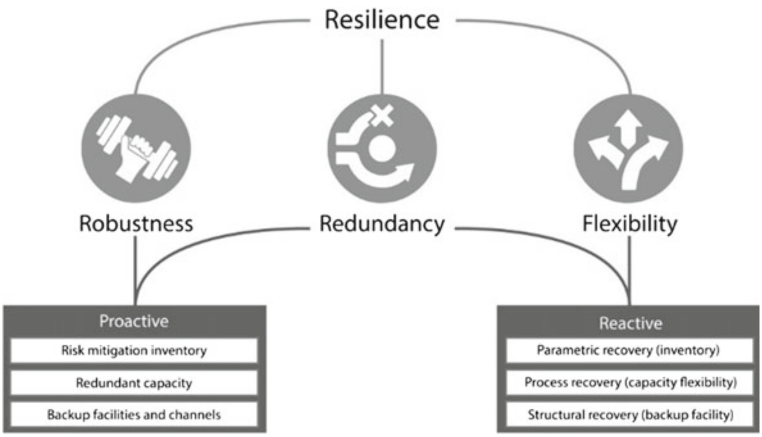

Fig. 6 Resilience control elements (Ivanov 2018b)

in supply chain structures in order to recover system performance and operational processes.

In Fig. 6, we summarize relations of redundancy, robustness, resilience and flexibility (see also Ivanov and Sokolov 2013 and Ivanov 2018b).

There is a strong and growing literature on robustness and resilience as two fundamental concepts to analyse SC performance with severe uncertainty consideration and with regards to scattered disruptive events resulting in SC structural dynamics. An SC is called *robust* if it is able to absorb disturbances and continue execution with minimal impact on performance. The performance of such an SC is insensitive to the negative impacts of disruptions (Ivanov and Sokolov 2013; Han and Shin 2016). Robustness is typically guaranteed by some redundancy such as structural diversification, flexible response options and system adaptation condition improvement. At the same time, we may distinguish between *being safe* and *performing safely*. In contrast to robustness that considers proactive redundancy (e.g. buffer capacities, backup suppliers, or risk mitigation inventory) at the pre-disruption stage, *resilience* deals with the system's ability to sustain or restore its functionality and performance following a significant change in the system and environment conditions (Aven 2017). SC resilience encompasses both proactive and reactive stages. As such, an integration of pro- and reactive decisions is important for increasing SC resilience by utilizing the synergetic effects between mitigation and contingency policies.

In Fig. 7, we summarize the relationships between redundancy, robustness, flexibility and resilience.

According to the ripple effect control framework (Dolgui et al. 2018) and other literature on the disruption propagation in the SC (e.g. Scheibe and Blackhurst 2018, Wang and Zhang 2018), disruption risks and their propagation in the SC are mainly caused by single sourcing, low risk mitigation inventory, overutilization of capacities, low-level safety technologies and missing contingency plans.

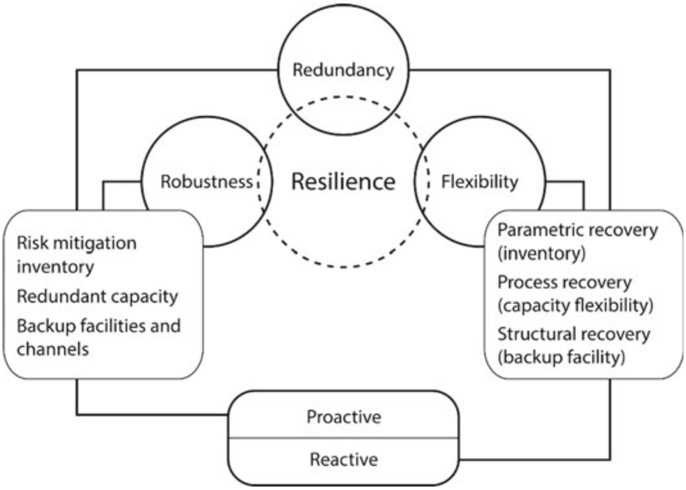

Fig. 7 Ripple effect control elements (Dolgui et al. 2018)

The width of the ripple effect and how it impacts economic performance is reliant on redundancies such as inventory or capacity buffers, also called robustness reserves, and on the speed and extent of recovery measures. As a result, it is necessary that, in the proactive mode, risk and SC resilience are assessed and incorporated at the design and planning stages. In the reactive mode, operationalization of contingency plans, such as alternative suppliers or shipping routes, must occur quickly in the control stage. This ensures quick stabilization and recovery, which is required to maintain supply continuity and prevent long-term impact. In order to assess the impact of the disruption on the SC, and both the costs and effects of material flow redirection, companies require a tool supported by collaboration and SC visibility solutions to implement these recovery policies.

Ripple effect control in the SC requires two critical capacities: resistance and recovery. For resistance, which is the SCs ability to protect against disruptions and reduce impact once the disruption occurs, some redundancy such as backup sourcing, risk mitigation inventory or capacity flexibility must be built in at the proactive stage. For recovery, this redundancy must be activated jointly with reactive contingency plans with regards to risk mitigation inventory, capacity flexibility and backup sources.

Recent literature has identified different methods to strengthen supply chains to mitigate uncertainty impacts and ensure supply chain robustness. Different robustness reserves can include material inventory, capacities buffers, etc. For this issue, valuable approaches and models for supply chain design and planning under uncertainty were elaborated. Increase in inventory, additional production capacities and alternative transportation methods or backup facilities would increase costs. At the same time, these so-called redundant elements would potentially lead to an increase in sales and service level. The robustness elements would also reduce the risk of perturbations which may influence schedule execution. Therefore, target objectives (e.g. on-time delivery) can be better achieved. This will positively influence sales and service level. Redundancy elements may also increase supply chain flexibility and have positive effects on both service level and costs. The resilient state of a supply chain requires a balanced robustness and flexibility which allows for achieving maximum performance with disruption risk considerations at acceptable redundancy costs.

2 Taxonomies of the Ripple Effect

2.1 Classification of the Ripple Effect Analysis Problems

Analysis of literature allows identification of several problem classes and datasets; it is recommended to analyse these using optimization, simulation, or hybrid simulation–optimization techniques. The literature has been analysed regarding the modelling techniques used, the problems addressed, the performance measures and the scope of the ripple effect analysis. More specifically, the following characteristics have been analysed to derive the classifications following a standard problem classifications in supply chain management at design, planning and control decision-making levels (Ivanov et al. 2019): (i) supply chain structural and operational parameters at the supply chain design level, (ii) inventory, sourcing, shipment and production control policies at the supply chain planning level and (iii) recovery policies at the supply chain control level. The following classification has been obtained (Fig. 8).

Let us consider these three classes of the ripple effect analysis in detail.

2.1.1 Problem Class 1. Static Ripple Effect Analysis

The models in the problem class allow computation of the performance impact of disruption and recommendation of a resilient supply chain design based on aggregate location and flow data subject to cost minimization or profit maximization. This problem class considers the following dataset:

Parameters:

- Possible site locations and connections (nodes and paths) with backups
- Discrete and limited number of time periods
- Deterministic or stochastic demand in periods
- Production, storage and shipment capacities in periods
- Lead time and service levels
- Operational costs
- Variables
- Location opening or closure

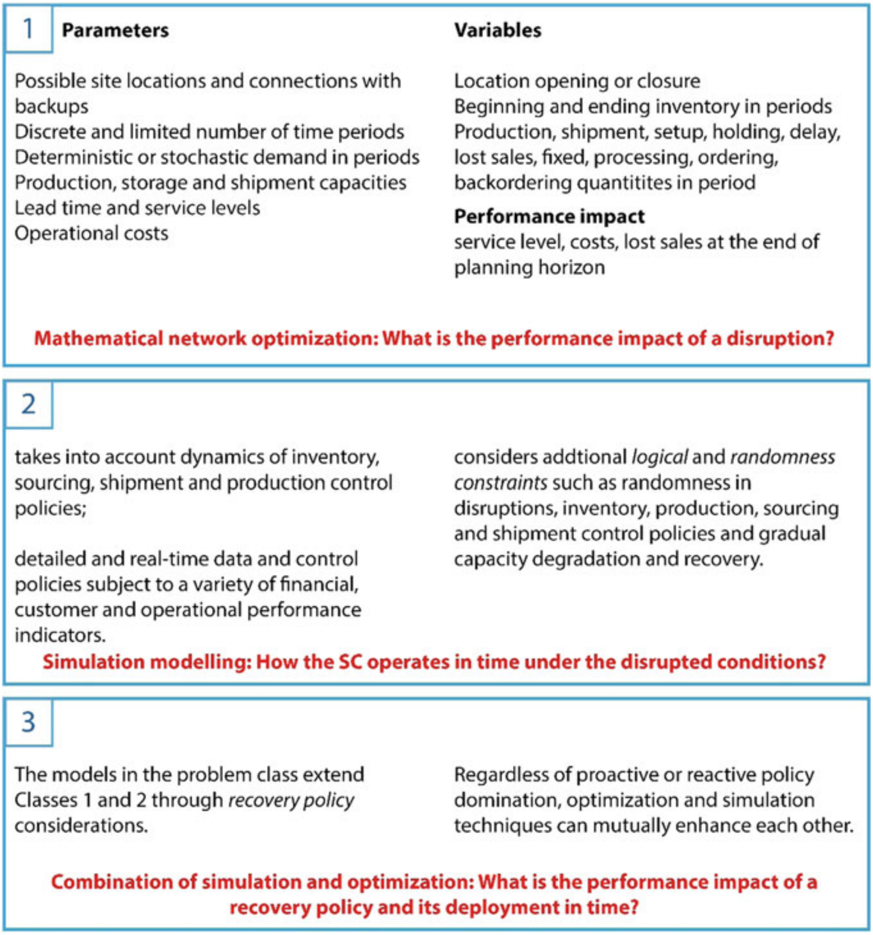

Fig. 8 Three problem classes in the ripple effect analysis

- Beginning and ending inventory in periods
- Production, shipment, setup, holding, delay, lost sales, fixed, processing, ordering, backordering quantities in periods.

Performance impact: service level, costs, lost sales at the end of planning horizon.

Mathematical network optimization has been typically used for this class. Those models are placed at the supply chain design level and help to analyse the impact of the disruption on the supply chain performance by deactivating some structural elements on changing some operational parameters (e.g. capacity) and observing the resulting changes on costs or sales. This analysis is helpful at the strategic decision-making level. At the same time, those models do not take into account the dynamics of inventory, sourcing, shipment and production control policies.

2.1.2 Problem Class 2. Dynamic Ripple Effect Analysis

The models in the problem class allow supply chain behaviour to be analysed over time, computation of the performance impact of the disruption and recommendation of a resilient supply chain design based on detailed and real-time data and control policies subject to a variety of financial, customer and operational performance indicators. In addition to the more detailed data from the Class 1 dataset, this problem class considers additional *logical* and *randomness constraints* such as randomness in disruptions, inventory, production, sourcing and shipment control policies, and gradual capacity degradation and recovery. For problems in this class, simulation has been dominantly applied. Since simulation studies on the ripple effect deal with time-dependent parameters, duration of recovery measures and capacity degradation and recovery, they have earned an important role in academic research. Simulation has the advantage that it can extend handling of the complex problem settings in Class 1 with situational behaviour changes in the system over time.

2.1.3 Problem Class 3. Dynamic Ripple Effect Analysis with Recovery Considerations

The models in the problem class extend Classes 1 and 2 through recovery policy considerations. Independent of proactive or reactive policy domination, optimization and simulation techniques can mutually enhance each other. For problems in this class, a combination of network optimization and simulation (e.g. simulation runs over optimization results) can be recommended. The research considering the recovery stage is still new and requires an extension. We consider the problem class 3 as an especially promising future research avenue.

2.2 Literature Classification Taxonomy

Ivanov and Dolgui (2018) proposed the following literature classification taxonomy (Table 3).

2.2.1 Semantic Level: Structural Properties, Complexity Role and Critical Nodes

Disruptions and the resulting ripple effect cause SC structural changes, and it is also referred to as SC structural dynamics. Structural SC properties have been recognized to have a crucial impact on the ripple effect and SC robustness and resilience. A body of literature has been established that examines the impacts of different structural variations on SC performance for various risk attitudes in a decision maker, ranging from risk neutral to risk-averse. This literature at the structural level targets semantic

Table 3 Literature classification scheme

Analysis levels		Proactive stage	Reactive stage			
Network structure and variety	I	Complexity	A, B, C, D, E, F	I	Complexity	A, B, C, D, E, F
		Centralization			Centralization	
	1	Diversification		7	Diversification	
		Localization			Localization	
	II	Complexity	A, B, C, D, E, F	II	Complexity	A, B, C, D, E, F
		Centralization			Centralization	
	2	Diversification		8	Diversification	
		Localization			Localization	
Process flexibility	I	Backup/dual s.	A, B, C, D, E, F	I	Backup/dual s.	A, B, C, D, E, F
		Postponement			Postponement	
	3	Product subst.		9	Product subst.	
		Coordination			Coordination	
	II	Backup/dual s.	A, B, C, D, E, F	II	Backup/dual s.	A, B, C, D, E, F
		Postponement			Postponement	
	4	Product subst.		10	Product subst.	
		Coordination			Coordination	
Parametric redundancy	I	Inventory	A, B, C, D, E, F	I	Inventory	A, B, C, D, E, F
		Capacity			Capacity	
	5	Lead time		11	Lead time	
	II	Inventory	A, B, C, D, E, F	II	Inventory	A, B, C, D, E, F
		Capacity			Capacity	
	6	Lead time		12	Lead time	

Legend:
I—Supply Chain Structural Design
II—Supply Chain Process Planning and Control
1–12—Research field numbers
A–F—Methodologies:
A—Mathematical Optimization (deterministic mixed-integer, stochastic, robust, goal and fuzzy optimization)
B—Simulation (discrete-event simulation, agent-based simulation, system dynamics)
C—Game Theory (cooperative/non-cooperative, dynamic differential and symmetric/asymmetric (incomplete information) games)
D—Control Theory (optimal control, model-predictive control, feedback control)
E—Reliability Theory (probabilistic, statistical, logic and graph models)
F—Hybrid Methodology
Coding example for Ivanov D., Sokolov, B., & Pavlov, A. (2014b). Optimal distribution (re)planning in a centralized multi-stage network under conditions of ripple effect and structure dynamics. European Journal of Operational Research, 237(2), 758–770:
10 – II – Ba – F:AD—this study focuses on the SC planning level and the impact of backup sourcing at the process recovery stage using a hybrid optimization-control theory methodology

network analysis in order to identify underlying interdependencies between network graph forms and SC robustness, flexibility, adaptability and resilience.

The semantic network analysis literature pertains to the dependencies of SC robustness and resilience on the structural complexity that increases uncertainty and disruption risk propagation. The quantitative methodologies used mostly include mathematical optimization, simulation, graph theory, game theory, control theory, complexity theory, financial analysis and reliability theory. The major findings in this research stream pose the impact of different structural SC designs, e.g. in terms of the critical nodes on disruption-based SC structural and performance dynamics. The issues of segmentation, diversification, backup suppliers, facility fortification, globalization and localization are considered important managerial levers to increase SC resilience at the proactive and reactive stages. In summary, *structural variety and recoverability* can be considered a major SC resilience driver, as identified at the semantic structural analysis level.

2.2.2 Process Level

Flexibility has been mostly analysed at the process level. The literature mostly focuses on product and process flexibility to ensure SC robustness and resilience. The literature recognizes flexibility as a major driver of resilient SCs. The papers in this research stream investigate the use of flexible production and sourcing processes to achieve SC robustness and resilience under disruptions. The coping strategies, the authors indicate, consider dual and multiple sourcing whereby the focus of analysis includes a tremendous variety of proactive and reactive measures such as backup supplier contracts, pricing policy adjustment, advanced, spot and contingency purchasing, risk mitigation inventory, capacity reservations, product flexibility and postponement and collaboration and visibility.

Flexibility is the central theme of the research conducted at the process level referring to the ability of production, sourcing and transportation systems in the SC to change (adapt) in dynamic environments. The methodologies used include mathematical optimization, discrete-event simulation, game theory and real options. Backup and dual sourcing, postponement, product substitution, production capacity flexibility and coordination have been identified as major elements of the contingency processes and SC resilience drivers to be addressed at the process management level. Increasing SC resilience is considered in the flexibility framework in light of some process redundancy (e.g. a more expensive backup source) as opposed to process leanness.

2.3 Control Level

The research focus at the control level is directed at process parameters such as inventory, capacity utilization and lead time. High inventory, capacity reservations and lead-time reserves may help to increase SC resilience, but might negatively affect efficiency. Parametric redundancy is a central research category at the control level. Insufficient redundancy is risky. Redundancy is costly. This trade-off presents a central issue in the research at the parametric redundancy control level. High inventory, capacity reservations and lead-time reserves may help in increasing SC resilience, but they negatively influence SC efficiency. The methodologies used in this research area include mathematical optimization, discrete-event simulation, system dynamics and control theory.

3 Future Research Perspectives on the Ripple Effect

While ripple effect and disruption risks have attracted considerable research attention, this research domain seems to be at the beginning stage of development. Some future research avenues are summarized in this section. With regards to the current research, we refer the readers to recent state-of-the-art survey in the given domain for more detailed analysis (Klibi et al. 2010; Ho et al. 2015; Fahimnia et al. 2015; Snyder et al. 2016; Ivanov et al. 2017; Dolgui et al. 2018).

3.1 Supply Chain Risk Analytics, Digitalization and Industry 4.0

Innovations in digital technologies influence the development of new paradigms, principles and models in SCs. The Internet of Things (IoT), cyber-physical systems, additive manufacturing and smart, connected products, facilitate the development of Industry 4.0-driven digital SC. Such technology advances are facilitated by the advent of big data analytics and advanced tracking and tracing technologies. Accompanying such technological advances are similar advances in organizational practice and culture, shaped by socio-technical considerations of new technology use. The dynamic nature of digitalization demands research that can help analyse, understand and evaluate its drivers, facilitators and performance outcomes. Such outcomes could range from time competitiveness to risk management and resilience.

The impact of digitalization on resilient operations and the SC can be quite complex. Consider some interplays. Risk in the SC can be mitigated by the descriptive and predictive use of big data analytics in gaining visibility and forecast accuracy, reduction in information disruption risks and improved contingency plan activation. Reductions in supply and time risks can be achieved by using advanced trace & tracking systems leading to real-time coordinated activation of contingency policies.

SCs typically hedge against disruptions by means of risk mitigation inventory, capacity reservations and backup sources. Such protection is expensive to maintain (in anticipation) and deploy. Blockchain digitalization could help reduce risk and associated preventive costs, if a record of activities and data needed for recovery exists for synchronized contingency plans. Similarly, additive manufacturing can reduce the need for risk mitigation inventory and capacity reservations, as well as diminish the need for expensive backup contingent suppliers. The decentralized control principles in Industry 4.0 systems make it possible to diversify risks and reduce the need for structural SC redundancy with the help of manufacturing flexibility. Big data analytics and advanced trace & tracking systems in general, and Blockchain technology in particular, can help us to trace the roots of disruptions, to observe disruption propagation (i.e. the ripple effect) (Dolgui et al. 2018; Ivanov 2018a), to select short-term stabilization actions based on a clear understanding of what capacities and inventories are available (emergency planning), to develop mid-term recovery policies, and to analyse the long-term performance impact of ripples effects. Additive manufacturing has a potential to reduce disruption propagation in the SC, since the number of SC layers and the resulting complexity would be reduced. Resilience may improve, resultantly.

Initial efforts to understand the impact of digital technologies on the SC risk management are underway. However, both conceptual and granular understandings of the contribution and the interplay of different digital technologies in regard to specific SC and operations resilience and sustainability requires further analysis.

The impact of digitalization and Industry 4.0 on the ripple effect and disruption risk control analytics in the SC is therefore a promising research avenue. The purpose of the research in the given area is to investigate the interplay between digitalization, SC resilience and SC risks. The scope synthesizes research from two distinct areas, i.e. the impact of digitalization on logistics, and the impact of supply chain management on risk control. As such, the topics of this domain connect business, information, engineering and quantitative analysis perspectives on digitalization to control and the supply chain risks issues. Such studies would connect business, information, engineering and analytics perspectives on digitalization and SC risks in order to bring the discussion further with the help of a conceptual framework for researching the relationships between digitalization and SC disruptions risks. Examples of the questions to be answered are, e.g. (1) what relations exist between big data analytics, Industry 4.0, additive manufacturing, advanced trace & tracking systems and SC disruption risks; (2) how digitalization can contribute to enhancing ripple effect control; and (3) what digital technology-based extensions can trigger the developments towards SC risk analytics.

At the proactive level, optimization and simulation models produce notable insights for managers and can be applied where the probability of disruption can be roughly estimated. On the one hand, big data analytics and advanced trace and tracking systems may help in predicting disruptions and providing more accurate data to build sophisticated disruption scenarios for resilient SC design analysis. Digital technologies open new problems for resilient SC design. For example, additive manufacturing changes SC designs whereby new resilient sourcing problems may arise. This area can further be enhanced using collaborative purchasing platforms.

At the reactive level and with regards to mitigation strategies and identifying disruption impact on finance and operational performance, digital technologies can be extensively used to obtain real-time information on the scope and scale of disruptions, their propagation in the SC and to simulate possible recovery strategies. In addition, at the reactive level, adaptation is necessary for achieving desired output performance by ensuring the possibility of changing SC plans and inventory policies. Adaptation processes in ripple effect control can be supported by feedback and adaptive control methods using decentralized agent techniques with the help of digital technologies. Visualizing these processes through virtual reality-supported simulation has not yet been done extensively to model the ripple effect in the supply chain. For this, simulation models, along with new digital technologies, can improve tools which are already used in developing SC agility and visibility in terms of disruption velocity.

3.2 Low-Certainty-Need Supply Chains

Uncertainty and risk predictions are commonly researched in studies of SC disruption management, mostly assuming known disruptive event or disruption scenario probability. The resulting resource allocation and costs have frequently resulted in expensive systems which help businesses cope with uncertainty. Without undermining the importance of further developing this common perspective, new approaches need to be developed that focus on the reduction of SC behaviour dependence on environmental changes.

The unpredictability of the occurrence of disruption and its magnitude suggests that designing SCs with a low need for "certainty" may be as important, if not more so, than predetermined pre-disruption strategies. While the problem of disruption impact investigation with disruption probability estimations has attracted considerable research attention, some fundamental issues in this research stream need to be pointed out, such as fair probability estimation of rare events, consideration of only "known" events and the exclusion of "unknown" events, and the consideration of mainly the direct effects of disruptions in model outputs rather than disruption propagation chains and the resulting indirect effects (Ivanov 2019; Pavlov et al. 2019; He et al. 2018; Mizgier 2017; Macdonald et al. 2018). Such new perspectives in SC disruption management can be placed under the umbrella of low-certainty-need (LCN) SCs. The ultimate objective of the LCN SCs is to develop the ability to operate according to planned performance regardless of environmental changes.

In the given research domain, the task is first to identify the characteristics of the LCN framework and its management. For example, structural variety, process flexibility and parametrical redundancy are identified as key LCN SC characteristics that ensure disruption resistance as well as recovery resource allocation, and that allow for SC operation in a broad range of environmental states. Two efficiency capabilities of the LCN SC, i.e. low need for uncertainty consideration in planning decisions and low need for recovery coordination efforts need to be investigated. The LCN SC does not necessarily imply higher costs, but rather seeks an efficient combination of lean and resilient elements. The results of this research would allow

Table 4 Research gaps at semantic, process and control levels

Analysis levels	Research gaps
Semantic level	The semantic network analysis pertains to the dependencies of SC robustness and resilience on structural network properties. Which structural SC designs, e.g. in terms of the critical nodes, can help to increase SC robustness and reduce the need for disruption-driven process changes? How can segmentation, diversification, backup suppliers, facility fortification, globalization and localization be applied to increase SC resilience whilst remaining lean and efficient? Which SC design patterns can provide quicker and more efficient recoverability?
Process level	Backup and dual sourcing, postponement, product substitution, production capacity flexibility and coordination are major elements of contingency processes and drivers of SC resilience. How can process redundancy be allocated to increase SC robustness and reduce the need for disruption-driven process changes? How can process redundancy (e.g. a backup source) be applied whilst remaining lean and efficient? Which reactive process flexibility policies can help in efficient SC recovery?
Control level	High inventory, capacity reservations and lead-time reserves may help in increasing SC resilience, but they negatively influence SC efficiency. How can parametric redundancy be applied to increase SC robustness and resilience whilst remaining lean and efficient? Which reactive control policies can help in efficient SC recovery?

the identification of an LCN SC framework as well as missing themes and new research questions which contribute to a better understanding of SC disruption risk management and control.

Table 4 summarizes the research gaps identified at semantic, process and control levels with regards to the LCN framework.

As shown in Table 4, a number of research gaps can be identified that motivate the development of the LCN SC framework. First, structural SC design patterns need to be identified that allow for both efficient robustness and recoverability. Second, process flexibility policies need to analysed which enable the reduction of disruption-driven process changes and efficient SC recovery. Finally, at the control level, the efficient usage of parametric redundancy and the development of reactive control policies are also research gaps that drive the pursuit to establish the LCN SC framework.

3.3 Proactive Planning, Network Redundancy Optimization and Situational Recovery Control

The research in ripple effect control needs to be united by three basic principles of system-cybernetic research. The *first* principle is the integrated modelling of resilient network structures. New principles and methods of SC structural dynamics control will be developed using a variety of methodologies for multi-criteria network synthesis and analysis. A particular focus will be directed towards the deployment of post-disruption management, and understanding which factors fit the particular dynamics the SC structures confront. The *second* principle is the proactive planning and network redundancy optimization. The given paradigm combines both SC robustness (i.e. the ability to absorb disturbances and continue execution with minimal impact on performance), monitoring (i.e. real-time disruption identification and data-driven replanning preparation) and resilience (i.e. the ability to sustain and restore SC functionality using recovery and adaptation policies).

The *third* principle is the situational proactive control. A disruptive event, planning of the recovery control policy and implementation of this policy are distributed in time and subject to SC structural and parametrical dynamics. In other words, both environment, SC structures and its operational parameters may change in the period between the planning of the recovery control policy and its implementation. As such, situational proactive control with a combined usage of simulation–optimization and analytics are needed to improve the transition processes from a disrupted to a restored SC state. This allows reducing investments in robustness and increasing resilience by obviating the transition process control problems. A combination of these three principles builds a framework of future decision-support systems for SC disruption risk management which utilizes two major ideas, i.e. (i) low-certainty-need SC designs and network redundancy optimization with an optimal combination of robustness and adaptation elements to ensure both efficient and resilient SCs and (ii) integrated SC ripple effect modelling with simulation, optimization and analytics components to support situational forecasting, predictive simulation, prescriptive optimization and adaptive learning.

3.4 Empirical Research and Simulation

Even if simulation and optimization studies provide valuable insights on preventing and mitigating the ripple effect in the SC, there is a lack of practical validation. Only a few studies incorporated real company data. At the same time, empirical research in SC management has also developed a variety of valuable approaches and methods to tackle the ripple effect. In this setting, combined empirical simulation, studies are encouraged. An example of an area for such integrated research is coordinated contingency plans. In addition, identification of information patterns needed to make decisions on ripple effect identification and recovery policies would be in the scope of this research (Macdonald et al. 2018).

3.5 Complexity Theory, Dynamics, Performance Analysis and Control

For dealing with the ripple effect in the SC, complexity management and system modelling might provide a theoretical basis. Based on Ashby's principle of requisite variety, the problem of a system under control and uncertainty implies an area under control and area under uncertainty, according to the perspective of complexity management. The system control can be adapted by widening one area and narrowing the other (Ivanov and Sokolov 2010; Ivanov 2010). Therefore, the connection between the system and the environmental spaces are categorized according to amplification of *control variety* or attenuation of *environmental variety*. A balance of control and disruption impact and maintenance of planned execution processes and a cost-efficient, fast recovery post-disruption can be achieved by amplifying the variety of the control area and reducing the area of uncertainty.

Further research can be initiated in this area as it regards to structural network properties and the identification of structural patterns in SC design which cause a greater or lesser ripple effect. In addition, the ripple effect and the impact of recovery and proactive strategies within one feedback framework including planning and adaptation control loops are revealed by applying methods of dynamic control theory.

Analysis of short-term and long-term impacts of the ripple effect on the SC and the creation of a performance measurement system is a promising research avenue. Even though some key performance indicators have been presented in literature episodically, there is a lack of systematic performance management techniques for the ripple effect in the SC.

3.6 Disruptions and Perishable Products

Generally, inventory constitutes an SC resilience drive in literature. In the case of SCs for perishable products, there are limits to inventory holding durations because of the short storage and expiration periods. The resilience of these kinds of SCs may be affected by the risk of goods write-off and customer segmentation by requirements for freshness. Safety stock reductions and an increase in transport frequency result from the constraints inherent with product perishability. However, when disruption risks are considered this may lead to an increase in safety stock. The bounded capacity of suppliers should also be analysed. Since customer demand tends to be vulnerable, there might be different requirements for the freshness of products and penalties when product is unavailable or freshness is decreased. Further, in perishable product SCs, issues of batching usually carry more weight.

3.7 Competition and Behavioural Aspects

Since severe disruptions may influence competition in the markets, a research agenda on the ripple effect needs to include this factor. In addition, managerial decisions are of a behavioural nature and subject to individual risk perceptions. Agent-based modelling can be applied to a broader scope of these problems. These principles may include collaboration (trust and information sharing) and an SC risk management culture (e.g. leadership and risk-averse behaviour). In this setting, agent-based modelling would be a suitable method for enhancing the existing simulation impact on SC ripple effect research in regard to non-engineering SC resilience principles.

3.8 Ripple Effect Visualization

Visualizing the ripple effect is an obvious next step for simulation features. Yet, it has not been very frequently used for modelling the ripple effect in the SC. Given this, simulation models would enhance the existing tools in SC agility and visibility concerning disruption velocity.

3.9 Closed-Loop SCs, Sustainability and Humanitarian Logistics

Resilience has a number of intersections with SC sustainability. Since SCs have become more and more global, these network structures build the backbone of the modern economy and directly influence such sustainability issues as employment rates, natural resource consumption, etc. SC sustainability issues include an assessment of SC design resilience and efficient SC structure reconfiguration in the case of disruptions from the perspectives of environmental, political and society impacts.

Disruptions in the reverse part of closed-loop SCs, as well as disruption-based reverse logistics flows have rarely been analysed. Approaches for analysing the disruptions in the reverse part of the closed-loop SCs (e.g. a temporary unavailability of a warehouse for collecting the used batteries for electric cars) in regard to (i) their impact on overall SC performance as well as to (ii) proactive and reactive policies with consideration of inventory control policies and sustainable manufacturing concepts are yet to be developed. In addition, disruptions in a region frequently result in both humanitarian catastrophe and industrial disruptions at the same time. In this setting, limited resources need to be fairly allocated to both human life rescue and the stabilization of everyday life and recovery of the industrial sector.

3.10 Human Aspects

Finally, yet importantly—the area of human factors needs to be developed in future. Our perception (partially derived from the experiments and literature) is that in a short-term perspective, SC adaptability to the disrupted mode is low and recovery actions are at the beginning of their implementation, which causes high coordination efforts. This means a very stressful time for SC recovery teams. It follows that the better the preparation, the less stressful and the more efficient the recovery work will be.

4 Data-Driven Ripple Effect Control: Towards Supply Chain Risk Analytics

Analysis of current and future research trend in ripple effect allows formulating two important insights which lead the discussion further towards SC risk analytics as shown in Sects. 4.1 and 4.2.

4.1 From Competition Between the Supply Chains to Competition Between the Information Services and Analytics Algorithms

The company is as good as the SC behind it. Today and looking at the near future, the SC will be as good as the digital technology behind it. Consider two examples to support this proposition. The first is the logistics service provider UPS. UPS and SAP developed a joint technology which allows UPS to manufacture items using 3D printing directly at the distribution centres (UPS 2018). The second example is Blockchain technology. Contracts in SCs often involve multi-party agreements, with regulatory and logistic constraints. Further complexities may arise from operations in different jurisdictions, as well as dynamic features embedded in the contracts. The flow of information in an SC plays a critical role in the efficiency of the operations. Regulatory processes (e.g. customs) can be expedited by improving confidence in documentations. This, in turn, will reduce waste, risk and insurance premiums. IBM and Maersk are collaborating to create trust and transparency in global SCs (IBM 2018). They are developing a distributed contract collaboration platform using Blockchain technology. Maersk estimates that shipping a single container of flower from Kenya to Rotterdam requires nearly 200 communications. In their approach, each distinct entity involved in the transaction is allowed to access this system. Shipping from the port of Mombasa requires signatures from three different agencies and six documents: the smart contract will automatically generate after the system receive the signatures. Simultaneously, when the documents about inspection, sealing of refrigerator, pick up by the trucker and approval from customs communicated to the port of Mombasa is uploaded, all the participants can see the data in the meantime, allowing the related entity to prepare for the container.

These and further recent examples of digital technology applications to SCs allow for the new proposition that the competition is not between SCs, but rather between SC *services* and the analytics algorithms behind the SCs based on cyber-physical system approach.

According to Zhuge (2011), the evolution from the cyberspace and systems to the cyber-physical-social space and systems can be described by three extensions. It distinguishes two types of cyberspaces: the first one allows users to read the information in the cyberspace like the web, and the other one allows users to read and write information in the cyberspace. Both rely on humans to add information to the cyberspace in order to share it with others.

The first extension to this basic concept depicts the extension of the cyberspace to the physical space through various sensors. Any significant information in the physical space can be automatically sensed, stored and transmitted through the cyberspace. Internet of Things can be considered as a kind of cyber-physical space.

The second extension is that user behaviours can be sensed and feedback to the cyberspace for analysing the patterns of behaviours, and humans can remotely control the actuators to behave in the physical space through the cyberspace. This enables the cyberspace to adapt his services according to the feedback since behaviour change may indicate some psychological change.

In the third extension, i.e. the cyber-physical system, not only the individual's behaviours, but also social interactions can be feedback into the cyberspace for further processing. Users are considered with their social characteristics and relations rather than as isolated individuals. Sensors are limited in their ability to collect all information in the physical space, so users still need to directly collect the significant information in the physical space and then put them into the cyberspace after analysis (including experiment). Users can also manipulate physical objects in the physical space, which can also be feedback into the cyberspace to reflect the real-time situation]. Users' status, interests and knowledge evolve with social interaction and operations in the cyberspace.

The afore-mentioned analysis can be presented as digital cyber-physical SC framework (Fig. 9).

According to Waller and Fawcett (2013) and KPMG (2017), the application areas of SC analytics can be classified into four areas, i.e.

- Descriptive and diagnostic analysis,
- Predictive simulation and prescriptive optimization,
- Real-time control and
- Adaptive learning.

Examples of SC and operations analytics applications include logistics and SC control with real-time data, inventory control and management using sensing data, dynamic resource allocation in Industry 4.0 customized assembly systems, improving forecasting models using Big Data, machine learning techniques for process

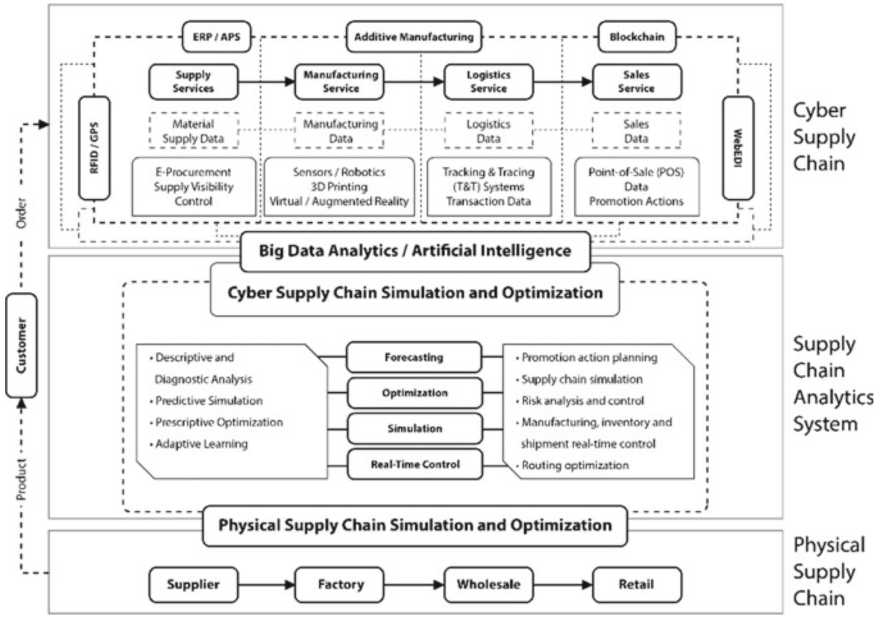

Fig. 9 Service and material flow coordination in the cyber-physical supply chain

control, SC visibility and risk control, optimizing systems based on predictive information (e.g. predictive maintenance), combining optimization and machine learning algorithms and simulation-based modelling and optimization for stochastic systems.

Success in SC competition will become more and more dependent on analytics algorithms in combination with optimization and simulation modelling. Initially intended for process automation, business analytics techniques now disrupt markets and business models and have a significant impact on SCM development. As such, new disruptive SC business models will arise where SCs will be understood not as rigid physical systems with a fixed and static allocation of some processes to some firms. Instead, different physical firms will offer services of supply, manufacturing, logistics and sales which will result in a dynamic allocation of processes and dynamic SC structures. Recent literature documented the possibility of modelling such integrated service-material flow SCs (Ivanov et al. 2014c, Yang et al. 2017).

In new disruptive SC business models SCs will no more be understood as a rigid physical system with a fixed and static allocation of some processes to some firms. Instead, different physical firms will offer services of supply, manufacturing, logistics and sales which will result in dynamic allocation of processes and dynamic SC structures. Indeed, this idea is not really new. We can recall the virtual enterprises concept developed about 15–20 years ago (Camarinha-Matos and Macedo 2010).

The SCs in virtual enterprises were expected to be formed dynamically thru so-called competence cell or agents networking (Teich 2003, Ivanov et al. 2004, Teich and Ivanov 2012, Ivanov and Sokolov 2012a, b). In essence, the suppliers were integrated in a tool that contained their technological processes and the related operational parameters (e.g. costs and lead time). A customer was able to place an order specification and an automatic algorithm was able to find the suppliers needed to be networked to fulfil this customer order. So while the individual contributors (e.g. robots, sensors, RFID—radio-frequency identification, agents, modular factories, etc.) are not really new, they are becoming more practical and companies more receptive to using them to stay competitive.

4.2 Risk Analytics in the Digital SC: Data-Driven Decision Analysis, Modelling, Control and Learning Systems

With the help of optimization and simulation approaches, current research generates new knowledge about the influence of disruption propagation on SC output performance considering disruption location, duration and propagation and recovery policies. New digital technologies create new challenges for the application of quantitative analysis techniques to SC ripple effect analysis and open new ways and problem statements for these applications.

In the past decades, simulation and optimization have played significant roles in solving complex problems. Successful examples include production planning and scheduling, SC design and routing optimization, to name a few. However, many problems remain challenging because of their complexity and large scale, and/or uncertainty and stochastic nature. In addition, the major application of optimization and simulation methods in the last decades was seen in decision support, meaning that decision makers were to manually provide the model input and interpret the model output. On the other hand, the rapid rise of business analytics provides exciting opportunities for Operations Research and the reexamination of these hard optimization problems, as well as newly emerging problems.

The modelling stage is devoted to predictive simulation and prescriptive optimization. Disruption scenario simulation, SC design optimization and recovery optimization belong to major decisions to be supported at this level. Structural dynamics control approach in combination with mathematical optimization can be used. Real-time control area contains supply flow real-time control, disruption identification and real-time performance and recovery control. Feedback control can be applied in this domain with modifications.

It is commonly known that feedback control in socio-organizational differs from technical systems where the feedback can be implemented almost immediately. In socio-organizational systems, the feedback information first needs to be evaluated by managers and the adjustment decisions need to be coordinated among different department in the firms or even cross-organizational. As such, the differences in the system states can be observed between the system state at the moment of starting to prepare the adjustment decisions on the basis of the feedback information and the system state at the moment of decision implementation. In other words, delayed feedbacks occur due to system inertia. The correction (adaptation) decisions need to be implemented at the object or system which is different from the object or system that has been considered for the reconfiguration decision planning.

Finally, the learning stage is comprised of risk mitigation learning, disruption recovery learning and disruption pattern recognition. A combination of control algorithms and artificial intelligence can provide a number of new insights in the given area.

Consider some practical examples. Sourcing, manufacturing, logistics and sales data are distributed among very different systems, such as ERP, RFID, sensors and Blockchain. Big data analytics integrates this data to information used by AI algorithms in the cyber SC and managers in the physical SC. As such, a new generation of simulation and optimization models is arising. The pervasive adoption of analytics and its integration with Operations Research shows that simulation and optimization are key, not only in the modelling of physical SC systems, but also in the modelling of cyber SC systems and learning from them.

PwC is working with a large car company looking to introduce autonomous vehicles for the public (Wilkinson 2018). Part of this work employs deep reinforcement learning to develop rules. Together with simulation, deep reinforcement learning is used to determine "optimal" decision rules that allow the vehicles to maximize efficiency while also satisfying customer trip demand. The software environment for the project uses the extensible and practical environment of AnyLogic multimethod simulation software to lever the capabilities of DL4 J for the deep learning environment. Autonomous cars are becoming more common and the features are already in many consumer cars. These examples show that artificial intelligence becomes more pervasive in the real world with every project, and necessarily it must be part of the simulation.

With regards to SC risks, Resilience360 at DHL allows comprehensive disruption risk management by mapping end-to-end SC, building risk profiles and identifying critical hotspots in order to initiate mitigation activities and alert in near-real-time mode on incidents that could disrupt the SC (DHL 2018). RiskMethods GmbH developed a software for proactive SC risk management that contains modules "Risk radar", "Impact analyzer" and "Action planner" for risk monitoring, impact assessment and planning of the mitigation actions (RM 2018).

As such, a new generation of simulation and optimization models can be observed that extends the decision-support systems (DSS) towards decision analysis, modelling, control and learning systems (DAMCLS). A DAMCLS example for ripple effect control in the SC that combines a simulation, optimization and data analytics is shown in Fig. 10.

The DAMCLS system for SC risk analytics aims at proactive, resilient SC design in anticipation of disruptions and structural–parametrical adaptation in the case of disruptions. The decision-support system is based on a concept that combines simulation, optimization and data analytics. The simulation–optimization part of the system is intended to provide proactive, resilient SC optimization and simulation of SC dynamic behaviour in the event of possible disruptions or disruption scenarios. In addition, this supports reactive, predictive simulation of disruption impacts on SC

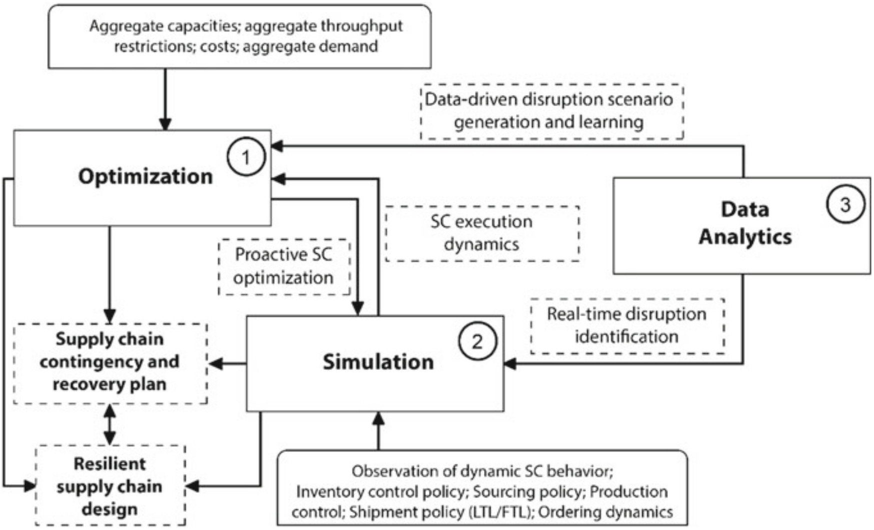

Fig. 10 Concept of a decision-support system for supply chain risk analytics

performance and of recovery policies which are subsequently optimized in a prescriptive manner using an analytical model. The data analytics part of the system is applied to disruption identification in real time using process feedback data, e.g. from sensors and RFID. In addition, this aims at automated data input of disruption data into the reactive simulation model for recovery policy simulation and optimization. Finally, data analytics is used as data-driven learning system at the proactive stage, helping to generate adequate disruption scenarios for resilient SC design and planning.

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A Multi-portfolio Approach to Integrated Risk-Averse Planning in Supply Chains Under Disruption Risks

Tadeusz Sawik

Abstract This chapter presents a multi-portfolio approach for the time and space integrated decision-making in a supply chain under disruption risks. In the context of supply chain disruptions, the portfolio is defined as the allocation of demand for parts among suppliers or the allocation of demand for products among production facilities. A disruptive event is assumed to impact both primary suppliers of parts and the firm primary assembly plant. Then, the firm selects recovery suppliers, recovery plants along with transshipment of parts from disabled primary plant to recovery plants and production and inventory planning in recovery plants. The mitigation and recovery decisions are integrated over time and space: the primary portfolios to be implemented before a disruptive event are optimized simultaneously with recovery portfolios for the aftermath period as well as the portfolios for both part suppliers and product manufacturers in different geographic regions are determined simultaneously. Using conditional cost at risk and conditional service at risk as risk measures, the risk-averse solutions are obtained. The solution results are compared for different demand patterns. The findings indicate that when the objective is to optimize service level with no regard to costs, both supply and demand portfolios are more diversified. The findings also demonstrate that the developed multi-portfolio approach leads to computationally efficient stochastic MIP models with a very strong LP relaxation. The proposed multi-portfolio approach that allows for the time and space integrated decision-making may help to better mitigate the impact of disruption propagation on supply chain performance, i.e., the ripple effect.

T. Sawik (✉)
Department of Operations Research, AGH University of Science & Technology, 30-059 Kraków, Poland
e-mail: ghsawik@cyf-kr.edu.pl

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1 Introduction

In global supply chains, material flows are more often being subject to unexpected disruptions and the resulting losses due to the shortage of material supplies may threaten the financial state of firms. For example, the disruptive events in the automotive and electronics supply chains that occurred in 2011 (the Great East Japan earthquake and tsunami in March and Thailand's floods in October) resulted in huge losses in automotive and high-tech industry, e.g., Marszewska (2016), Matsuo (2015), Park et al. (2013). In order to reduce potential losses, different disruption management strategies are applied in practice. Whenever a primary supplier is hit by a disruption, recovery of disrupted primary supplier can be supported by the firm (e.g., the case of Toyota helping supplier of automotive semiconductors, Renesas Electronics after the earthquake in 2011, Matsuo 2015, and after the Kumamoto earthquake in 2016, Marszewska 2016) or the firm selects an alternate (recovery) supplier, non-disrupted or disrupted less severely than the primary supplier. Similarly, when a disruptive event hits the firm primary production facility, then, a reasonable disruption management strategy would be to move production to alternate production facilities of the firm.

Supply chain disruptions rarely occur as isolated events. Therefore, they must be contained before they propagate through the supply chain and create greater losses, see Blackhurst et al. (2011). Supply chain disruption propagation in Scheibe and Blackhurst (2018) was defined as the spread of the disruption effects beyond the initial disruption location. In the literature, supply chain disruption propagation is also known as domino effect, snowball effect, and more recently as the ripple effect, e.g., Basole and Bellamy (2014), Dolgui et al. (2018), Ivanov (2018), Ivanov et al. (2014a, b), Liberatore et al. (2012). The ripple effect depends on the supply chain resilience (Ivanov 2018): multiple sourcing, prepositioning of emergency inventory, suppliers and plants fortification, production, and logistics flexibility are typical factors that might help to mitigate the impact of the ripple effect. In order to contain disruptions and prevent them from spreading through the supply chain, the decision-making on disruption management should be better coordinated and both proactive and reactive decisions integrated over time and space.

This chapter presents a multi-portfolio approach for the time and space integrated decision-making in a supply chain under disruption risks to better mitigate the impact of disruption propagation on supply chain performance, i.e., the ripple effect. In the context of supply chain disruptions, the portfolio is defined as the allocation of demand for parts among suppliers or the allocation of demand for products among production facilities. A disruptive event is assumed to impact both primary suppliers of parts and the firm primary assembly plant. Then the firm selects recovery suppliers, recovery plants along with transshipment of parts from the disabled primary plant to recovery plants and production and inventory planning in recovery plants. The proactive and reactive decisions are integrated over time and space: the primary portfolios to be implemented before a disruptive event is optimized simultaneously with recovery portfolios for the aftermath period as well as the portfolios for both part suppliers and product manufacturers in different geographic regions are determined simultaneously. The portfolio approach to supply chain disruption management, first proposed for the selection of primary suppliers to mitigate the impact of disruption risks, Sawik (2011b, 2013a), was next enhanced for the selection of primary and recovery suppliers, Sawik (2017), and recently (Sawik 2018a, c, 2019) also for the selection of recovery assembly plants. In addition, dynamic supply portfolio approach was proposed in Sawik (2011c, 2018b) to simultaneously mitigate the impact of the low probability and high impact supply disruptions and the high probability and low impact supply delays.

The chapter is organized as follows. The review of relevant literature is presented in Sect. 2. The problem of selecting primary and recovery suppliers and assembly plants subject to partial disruptions is briefly described in Sect. 3. Stochastic mixed-integer programs for the integrated risk-averse supply, production, and inventory planning in a supply chain under disruption risks are developed in Sect. 4. Numerical examples are provided in Sect. 5 and final conclusions and directions for further research are presented in Sect. 6.

2 Literature Review

The supply chain disruption management utilizes various quantitative methods to optimize disruption mitigation and recovery strategies. Typical methods include scenario-based stochastic programming, mixed- integer programming, fuzzy set theory, game theory, control theory, simulation, genetic algorithms, etc. Reviews of literature on supply chain disruptions and recovery were presented in Snyder et al. (2016), where scholarly works were discussed and organized into six categories: evaluating supply disruptions; strategic decisions; sourcing decisions; contracts and incentives; inventory; and facility location. A systematic literature review and a comprehensive analysis of the decision-making models for supply chain risk was presented in Rajagopal et al. (2017). Stochastic programming and mixed-integer linear programming was found to be the commonly studied modeling methods. The literature on disruption recovery in supply chains was recently reviewed in Ivanov et al. (2017). The paper structured and classified existing research streams and application areas of different quantitative methods subject to different disruption risks and recovery measures.

Typical relevant works are briefly reviewed below. An interesting model for severe disruptions was proposed in MacKenzie et al. (2014) and applied to a simulation based on the Great East Japan earthquake and tsunami in 2011. In the model a disruption simultaneously impacts several suppliers. The model incorporated decisions made by both suppliers and firms during the disruption of random duration. The decisions may include whether or not suppliers move production to an alternate facility, hold parts inventory; a firm purchases parts from alternate suppliers that are not impacted, helps a primary supplier recover more quickly or holds finished products inventory.

In Meena et al. (2014), the problem of determining the number of suppliers under risks of supplier failure due to catastrophic events was studied. A simple heuristic algorithm was proposed to determine the number of suppliers to minimize total costs subject to a target service level and to maximize the service level subject to a total costs constraint.

In Namdar et al. (2018), a scenario-based stochastic mixed-integer programming model was developed for single and multiple sourcing in the presence of disruption and operational risks. To achieve supply chain resilience under disruptions, backup supplier contracts, spot purchasing, and collaboration and visibility were considered.

In Ruiz-Torres et al. (2013), the optimal supply allocation and contingency planning in supply networks made up of multiple suppliers with different cost and reliability characteristics, and a set of separate demand points was considered. Suppliers have production flexibility that allows them to deliver a contingency quantity in case other suppliers fail. The problem objective was to minimize the total network costs and was formulated as a mixed-integer program.

A bi-objective mixed possibilistic, two-stage stochastic programming model was developed in Torabi et al. (2015) to address supplier selection and order allocation problem to build the resilient supply base under operational and disruption risks. To enhance the resilience level, the model applies several proactive strategies, suppliers' business continuity plans, fortification of suppliers, and contracting with backup suppliers.

In Yoon et al. (2018), a bi-objective stochastic mixed-integer programming model that integrates supplier selection and risk mitigation strategy selection was proposed. The authors suggested that a combination of upstream and downstream risk mitigation strategies should be jointly considered with supplier selection rather than considering these decisions separately. A similar integrated approach was also proposed in Sawik (2013b, 2014, 2015, 2016).

Most approaches, including the abovementioned, used in supply chain disruption management assume that some estimation of disruptive events probability and potential losses are available. At the same time, a fair probability estimation of rare events is a complicated problem and even small errors in those estimations may significantly impact the modeling results. In Simchi-Levi et al. (2015), a novel risk-exposure model was proposed for analyzing operational-disruption risk with no need to estimate the probability of any specific disruptive events. The model is capable of assessing the impact of a disruption originating anywhere in a supply chain and has been applied by Ford Motor Company to identify risk exposures, evaluate risk mitigation actions, and develop optimal contingency plans.

3 Selection of Supply and Demand Portfolios

In this section the problem of integrated selection of primary and recovery supply, demand, and transshipment portfolios under disruption risks are presented.

Table 1 Notation

Indices
i = supplier, $i \in I$
j = assembly plant, $j \in J$
k = region, $k \in K$
l = disruption level, $l \in L_i, i \in I, l \in L^j, j \in J$
s = disruption scenario, $s \in S$
t = planning period, $t \in T$
Input Parameters
ξ = per unit product inventory holding cost
ζ = per unit and per period penalty cost of delayed demand for products
η = per unit penalty cost of unfulfilled demand for products
c_j = per period capacity of non-disrupted plant j
c^s_{jt} = capacity in period t of plant j under disruption scenario s
d_t = demand for products in period t
e_i = per unit price of parts purchased from supplier i
f_i = fixed ordering cost for supplier i
ε_j = additional per unit production cost at recovery plant $j > 1$
φ_j = fixed production setup cost at recovery plant $j > 1$
g_j = per unit transshipment cost from primary plant $j = 1$ to plant $j > 1$
p_{il} = probability of disruption level l for supplier i
π_{jl} = probability of disruption level l for plant j
p^k = regional disruption probability for region k
t_s = start time period of disruption event s
γ_{il} = fraction of an order delivered by supplier i under disruption level l
γ^s_i = fraction of an order delivered by supplier i under scenario s
δ_{jl} = fraction of capacity of plant j available under disruption level l
δ^s_j = fraction of capacity of plant j available under scenario s
τ_{ij} = delivery lead time from supplier i to plant j
σ_j = transshipment time from primary plant $j = 1$ to plant $j > 1$
θ_{is} = time to recover of supplier i from disruption under scenario s
ϑ_{js} = time to recover of plant j from disruption under scenario s
ρ_{is} = cost to recover of supplier i from disruption under scenario s
ϱ_{js} = cost to recover of plant j from disruption under scenario s

Consider a supply chain in which a single producer assembles one product type in several assembly plants to meet customer demand, using a critical part type that can be manufactured and provided by several suppliers. (for notation used, see Table 1).

Let $I = \{1, \ldots, m\}$ be the set of m suppliers, $J = \{1, \ldots, n\}$, the set of n assembly plants, and $T = \{1, \ldots, h\}$, the set of h planning periods.

If we denote by d_t the demand for product in period t, then $D_t = \sum_{t' \in T: t' \le t} d_{t'}$ is the cumulative demand for products by period t and $D = \sum_{t \in T} d_t$ is the total demand for the entire planning horizon. If we assume that one part is required to produce one product, then demand for parts is identical with demand for products.

Let $j = 1$ be the primary plant, where the total demand for products, D, is initially assigned.

The suppliers of parts and assembly plants are located in different geographic regions, subject to potential regional disasters that may result in complete shutdown of all suppliers and plants in the same region simultaneously. Denote by I^k and J^k, respectively the subsets of suppliers and plants in region $k \in K$, and by p^k, the regional disruption probability for region k.

In addition, each supplier $i \in I$ is subject to random local disruptions of different levels, $l \in L_i = \{0, \ldots, \overline{L}_i\}$, where disruption level refers to the fraction of an order that can be delivered, e.g., Sawik (2015). Level $l = 0$ represents complete shutdown of a supplier, i.e., no order delivery, while level $l = \overline{L}_i$ represents normal conditions with no disruption, i.e., full order delivery. Denote by p_{il}, the probability of disruption level l for supplier i, and by γ_{il}, the fraction of an order that can be delivered by supplier i under disruption level l (fulfillment rate)

$$\gamma_{il} = \begin{cases} 0 & \text{if } \ l = 0 \\ \in (0, 1) & \text{if } \ l = 1, \ldots, \overline{L}_i - 1 \\ 1 & \text{if } \ l = \overline{L}_i. \end{cases} \tag{1}$$

Similarly to suppliers, each plant $j \in J$ is subject to random local disruptions of different levels, $l \in L^j = \{0, \ldots, \overline{L}^j\}$, where disruption level refers to available fraction of full capacity, c_j, available per period under normal conditions. Level $l = 0$ represents complete shutdown of an assembly plant, while level $l = \overline{L}^j$ represents normal conditions, i.e., full capacity, c_j, available. Denote by π_{jl}, the probability of disruption level l for plant j, and by δ_{jl}, the fraction of available capacity of plant j under disruption level l.

$$\delta_{jl} = \begin{cases} 0 & \text{if } \ l = 0 \\ \in (0, 1) & \text{if } \ l = 1, \ldots, \overline{L}^j - 1 \\ 1 & \text{if } \ l = \overline{L}^j. \end{cases} \tag{2}$$

The total number of all potential scenarios is $\prod_{i \in I}(\overline{L}_i + 1) \prod_{j \in J}(\overline{L}^j + 1)$. Each scenario $s \in S$ is represented by an $(m + n)$- dimensional vector $\lambda_s = \{\lambda_{1s}, \ldots, \lambda_{ms}, \lambda_{m+1,s}, \ldots, \lambda_{m+n,s}\}$, where $\lambda_{is} \in L_i$ is the disruption level of supplier $i \in I$ and $\lambda_{m+j,s} \in L^j$ is the disruption level of plant $j \in J$, under scenario $s \in S$. Disruption s is assumed to occur in period t_s, and the corresponding suppliers $i \in I$ (such that $\lambda_{is} < \overline{L}_i$) and plants $j \in J$ (such that $\lambda_{m+j,s} < \overline{L}^j$) are assumed to be simultaneously hit by the disruption.

The probability P_s of disruption scenario $s \in S$ is $P_s = \prod_{k \in K} P_s^k$, where P_s^k is the probability of realizing disruption scenario s in region k (see Sawik 2015)

$$P_s^k = \begin{cases} (1-p^k)(\prod_{i \in I^k} \prod_{l \in L_i : \lambda_{is}=l} p_{il})(\prod_{j \in J^k} \prod_{l \in L^j : \lambda_{m+j,s}=l} \pi_{jl}), \\ \text{if } \sum_{i \in I^k} \lambda_{is} + \sum_{j \in J^k} \lambda_{m+j,s} > 0 \\ p^k + (1-p^k)(\prod_{i \in I^k} p_{i0})(\prod_{j \in J^k} \pi_{j0}), \\ \text{if } \sum_{i \in I^k} \lambda_{is} + \sum_{j \in J^k} \lambda_{m+j,s} = 0. \end{cases} \tag{3}$$

When supplier i is hit by disruption at level l, its recovery process to normal conditions takes $TTR(i,l)$ time periods (time to recover) and let $CTR(i,l)$ be the firm's portion of cost to recover. For each supplier i, denote by θ_{is} and ρ_{is}, respectively, time to recover and firm's portion of cost to recover from disruption under scenario s

$$\theta_{is} = TTR(i,l);\ i \in I, s \in S : l = \lambda_{is} \tag{4}$$

$$\rho_{is} = CTR(i,l);\ i \in I, s \in S : l = \lambda_{is}. \tag{5}$$

Similarly, when plant j is hit by disruption at level l, its recovery process to normal conditions takes $PRT(j,l)$ time periods (plant recovery time) and cost $PRC(j,l)$ (plant recovery cost). For each plant j, denote by ϑ_{js} and ρ_{js}, respectively time to recover and cost to recover from disruption under scenario s

$$\vartheta_{js} = PRT(j,l);\ j \in J, s \in S : l = \lambda_{m+j,s} \tag{6}$$

$$\varrho_{js} = PRC(j,l);\ j \in J, s \in S : l = \lambda_{m+j,s}. \tag{7}$$

The orders for parts are assumed to be placed at the beginning of the planning horizon, and under normal conditions the parts ordered from supplier i are delivered to assembly plant j in period τ_{ij}, where τ_{ij} is the total of manufacturing lead time and transportation time. Denote by σ_j transshipment time from the primary plant $j=1$ to recovery plant j.

The firm who moves production to an alternate assembly plant j incurs a fixed cost φ_j and encounters additional per unit cost of production ε_j, and per unit cost, g_j, of transshipment of parts from the primary plant, where $\varphi_1 = 0$, $\varepsilon_1 = 0$ and $g_1 = 0$. A recovery plant can be a disrupted primary plant $j=1$ with reduced capacity during recovery process and then with its full capacity or a new plant, non-disrupted or disrupted less severely than the primary plant.

The following assumptions are made to formulate the problem.

- Each supplier has sufficient capacity to meet total demand for parts.
- One unit of a critical part is needed to assemble one unit of product.
- If supplier $i \in I$ (assembly plant $j \in J$) is hit by disruption s in period t_s, its recovery process starts in period $t_s + 1$, so that the disrupted supplier (disrupted plant) returns to its full capacity in period $t = t_s + \theta_{is}$ $(t = t_s + \vartheta_{js})$.
- A single disruption scenario is assumed to realize over the entire planning horizon. Multiple disruptions, one after the other in a series, during the recovery process are not considered.

- Period-dependent demand for products is considered that should be satisfied during the planning horizon using buildup inventory of products and a penalty cost is charged for demand fulfilled with delay and not fulfilled at all.
- A recovery supplier can be a disrupted primary supplier after its recovery to full capacity or a new supplier.
- A recovery assembly plant can be a disrupted primary assembly plant during and after its recovery to full capacity or a new assembly plant.

4 Risk-Averse Decision-Making

In this section, two stochastic MIP models **Support_CV(c)** and **Support_CV(sl)** are proposed for integrated, risk-averse selection of primary and recovery supply portfolios, recovery demand and transshipment portfolios, and production and inventory planning. The objective is to reduce the risk of worst-case cost by minimizing conditional cost at risk, CVaR^c, and reduce the risk of worst-case service level by maximizing conditional service at risk, CVaR^{sl}, respectively. Problems **Support_CV(c)** and **Support_CV(sl)** are stochastic multi-portfolio selection problems in which primary and recovery supply, demand and transshipment portfolios are simultaneously selected for all potential disruption scenarios (for definitions of first- and second-stage variables, see Table 2). The portfolios are defined below.

The primary supply portfolio

$$(v_1, \dots, v_m),$$

specifies supplies of parts from the primary suppliers to primary assembly plant $j = 1$, where

$$v_i \in [0, 1]; i \in I, \ \sum_{i \in I} v_i = 1.$$

The recovery supply portfolio for scenario s

$$(V^s_{1j}, \dots, V^s_{mj}); \quad j \in J,$$

specifies supplies of parts from recovery suppliers to recovery assembly plants, where

$$V^s_{ij} \in [0, 1]; i \in I, j \in J, \ \sum_{i \in I}(\gamma^s_i v_i + \sum_{j \in J} V^s_{ij}) = 1,$$

$\sum_{i \in I} \gamma^s_i v_i$ denotes delivery of parts from the primary suppliers to primary plant.

The recovery transshipment portfolio for scenario s

$$(w^s_1, \dots, w^s_n),$$

Table 2 Two-stage problem variables

First-Stage Variables
$u_i \in \{0, 1\}$, such that the value 1 means that supplier i is selected as a primary supplier; otherwise $u_i = 0$ (primary supplier selection)
$v_i \in [0, 1]$, fraction of total demand for parts, ordered from the primary supplier i, to be delivered to primary plant $j = 1$ (primary supply portfolio)
Second-Stage Variables
$q_j^s \in \{0, 1\}$, such that the value 1 means that assembly plant j is selected as a recovery plant under disruption scenario s; otherwise $q_j^s = 0$ (recovery plant selection)
$r_j^s \in [0, 1]$, fraction of total demand for products to be completed by recovery plant j under disruption scenario s (recovery demand portfolio)
$U_i^s \in \{0, 1\}$, such that the value 1 means that supplier i is selected as a recovery supplier under disruption scenario s; otherwise $U_i^s = 0$ (recovery supplier selection)
$V_{ij}^s \in [0, 1]$, fraction of total demand for parts, ordered from recovery supplier i to recovery plant j, under disruption scenario s (recovery supply portfolio)
$w_j^s \in [0, 1]$, fraction of total demand for parts, transshipped from the primary plant $j = 1$ to recovery plant, j, under scenario s, where w_1^s represents parts that remain in the primary plant $j = 1$ (recovery transshipment portfolio)
$x_{jt}^s \geq 0$, production in plant j in period t under disruption scenario s (production planning)
$y_t^s \geq 0$, inventory of products at the beginning of period t under disruption scenario s (inventory planning)
$z_t^s \geq 0$, shortage of products at the beginning of period t under disruption scenario s (inventory planning)
Auxiliary Variable
$a_t^s \in \{0, 1\}$, such that value 1 means that there exists inventory of products at the beginning of period t under disruption scenario s
$b_t^s \in \{0, 1\}$, such that value 1 means that there exists shortage of products at the beginning of period t under disruption scenario s
$\mu_i^s \in \{0, 1\}$, such that the value 1 means that $u_i = U_i^s = 1$; otherwise $\mu_i^s = 0$ (elimination of double fixed ordering costs)

specifies transshipment of parts from the primary assembly plant to recovery plants, where

$$w_j^s \in [0, 1];\ j \in J,\ \ \sum_{j\in J} w_j^s = \sum_{i\in I} \gamma_i^s v_i - \sum_{t\in T: t<t_s} x_{1t}^s / D,$$

and $\sum_{t\in T:t<t_s} x_{1t}^s$ denotes production at primary assembly plant $j = 1$, before disruption.

The recovery demand portfolio for scenario s

$$(r_1^s, \dots, r_n^s),$$

specifies an allocation of unfulfilled demand for products among recovery plants, where

$$r_j^s \in [0, 1];\ j \in J, \quad \sum_{t \in T: t < t_s} x_{1t}^s / D + \sum_{j \in J} r_j^s = 1.$$

Models **Support_CV(c)** and **Support_CV(sl)** presented below are deterministic equivalent mixed-integer programs of the two-stage stochastic mixed-integer programs with recourse (e.g., Birge and Louveaux 2011). The primary supply portfolio selection variables, u_i, v_i, are referred to as first-stage decisions, and the scenario-dependent recovery supply, demand and transshipment portfolio selection variables, U_i^s, V_{ij}^s, q_j^s, r_j^s and w_j^s, and production and inventory planning variables, x_{jt}^s, y_t^s, z_t^s, a_t^s, b_t^s, are referred to as recourse or second-stage decisions (cf. Table 2).

Support_CV(c): *Selection of* **Sup***ply, transshipment and demand* **port***folios with production and inventory planning to minimize* **CV***aR of* **c***ost*

Minimize

$$CVaR^c = VaR^c + (1-\alpha)^{-1} \sum_{s \in S} P_s \mathscr{C}_s \tag{8}$$

subject to

Primary supply portfolio selection constraints

$$\sum_{i \in I} v_i = 1 \tag{9}$$

$$v_i \le u_i;\ i \in I \tag{10}$$

Recovery supply and demand portfolio selection constraints

$$V_{ij}^s \le U_i^s;\ i \in I, j \in J, s \in S \tag{11}$$

$$V_{ij}^s \le q_j^s;\ i \in I, j \in J, s \in S \tag{12}$$

$$r_j^s \le q_j^s;\ j \in J, s \in S \tag{13}$$

$$w_j^s \le q_j^s;\ j \in J, s \in S \tag{14}$$

$$\sum_{i \in I} (\gamma_i^s v_i + \sum_{j \in J} V_{ij}^s) = 1;\ s \in S \tag{15}$$

$$\sum_{t \in T: t < t_s} x_{1t}^s / D + \sum_{j \in J} r_j^s = 1;\ s \in S \tag{16}$$

$$\sum_{i \in I} V_{ij}^s + w_j^s = r_j^s;\ j \in J, s \in S \tag{17}$$

$$\sum_{j \in J} w_j^s = \sum_{i \in I} \gamma_i^s v_i - \sum_{t \in T: t < t_s} x_{1t}^s / D;\ s \in S \tag{18}$$

$$\mu_i^s \le (u_i + U_i^s)/2;\ \ i \in I, s \in S. \tag{19}$$

Production capacity constraints

$$x_{1t}^s \le c_1;\ \ t \in T, s \in S : t < t_s \tag{20}$$

$$x_{jt}^s \le c_{jt}^s q_j^s;\ \ j \in J, t \in T, s \in S : t \ge t_s \tag{21}$$

$$\sum_{t \in T: t \ge t_s} x_{jt}^s / D \le r_j^s;\ \ j \in J, s \in S. \tag{22}$$

Supply-transsshipment production coordinating constraints

$$\sum_{t' \in T: t' \le t} x_{1t'}^s \le \sum_{i \in I: \tau_{i1} \le t-1} \gamma_i^s v_i + \sum_{i \in I: t_s + \theta_{is} + \tau_{i1} \le t-1} V_{i1}^s - (\text{if } t \le \bar{t}_s \text{ then } 0 \text{ else } \sum_{j \in J: j > 1} w_j^s);\quad t \in T, s \in S \tag{23}$$

$$\sum_{t' \in T: t' \le t} x_{jt'}^s \le \sum_{i \in I: t_s + \theta_{is} + \tau_{ij} \le t-1} V_{ij}^s + (\text{if } t \le \bar{t}_s + \sigma_j \text{ then } 0 \text{ else } w_j^s);\quad j \in J, t \in T, s \in S : j > 1, \tag{24}$$

where $\bar{t}_s = \max\{t_s, \max_{i \in I} \tau_{i1}\}$ and, $\bar{t}_s + 1$, is the start period of transshipment of parts to recovery plants.

Product inventory constraints

$$y_{t+1}^s - z_{t+1}^s = \sum_{j \in J} \sum_{t' \in T: t' \le t} x_{jt'}^s - D_t;\ \ t \in T, s \in S \tag{25}$$

$$y_{t+1}^s \ge \sum_{j \in J} \sum_{t' \in T: t' \le t} x_{jt'}^s - D_t;\ \ t \in T, s \in S \tag{26}$$

$$z_{t+1}^s \ge D_t - \sum_{j \in J} \sum_{t' \in T: t' \le t} x_{jt'}^s;\ \ t \in T, s \in S \tag{27}$$

$$a_t^s + b_t^s \le 1;\ \ t \in T, s \in S \tag{28}$$

$$y_t^s / D \le a_t^s;\ \ t \in T, s \in S \tag{29}$$

$$z_t^s / D \le b_t^s;\ \ t \in T, s \in S \tag{30}$$

$$y_{h+1}^s = 0;\ \ s \in S. \tag{31}$$

Risk constraints:

- the tail cost for scenario s, $\mathscr{C}_s$, is defined as the nonnegative amount by which cost in scenario s exceeds VaR^c,

$$\mathscr{C}_s \geq \sum_{i \in I}(f_i(u_i + U_i^s - \mu_i^s) + \rho_{is}U_i^s + e_i(\gamma_i^s v_i + \sum_{j \in J} V_{ij}^s))/D$$
$$+ \sum_{j \in J}(g_j w_j^s + (\varphi_j + \varrho_{js})q_j^s + \sum_{t \in T} \varepsilon_j x_{jt}^s)/D$$
$$+ \sum_{t \in T}(\xi y_t^s + \zeta z_t^s)/D + \eta z_{h+1}^s/D - VaR^c;\ s \in S \qquad (32)$$

Non-negativity and integrality conditions

$$\mathscr{C}_s \geq 0;\ s \in S \qquad (33)$$
$$a_t^s \in \{0, 1\};\ t \in T, s \in S \qquad (34)$$
$$b_t^s \in \{0, 1\};\ t \in T, s \in S \qquad (35)$$
$$q_j^s \in \{0, 1\};\ j \in J, s \in S \qquad (36)$$
$$r_j^s \in [0, 1];\ j \in J, s \in S \qquad (37)$$
$$u_i \in \{0, 1\};\ i \in I \qquad (38)$$
$$v_i \in [0, 1];\ i \in I \qquad (39)$$
$$U_i^s \in \{0, 1\};\ i \in I, s \in S \qquad (40)$$
$$V_{ij}^s \in [0, 1];\ i \in I, j \in J, s \in S \qquad (41)$$
$$w_j^s \in [0, 1];\ j \in J, s \in S \qquad (42)$$
$$x_{jt}^s \geq 0;\ j \in J, t \in T, s \in S \qquad (43)$$
$$y_t^s \geq 0;\ t \in T, s \in S \qquad (44)$$
$$z_t^s \geq 0;\ t \in T, s \in S \qquad (45)$$
$$\mu_i^s \in \{0, 1\};\ i \in I, s \in S, \qquad (46)$$

where

$$c_{jt}^s = \begin{cases} \delta_j^s c_j, & \text{if } t_s \leq t \leq t_s + \vartheta_{js} - 1 \\ c_j, & \text{if } t \leq t_s - 1, t \geq t_s + \vartheta_{js}. \end{cases} \qquad (47)$$

$\delta_j^s = \delta_{j,\lambda_{m+j,s}}$, and $\lambda_{m+j,s}$ is disruption level of plant j under scenario s.

Equation (9) is the primary supply portfolio selection constraint and Eq. (10) ensures that demand for parts cannot be assigned to nonselected primary suppliers. Equations (11) and (12) ensure that the unfulfilled demand for parts cannot be assigned to nonselected recovery suppliers and cannot be ordered for nonselected recovery plants, respectively. Equation (13) ensures that the unfulfilled demand for products cannot be assigned to nonselected recovery plants, and Eq. (14) ensures that parts from the primary plant cannot be transshipped to nonselected recovery plants. Equations (15) and (16) are the recovery supply portfolio and the recovery demand portfolio selection constraints, respectively. The supply and demand portfolio flow conservation constraints (17) ensure that for each recovery plant, the recovery supplies and transshipment of parts are in balance with the demand for products to be fulfilled by that plant. The balance constraints for parts, (18), ensure that the total transshipments of parts from the primary supplier are equal to the partially fulfilled supplies from the primary suppliers less the usage of parts for production before disruption. Equation (19) ensures that each supplier selected to both primary and recovery portfolio is charged exactly once with fixed ordering cost in the objective function. Equations (20) and (21) ensure that before a disruptive event, the production at primary plant in every period cannot exceed its capacity, and after a disruptive event, the production at each selected recovery plant in every period cannot exceed the plant available capacity, respectively. Equation (22) guarantees that the total production at each recovery plant cannot exceed the assigned portion of total demand for products.

The supply-transshipment-production coordinating constraints (23)–(24) ensure that

In primary assembly plant, the cumulative demand for parts cannot exceed the cumulative deliveries from the primary and recovery suppliers, less transshipment of parts to recovery plants, if $t > \bar{t}_s$, Eq. (23),

In recovery assembly plants, the cumulative demand for parts cannot exceed the cumulative deliveries from recovery suppliers, plus transshipment of parts from the primary plant, if $t > \bar{t}_s + \sigma_j$, Eq. (24).

The product inventory constraints (25)–(27) ensure that inventory or shortage of products in period $t + 1$ are, respectively, positive or negative difference between cumulative production and demand by period t. Equations (28)–(30) indicate that in each period, there is either inventory or shortage or production and demand are in balance. Finally, Eq. (31) ensures that no inventory of products remains at the end of the planning horizon.

The cost per product (see (32)), consists of different fixed and variable cost per product. The fixed cost includes the cost of ordering parts from the primary and recovery suppliers, cost of recovery processes of suppliers and plants, and cost of moving production from the primary to recovery plants, The variable cost includes the cost of purchasing parts from the primary and recovery suppliers, cost of transshipment of parts, cost of additional production cost in recovery plants, cost of holding inventory of products, cost of penalty for demand fulfilled with delay, and cost of penalty for unfulfilled demand.

Notice that the supply and demand portfolio selection constraints form an embedded network flow problem, (see Fig. 1). In particular, Eqs. (17) and (18) are flow conservation constraints under scenario s for each node j (assembly plant) and node $j = 1$ (primary assembly plant), respectively. $\gamma_i^s v_i$ represents flow of parts from supplier i (source node) to primary plant $j = 1$ (sink/transshipment node), V_{ij}^s represents flow of parts from recovery supplier i (source node) to recovery plant j (sink node) and w_j^s represents flow of parts from the primary plant $j = 1$ (transshipment node) to recovery plant j (sink node). Finally, r_j^s represents outflow of products from recovery plant j.

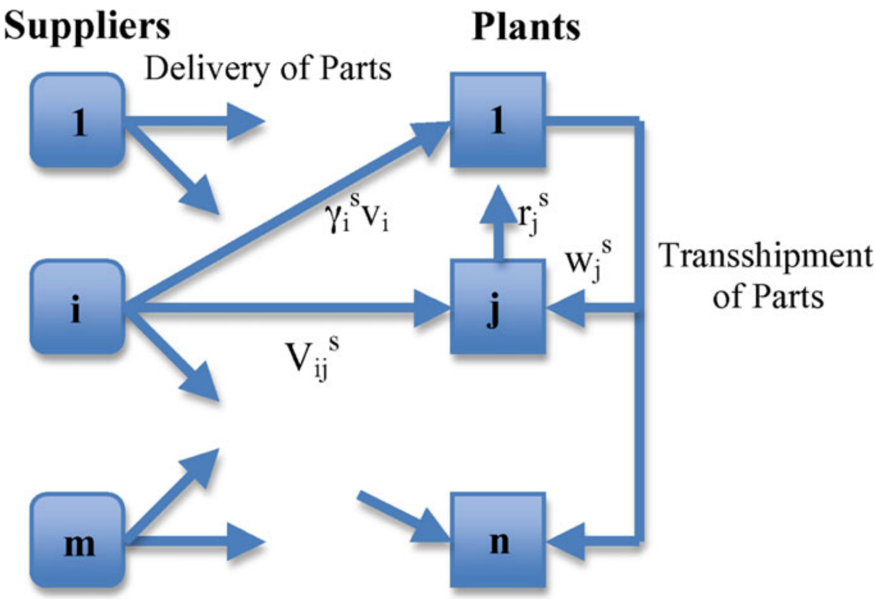

Fig. 1 Primary ($\gamma_i^s v_i$) and recovery (V_{ij}^s, w_j^s) flow of parts, and products (r_j^s)

Support_CV(sl): *Selection of* **Sup***ply, transshipment and demand* **port***folios with production and inventory planning to maximize* **CV***aR of* **s***ervice* **l***evel*

Maximize

$$CVaR^{sl} = VaR^{sl} - (1-\alpha)^{-1} \sum_{s \in S} P_s \mathscr{S}_s \tag{48}$$

subject to (9)–(31), (34)–(47) and

Risk constraints:

- the tail service level for scenario s, $\mathscr{S}_s$, is defined as the nonnegative amount by which VaR^{sl} exceeds service level in scenario s,

$$\mathscr{S}_s \geq VaR^{sl} + z^s_{max}/D - 1; \;\; s \in S \tag{49}$$

$$\mathscr{S}_s \geq 0; \;\; s \in S, \tag{50}$$

where, $z^s_{max} = \max_{t \in T} z^s_t$, is the maximum shortage of products under disruption scenario s.

In the proposed models, CVaR is represented by auxiliary functions (8) and (48), where $\alpha \in (0, 1)$ is the confidence level, VaR$^{(c)}$ (VaR^{sl}) is the targeted cost (targeted service level) such that for a given confidence level α, for $100\alpha\%$ of the scenarios, the outcome is below VaR$^{(c)}$ (above VaR^{sl}).

In the risk-averse decision-making, the confidence level α is fixed by the decision maker to control the risk of losses due to supply disruptions. The higher the confidence level α, the more risk aversive is the decision maker and the smaller percent of the highest cost (lowest service) outcomes are focused on. The decision maker is willing to accept only solutions for which the total probability of scenarios with cost greater than VaR^c (service smaller than VaR^{sl}) is not greater than $1 - \alpha$.

Worst-case service level

Proposition 1 *The lowest service level, $\underline{SL}$, can be calculated as below.*

$$\underline{SL} = \min\{\underline{SL1}/D, \underline{SL2}/D\}. \tag{51}$$

$\underline{SL1} = D - \sum_{t \in T: t \leq t^{SL}} d_t$, *is the greatest unfulfilled demand due to non available production capacity in disabled plants, where*

$$t^{SL} = \max_{s \in S}\{t_s + \max_{j \in J}(\max(\max_{i \in I}\{\theta_{is} + \tau_{ij}\}, \vartheta_{js}, \sigma_j))\},$$

is the longest time required to resume production after disruption.

$\underline{SL2} = \min_{j \in J} \sum_{t \in T: t > \max_{s \in S}\{t_s + \max(\max_{i \in I}\{\theta_{is} + \tau_{ij}\}, \vartheta_{js}, \sigma_j)\}} c_j$, *is minimum production capacity available after recovery.*

Proof 1 The lowest service level is associated with worst-case disruption scenario $s \in S$ for which primary supplier and primary assembly plant are both shutdown by disruption at time t_s before any production was started. Then, production resumes at plant j with the latest recovery time (after $t_s + \vartheta_{js}$ periods), after the latest delivery of parts by a recovery supplier (i.e., after $t_s + \max_{i \in I}\{\theta_{is} + \tau_{ij}\}$ periods) and after transshippment of parts from the primary plant (i.e., after $t_s + \sigma_j$ periods), whichever occurs later. Thus, $\sum_{t \in T: t \leq t^{SL}} d_t$, is the maximum shortage due to disruption, i.e., shortage of products under worst-case scenario. On the other hand, the lowest service level is associated with minimum recovery capacity. The smallest recovery capacity of plant j is determined by the number of periods, $\sum_{t \in T: t > \max_{s \in S}\{t_s + \max(\max_{i \in I}\{\theta_{is} + \tau_{ij}\}, \vartheta_{js}, \sigma_j)\}}$, remaining for production after its full recovery.

5 Computational Examples

The basic input data for the computational examples presented in this section are available in Sawik (2018a, b, 2019). Although the input data are hypothetical, their relations to each other are real and in part, they have been taken from a real case study. In particular, the case studies of Toyota supply chain disruption and recovery after the Great East Japan earthquake and tsunami of March 11, 2011 (e.g., Marszewska 2016; Matsuo 2015; Park et al. 2013) have been analyzed. Moreover, demand patterns are based on a real-world data from a high-tech manufacturer (Sawik 2011a). The

Table 3 Input parameters

$m = 4$ suppliers, $n = 2$ plants, $h = 30$ planning periods	
$K = \{1, 2\}$	two geographic regions
$I^1 = \{1, 2\}, \ J^1 = \{1, 2\}$	two suppliers and two plants in region $k = 1$
$I^2 = \{3, 4\}$	two suppliers in region $k = 2$
Total demand for parts/products	$D = 300000$
Demand per period for parts/products	
Constant demand pattern:	$d_t = 10000, \forall t \in T$
Increasing demand pattern:	
$d = (0, 2, 7, 0, 10, 8, 6, 0, 9, 8, 9, 11, 2, 5, 5, 10, 11, 13, 17, 7, 17, 13, 18, 10, 7, 19, 28, 18, 15, 15) \times 1000$	
Decreasing demand pattern:	
$d = (0, 23, 21, 14, 15, 20, 13, 9, 18, 18, 16, 7, 10, 12, 11, 10, 5, 5, 2, 13, 9, 10, 9, 0, 6, 8, 0, 3, 7, 6) \times 1000$	
Disruption levels	
$\overline{L}_i = 3$	four disruption levels for each supplier $i \in I$
$\overline{L}^j = 1$	two disruption levels for each plant $j \in J$
Local disruption probability for suppliers:	
$p_{i0} = 0.1(1 - p_{i3})$	complete shutdown (level $l = 0$)
$p_{i1} = 0.3(1 - p_{i3})$	major disruption (level $l = 1$)
$p_{i2} = 0.6(1 - p_{i3})$	minor disruption (level $l = 2$)
$p_{i3} \in [0.75, 0.95]; \ i \in I^1, p_{i3} \in [0.65, 0.75]; \ i \in I^2$	non disruption (level $l = 3$)
Local non disruption probability for plants:	$\pi_1 = 0.75, \pi_2 = 0.85$
Regional disruption probability:	$p^1 = 0.001, p^2 = 0.01$
Fulfillment rates of suppliers:	
$\gamma_{i0} = 0 \ \forall i \in I, \gamma_{i3} = 1 \ \forall i \in I$	
$\gamma_{i1} \in [0.01, 0.50] \ \forall i \in I^1 \ \gamma_{i1} \in [0.01, 0.30] \ \forall i \in I^2, \gamma_{i2} \in [0, 51, 0.99] \ \forall i \in I^1 \ \gamma_{i2} \in [0, 31, 0.99] \ \forall i \in I^2$	
Plant capacity:	
$c_1 = 10000, \ c_2 = 5000$	
Cost parameters:	
$e = (14, 12, 8, 9), \ f = (8000, 6000, 12000, 13000)$	
$\varepsilon_2 = 1, \varphi_2 = 100, g_2 = 0.1, \xi = \max_{i \in I} e_i/10 = 1.4, \zeta = 10, \eta = 100$	
$CTR(i, l)$=if $l = 0$ then $100000 f_i$; if $l = 1$ then $10000 f_i$; if $l = 2$ then $1000 f_i \ \forall i \in I$	
$PRC(1, 0) = PRC(2, 0) = 10000$	
Time parameters:	
$\tau_{1j} = \tau_{2j} = 2, \ \tau_{3j} = \tau_{4j} = 4, \forall j \in J, \sigma_2 = 2$	
$TTR(i, l)$=if $l = 0$ then 12; if $l = 1$ then 10; if $l = 2$ then 8 $\forall i \in I$	
$PRT(1, 0) = 10, \ PRT(2, 0) = 5$	

computational experiments were performed using the AMPL programming language and the Gurobi 7.5.0 solver on a MacBookPro laptop with Intel Core i7 processor running at 2.8 GHz and with 16 GB RAM. The basic input parameters are shown in Table 3.

In order to emphasize the impact of disruptions on the primary assembly plant $j = 1$, the plant has greater capacity and is modeled to be less reliable than plant $j = 2$ ($c_1 = 10000 > c_2 = 5000$, $\pi_1 = 0.75 < \pi_2 = 0.85$).

The total number of all potential disruptive events was $(\overline{L} + 1)^m(\overline{L^1} + 1)(\overline{L^2} + 1) = (4^4)(2^2) = 1024$. In the computational examples, a disruption scenario was defined as a combination of disruptive event and its start time. The start time t_s of each disruptive event was assumed to be not greater than the maximum delivery lead time to primary assembly plant $j = 1$, $\max_{i\in I}(\tau_{i1}) = 4$. Thus $t_s \in \{1, 2, 3, 4\}$, and the total number of all potential scenarios to be considered was $1024 \times 4 = 4096$, since each disruptive event $s = 1, \ldots, 1024$ may occur at four different start times. Notice that $\gamma_i^s = 1$, if $t_s > \tau_{i1}$, i.e., full order is delivered by supplier i, if disruption occurs after delivery lead time to primary assembly plant.

The probability P_s of realizing each disruption scenario $s \in S$ was calculated as follows:
$P_s = 0.1 P_s^1 P_s^2$ for $s \le 1024$,
$P_s = 0.2 P^1_{s-1024} P^2_{s-1024}$ for $1025 \le s \le 2048$,
$P_s = 0.3 P^1_{s-2048} P^2_{s-2048}$ for $2049 \le s \le 3072$, and
$P_s = 0.4 P^1_{s-3072} P^2_{s-3072}$ for $3073 \le s \le 4096$,

where probabilities $P_s^k;\ k = 1, 2,\ s \le 1024$ were obtained using formula (3). Notice that disruptive events with later start times were modeled to be more likely.

The solution results are summarized in Tables 4 and 5, respectively, for model **Support_CV(c)** and **Support_CV(sl)**. The tables show primary supply portfolio and expected demand portfolios for different values of confidence level $\alpha = 0.5, 0.75, 0.9, 0.95, 0.99$. The solution values, CVaR and VaR, are presented along with the associated expected values of cost per product,

$$
\begin{aligned}
E(c) = \sum_{s\in S} P_s \sum_{i\in I}(f_i(u_i + U_i^s - \mu_i^s) + \rho_{is}U_i^s + e_i(\gamma_i^s v_i + \sum_{j\in J} V_{ij}^s))/D \\
+ \sum_{s\in S} P_s \sum_{j\in J}(g_j w_j^s + (\varphi_j + \varrho_{js})q_j^s + \sum_{t\in T} \varepsilon_j x_{jt}^s)/D \\
+ \sum_{s\in S}\sum_{t\in T} P_s(\xi y_t^s + \zeta z_t^s)/D \\
+ \eta \sum_{s\in S} P_s z_{h+1}^s / D, \quad (52)
\end{aligned}
$$

and expected service level,

$$
E(sl) = 1 - \sum_{s\in S} P_s z_{max}^s / D, \quad (53)
$$

as well as with solution value of LP relaxation of stochastic MIP models **Support_CV(c)** and **Support_CV(sl)**. Table 4 shows that while CVaR, VaR, and E(c) increase with the confidence level α, the expected service level, E(sl), decreases as the

Table 4 Solution results for model **Support_CV(c)**

Confidence level α	0.50	0.75	0.90	0.95	0.99
Constant demand pattern					
Var. = 365531, Bin. = 56064, Cons. = 693807, Nonz. = 7804322[a]					
CVaR	64.20	92.25	104.80	120.01	136.71
VaR	34.53	69.26	87.49	90.87	134.92
Exp.Cost E(c), (52)	49.32	59.67	71.63	72.67	90.40
Exp.Service E(sl), (53) × 100%	87.90	85.02	81.69	81.84	80.22
Primary Supply Portfolio:	1(5)				
Supplier(% of total demand)[b]	2(8)	2(5)	2(4)	2(13)	2(100)
	3(78)	3(82)	3(83)	3(74)	
	4(9)	4(13)	4(13)	4(13)	
Exp.Recovery Demand Portfolio:			1(90)		
Plant (% of total demand)[c]			2(10)		
LP[d]	63.95	92.06	104.46	119.34	134.96
Increasing demand pattern					
Var. = 596787, Bin. = 207504, Cons. = 1003583, Nonz. = 9671394[a]					
CVaR	39.00	57.45	67.71	83.54	96.41
VaR	19.39	46.61	51.57	53.43	94.58
Exp.Cost E(c), (52)	29.19	44.27	47.78	50.77	56.00
Exp.Service E(sl), (53) × 100%	93.42	82.47	80.90	79.45	79.83
Primary Supply Portfolio:	2(9)	2(3)	2(4)	2(16)	2(100)
Supplier(% of total demand)[b]	3(83)	3(88)	3(87)	3(75)	
	4(8)	4(9)	4(9)	4(9)	
Exp.Recovery Demand Portfolio:			1(89)		
Plant (% of total demand)[c]			2(10)		
LP[d]	38.85	56.85	67.37	82.08	94.80
Decreasing demand pattern					
Var. = 375267, Bin. = 59824, Cons. = 699143, Nonz. = 7778870[a]					
CVaR	96.97	125.04	137.69	152.87	169.64
VaR	67.46	100.42	120.41	123.80	167.86
Exp.Cost E(c), (52)	82.21	98.35	104.28	106.33	128.97
Exp.Service E(sl), (53) × 100%	69.12	64.52	62.99	62.59	60.58
Primary Supply Portfolio:	1(5)				
Supplier(% of total demand)[b]	2(8)	2(5)	2(3)	2(14)	2(100)
	3(78)	3(82)	3(84)	c(76)	
	4(9)	4(13)	4(13)	4(10)	
Exp.Recovery Demand Portfolio:	1(89)	1(90)	1(89)	1(90)	1(87)
Plant (% of total demand)[c]	2(10)	2(10)	2(10)	2(10)	2(13)
LP[d]	96.80	124.85	137.36	152.20	167.90

[a] Var. = total number of variables, Bin. = number of binary variables, Cons. = number of constraints, Nonz. = number of nonzero coefficients

[b] $1(v_1 \times 100), 2(v_2 \times 100), 3(v_3 \times 100), 4(v_4 \times 100)$

[c] $1(\sum_{s \in S} P_s r_1^s \times 100), 2(\sum_{s \in S} P_s r_2^s \times 100)$

[d] LP relaxation solution value of (8)

Table 5 Solution results for model **Support_CV(sl)**

Confidence level α	0.50	0.75	0.90	0.95	0.99
Constant demand pattern					
Var. = 365531, Bin. = 56064, Cons. = 693807, Nonz. = 7544834[a]					
CVaR	82.55	71.83	70.17	69.10	68.32
VaR	93.33	78.33	71.67	70.00	68.33
Exp.Service E(sl), (53) × 100%	87.94	82.70	82.67	82.34	82.16
Exp.Cost E(c), (52)	534.65	554.09	553.47	556.06	556.38
Primary Supply Portfolio:	1(33)	1(28)	1(30)	1(25)	1(28)
Supplier(% of total demand)[b]	2(27)	2(25)	2(21)	2(27)	2(27)
	3(13)	3(21)	3(24)	3(21)	3(21)
	4(27)	4(26)	4(25)	4(27)	4(24)
Exp.Recovery Demand Portfolio:	1(89)	1(92)	1(90)		
Plant (% of total demand)[c]	2(10)	2(8)	2(10)		
LP[d]	82.55	71.83	70.17	69.10	68.32
Increasing demand pattern					
Var. = 596787, Bin. = 207504, Cons. = 1003583, Nonz. = 9332090[a]					
CVaR	91.24	89.14	87.12	86.27	84.96
VaR	93.33	93.33	88.67	86.67	85.00
Exp.Service E(sl), (53) × 100%	93.55	93.55	90.66	88.78	87.10
Exp.Cost E(c), (52)	513.63	513.62	516.70	519.23	521.70
Primary Supply Portfolio:	1(35)	1(35)	1(31)	1(32)	1(33)
Supplier(% of total demand)[b]	2(32)				
	3(11)	3(11)	3(17)	3(16)	3(12)
	4(22)	4(22)	4(20)	4(20)	4(23)
Exp.Recovery Demand Portfolio:	1(88)		1(89)		
Plant (% of total demand)[c]	2(10)		2(11)		
LP[d]	91.24	89.14	87.12	86.27	84.96
Decreasing demand pattern					
Var. = 375267, Bin. = 59824, Cons. = 699143, Nonz. = 7513406[a]					
CVaR	63.99	53.69	51.92	51.10	50.31
VaR	74.33	61.00	53.67	52.00	50.33
Exp.Service E(sl), (53) × 100%	69.16	63.92	63.87	63.62	63.32
Exp.Cost E(c), (52)	569.41	588.41	588.60	590.24	593.00
Primary Supply Portfolio:	1(33)	1(26)	1(30)	1(27)	1(26)
Supplier(% of total demand)[b]	2(28)	2(26)	2(21)	2(22)	2(28)
	3(12)	3(23)	3(24)	3(23)	3(21)
	4(27)	4(25)	4(25)	4(28)	4(25)
Exp.Recovery Demand Portfolio:	1(88)	1(90)			
Plant (% of total demand)[c]	2(10)	2(10)			
LP[d]	63.99	53.69	51.92	51.10	50.31

[a] Var. = total number of variables, Bin. = number of binary variables, Cons. = number of constraints, Nonz. = number of nonzero coefficients

[b] $1(v_1 \times 100), 2(v_2 \times 100), 3(v_3 \times 100), 4(v_4 \times 100)$

[c] $1(\sum_{s \in S} P_s r_1^s \times 100), 2(\sum_{s \in S} P_s r_2^s \times 100)$

[d] LP relaxation solution value of (48)

decision maker becomes more risk aversive with respect to cost. Similar results for model **Support_CV(sl)** are shown in Table 5. While CVaR, VaR, and E(sl) decrease with the confidence level α, E(c) increases as the decision maker becomes more risk aversive with respect to the service level.

Table 4 indicates that the primary supply portfolio for model **Support_CV(c)** becomes less diversified as the confidence level increases and for the highest $\alpha = 0.99$ a single supplier $i = 2$ is selected only, the cheapest among the most reliable suppliers. In contrast, for model **Support_CV(sl)**, a diversified supply portfolio with all suppliers is selected for all confidence levels, see Table 5. The expected recovery demand portfolios are similar for both models and all confidence levels, with the primary plant $j = 1$ selected as a major recovery supplier.

For model **Support_CV(c)** and three different demand patterns, Fig. 2 presents expected cumulative production at each plant $j \in J$, by each period,

$$\sum_{s\in S} P_s \sum_{t'\in T: t'\leq t} x^s_{jt'};\ t \in T,$$

and expected shortage of products, at the end of each period,

$$\sum_{s\in S} P_s z^s_{t+1};\ t \in T,$$

associated with the risk-averse solution for $\alpha = 0.99$. In addition, Fig. 2 shows cumulative demand for products by each period $t \in T$,

$$D_t = \sum_{t'\in T: t'\leq t} d_{t'}.$$

For the top $100(1-\alpha)\% = 1\%$ of the worst-case scenarios $s \in S$ with cost,

$$\begin{aligned}\sum_{i\in I}(f_i(u_i + U^s_i - \mu^s_i) + \rho_{is}U^s_i + e_i(\gamma^s_i v_i + \sum_{j\in J} V^s_{ij}))/D\\ + \sum_{j\in J}(g_j w^s_j + (\varphi_j + \varrho_{js})q^s_j + \sum_{t\in T}\varepsilon_j x^s_{jt})/D\\ + \sum_{t\in T}(\xi y^s_t + \zeta z^s_t)/D + \eta z^s_{h+1}/D,\end{aligned}$$

exceeding VaR^c, Fig. 3 presents expected worst-case cumulative production at each plant $j \in J$, by each period,

$$\frac{\sum_{s\in S:\mathscr{C}_s>0} P_s \sum_{t'\in T:t'\leq t} x^s_{jt'}}{\sum_{s\in S:\mathscr{C}_s>0} P_s};\ t \in T,$$

and expected worst-case shortage of products, at the end of each period,

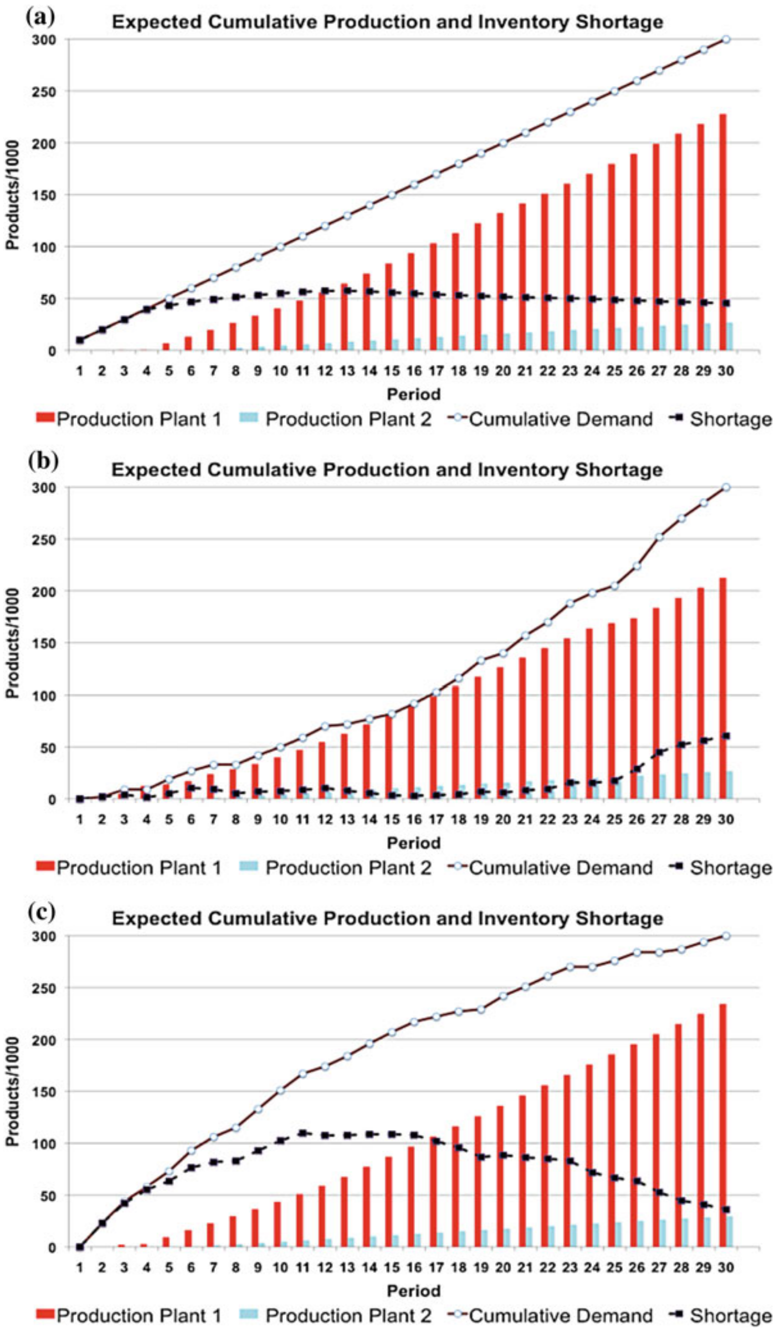

Fig. 2 Expected cumulative production and shortage of products for model **Support_CV(c)**, $\alpha = 0.99$: **a** constant demand pattern, **b** increasing demand pattern, **c** decreasing demand pattern

$$\frac{\sum_{s\in S:\mathscr{C}_s>0} P_s z_{t+1}^s}{\sum_{s\in S:\mathscr{C}_s>0} P_s};\ t\in T.$$

Similar diagrams for model **Support_CV(sl)**, three different demand patterns and $\alpha = 0.99$ are shown in Figs. 4 and 5. Figure 4 presents expected cumulative production at each plant and expected shortage of products and Fig. 5 shows expected worst-case cumulative production,

$$\frac{\sum_{s\in S:\mathscr{S}_s>0} P_s \sum_{t'\in T:t'\le t} x_{jt'}^s}{\sum_{s\in S:\mathscr{S}_s>0} P_s};\ t\in T,$$

and expected worst-case shortage of products,

$$\frac{\sum_{s\in S:\mathscr{S}_s>0} P_s z_{t+1}^s}{\sum_{s\in S:\mathscr{S}_s>0} P_s};\ t\in T,$$

for the top $100(1-\alpha)\% = 1\%$ of the worst-case scenarios $s \in S$ with service level, $1 - z_{max}^s/D$, below VaR^{sl}.

Comparison of solution results for different demand patterns demonstrate that decreasing demand pattern with the most demand for products concentrated at the beginning of the planning horizon leads to highest cost and lowest service level for both expected and expected worst-case scenarios, see Tables 4 and 5 and Figs. 2, 3, 4, and 5. In contrast to increasing demand pattern, for which the impact of disruption risks can be mitigated much better. Comparison of solution results for the two different models indicate that when the primary objective is to optimize service level with no regard to costs, both supply and demand portfolios are more diversified. Both demand for parts and unfulfilled demand for products are more evenly allocated among all primary suppliers and recovery plants, respectively.

For comparison, Fig. 6 presents expected results for model **Support_CV(c)** and the lowest confidence level $\alpha = 0.5$. The figure demonstrates that for the risk-aversive primary supply portfolio focusing on the highest 50% of cost outcomes, i.e., oriented more on business as usual, the expected results are better than for a more risk-aversive portfolio, i.e., for a higher confidence level. Clearly, the best-expected results can be achieved for the risk-neutral decision-making, i.e., for $\alpha = 0$.

Proven optimal solutions were obtained for all examples with CPU time ranging from around 100 s for model **Support_CV(sl)** to over 600 s for model **Support_CV(c)**.

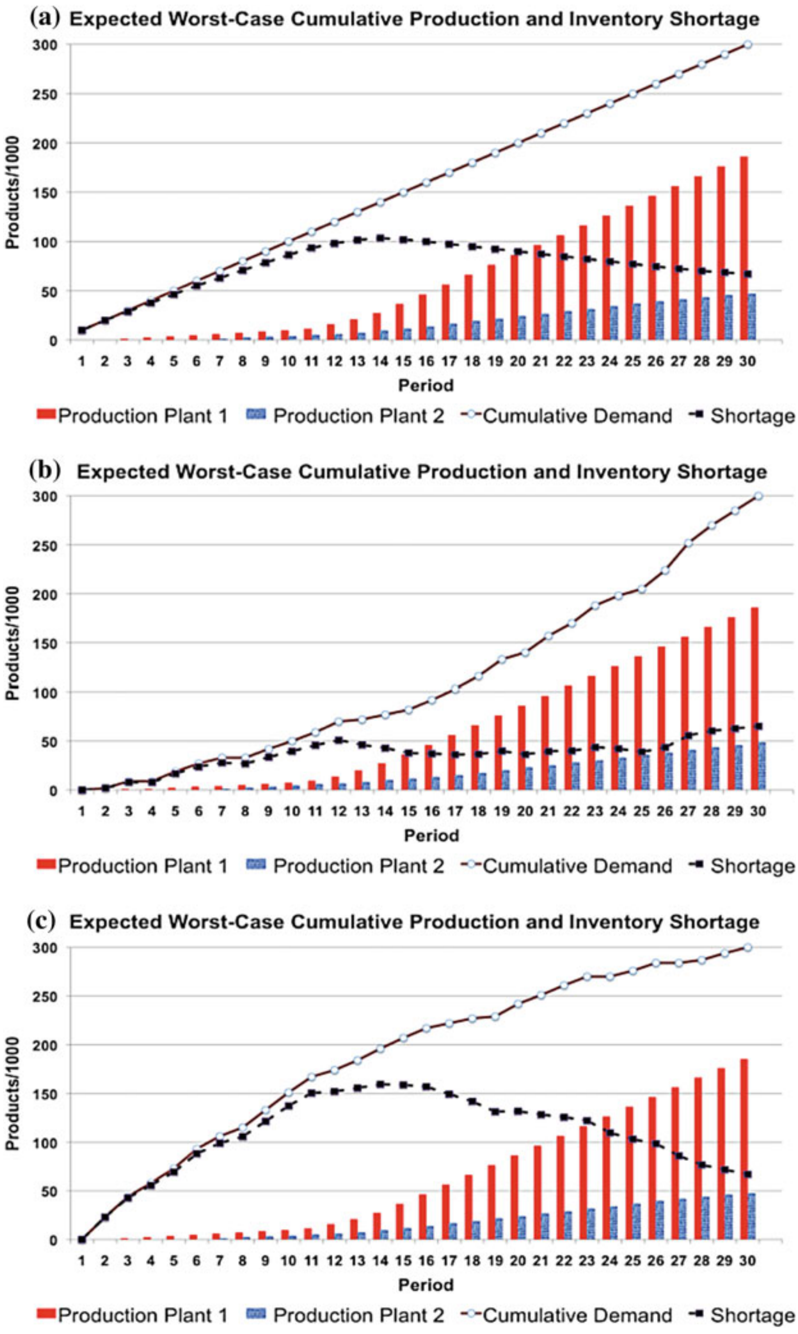

Fig. 3 Expected worst-case cumulative production and shortage of products for model **Support_CV(c)**, $\alpha = 0.99$: **a** constant demand pattern, **b** increasing demand pattern, **c** decreasing demand pattern

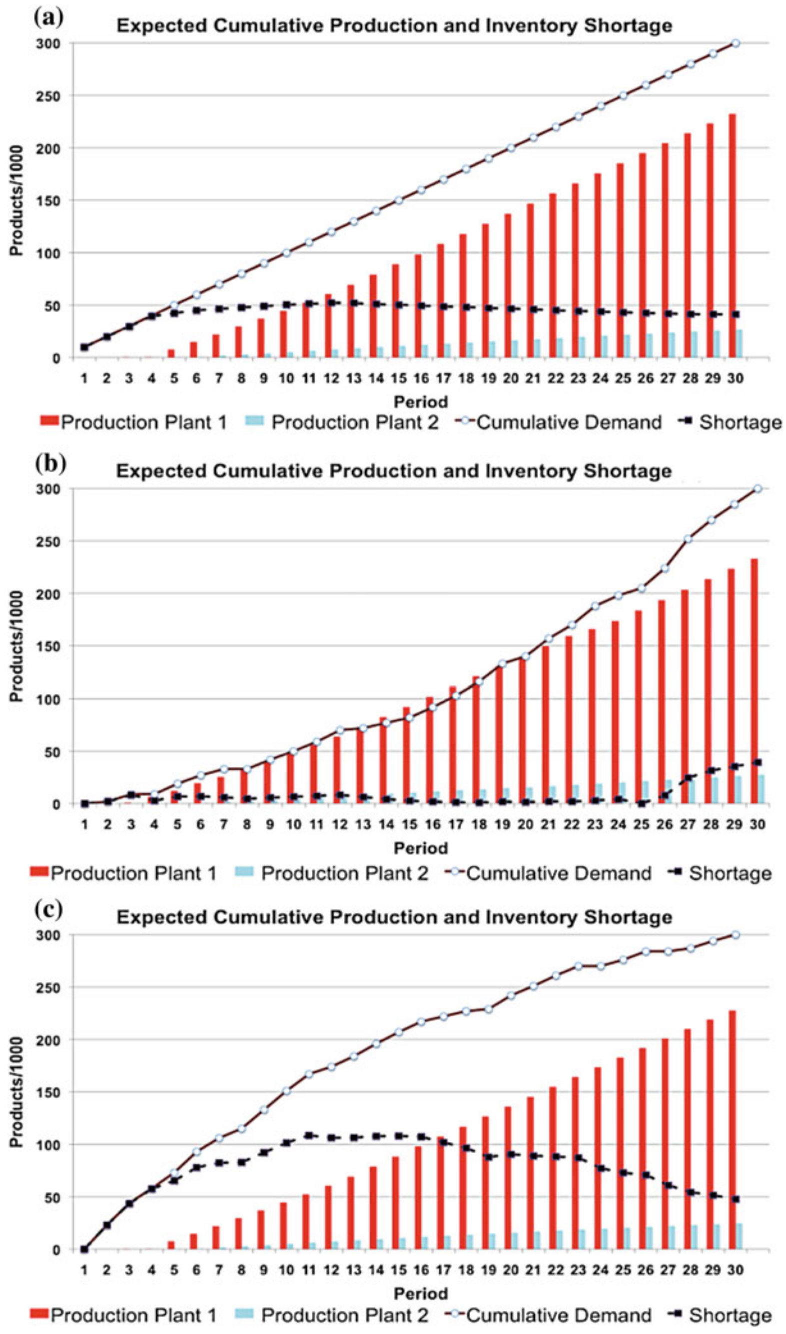

Fig. 4 Expected cumulative production and shortage of products for model **Support_CV(sl)**, $\alpha = 0.99$: **a** constant demand pattern, **b** increasing demand pattern, **c** decreasing demand pattern

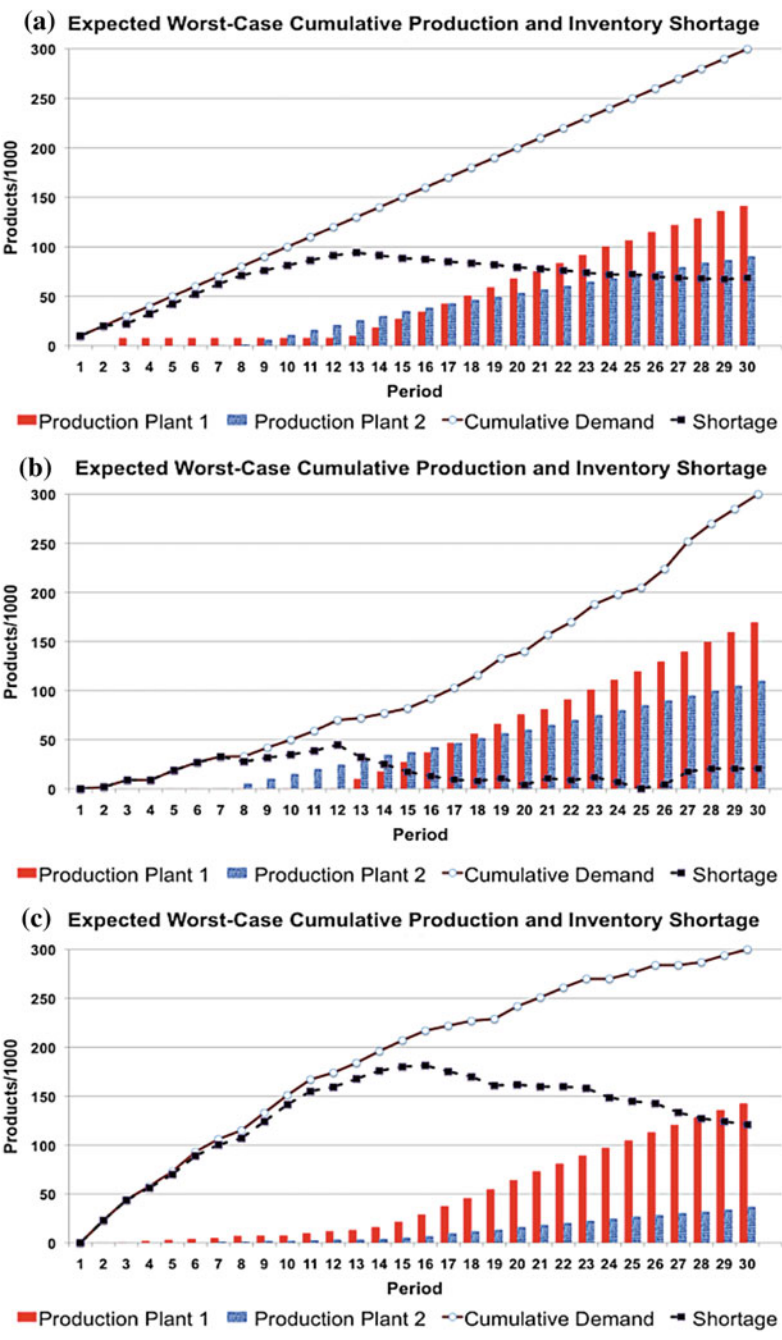

Fig. 5 Expected worst-case cumulative production and shortage of products for model **Support_CV(sl)**, $\alpha = 0.99$: **a** constant demand pattern, **b** increasing demand pattern, **c** decreasing demand pattern

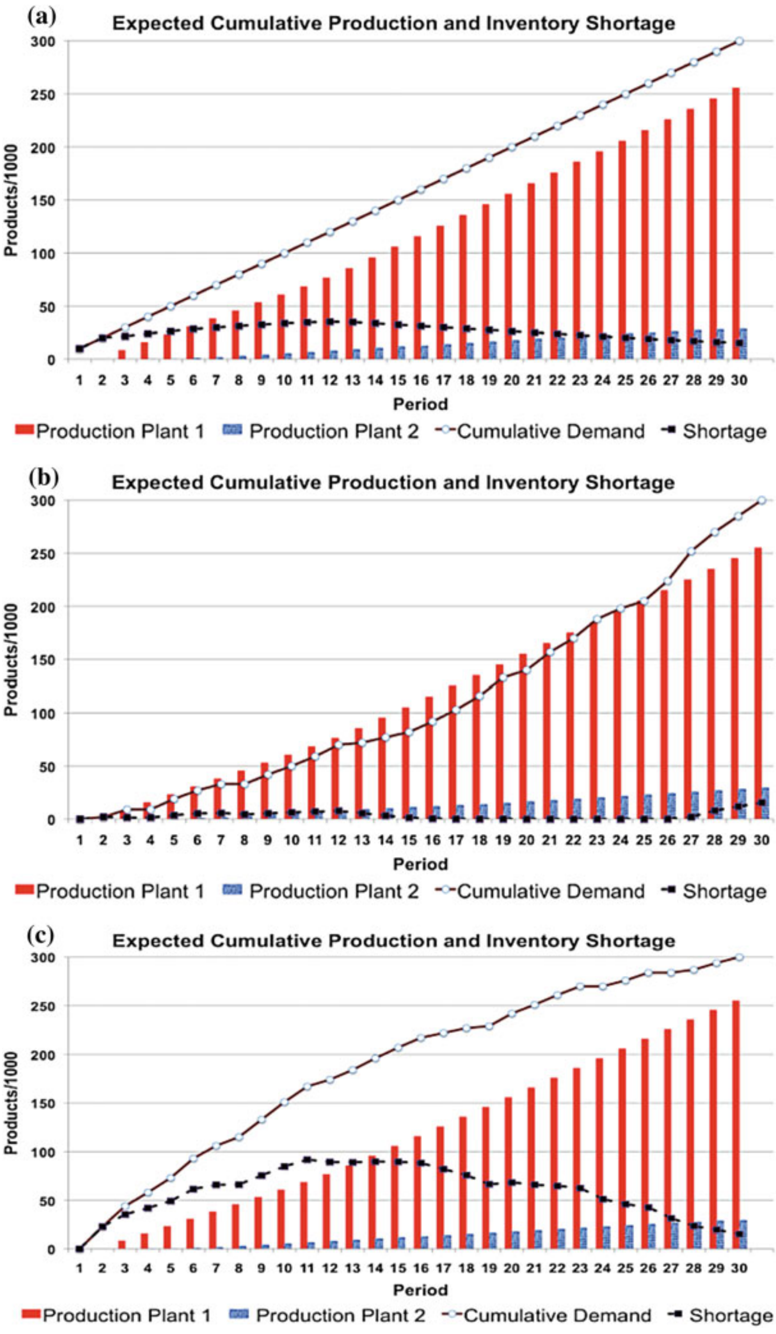

Fig. 6 Expected cumulative production and shortage of products for model **Support_CV(c)**, $\alpha = 0.5$: **a** constant demand pattern, **b** increasing demand pattern, **c** decreasing demand pattern

6 Conclusions

The proposed multi-portfolio approach for the time and space integrated supply chain disruption management may help to better mitigate the ripple effect. Due to an embedded network flow structure, the proposed stochastic MIP models have a very strong LP relaxation and as a result proven optimal solutions can be obtained in a very short CPU time using commercially available MIP solvers.

The future research should concentrate on relaxations of the various simplified assumptions used to formulate the problem. A straightforward enhancement is a multiple part type and product types setting with subsets of suppliers available for each part type and assembly plants for each product type. A partial recovery can also be considered with the fraction of capacity recovered and available in each period. Moreover, different recovery modes with different recovery time and cost can be selected by the decision maker. In the scenario analysis, a disruptive event is assumed to hit the corresponding suppliers and assembly plants simultaneously. In order to more precisely account for the ripple effect, i.e., the disruption propagation from its initial location, disruption of different supply chain members should be delayed by disruption propagation time. Thus, instead of a common disruption start time, each disruption scenario should be associated with different start times, for different locations of impacted suppliers and plants. Then some estimation of the disruption propagation time would be needed. The proposed scenario-based modeling approach also assumes that some estimation of disruptive events probability and potential losses is available. However, a fair probability estimation of rare events is a complicated problem and even small errors in those estimations may significantly impact the modeling results. The future research should concentrate on developing the probability-independent approaches for supply chain disruption management (e.g., Simchi-Levi et al. 2015). For example, by focusing on worst-case scenarios only, in particular when the ripple effect is considered.

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The Rippling Effect of Non-linearities

Virginia L. M. Spiegler, Mohamed M. Naim and Junyi Lin

Abstract Non-linearities can lead to unexpected dynamic behaviours in supply chain systems that could then either trigger disruptions or make the response and recovery process more difficult. In this chapter, we take a control-theoretic perspective to discuss the impact of non-linearities on the ripple effect. This chapter is particularly relevant for researchers wanting to learn more about the different types of non-linearities that can be found in supply chain systems, the existing analytical methods to deal with each type of non-linearity and future scope for research based on the current knowledge in this field.

1 Introduction

As a result of globalisation and increasing competitive pressures, modern supply chains have gone through a leaning and lengthening process (Christopher and Peck 2004) and now back to reshoring (Gray et al. 2013). The managers have attempted to optimise supply chains by reducing holding inventory, outsourcing noncore activities, cutting the number of suppliers and sourcing globally, forgetting that the world market is an erratic and unpredictable place (Kearney 2003). In addition to this, current trade restrictions as a result of protectionist political environment emerging in North America and Europe introduce additional uncertainty and complexity into supply chains, which are more vulnerable to disruptions than ever before (Manners-Bell 2018).

V. L. M. Spiegler (✉)
Kent Business School, University of Kent, Canterbury CT2 7PE, UK
e-mail: v.l.spiegler@kent.ac.uk

M. M. Naim · J. Lin
Cardiff Business School, Cardiff University, Aberconway Building, Colum Drive, Cardiff CF10 3EU, UK
e-mail: naimmm@cardiff.ac.uk

J. Lin
e-mail: linj17@cardiff.ac.uk

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The resulting complex business environment has increased the importance of handling risks which can emerge from the customers, suppliers, manufacturing processes and control systems (Spiegler et al. 2012) and of designing ripple effect mitigation strategies through agile and resilient practices (Dolgui et al. 2018). Increased complexity also means that supply chain researchers can no longer disregard capacity limitations, restrictive policies and other system constraints, i.e. that the real world is non-linear. Non-linearities can introduce unexpected behaviour in a system causing instability and uncertainty (Wang and Disney 2012; Spiegler et al. 2016b), therefore it is important to understand how control systems can be designed to influence dynamic behaviours and how non-linearities impact the performance of supply chains.

When looking at supply chain problems, the researchers have created a number of production and inventory models to represent the flows of information and material between different supply chain players. There are a number of research streams that deal with such problems such as Markov demand process, Bayesian approach, moving average or ARIMA process (Zhao et al. 2016), mixed-integer programming, stochastic programming, simulation (via system dynamics, agent-based modelling, discrete event), graph theory (Dolgui et al. 2018) and control theory (via feedback control and optimal control mechanism) (Dolgui et al. 2018; Zhao et al. 2016). The latter approach concerns determining transient responses and systems stability, i.e. understanding and controlling supply chain dynamics. These dynamics are normally driven by the application of different control system policies and can be considered as a source of disruption depending on the control system design (Colicchia et al. 2010). Moreover, a number frameworks exist for tackling the ripple effect in the supply chain dynamics, control and disruption management domain (Ivanov et al. 2014).

In this chapter, we will discuss the impact of non-linearities on the ripple effect from a control structure perspective, by revisiting the literature on non-linear control theory application in supply chain management. As Ivanov and Sokolov (2013) pointed out 'useful tools for quantitative analysis of control and systems theory for a wide supply chain management research community remain undiscovered'. This chapter reviews new research techniques and recent progress in the analytical understanding of how non-linearities influence dynamic behaviours and affect the performance of the supply chains. We start by introducing different types of non-linearities and their typical effect on system transient output response. Then, we suggest the existing methods to analyse each type of non-linearity and detail a selected number of mathematical approaches that can be used alongside simulation methods to explore the hidden dynamics caused by such non-linearities. Next, we discuss the applications of these methods and compile key findings on the rippling effect of non-linearities. Finally, the chapter concludes with a future research agenda.

2 Types of Non-linearities

A non-linear system is one whose performance does not obey the principal of superposition. This means that the output of a non-linear system is not directly proportional to the input and the variables to be solved cannot be expressed as a linear combination of the independent parts (Rugh 2002). In supply chain systems, non-linearities can naturally occur due to the existence of physical and economic constraints, for instance, fixed and variable capacity constraints in the manufacturing and shipping processes, resource availability, variable delays and variable control parameters, trade and infrastructure constraints (Spiegler et al. 2016b).

Since the variety of possible non-linearities in supply chain systems is extremely wide, it may be worthwhile to classify them into different categories, for which appropriate analytical methods will be suggested. The first research found on categorisation of non-linearities in business system dynamics research were done by Mohapatra (1980) who identified three types of non-linearities: limiting functions, table functions and product operators. He also recommends some techniques to deal with such properties, including the omission of redundant functions, linearisation through averaging, best-fit line approximations and small perturbation theory. In the control systems literature, non-linearities are more extensively classified as inherent or intentional, continuous or discontinuous and single- or multiple-valued (Cook 1986; Vukic et al. 2003), as in Fig. 1.

Inherent non-linearities are intrinsic to the nature of the system and arise from the system's hardware and motion. They are normally undesirable and need to be compensated for by the system designer. Intentional non-linearities are artificial and deliberately introduced by the designer in order to improve system performance (Cook 1986). Normally in supply chain systems, non-linearities are intrinsic to the system due to physical and economic constraints. These non-linearities may or may not be considered in the system modelling depending on the degree of accuracy and complexity necessary for the supply chain design. On the other hand, supply chain designers may want to include non-linearities that do not exist in reality for the sake of improving certain performance measures. This type of research has only recently been considered (Spiegler et al. 2018) but yet to be duly explored. Other studies have shown that while the presence of non-linearities may worsen some performance measures, they may improve others. For example, Evans and Naim (1994)—demand amplification versus service level, Grübbstrom and Wang (2000)—complexity of the

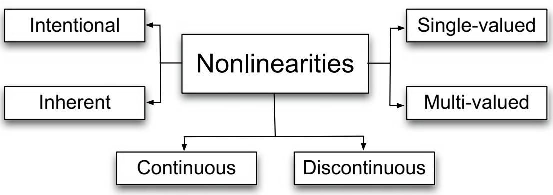
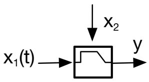
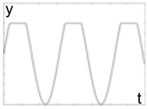
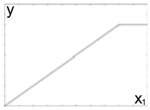
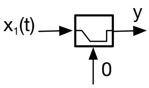
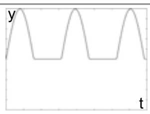
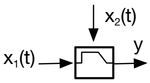
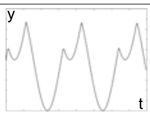
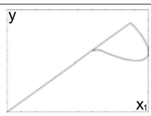
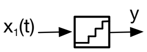
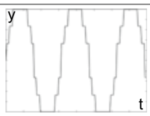
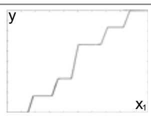
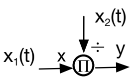
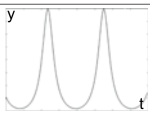
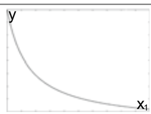
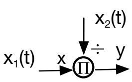
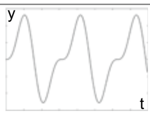
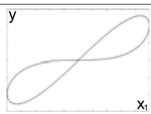


Fig. 1 Types of non-linearities

production plan versus production cost, Wikner et al. (2007)—lead-time expectations versus dynamic behaviour in the system.

Continuous and discontinuous non-linearities are associated with the rate of change between input and output. Table 1 contains examples of discontinuous (the first four rows) and continuous (the last two rows) non-linearities found in production

Table 1 Non-linearities in production and inventory control systems

Non-linearity	Block diagram symbol	Typical output response	Input–output profile
Fixed capacity constraint (discontinuous, single-valued)			
Non-negativity constraint (discontinuous, single-valued)			
Variable capacity constraint (discontinuous, multiple-valued)			
Rounding (discontinuous, single-valued)			
Time-varying parameter (continuous, single-valued)			
Time-varying parameter (continuous, multiple-valued)			

and inventory control models for supply chain management and their block diagram symbol, typical output response given a sinusoidal input and the rate of change between output and input. A feature of the outputs in continuous functions is that they are smooth enough to possess convergent expansions at all points and therefore can be linearised. Examples include any adaptive control system, where certain control parameters, instead of being fixed, vary depending on the state of other variables (Vukic et al. 2003). Sharp changes in output values or gradients indicate discontinuities. The most common type of discontinuous non-linearity is the piecewise linear functions, which consist of a set of linear relations for different regions.

In the case of single-valued non-linearities, the output is a result of the current value of the input, whereas two or more values of output may be possible for the same input value in the case of multiple-valued non-linearities. The multiple values of the output will depend on the previous history of the input; thus such non-linearities are said to possess memory. The last column of Table 1 demonstrates the difference between these characteristics. Multiple-valued functions are often used in engineering to model hysteresis of magnetic and elastic materials and mechanical backlash of friction gears (Cook 1986). In business studies, this kind of non-linear behaviour has been described in economics (Göcke 2002), for instance between buying/selling states and price (Cross et al. 2009) and unemployment and economy growth rate (Lang and de Peretti 2009). In supply chain management research, multi-valued non-linearities are not so commonly reported. They have been used to model switching of certain operation strategies depending on cost directions. Examples include investigations on changes in global sourcing (Kouvelis 1998) and manufacturing strategies (Kogut and Kulatilaka 1994) depending on foreign exchange rate directions. From a purely production-inventory control system perspective, this kind of effect has been identified in outbound shipments which depend on relational fluctuations between inventory levels and current demand (Spiegler et al. 2016b). The normal thinking is that independent of demand growing direction, the order quantities placed to suppliers or shipped to customers will always match demand. However, when a variable capacity is put in place, these outputs can result in a complex multiple-valued non-linear behaviour.

3 Methods for the Analysis of Non-linearities

When confronted with a non-linear system, the first approach is to linearise it. The rationale for this is that techniques to analyse linear systems are much more established and better understood than non-linear control theory methods (Vukic et al. 2003). Linearisation is generally considered as an appropriate choice when the solution can be obtained in this manner. While linear system theory is well acknowledged, the literature in non-linear theory is less conclusive when it comes to generality and applicability (Rugh 2002). Because of a lack of common terminology and lack of detailed research methods in the non-linear control systems literature, the complete catalogue of all the existing methods and their applicability in the analysis of non-linear feedback systems are laborious. Table 2 presents a list of the methods that have been sufficiently acknowledged in the literature and whose full details were accessible.

There are a number of methods for system linearisation such as small perturbation theory, describing function and averaging or best-fit line approximations. The former allows the system with continuous non-linearities to be analysed through successive approximations in the form of power series around a specific operating point (Cook 1986). If the system can be represented by the Taylor series or Volterra series, then it can be approximated using perturbation theory (Odame and Hasler 2010). The Volterra series is often compared with Taylor series but it is also suitable to approximate outputs with memory, which means that the Volterra series can mimic systems where the output depends on past inputs so they are suitable for multi-valued non-linearities (Rugh 2002). The describing function method is attributed to as a quasi-linearisation, since the approximation process of the non-linear system is for specific inputs. For instance, sinusoidal inputs are more often used since the frequency response approach is a powerful tool for the analysis and design of systems (Gelb 1968). Averaging and best-fit line techniques produce rough estimations and can be a simpler alternative for comprehending more complex systems in a qualitative manner (Mohapatra 1980). However, whenever precision and reliability are needed these methods should be avoided (Vukic et al. 2003).

Then there are graphical techniques, such as the phase plane analysis. However, this technique is limited to second-order systems (Vukic et al. 2003). The point transformation method allows periodicity and stability of piecewise linear systems to be investigated by studying the behaviour of trajectories that cross repeatedly from one region to another (Cook 1986), but it can be complicated for high order systems. There are also exact solutions for a finite number of non-linear control systems with low order (Vukic et al. 2003), making its application very limited. More complex and sophisticated techniques such as the one developed by Johansson (2003) are used for stability analysis of piecewise linear systems by combining Lyapunov functions and convex optimisation process.

Finally, there is a simulation, which although is a very helpful technique, it should be in principle used as a complementary tool to the above analytical methods. Simulation has many advantages, offering a 'middle ground between pure mathematical modelling, empirical observation and experiments for strategic issues in supply chain research' Größler and Schieritz (2005). Because simulation is a numerical technique that allows the analysis of complex models, it does not require specific mathematical forms that are analytically solvable.

In the next subsection, we provide instructions on how to adopt the following linearisation methods: describing functions, small perturbation theory with Taylor and Volterra series expansion. These methods were chosen given their wide applicability, versatility and power in uncovering hidden dynamics caused by different types of non-linearities and in tracing the transient behaviour, which is necessary to estimate the system's performance. In supply chain systems, the understanding of transient responses can elucidate the occurrence of disruptions and how to mitigate its cascading effects on other supply chain members.

Table 2 Summary of methods used to analyse non-linear systems

	Method of analysis	Applications	Considerations
Linearisation methods	Small perturbation theory with Taylor series expansion	Continuous Single-valued	Assumption that the amplitude of the excitation signal is small. Local stability analysis only
	Describing function	Continuous, Discontinuous Single-valued, Multi-valued	Less accurate when non-linearities contain higher harmonics. Analysis of systems with periodic or Gaussian random input only
	Small perturbation theory with Volterra/Wiener series expansion	Continuous Multi-valued	Assumption that the amplitude of the excitation signal is small. Difficulty in calculating the kernels and operators of the system, making it impractical for high order systems
	Averaging and best-fit line approximations	Continuous, Discontinuous Single-valued, Multi-valued	Gross approximation of real responses. Only when better estimates are not possible
Graphical and simple methods	Phase plane and graphical solutions	Continuous, Discontinuous Single-valued, Multi-valued	Limited to 1st and 2nd order systems only
	Point transformation method	Discontinuous Single-valued, Multi-valued	Piecewise linear systems only. For high order systems, automated numerical methods must be employed
Exact solutions	Direct solution	Continuous Single-valued	Limited to a finite number of equations
Stability method	Lyapunov-based stability analysis for piecewise linear systems	Discontinuous Only single-valued examples were found	Piecewise linear systems only. Computation can be complex depending on the system
Simulation	Numerical and simulation solution	Continuous, Discontinuous Single-valued, Multi-valued	Can be time consuming. Dependent on computer and software calculations capacity

3.1 Describing Function

The describing function method is a quasi-linear representation for a non-linear element subjected to a specific input. This is a method that attempts to estimate the output properties, such as frequency, amplitude and stability, after being affected by a non-linear component (Gelb 1968). This method is also used to predict limit cycles or sustained oscillations (Spiegler and Naim 2017).

The basic idea of the describing function is to express a non-linear element in the form of a transfer function, or a gain, determined from its effects on a particular input signal. For asymmetric non-linearities, or symmetric non-linearities subjected to biased inputs, at least two terms of the describing function are needed: one that expresses the change in the output amplitude (N_A) and another that considers the change in the output mean (N_B). This leads to the so-called dual-input describing function (Vukic et al. 2003; Cook 1986). Another effect caused by this type of non-linearity is the possible change in phase angle (ϕ) of the output response in relation to its input. Next, we give an example of how sinusoidal describing functions can be determined.

Consider the input to the non-linearity:

$$x_1(t) = A.cos(\omega t) + B \tag{1}$$

where ω is the angular frequency and $\omega = 2\pi/T$. The output y can be approximated to

$$y(t) = N_A.A.cos(\omega t + \phi) + N_B.B \tag{2}$$

In order to determine the terms of the describing function (N_A, N_B and ϕ) the series has to be expanded and its first harmonic coefficients must be determined. The Fourier series expansion method is used to represent the output y such as

$$y(t) \approx b_0 + a_1 cos(\omega t) + b_1 sin(\omega t) + a_2 cos(2\omega t) + b_2 sin(2\omega t) + \cdots$$

$$y(t) \approx b_0 + \sum_{k=1}^{\infty}[a_k cos(k.\omega t) + b_k sin(k.\omega t)] \tag{3}$$

where the Fourier coefficients are given by

$$a_k = \frac{1}{\pi}\int_{-\pi}^{\pi} y(t)cos(k.\omega t)d\omega t \tag{4}$$

$$b_k = \frac{1}{\pi}\int_{-\pi}^{\pi} y(t)sin(k.\omega t)d\omega t \tag{5}$$

$$b_0 = \frac{1}{2\pi}\int_{-\pi}^{\pi} y(t)d\omega t \tag{6}$$

The non-linear function y is then approximated to the first harmonic, resulting in:

$$y(t) = b_0 + a_1 cos(\omega t) + b_1 sin(\omega t) = b_0 + \sqrt{a_1^2 + b_1^2}.cos(\omega t + \phi) \tag{7}$$

where $\phi = arctan\left(\frac{b_1}{a_1}\right)$

In this way, the two terms of the describing function can be determined as

$$N_A = \frac{\sqrt{a_1^2 + b_1^2}}{A} \tag{8}$$

$$N_B = \frac{b_0}{B} \tag{9}$$

For single-valued non-linearities, the coefficient b_1 will be equal to zero and therefore, the phase angle ϕ will be also zero. In case of dynamic multi-valued non-linearities, the describing function will be in the form of $N_A(A, \omega)$. Normally, a plot of $N_A(A, \omega)$ versus $\phi(A, \omega)$ for various values of A and ω are used to understand such complex non-linearities (Gelb 1968).

Examples of supply chain applications of such methods can be found in Spiegler et al. (2016b); Spiegler and Naim (2017); Wang et al. (2015); Spiegler et al. (2016a); Lin et al. (2018). By replacing the different describing function values in the system transfer functions, these studies were able to determine the effect of non-linearities on the system's natural frequency, damping ratio and stability.

3.2 Small Perturbation Theory with Taylor Series Expansion

The Taylor series can be used for approximating the response of a non-linear system to a given input if the output of this system depends strictly on the input at that particular time.

Given a system with single-valued continuous non-linearity

$$\begin{aligned} \dot{x} &= f(x, u) \\ y &= h(x, u) \end{aligned} \tag{10}$$

where x is the state vector, $\dot{x}$ is the time derivative of the state vector, y is the output vector and u is the input vector, we can derive an approximate linear system about a nominal operating state space x^* and for a given input u^* by using small perturbation theory with Taylor series expansion. The linearisation process involved in this approach is such that departures from a steady-state point are small enough to produce transfer function coefficients. Hence, by assuming a small amplitude of the excitation signal, the non-linear differential equations are replaced by a set of linearised differential equations with coefficients dependent upon the steady-state operating point.

The first-order Taylor series approximation of the non-linear state derivatives leads to the following linearised function:

$$\Delta\dot{x} = A\Delta x + B\Delta u \tag{11}$$

$$\Delta y = C\Delta x + D\Delta u \tag{12}$$

where $\Delta x = x - x^*$, $\Delta\dot{x} = \frac{d\Delta x}{dt}$, $\Delta y = y - y^*$, $\Delta u = u - u^*$ and A, B, C, D can be found through the following partial derivatives:

$$\left(\begin{array}{c|c} A & B \\ \hline C & D \end{array}\right) = \left(\begin{array}{ccc|ccc} \frac{\partial f_1(x^*,u^*)}{\partial x_1} & \cdots & \frac{\partial f_1(x^*,u^*)}{\partial x_n} & \frac{\partial f_1(x^*,u^*)}{\partial u_1} & \cdots & \frac{\partial f_1(x^*,u^*)}{\partial u_k} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_n(x^*,u^*)}{\partial x_1} & \cdots & \frac{\partial f_n(x^*,u^*)}{\partial x_n} & \frac{\partial f_n(x^*,u^*)}{\partial u_1} & \cdots & \frac{\partial f_n(x^*,u^*)}{\partial u_k} \\ \hline \frac{\partial h_1(x^*,u^*)}{\partial x_1} & \cdots & \frac{\partial h_1(x^*,u^*)}{\partial x_n} & \frac{\partial h_1(x^*,u^*)}{\partial u_1} & \cdots & \frac{\partial h_1(x^*,u^*)}{\partial u_k} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \frac{\partial h_m(x^*,u^*)}{\partial x_1} & \cdots & \frac{\partial h_m(x^*,u^*)}{\partial x_n} & \frac{\partial h_m(x^*,u^*)}{\partial u_1} & \cdots & \frac{\partial h_m(x^*,u^*)}{\partial u_k} \end{array}\right) \tag{13}$$

where n is the number of state variables, m is the number of outputs and k is the number of inputs.

The nominal operating point (x^*, u^*) normally corresponds to the equilibrium or resting points where all state derivatives are equal to zero and they can be found by applying the final value theorem:

$$x^* = \lim_{t\to\infty} x(t) = \lim_{s\to 0} s.X(s) \tag{14}$$

for a constant input u.

The reader can refer to the works of Spiegler et al. (2016b), Jeong et al. (2000), Wang and Gunasekaran (2017), Lin et al. (2018a) for application of this method in supply chain models. After linearisation is performed, it is possible to find the system transfer function and system design will follow linear control system theory.

3.3 Small Perturbation Theory with Volterra–Wiener Series Expansion

The Volterra series has the ability to deal with multi-valued non-linearities by capturing memory effects. The output from the Volterra series depends on the previous history of the input to the system. Hence, a continuous multi-valued non-linear output can be approximated to

$$
\begin{aligned}
y(t) &= h_0 + \int_{\mathbb{R}} h_1(\tau_1)x(t-\tau_1)d\tau_1 + \int_{\mathbb{R}} h_2(\tau_1,\tau_2)x(t-\tau_1)x(t-\tau_2)d\tau_1 d\tau_2 + ... \\
&= h_0 + \sum_{n=1}^{N} \int_{\mathbb{R}} h_n(\tau_1, ..., \tau_n) \prod_{j=1}^{N} x(t-\tau_j)d\tau_j
\end{aligned} \tag{15}
$$

where h_0 is a constant and for n=1, 2...N, the function $h_n(\tau_1, ..., \tau_n)$ is referred as nth-order Volterra kernel. Note that when $h_0 = 0$ and $N = 1$, the formula describes the system's impulse response by a convolution of $x(t)$. Volterra extended the linear system representation to non-linear systems by adding a series of non-linear integral operators.

The convergence of the Volterra series is comparable to the convergence of the Taylor series expansion of a function which often allows only for small deviations from the starting point. However, the type of convergence required is very rigorous since not only the error has to approach zero with increasing number of terms, but also the derivatives of the error. Hence, the estimation of Volterra coefficients are generally performed by estimating the coefficients of an orthogonalised series, e.g. the Wiener series, and then recomputing the coefficients of the original Volterra series. The readers can refer to Rugh (2002) for more details. No application of this method was found in the supply chain management literature.

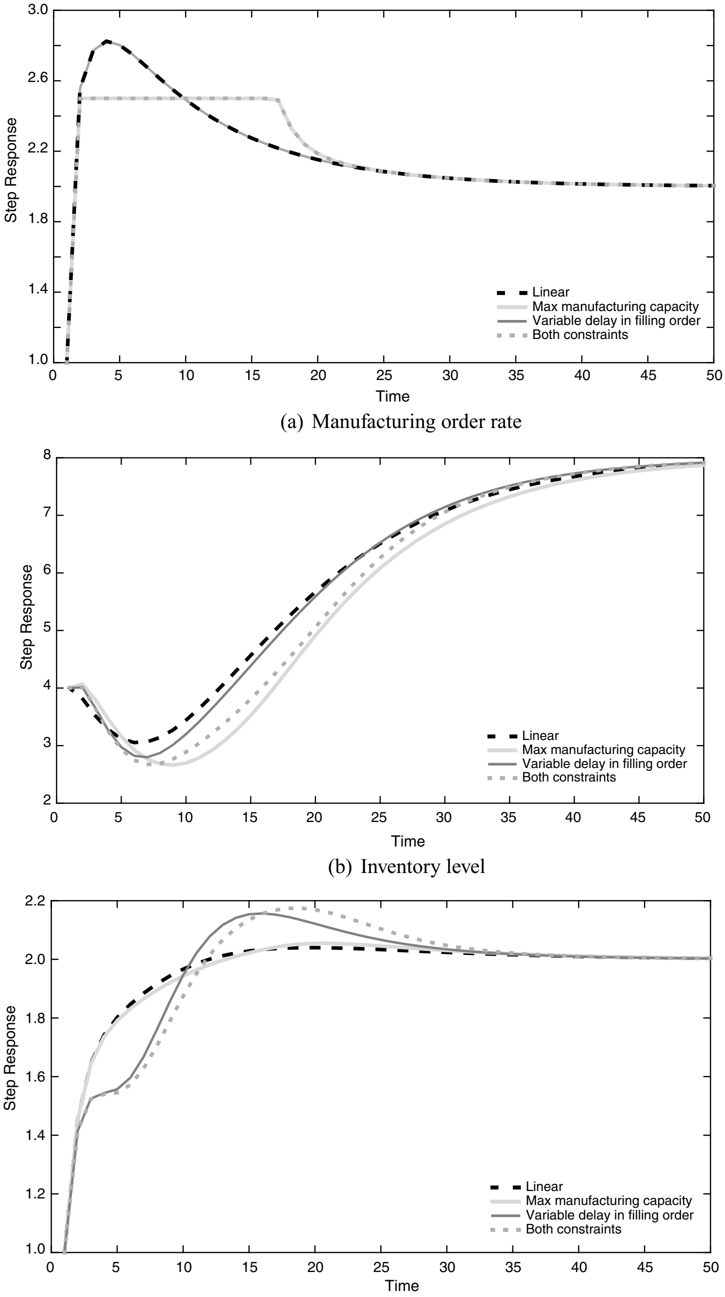
4 The Effects of Non-linearities

In recent years, the researchers have put an effort in shaping stability regions of non-linear supply chain systems and understanding the factors which will lead to chaotic behaviours. These studies made contributions in explaining and tackling uncertainties, dynamics and disruptions in complex supply chain systems, since they elucidated how non-linearities can change a system's transient response by monitoring the variation in terms of output's amplitude, mean and phase and consequently its repercussion on the system's natural frequency and damping ratio. Figure 2 illustrates a few examples on the effect of some non-linearities (maximum manufacturing capacity and variable delay in filling order from the model in Spiegler et al. 2016b) on the system's step response. The figure demonstrates how simplistic linear assumptions can be and that indeed non-linearities can make significant changes to responses' amplitude and settling time. Another observation is that non-linearities affect different performances in different ways. For instance, while the maximum production capacity seems to diminish inventory levels, it helps to decrease the amplification in manufacturing order rate (bullwhip). The variable delay in filling orders will have more negative impact on the outbound shipment rate than on the inventory response. When both non-linearities are considered at the same time, outbound shipments' amplitude and recovery time is further worsened. Response and recovery time as well as over/undershoot are good indicative of the system's resilience (Spiegler et al. 2012) and the diminishment in this performance can affect other players in the supply chain.

Table 3 summarises the current understanding of some types of non-linearities and their impact on the ripple effect. Discontinuous, single-valued non-linearities such as maximum capacity constraints, buying quantity constraints and non-negativities have been predominantly studied by describing function methods (Spiegler et al. 2016b; Spiegler and Naim 2017; Wang et al. 2015; Spiegler et al. 2016a; Lin et al. 2018). This method enabled understanding of the impact of such non-linearities on system output responses, for example manufacturing and supplier orders and production rates. Although this non-linearity does not provoke a shift in the output phase, it will change the output's mean and amplitude. These distortions increase complexity of supply chain dynamics making it difficult for supply chains to respond and recover from disruptions, therefore potentially aggravating the ripple effect. For instance, studies on fixed manufacturing capacity suggest that this non-linearity decreases the amplification of manufacturing orders, consequently decreasing the Bullwhip effect. However, its impact of the manufacturing output mean can slow down the ripple effect mitigation process. In the case of asymmetrical non-linearities, such as in Lin et al. (2018), the output will be relative depending on the relationship between the minimum (non-negative) and maximum capacity constraints. If the mean of the orders received is less than half of the maximum capacity, then the non-negative order boundary dominates. This leads to the increase in average inventory level and orders, therefore increasing costs. If the mean of the desired orders exceeds half of the maximum capacity, then the dominant impact on system dynamics will be the capacity constraint rather than the non-negative order low boundary. Under such condition, mean gain will increase with demand amplitude, leading to the decrease in average inventory level and orders, therefore increasing the risk of disruption.

Describing functions have also been used to analyse discontinuous multi-valued non-linearities such as variable shipment constraints due to changes in customer orders and inventory levels (Spiegler et al. 2016b; Spiegler and Naim 2017; Spiegler et al. 2016a). For low-frequency orders, this dynamic capacity constraint can decrease the output's amplitude and mean and shift the output's phase making the output response lag behind the input. Hence, disruptions are less likely to affect supply chains with high- and medium-frequency demands. Ripple effect mitigation strategies would include encouraging high- frequency purchasing by developing resilient demand management strategies. In Lin et al. (2018, 2018a), a similar non-linearity is applied to switch between 'push' and 'pull' production modes, but the authors decided to evaluate both modes separately through transfer function analysis. This analysis was not able to capture the effect of the switch non-linearity, but the authors were able to conclude that when the upstream operates in make-to-stock mode, other capacity constraints can reduce the bullwhip effect at the expense of increased inventory variability, therefore at the expense of decreased resilience.

Only single-valued continuous non-linearities have been identified in the production and inventory control literature, therefore only Taylor series expansion has been applied as small perturbation method to predict non-linear responses of continuous constraints, such as time-varying delays, resource depletion and real lead-time estimation (Spiegler et al. 2016b; Jeong et al. 2000; Wang and Gunasekaran 2017; Lin et al. 2018a). In Spiegler et al. (2016b); Jeong et al. (2000); Lin et al. (2018a), the



(a) Manufacturing order rate

(b) Inventory level

(c) Outbound shipment rate

Fig. 2 Example of non-linearity effects on transient responses

Table 3 Summary of rippling effects of non-linearities in production and inventory control systems

Source	Non-linearity	Non-linearity type	Method used	Non-linearity output	Effect on output			Potential consequences to Ripple effect
					Amp.	Mean	Phase	
Spiegler et al. (2016b)	Manufacturing constraint	Discontinuous, single-valued	Describing Function	Manufacturing order	$\downarrow$	$\downarrow$	0	Although manufacturing constraints decrease the amplification of manufacturing orders forcing the production manager to prioritise a level production strategy, it substantially decreases the mean of the output, suggesting difficulties in responding to sudden changes in demand and lead time. Hence, this non-linearity can cause disruptions that may cascade downstream affecting all other companies in the supply chain
Spiegler et al. (2016b, a); Spiegler and Naim (2017)	Shipment constraint	Discontinuous, multi-valued	Describing Function	Shipment	$\downarrow$[a]	$\downarrow$[a]	$\leftarrow$[a]	This dynamic capacity constraint in the outbound shipment occurs due to variation in inventory levels and customer orders. A decrease in the output's amplitude and mean is observed and a phase shift makes the output response lag behind the input, only for low frequency orders. Hence, disruptions are less likely to affect supply chains with high and medium frequency demands
Jeong et al. (2000); Spiegler et al. (2016b)	Time-varying delay in filling orders	Continuous, single-valued	Small perturbation with Taylor series	Shipment	$\downarrow\uparrow$	$\downarrow\uparrow$	0	This continuous non-linearity can have cause different impacts to the system output response depending on the parameter choice. Linearisation with Taylor series expansion enables to determine parameter settings that minimises disruptions
Spiegler et al. (2016a)	Buying quantity constraint	Discontinuous, single-valued	Describing Function	Supplier order	$\downarrow$	$\uparrow$	0	A combination of non-negativity and batching constraints made this non-linearity very complex to analyse. Insights obtained in the work suggest that products with the same demand pattern should be grouped together to determine order quantities that minimises disruptions

(continued)

Table 3 (continued)

Source	Non-linearity	Non-linearity type	Method used	Non-linearity output	Effect on output			Potential consequences to Ripple effect
					Amp.	Mean	Phase	
Wang et al. (2015); Spiegler and Naim (2017)	Forbidden return of orders	Discontinuous, single-valued	Describing Function	Supplier order	↓	↑	0	Non-negative constraints in the ordering rule, known as forbidden return constraint, can cause limit cycles, which are oscillations intrinsic to the non-linear production and inventory control system itself and not imposed by the demand. This problem may be exacerbated as this information signal propagates upstream in the supply chain. Distorted orders sent upstream are more likely to cause disruptions through its backlash downstream
Wikner et al. (1992); Naim et al. (2017)	Time-varying delay in filling orders	Continuous, single-valued	Averaging technique + simulation	Shipment	Not able to capture			Although method was unable to understand the impact of this non-linearity on system response, averaging technique enabled researcher to propose a design that minimises disruptions and cost
Wang and Gunasekaran (2017)	Resource availability	Continuous, single-valued	Small perturbation with Taylor series	Production rate	↓	↓	0	The effective production rate is related to the amount of available resources in the current environment. As available resources decrease, the production rate decreases in a non-linear fashion, increasing the risk of disruptions
Wang and Disney (2012); Wang et al. (2014)	Forbidden return of orders	Discontinuous, single-valued	Lyapunov-based stability analysis for piecewise- linear systems	Supplier order	Not able to capture			Although the method was not able to provide understanding on the impact of this non-linearity on system's responses, it enables to undertake an in-depth stability analysis of the system and recommendations for parameter settings

(continued)

Table 3 (continued)

Source	Non-linearity	Non-linearity type	Method used	Non-linearity output	Effect on output			Potential consequences to Ripple effect
					Amp.	Mean	Phase	
Lin et al. (2018))	Manufacturing constraint (non-neg + max capacity)	Discontinuous, single-valued	Averaging technique + simulation	Production rate	$\downarrow$	$\downarrow\uparrow$ 0^{b}	0	Method enables to compare the results between linear and non-linear assumptions under the same control policy settings. A slower recovery speed of assembly work in process and production rate is observed in the non-linear environment due to the effect of non-linearity on the output's amplitude
Lin et al. (2018, a)	Push–Pull decision	Discontinuous, multi-valued	Transfer function analysis of different modes	Assembly rate	Not able to capture			Very complex non-linearity that was analysed only by transfer function analysis of different operating modes. Insights suggests that the non-linearity would behave similarly to the shipment constraint in Spiegler et al. (2016b, a); Spiegler and Naim (2017) due to limited recovery inventory. However, further research needs to be done. Other insights suggest that when upstream operates in make-to-stock mode, non-linearities can reduce the bullwhip effect at the expense of increased inventory variability
Lin et al. (2018a)	Rate change between backlog level and shipment rate	Continuous, single-valued	Small perturbation with Taylor series	Lead time	$\downarrow\uparrow$	$\downarrow\uparrow$	0	This continuous non-linearity can have cause different impacts to the system output response depending on the parameter choice. Linearisation with Taylor series expansion enables to determine parameter settings that minimises disruptions

$\downarrow$ decrease; $\uparrow$ increase; $\leftarrow$ lag;
[a]only for low frequencies;
[b]if symmetrical

non-linear differential equation involved more than one variable, hence, the impact on the output's amplitude and mean will depend on the input and parameter settings. However, linearisation with Taylor series expansion enabled determination of parameter settings that minimise operational disruptions and increase supply chain resilience. In the case of Wang and Gunasekaran (2017), the non-linear differential equation is used to represent the depletion in resources that will certainly have a negative impact on production rate and therefore on the ripple effect. The analysis of this non-linearity can shed light on how to best allocate scarce resources to ensure seamless flows of information and material.

It is worth mentioning that other authors have used analytical methods to analyse non-linearities such as averaging (Wikner et al. 1992; Naim et al. 2017) and stability methods (Wang and Disney 2012; Wang et al. 2014), which even though was not able to capture the effect of non-linearities on system's responses, it allowed establishing parameter settings that minimise cost and disruptions and meet stability requirements indispensable for supply chain resilience.

5 Conclusion and Future Scope

This chapter has revisited the literature of non-linear control theory application in supply chain management. The chapter instructed readers on the different types of non-linearities that can commonly appear in supply chain systems and provoke undesirable dynamic behaviours. A number of methods and references to their application have been introduced and key findings on the rippling effect of non-linearities have been discussed. From the main points discussed in this chapter, we outline the following directions for future research:

1. **Supply chain structural development**: There is an opportunity to explore the effect of different capacity constraints to devise tactical and strategic plans regarding potential adjustments in supply chain structure such as investment in infrastructure and resource efficiency and flexibility. Previous research suggests that adequate capacity levels can help attain desired supply chain performance, therefore a performance-based structure plan can help companies to make right investments depending on their focus: customer service, cost efficiency, risk management and so on. For ripple effect mitigation, this performance-based structure plan should include all members of the supply chain.
2. **Supply chain design development**: There is an important avenue for future research regarding the deliberate employment of non-linearities for improved system's design. Computer simulation enabled the researchers to increase model accuracy and validation to better represent reality. However, the analytical methods here presented bring us one step forward in unravelling the mechanisms of non-linear supply chain dynamics. This knowledge can be used as a advantage in the improvement of the supply chain performance, from operational, economic and environmental viewpoints.

3. **Continuous, multi-valued non-linearities**: Despite not being referenced in the supply chain literature, continuous non-linearities with memory can appear in supply chain models, for example in circular economy supply chains where there is uncertainty of the volume, timing and quality of both demand and returns, therefore multiple inputs should be considered. Hence, future research can build on previous efforts and discoveries to identify new non-linearities in supply chain systems to investigate which limitations and constraints they represent and their effect on system's dynamics.
4. **Discontinuous, multi-valued non-linearities**: Limited study has explored the multi-valued discontinuous non-linearities analytically, even though some insights are obtained by the simulation approach. Discontinuous non-linearities with memory are very common in supply chain systems. For example, the shipment constraint in assemble-to-order systems due to the limited customer order decoupling point (CODP) inventory. Also, the constrained remanufacturing order rate in hybrid manufacturing/remanufacturing systems, driven by the availability of recoverable inventory (limited returned products), is also a multi-valued non-linearity. Future research should analytically predict its impact on ripple effect and suggest the corresponding control strategies in mitigating the unwanted dynamic behaviour.
5. **Effect of lead-time disturbances**: Most research in the application of both linear and non-linear control theories in supply chain management focus on understanding the impact of demand uncertainty and on improving demand forecasting methods. Lead-time fluctuations can lead to performance degradation and increased production costs, just as demand uncertainties can Dolgui et al. (2013) and disturbances and uncertainties in production and supply lead times are reported to be the main sources of supply chain risk Colicchia et al. (2010). Supply chain control theorists have avoided tackling lead-time disturbance under the assumption that models become non-linear.

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Systemic Risk and the Ripple Effect in the Supply Chain

Kevin P. Scheibe and Jennifer Blackhurst

Abstract Supply chains are highly complex systems, and disruptions may ripple through these systems in unexpected ways, but they may also start in unexpected ways. We investigate the causes of ripple effect through the lens of systemic risk. We derive supply chain systemic risk from the finance discipline where sources of risk are found in systemic risk-taking, contagion, and amplification mechanisms. In a supply chain context, we identify three dimensions that influence systemic risk, the nature of a disruption, the structure, and dependency of the supply chain, and the decision-making. Within these three dimensions, there are several factors including correlation of risk, compounding effects, cyclical linkages, counterparty risk, herding behavior, and misaligned incentives. These factors are often invisible to decision makers, and they may operate in tandem to exacerbate ripple effect. We highlight these systemic risks, and we encourage further research to understand their nature and to mitigate their effect.

1 Introduction

There is no doubt regarding the complexity of today's supply chains. Academic literature, consulting reports, and popular press all discuss the challenges associated with handling disruption events in supply chains that span the globe. A company is only as robust as its supply chain, and risk management is becoming increasingly important as companies extend their global reach. Similarly, a survey of global firms noted that disruptions in the supply chain have a significant impact on performance

K. P. Scheibe (✉)
Department of Supply Chain & Information Systems, Ivy College of Business, Iowa State University, 2340 Gerdin Business Building, 2167 Union Drive, Ames, IA 50011-1350, USA
e-mail: kscheibe@iastate.edu

J. Blackhurst
Henry B. Tippie Research Fellow Tippe College of Business, The University of Iowa, W236 Pappajohn Business Building, Iowa City, IA 52242-1994, USA
e-mail: jennifer-blackhurst@uiowa.edu

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(Levi et al. 2013). As such, understanding and managing supply chain disruptions has become a key focus for companies (Blackhurst et al. 2008).

Global supply chains are complex in many ways including the sheer number of connections, as well as the fact that total visibility within these systems is difficult. Indeed, many of the intricacies of the structure and relationships in a supply chain are often unknown or partially known at best. Moreover, supply chain complexity is increasing due to a number of reasons including the following:

- Increased dependencies amongst partners in the supply chain.
- Increased changes in supply chain design.
- Increased new product introductions coupled with increased customization of products.
- Increased number of partners in the supply chain.
- Decreased transparency in supply chain relationships (Levi et al. 2013).

Companies often have little to no visibility of supply chain design past tier 1 suppliers. In other words, a firm may know whom their direct supplier are, but they may not know the suppliers to those suppliers. Likewise, they may be unaware of the partnerships and competitive relationships that exist upstream in their supply chain. All of these factors increase the complexity of supply chains and as a result, vulnerability to disruption events interrupts the flow of goods and services.

As an example of a disruption hitting a supply chain, many reports note the Japanese earthquake in 2011, the largest earthquake to hit Japan in 1500 years of recorded history (Sheffi 2015). Reports track the impacts of the earthquake on companies such as Nissan (Levi et al. 2013) and Intel (Sheffi 2015). Other well-known disruptions include floods in Thailand or Hurricane Sandy in the United States in 2012 (Bhatia et al. 2013). These high-impact disruptions are well known as they affect many companies in a supply chain. In addition, the impact of the disruption propagates to other areas and partners in a supply chain. This propagation is termed the "ripple effect" of the disruption in the supply chain (Ivanov et al. 2014).

These "low probability/high impact" events such as the 2011 Japanese earthquake are considered to be a primary cause of ripple effect (Ivanov et al. 2014). However, we contend that also seemingly small disruptions can grow and propagate throughout the supply chain with devastating impacts. These disruptions may not make popular press outlets, but the effects can still be large and impactful. In addition, unlike low probability events, many "high probability/low impact events" are actually much larger than ever anticipated. One such example is demonstrated in a recent conversation with a manager at a global aerospace firm headquartered in the United States. The discussion centered around dynamically managing safety stock in real time and in response to current events in the supply chain. While low probability/high-impact events were discussed, it was also noted that the everyday glitches (or high probability/low-impact events) in the supply chain can have a significant and negative impact. A recent shortage of screws costing less than $100.00 USD each cost the company over $2 million USD in lost sales. In this example, a seemingly small disruption rippled out from a point of origin to other parts of the supply chain with noticeably growing impact.

In this chapter, we expand on the concept of ripple effect and focus on potential causes through the lens of systemic risk. Specifically, we identify each of the three dimensions of systemic risk: (1) the nature of a disruption, (2) the structure and dependency within the supply chain, and (3) the decision-making of supply chain managers. Within these dimensions, we discuss six factors: (1) correlation of risk, (2) compounding effects, (3) cyclical linkages, (4) counterparty risk, (5) herding behavior, and (6) misaligned incentives that influence the ripple effect. We first describe ripple effect. Next, we discuss the origin of systemic risk in the world of finance. This is followed by defining supply chain systemic risk, its dimensions, and factors. We then describe how each factor can influence ripple effect. Finally, we discuss implications for managers and call for more research in this area.

2 Ripple Effect

Ripple effects have been discussed in many different disciplines and share the similar characteristic of the continued propagation of an effect within a system. For example, it has been shown that moods can be passed among members of a group in a form of emotional contagion (Barsade 2002). Customer loyalty is also contagious with happy customers making new customers by sharing their positive experiences through word of mouth (Gremler and Brown 1999). The price of houses is influenced by other house prices (Meen 1999). The happiness a pet brings to its owner will extend to non-pet owners and beyond (Wood et al. 2007). When an error is introduced in software development, the effect will cascade throughout the code well beyond the originating module (Black 2001, 2006; Haney 1972; Yau et al. 1978).

Within the context of the supply chain, Ivanov, Sokolov, and Dolgui define the ripple effect as "the impact of a disruption on the SC performance and disruption-based scope of changes in the SC structures and parameters" (Ivanov et al. 2014). It is also known as the domino effect (Dolgui et al. 2018). Dolgui et al. (2018) differentiate between ripple effect and bullwhip effect in terms of frequency and severity of disruptions. They contend that a ripple effect occurs with low frequency and high intensity, while the bullwhip effect has a higher frequency and lower severity. The ripple effect has also been described by Hearnshaw and Wilson (2013) in terms of cascading failures in the supply chain.

However, as laid out in the introduction, we believe that the bullwhip effect is one type of ripple effect, and that frequency and intensity are not distinctions of the two. In fact, we argue that it is possible for small disruptions to gain intensity and become very problematic based on how the supply chain system responds. It is due to the highly connected and interdependent nature of relationships in the supply chain that create this environment. Because the dependence of one partner on another may be large, there is a systemic nature to supply chain risk where a disruption can occur not only at one specific point in the supply chain but ripple, extend, and intensify to other parts of the supply chain.

Moreover, the lack of visibility into the depths of the supply chain as well as the fact that a company's partners may be part of other, unknown supply chains can create higher levels of risk not previously studied. We discuss the impact of systemic risk on ripple effect of disruption events in the supply chain.

3 Systemic Risk

The concept of systemic risk comes from finance and economics, and there is a growing body of literature investigating the causes and effects of systemic risk in the finance literature. In fact, Basole and Bellamy (2014) study risk diffusion in supplier networks and note the finance literature for insights in studying the propagation of risks such as contagion stemming from shocks in financial networks and the impact of different forms of systemic risk on financial stability.

Systemic risk is "the risk or probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components, and is evidenced by co-movements (correlation) among most or all the parts" (Kaufman and Scott 2003). Similarly, Acharya (2009) discusses systemic risk where one bank's failure propagates as a contagion causing the failure of many banks in the financial system. Agca et al. (2017) note that supply chains are a mechanism through which disruptions (in the context of financial shocks) can spread. In this regard, the intersection of systemic risk and supply chains is interesting and timely.

In their survey of financial systemic risk literature, Benoit et al. (2017) group research by the sources of systemic risk. The three groups are:

1. Systemic risk-taking—why financial institutions take risks that are large and connected or correlated.
2. Contagion mechanisms—how losses spill over from one part of a financial system to another.
3. Amplification mechanisms—why small disruptions or shocks can have much larger impacts.

The concept of systemic risk is likened to understanding the fragility of a network—consideration of where the system is susceptible to the ripple effect of a disruption. We use systemic risk as a lens though which to examine and understand supply chain risk and the ripple effect of a disruption.

3.1 Dimensions of Supply Chain Systemic Risk

Scheibe and Blackhurst (2018) link systemic risk to supply chain ripple effect through a qualitative study investigating 21 companies in 7 supply chains, at 3 levels each. In this research, 3 aggregate dimensions of systemic risk factors that influence the ripple effect emerged:

- Nature of the disruption
- Supply chain structure and dependence
- Managerial decision-making.

Under each of the three dimensions are systemic risk themes. First, under the dimension of understanding the nature of the disruption, we discuss the conception of correlation of risk and the compounding effects of a disruption as it ripples through the supply chain. Next, under the dimension of the structure of the supply chain and the dependence within that structure, we discuss the interesting phenomenon of cyclical linkages (a type of structure that impacts the ripple effect) and counterparty risk (hidden relationships and dependency that increase risk exposure). Finally, under the dimension of managerial decision-making in the supply chain, we discuss herding behaviors and the influence of misaligned incentives.

3.1.1 Nature of Disruption

The first of the three aggregated dimensions is the nature of the disruption itself. Disruptions will vary in frequency and severity, and the disruptions themselves have characteristics that will influence the way in which they will ripple through a system. Specifically, disruptions are influenced by the correlation of risks and the way in which some types of disruptions have a compounding effect.

Correlation of Risk

When Chopra and Sodhi (2004) described different risk mitigation strategies, they depicted how it would be possible to reduce some risks and increase others. For example, a company could add inventory and that would have a small reduction of risk in disruptions, a greater reduction in delay risk, a small reduction in procurement risk and capacity risk, but would increase inventory risk. This is shown in Table 1 and is an excellent example of the correlation of risk events in a supply chain. Risks cannot be considered in isolation, and supply chain managers must understand the related nature of the risks, or they may inadvertently cause a disruption while trying to mitigate the risk of a disruption in another area.

Ackermann et al. (2007) notes that it is the *interaction* of risks that can cause the most damage. Therefore, the managers must consider more than just individual risks themselves. In fact, one risk can reinforce the likelihood of another risk occurring. The managers should be continually looking for and understanding these interactions by employing the functional expertise of many within the company. In other words, managing the ripple effect in the supply chain should span beyond functional boundaries.

Moreover, the managers should look to new technologies and the use of analytics to understand risk correlations. For example, Sheffi (2015, p. 207) notes the emergence of firms like Verisk Analytics who "use data science to find possible

Table 1 Mitigation strategies from Chopra and Sodhi (2004)

Mitigation Strategy	Disruptions	Delays	Forecast risk	Procurement risk	Receivables risk	Capacity risk	Inventory risk
Add capacity		⬇		▼		⬆	▼
Add inventory	▼	⬇		▼		▼	⬆
Have redundant suppliers	⬇			▼		▲	▼
Increase responsiveness		⬇	⬇				
Increase flexibility		▼		▼		⬇	▼
Aggregate or pool demand			⬇			⬇	⬇
Increase capability		▼					▼
Have more customer accounts					▼		

Greatly Increase Risk ⬆ ▼ Decrease Risk

Increase Risk ▲ ⬇ Greatly Decrease Risk

correlations between various incidents and impending geopolitical events that may disrupt businesses." Many firms are creating and enhancing in-house systems leveraging analytics.

Compounding Effects

The compounding effect of risk is similar to the concept of flutter in the physical sciences. A classic example of flutter is the "Galloping Gertie" (Kambhu et al. 2007) where the Tacoma Narrows Bridge, a suspension bridge spanning a part of the Puget Sound in Washington, was subjected to strong winds and began to twist and vibrate until it collapsed into the water. By itself, the wind was not enough to destroy the bridge, but as the bridge oscillated, the vibrations fed on themselves and worsened. This cyclical compounding effect, in combination with shock and contagion, is in great part responsible to the collapse of the stock market and the resulting Great Depression.

The bullwhip effect is a classic example of the compounding nature of disruptions (Fig. 1). Small variations in demand can grow in intensity up the supply chain, particularly when there is information lag. Another contribution to the compounding nature of disruptions is the decisions made by actors in the supply chain. This is

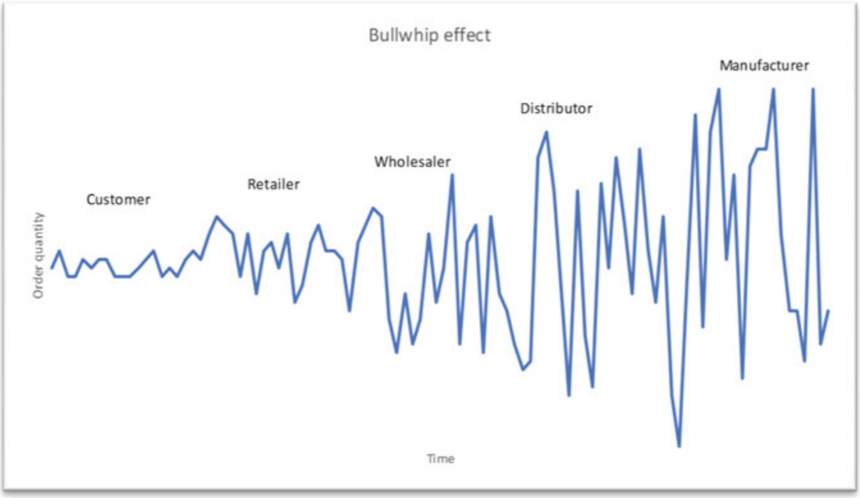


Fig. 1 Bullwhip effect

especially true when the decisions are self-preserving and potentially at the cost of the other actors. When decision makers engage in protectionist or even opportunist type decisions, the disruption may grow as it is passed onto supply chain partners and suppliers. A company may decide to increase inventory to withstand a particular disruption but by doing so, they encourage ripple effect.

We encourage managers to monitor and understand the impact of these compounding effects where a seemingly minor disruption can cause massive damage. Sheffi (2015, p. 161) notes that while firms have visibility of tier 1 partners, there is little visibility into "deep-tier" supply chain partners and warn of "the impact of a disrupted supplier ripples outward from the supplier to more distant customers."

3.1.2 Supply Chain Structure and Dependence

The second aggregate dimension in systemic risk is the structure of the supply chain and the dependencies of the partners. When supply chains are tightly coupled with high levels of dependencies, they are more susceptible to disruptions. Basole and Bellamy (2014) note that network structure influences the rate at which risk ripples through the supply network like a line of dominos (Fig. 2).

Interestingly, technology has enabled supply chain partners to become more dependent upon each other, which can increase efficiencies, but also increase the risk of ripple effect. Scheibe and Blackhurst (2018) found two factors that greatly influenced the systemic risk nature of ripple effects in supply chains, cyclical linkages, and counterparty risk.

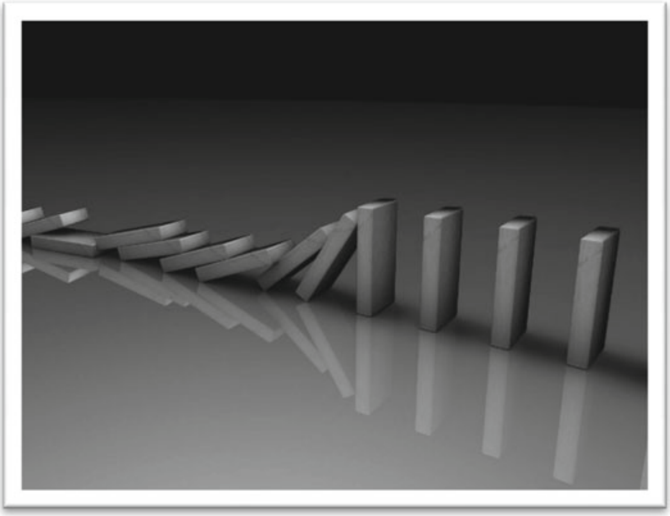


Fig. 2 Dominos

3.1.3 Cyclical Linkages

To explain cyclical linkages, let us note that it is not uncommon for final/assembled products to have subassemblies. Consider the simple example in Fig. 3 where A supplies a part to B. B then takes the part that was supplied by A and modifies it and sends it on to C, which does the same and sends it to D. D takes the subassembly, modifies it, and finally ships it to A where it may be put into final assembly. Therefore, if there is a disruption in A, the cyclical nature of this supply chain will cause A to experience the disruption not only in the first round but also in the second. If there are additional loops in subassembly modification, this problem will only increase. This possibility of structure increasing risk exposure is discussed through the lens of systemic risk by Eisenberg and Noe (2001) by looking at risk prorogation in a financial network. The same logic applies in a supply chain context, especially in industries where circular linkages are common and perhaps not readily visible.

Ackermann et al. (2007) note that circular linkages can cause vicious cycles where a risk event evolves into a self-sustaining disaster. The managers must be vigilant in understanding these structural pitfalls in their supply chains.

3.1.4 Counterparty Risk

A supplier to a company may be a supplier to a competitor or even a company in a different industry. As such, a supply chain supply partner may be a part of multiple supply chains. In financial systemic risk literature, Acharya and Engle (2009) state

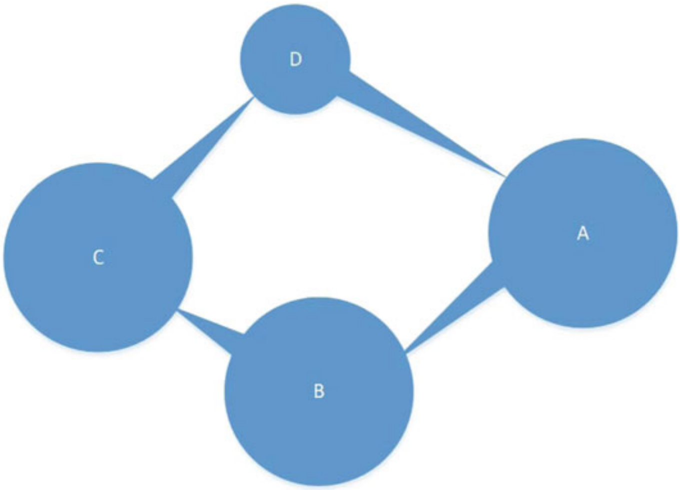


Fig. 3 Cyclical linkages

that "a party to a financial contract may sign a second, similar contract with someone else—increasing the risk that it may be unable to meet its obligations on the first contract. So, the actual risk on one deal depends on what other deals are being done." This exemplifies counterparty risk. It occurs when one partner in a supply chain is affected by the decision of other partners in hidden ways.

Consider Fig. 4. Two separate supply chains share a common partner, Company A. In supply chain 1 (SC1), a supplier to Company A experiences some kind of disruption and are not able to supply product. This will cause a disruption to ripple through SC1. However, since Company A is engaged in both SC1 and supply chain 2 (SC2), it is possible that it will need to refocus efforts to mitigate the disruption in SC1. This might be done by reallocating resources that might have been used in SC2, thus the ripple of the disruption in SC1 can also be felt in SC2 even though the actual disruption did not occur in SC2. It is unknown whether the disruption will ripple in SC2 based on the disruption in SC1. Several factors will influence the ripple. For example, if the customer of Company A in SC1 is significant, then they may be motivated to shift resources from SC2 to satisfy the needs of the customer in SC1. However, if the partners in SC2 are more important, then the ripple may never be felt in SC2 but would be exacerbated in SC1. This is almost impossible to proactively plan for this type of disruption because it is difficult enough to know one's own supply chain beyond the first tier, let alone an entirely different supply chain that may be shared by common partners. Therefore, it is important for suppliers to maintain some level of agility to be able to overcome these unforeseen disruptions.

This risk is particularly interesting as it has not been discussed in the supply chain literature. We believe that counterparty risk is a source of great and not-well-understood danger. Counterparty risk is a risk that needs to be better understood.

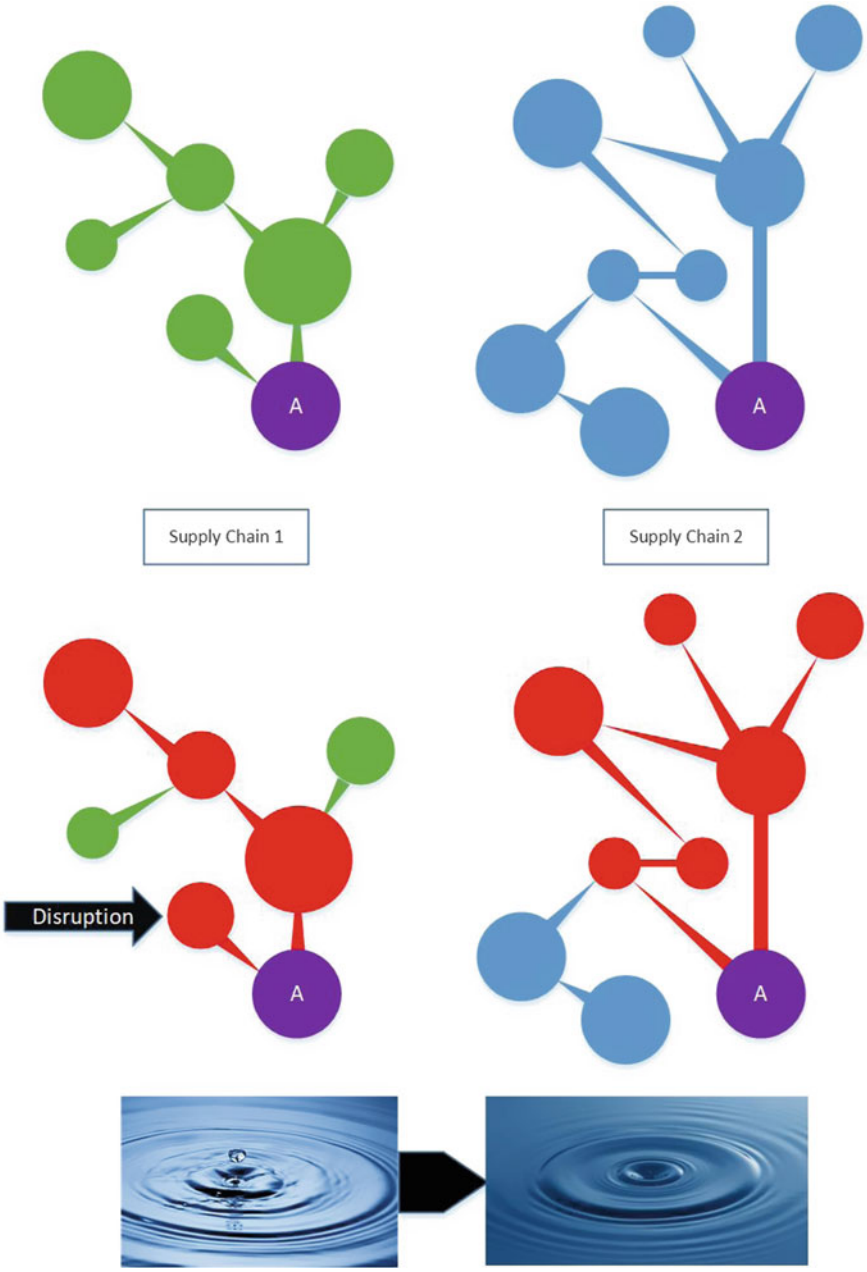


Fig. 4 Counterparty risk

However, we warn that this is much more than understanding one's own supply chain. Rather, understanding one's supply chain partners and with whom they are connected and exposed to risk. Sheffi (2015) notes that the detection of disruptions in deep-tier or hidden parts of the supply chain is essential. Again, this is a prime opportunity for supply chain analytics.

3.1.5 Managerial Decision-Making

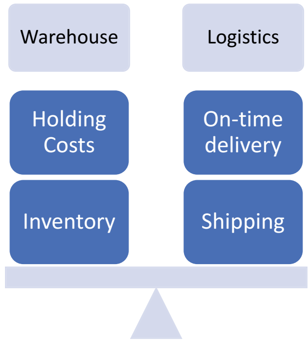
Herding

Herding behavior (Fig. 5) occurs when firms behave in a similar fashion after a disruption occurs. The reaction to a disruption will most likely be to protect their own interests, but in doing so, they can increase the effect of the disruption. For example, when a fire occurred in a memory manufacturer in China, the prices of memory soared as suppliers all competed for the remaining stock of memory remaining in the market. As memory was purchased to increase the safety stock levels in individual companies, the entire supply chain suffered. Organizations that may not have actually needed the memory still purchased it just to be safe.

Here, the manager should understand trends and risk event worldwide to get ahead of herding disasters. Certainly, risk hedging is a part of this, but we caution the managers to think "bigger" and perhaps include these conversations in new product development initiatives or even redesign initiatives. We also wonder whether being "ahead of the curve" on herding decisions could be used as a competitive advantage in the supply chain. If a shortage on material or part is looming, could a firm purchase inventory ahead of the need? If a logistics channel is challenged, could capacity be

Fig. 5 Heard of Lamas

Fig. 6 Misaligned incentives



purchased in advance? Of course, that may not address the danger of herding. It would simply be an attempt to be in the front of the heard.

Misaligned Incentives

Misaligned incentives occur when individuals, groups, divisions, or organizations are rewarded for behaviors that would conflict with others within and across organizations. For example, consider a company with separate division of warehousing and logistics. If a company wants to reward keeping costs low, a conflict will exist. For a warehouse to keep costs low, a manager would want to keep the inventory levels as low as possible which would require more frequent shipping. However, for the shipping manager to keep costs low, it would be better to wait to optimally fill trucks before they left dock. Thus, cost savings from one division would come at the expense of the other. From an organizational perspective, it would be better for both warehousing and shipping to find a happy medium where both would incur greater costs, but the savings to the entire company would be higher (Fig. 6). This problem exists not only within an organization, but across organizations, and that makes it even more difficult to see, where information may not be shared (Narayanan and Raman 2004).

Managers should remember that looking at the whole system is important. While tactical or lower level incentives are critical to measure performance, do they link up to the strategic and long-term goals of the firm?

4 Discussion and Conclusions

We end this chapter with an interesting example of the ripple effect and systemic risk related to the 2011 earthquake. Sheffi (2015) studied this event from the point of view of General Motors. General Motors had estimated that 390 parts might be disrupted based on their knowledge of their supply chain and the extent of the disaster. However,

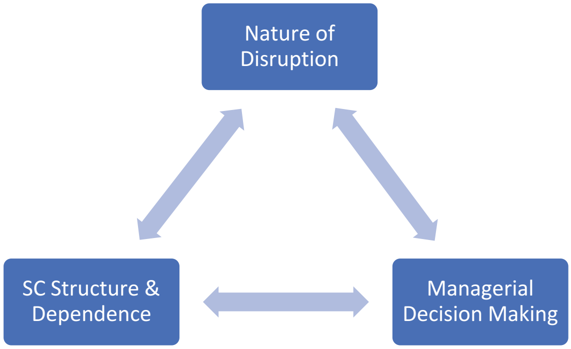


Fig. 7 Interrelated nature of systemic risk (Scheibe and Blackhurst 2018)

that estimate was greatly underestimated due to hidden impacts and relationships in the supply chain. In fact, over 6,000 parts were affected.

The challenge that systemic risk presents with ripple effect is that each of the dimensions is influential and is often unseen, but it is the combination of dimension that really drives ripples throughout a system. It is important for firms to be aware of the interconnectedness of the three dimensions and that the systemic risk themes rarely occur in isolation. The literature often discusses disruptions from a natural disaster perspective, but these disruptions may occur as a consequence of the structure of the supply chain or the choices made by managers.

Researchers are attempting to focus on the relationship between these dimensions, but given the complexity of supply chains, the hidden nature of many risks, and the unexpected interactions of these dimensions, it is common to only address one or two of the risk factors at a time. There still remains a tremendous amount of research investigating how these systemic risk factors interact, and how that affects the ripple effect, supply chain robustness, and resiliency, and how risk managers can adequately plan for and mitigate the effect of disruptions.

We present risk types along the following three interrelated dimensions: Nature of the Disruption, Structure and Dependence of the Supply Chain, and Managerial Decision Making (Fig. 7).

Nature of the Disruption:
In this dimension, we discuss the conception of correlation of risk and the compounding effects of a disruption as it ripples through the supply chain. With regards to the correlation of risk, we encourage the managers to build cross-functional teams to understand the impact of risk events on each other. For example, if a supply manager institutes a JIT policy on key inventory items to reduce the risk of obsolesce and high inventory cost, this might increase the risk of customer shortages and high expediting costs if there is a disruption in the supply chain. We also encourage the use of analytics to understand the nuances and links between risk types. With regards to the compounding effects, much attention is given to large and well-known events such as earthquakes. While it is important to manage these risks, the smaller everyday occurrences have the potential to grow and ripple through the supply chain. As

such, the managers must be ever vigilant with planning frameworks for high impact, low probability events but also the flexibility and resources for the high probability, low-impact events that can escalate is not addressed.

Structure of the Supply Chain

Modern supply chains are information driven. The world continues to increase in connectivity. Industry 4.0 is driving real-time data analysis, and this allows supply chains to become extremely efficient. However, this efficiency may come at a cost. In one respect, it is as though the dominos are being placed even closer together, so when one begins to topple, it becomes nearly impossible to prevent others from falling as well.

In this dimension, we not also discuss the structure of the supply chain but also the dependence within that structure. Here, the concepts of cyclical linkages (a type of structure that impacts the ripple effect) and counterparty risk (hidden relationships and dependency that increase risk exposure) are presented. We encourage the managers to strive to better understand the structure and links within the supply chain. From supply management frameworks and mapping exercises to more extensive deep dives into the supply chain and employing supply chain risk monitoring firms. Not only is your supply chain susceptible to disruptions from your partners and suppliers, but it could also be exposed to disruptions in entirely different supply chains. We believe that this dimension is the least understood dimension and poses the highest threat to firms. Academic research in this area is encouraged to understand and manage these risk types. We have been able to demonstrate its existence, but more research should be devoted to this effect.

Managerial Decision-making

In this dimension, we discuss herding behaviors and the impact of misaligned incentives. We encourage the managers to leverage improved decision-making for a competitive advantage and work to truly align incentives across the supply chain. The mangers ought to consider a bigger picture, but that also presents its own problems. We had several conversations with a large organization developing highly complex products. This manufacturer had 300 tier 1 suppliers, and 3000 tier 2 and above. Some of their tier 1 was also their tier 2, 3, and 4. They had no clear picture of how exposed their product was based upon disruption events. They told us that when the tsunami hit Japan, they went to their tier 1 suppliers to see if they were going to be affected. They even looked into their tier 2, and they determined they were okay, only to find they had a tier 4 supplier that was greatly affected, and this rippled through the system and did, indeed, affect the company's products.

The concept of supply chain ripple effect has grown in popularity over the last few years. Because disruption will ripple through a system, a systemic risk perspective is crucial to understand not only the nature of the disruption but also the effects of the structure of the supply chain and the consequences of choices made by decision makers. Researcher and practitioners should expand their risk analysis to consider the effects of systemic risk and how it influences the ripple effect.

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Leadership For Mitigating Ripple Effects in Supply Chain Disruptions: A Paradoxical Role

Iana Shaheen, Arash Azadegan, Robert Hooker and Lorenzo Lucianetti

Abstract For leadership, responding to supply chain disruptions can be paradoxical. Supply chain disruptions can rattle the stability and operational norms of a company and its stakeholders. Without an unwavering effort to contain the damage, such disruptions can easily propagate and become even more damaging. This assertion suggests that decisive leadership is fit for the purpose. However, supply chain disruptions often sever multiple value-generating streams, creating a ripple effect across organizations. Re-establishing production links in a web of inter-organizational exchanges requires careful examination of what is at stake by purchasing and supply managers. This alternative assertion suggests that an adaptive leader is fit for the purpose. The concurrent need for decisiveness in leadership and adaptiveness in leadership can be paradoxical. In this study, we explore this issue by assessing how leader's adaptive decision-making (ADM) affects the extent of operational performance damage caused by different forms of supply chain disruptions. Using paradox and leadership theories, we offer hypotheses related to unexpected, complicated and enduring supply chain disruptions. We empirically test our hypotheses using secondary (financial) and primary (managerial assessment) data from a cross-section of 251 manufacturing firms. Results show a concave curvilinear relationship between leader's ADM and operational damage from supply chain disruptions, suggesting that moderate levels of ADM are optimal. Higher ADM is particularly effective to diminish ripple effects in the face of rare disruptions. Instead, low ADM is more effective in the face of unexpected and complicated disruptions.

I. Shaheen (✉) · R. Hooker
University of South Florida Tampa, Tampa, Florida, USA
e-mail: ianalukina@usf.edu

A. Azadegan
Rutgers Business School New Brunswick, Piscataway Township, New Jersey, USA

L. Lucianetti
University of Chieti and Pescara, Pescara, Italy

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1 Introduction

Disruptions have the ability to cause notable damage to a supply chain. As of late, supply chain disruptions have become seemingly more commonplace (Bode and Wagner 2015). Today's globally interconnected, time-sensitive, and efficiency focused operations set the stage for disruptions to disperse and affect multiple entities (Brandon et al. 2014; Ivanov et al. 2014). Disruptions may significantly impact the supply management function, because failures in handling the disruption in one company can easily spill-over effects to others (Sokolov et al. 2016). The "ripple" is characterized by disruption's cascading effect downstream, impacting supply chain performance (Dolgui et al. 2018). UPS Capital Report 2014 survey shows that more than half of the surveyed firms had suppliers who could not continue supplying within a reasonable time frame if they suffered a disaster in one location (Dittmann 2014). These factors place pressure on supply chain executives. While unforgiving to poor decisions, supply chain supply chain disruptions require the short-order assembly of resources alongside prudent decisions to prevent the disruption from further propagation and to re-establish organizational norms. By definition, supply chain disruptions create unstructured, vague, and urgent dilemmas for leaders and arise from the intricate interactions among suppliers that make supply chains more vulnerable (Azadegan and Jayaram 2018; MacDonald and Corsi 2013; Wagner and Bode 2006).

Leadership plays a critical role in addressing supply chain disruptions. The business scene is replete with cases where an unwavering leader organized resources, directed efforts, and motivated members to rally in front of disruptive events (Howell and Shea 2006). In contrast, the absence of a decisive leader has led to mismanagement of response and recovery efforts and caused further disorganization and damage (Shaw and Goda 2004). Some believe that errors and omissions by leaders are the second major source of harmful outcomes during disruptions (Dynes et al. 1981).

It is unclear as to how leaders are best to deal with supply chain disruptions. Contrasting leadership approaches have been shown to be effective in the face of similar disruptions. For example, consider the now classic case of responding to a major product recall by Johnson and Johnson. James Burke, the company's chairman, made a decisive move to replace the entire stock of Tylenol tablets off of the market. This bold move costs more than $100 million but saved the company's reputation and potentially many lives (Prokesh 1986). Burke was widely admired for his "take charge" leadership style. This contrasts with how PepsiCo's CEO, Craig Weatherup, addressed a similar product contamination crisis. In 1993, reports from several sources surfaced that syringes had been found in cans of Diet Pepsi. Instead of jumping in with a reflexive response to recall products, Weatherup pulled company executives together and formed a crisis response team to carefully analyze all potential means for foreign objects to enter the production stream across the value chain (Novak 2009). This thorough and prudent assessment allowed him to appear on national TV with visual evidence that cast heavy doubts on the legitimacy of the reported cases.

Leadership in the face of supply chain disruptions can be challenging. On the one hand, there is need for decisiveness in action to effectively contain the situation (Shaheen et al. 2017; Eisenstat et al. 2008). A strong and unbending leader that can set the agenda and enforce strict protocols seems well suited for the purpose (Özçelik and Cenkci 2014). Indeed, crisis managers have often been recognized because they confidently "took charge" and unwaveringly led the organization (James and Wooten 2005; Yukl 2005). On the other hand, supply chain disruptions can be ambiguous and complicated. Given the tangled and complex nature of supply chains, leaders must carefully consider pertinent facts, intricacies of the issues, and potential ramifications of their decisions. Like Weatherup, leaders are often admired because of their considerate and adaptive approach in such settings.

Whether decisiveness or adaptiveness is more effective for a leader facing supply chain disruptions is unclear. Whereas decisiveness relates to uncompromising sternness on one's attitude and the manner in approaching a disruption, adaptiveness implies flexibility in decision-making by considering multiple views. We explore this tension by delving into how a leader's adaptive decision-making (ADM) affects the outcome of various types of supply chain disruptions. ADM is the leader's capacity to adjust thoughts and behaviors so as to enact appropriate responses to evolving situations (Hannah et al. 2013). In this perspective, we consider ADM as a continuum ranging from leader decisiveness (i.e., a resolute and stern leader) to leader adaptiveness (i.e., a flexible and integrative leader). We ask: How does a leader ADM help (or hinder) response and recovery efforts in the face of different forms of supply chain disruptions? We leverage theories in paradox and leadership to explain how leadership can be effective in the face of supply chain disruptions.

2 Leadership and Supply Chain Disruptions—A Literature Review

By now, it is well established that supply chain disruptions can be challenging and harmful (Hendricks and Singhal 2003). However, not all of such disruptions cause the same level of harm, nor they do create the same type of challenge for leaders (Ketchen et al. 2014). A review of the literature suggests that among the primary differentiators of supply chain disruptions is the extent to which they are (i) unexpected (ii) complicated, and (iii) rare (Craighead et al. 2007). Unexpected supply chain disruptions are those that happen without pre-warning or act unpredictably as they unfold (Cunha et al. 2006). Unexpected supply chain disruptions are challenging because they leave no preparation time to collect information or to prepare for the ensuing damage (Ansoff 1975). For instance, General Motors management had a 30-minute alert before a tornado touched down on their plant in Oklahoma City causing extensive damage to the paint shop, body shop, and powerhouse (Sheffi and Rice 2005). Complicated disruptions are those that sever numerous value adding streams across organizations. The great Japan Tsunami of 2011 was quite complicated for the auto industry as it affected a multitude of parts suppliers and manufacturers while simultaneously severed transportation and distribution links (Park et al. 2013). Finally, rare supply chain disruptions are unique in the sense of offering no past experience that parallels them such that the firm can draw lessons from (Lampel et al. 2009). This lack of familiarity lowers the organization's confidence in their ability to effectively deal with the situation. For example, the West Coast Port slowdown in 2015 was a rare disruption, creating issues for companies not prepared to deal with the long-term impact of being left without access to Californian ports of entry (Soergel 2016). In the remainder of the manuscript, we delve in-to how these different forms of supply chain disruptions affect organizations and how leadership can address them.

Table 1 provides a selective group of literature about leadership as explored in related streams. This literature review suggests that there is a diversion in interpretation between crisis management and supply chain management literature. Whereas the former group highlights leader's resolute decision making to address the crisis (i.e., decisiveness), the latter emphasizes the need to be prudent and to recognize the intricacies of the supply system through analytical thinking and integration (i.e., adaptiveness). Rooted in disaster studies, crisis and humanitarian research views addressing the needs of human victims as a principal objective of leadership. Instead, rooted in operations management, supply chain research views the restoration of production systems as an essential responsibility for the leader. As interpreted by supply chains researchers, an effective leader not only addresses the needs of any potential victim (e.g., an employee, consumer, or supplier personnel), but also is responsible for alleviating the bottom line financial or reputational effects of the supply chain disruption.

The dichotomy between leader decisiveness and adaptiveness becomes more confounding as supply chain disruptions become more challenging. Earlier we explained how challenging disruptions come in (a) unexpected, (b) complicated, and (c) enduring forms. Supply chain disruptions become even more difficult as they take on one or more of these forms. In the next section, we explore how such paradoxical phenomena can be explained. We then offer hypotheses on how leader ADM can be effective in facing disruptions with different characteristics.

3 Theory—Supply Chain Disruptions as Paradox and Leadership ADM

Paradox involves the simultaneous presence of contradictory and mutually exclusive elements (Poole and Van de Ven 1989). The common features of supply chain disruptions—urgency, ambiguity, and high stakes—also severely constrain the leader's ability to assess information and make decisions effectively (Pearson and Clair 1998). This creates consternations for the leader. As Dutton (1986) notes, it may be impossible to achieve a full understanding of the nature, underlying reasons, and conse-

Table 1 Key findings from crisis leadership and supply chain leadership literature

Crisis leadership literature		Emphasis on	
Authors (year)	Key findings	Decisiveness	Prudence
House (1971)	A decisive decision making style is important in leadership contexts	I	
Mulder et al. (1971)	Naval officers with directive and autocratic capabilities are more effective during emergency situations	I	
Roberts and Bradley (1988)	During crisis, the charismatic leadership provides only limited results	I	
Pillai and Meindl (1998)	Employees' perceptions of crisis management were negatively related to charismatic leadership		I
Hunt et al. (1999)	During a crisis, crisis-responsive charismatic leaders are important	I	
Shenkman (2000)	One of the qualities of a great president during crisis is decisiveness and quick response	I	
James and Wooten (2005)	Effective crisis leadership involves the leaders' ability to make wise and rapid decisions	I	
Yukl (2005)	Strong and decisive leadership appears to be especially important when crisis exists	I	
Van Wassenhove (2006)	When facing a humanitarian crisis, leaders often need to take actions quickly	I	
Ginter et al. (2006)	When responding to crisis, high reliability team need to have clear and decisive leaderships	I	
Cavanaugh et al. (2008)	As the damage cause by disruption grows, the need for a decisive and determined leader grows	I	
Peterson and Van Fleet (2008)	Nonprofit firms prefer leaders to use directive behavior over supportive behavior in a crisis	I	

(continued)

Table 1 (continued)

Crisis leadership literature		Emphasis on	
Authors (year)	Key findings	Decisiveness	Prudence
Tatham and Kovács (2010)	An effective crisis manager needs to emphasize immediate results and decisiveness over inclusiveness	I	
Bechky and Okhuysen (2011)	During emergencies, SWAT team officers are required to reinforce task activities, and make timely decisions	I	
Van Wart et al. (2011)	Decisiveness is one of the top two competencies for emergency managers	I	
Stern (2013)	Leaders need to make crucial decisions in a timely fashion under difficult conditions	I	
DuBrin (2014)	Directive and decisive leaders are generally successful in extreme contexts	I	
Haddon et al. (2015)	During financial crisis, employees expect leaders to take actions quickly and provide rapid response	I	
Supply chain leadership literature			I
Spekman et al. (1998)	Supply chain managers' trust and commitment contribute to performance as the elements of collaboration		I
Gammelgaard and Larson 2001	Listening/team work are the top skills for supply chain leaders, while performance under pressure is lower in ranking		I
Harvey and Richey (2001)	Analytical, Practical, and Creative Intelligence are key capabilities for global supply chain manager		I
Parker and Anderson (2002)	Supply chain manager should be an integrator who coordinates activities from product concept to delivery across firm		I
van Hoek et al. 2002	Supply chain managers need to concentrate on self-motivation and adaptability toward the change		I

(continued)

Table 1 (continued)

Crisis leadership literature		Emphasis on	
Authors (year)	Key findings	Decisiveness	Prudence
Williams et al. (2002)	In eSC, autocratic/participative leaders are ineffective. Instead, transformational leader is cost effective		I
Mangan and Christopher (2005)	The key skills for supply chain manager included analytical, interpersonal, leadership and change management		I
Richey et al. (2006)	Supply chain managers with high adaptability can drive firm competitive advantage and performance		I
Hult et al. (2007)	Transformational leadership has a stronger relationship than transactional leadership on outcomes	I	
Defee et al. 2009	Transformational supply chain leaders showed higher performance by incorporating the behaviors of all supply chain members	I	
Fawcett et al (2010)	Supply chain manager needs to not only understand the key supply chain functions, but also keep them rolling in synch		I
Cousins et al. (2006)	Supply chain managers need to acquire strategic skills that add value and enable effective alignment with business		I
Youn et al. (2012)	Integrative leadership with shared goals improves intangible and value-based supply chain performance goals		I
Overstreet et al. (2013)	Positive relationship between transformational leadership and organizational performance	I	
Ellinger et al. (2013)	Managing changes and complexities and providing leadership are fundamental to the success of supply chain managers		I

(continued)

Table 1 (continued)

Crisis leadership literature		Emphasis on	
Authors (year)	Key findings	Decisiveness	Prudence
Essex et al. (2016)	Supply chain manager needs to fully understand the processes of reconfiguration, integration and learning		I
Wilson and Barbat (2015)	Supply chain manager is a relationship manager who is employed to resolve problems and create value		I
Ambulkar et al. (2016)	Supply chain managers should have a greater level of ability to acquire, disseminate, and integrate external knowledge		I
Shou and Wang (2017)	Supply chain manager competences include generic/functional skills, SCM qualifications, expertise, and industry skills		I

quences involved in a crisis. Nevertheless, the high stakes involved require the leader to generate the best course of action.

One way to work through contradictions is to separate the tensions by splitting the explanations (Poole and Van de Ven 1989). For instance, if "a" and "b" are antithetical, one should first focus on explaining "a", and then on "b" to enable a more workable certainty (Lewis 2000). By examining them separately, new perspectives may emerge which can help generate a meaning that could accommodate contradictions (Lüscher and Lewis 2008).

We base our analysis on adaptive decision making (ADM), a leadership trait that helps capture the observed dichotomy (Bauer et al. 2013; Payne et al. 1993). ADM is a leader's capability to adjust thoughts and behaviors so as to enact appropriate responses to evolving situations (Hannah et al. 2013). Leaders who apply ADM emphasize seeking different views, re-examining their assumptions, and considering new ways of looking at problems. There are trade-offs to ADM (Payne et al. 1993). Extensive ADM can lead to better quality decisions, at the expense of more comprehensive selection process, which can be taxing on leadership and on firm resources. Instead, limited ADM can lead to exacting and unyielding decisions that make them easier to follow and implement. Management literature has investigated the effectiveness of ADM (e.g., Bauer et al. 2013). However, whether ADM can be helpful in the face of crises or supply chain disruptions is unclear. The section below explains the effect of ADM in more detail.

3.1 Leader ADM and Supply Chain Disruptions

There is evidence in support of both leadership decisiveness and adaptiveness in facing crises (Lukina et al. 2017; Dooley and Lichtenstein 2008). For instance, in support of decisiveness, Eisenstadt et al. (2008) explain how uncompromising managers, that refuse to lower their expectations, are able to lead their companies through difficult situations. Jim Collins, in his highly acclaimed book “Good to Great”, argues for a leader’s fierce resolve as a key ingredient to enhance company performance (Collins 2005). In support of adaptiveness, Heifetz et al. (2009) suggest that leaders can be effective by recognizing and incorporating input from employees. Yukl and Mahsud (2010) suggest that success in facing external crises requires collective learning and collaboration by many members of the organization. Crisis leaders that can encourage and facilitate these processes can be more effective

At first glance, these two perspectives sound contrary. However, a more careful assessment of the literature suggests that the concern may be in *extensive* use of either decisiveness or adaptiveness. To start, crises occur under high stress, high stakes conditions where response efforts need to be definitive so as to leave no doubt on how to take action (Boin and Lagadec 2000). Resources need to be applied in a precise manner to ward off the crisis from spreading and to avoid wasted effort. Too much emphasis on adaptiveness (i.e., on gathering input and seeking different views) can take away from taking action and lead to “paralysis through analysis.” There are also strong organizational pressures that work against too much contemplation over alternative courses of action. For instance, there may be heavy concerns over the potential for further damage caused by the disruption or other secondary “aftershock” events that may follow. Finally, there is also strong evidence that leaders limit their information input when facing threats (Deverell 2010). Based on experimental research on corporate response to threats, Staw et al. (1981) show how decision-makers narrow their attention to a few more important issues. In this process, leaders tend to simplify and reduce the number of information channels they access, to lower their reliance on multiple inputs (Seeger et al. 2003).

On the other hand, too much emphasis on decisiveness can also be detrimental to how the crisis is handled (Deverell 2010). A number of empirical studies highlight the downsides of extensive focus on leadership decisiveness. Bechky and Okhuysen (2011) highlight the importance of seeking multiple views and examining work arrangements in organizations that are routinely faced with unpredictable and instable situations. Bigley and Roberts (2001) find that fire department leaders, who assess the situation and identify contingencies, instead of deterministically approaching the issue can enhance their team’s performance. Van Vugt et al. (2004) find that the procedural focus on leader decisiveness (i.e., autocratic style) can have a destabilizing influence on the organization.

These studies echo the dichotomy noted in the earlier section from theoretical explanations and literature reviews on leadership during crises. While leader decisiveness and leader adaptiveness are not fundamentally disadvantageous, too much emphasis on either may limit the effectiveness of the organization’s response effort.

The above observations suggest that a moderate level of ADM, one that considers the need for decisiveness, while recognizing the need for input from multiple sources may offer the best advantage for the company. Whereas extensive ADM can lead to better quality decisions, it is at the expense of more comprehensive selection process, which can be taxing on managerial attention and firm resources. Instead, limited ADM can lead to exacting and unyielding decisions that make them easier to follow and implement. Management literature has investigated the effectiveness of ADM (e.g., Bauer et al. 2013). We capture this relationship by suggesting for a curvilinear (u-shaped) relationship between leader ADM and damage from supply chain disruptions.

3.2 Leader ADM and Unexpected Supply Chain Disruptions

Unexpected disruptions are challenging because they leave no time for the company to gather information or to prepare for the ensuing damage (Yang and Xie 2000). Since there is limited warning, by the time sufficient information about the event becomes available, there may be no time left to adequately develop an effective response strategy (Stamatis 2003). For example, in the face of hurricane Katrina, many suppliers and manufacturers were caught by surprise, which paralyzed their response systems (Sheffi 2015).

Companies facing unexpected supply chain disruptions can benefit by using a decisive leader. Given their ambiguous nature, how unexpected disruptions are interpreted can be quite subjective. This can lead to multiple, and possibly, divergent interpretations on how response efforts should be managed (Tukiainen et al. 2010). Under these circumstances, a key priority for the leader is to maintain cohesion among the parties involved, even at the expense of placing constraints on how thoroughly decisions are examined. Leader's unwavering resolve and confidence are necessary to tame doubters and skeptics. Another common fallout of unexpected disruptions is confusion among the rank-and-file. If their confusion grows into "paralysis," it can cause other issues and may generate surprises of its own. Confusion between trade-partners (buyers and suppliers) can undermine cooperative efforts between their personnel and make their relationships fray (Floricel and Miller 2001). Literature confirms the points offered above: that response to unexpected disruptions can be made more effective by having a leader that displays determination and resolve (Geraldi et al. 2010).

The above factors suggest that, with rising unexpectedness in supply chain disruptions, leader decisiveness becomes more effective. Therefore, we posit that with rising unexpectedness in supply chain disruptions, low-to-moderate levels of ADM become effective in minimizing damage from supply chain disruption.

3.3 Leader ADM and Complicated Supply Chain Disruptions

Supply chain disruptions become complicated when either more members of the supply chain are affected, or when multiple value streams (i.e., goods, information or finances) are severed. Complicated supply chain disruptions are challenging not only because there are multiple issues that have to be simultaneously addressed, but also because the issues are likely to be inter-related and interconnected (Cunha et al. 2006). Precipitating (initial) failures can lead to secondary failures causing further damage (Sundnes and Birnbaum 2003). The multiplicity and interaction of issues mean that company resources and management attention are often divided in trying to tackle several problems and their potential ramifications all at once.

As disruptions become more complicated, it becomes more difficult for the leader to appraise the likely outcomes of every step taken in response to the disruption. Careful assessment of complicated disruptions helps with assigning roles and responsibilities in the response effort. The careful assessment also helps consider intricacies to better prioritize tasks and to place resources where necessary. For instance, as members responsible for implementing solutions in one part of the chain take action, they affect the decisions and actions in other parts of the chain.

Careful assessment of complicated disruptions helps with leader effectiveness. Considering the full extent of the effects that the supply chain disruption is helpful because it allows the leader to incorporate multiple issues and interaction of the complicated supply chain disruption. Instead, a partial understanding of the situation can lead to decisions that may not resolve all aspects of the disruption. Svensson labels this as "holistic vulnerability approach," or the ability to consider a system-wide view of the disruption (Svensson 2000). In contrast, an "atomistic vulnerability approach" is constrained to a minor and limited part of the supply chain (Manuj and Mentzer 2008). A holistic view allows for properly placing company resources in front of the more urgent, or more damaging facets of the disruption.

Literature in crisis leadership offers further support to the above. Leaders that appreciate the complicated nature of problems (i.e., pragmatic leaders) tend to perform better than others in the face of complicated situations (Hunter et al. 2009). Interestingly, results from a simulated experiment suggest that pragmatic leaders actually improve their performance when faced with more complicated settings (Bedell-Avers et al. 2008). In short, a thorough assessment of the situation by the leader can make company response efforts more effective in the face of complicated supply chain disruptions.

The above factors suggest that, with rising complicatedness in supply chain disruptions, leader adaptiveness becomes more effective. We posit that with rising complicatedness in supply chain disruptions, moderate-to-high levels of ADM become effective in minimizing damage from supply chain disruption.

3.4 Leader ADM and Rare Supply Chain Disruptions

Familiar disruptions reside in the organization's task domains and can be more easily recalled, making them easier to manage (Kovoor-Misra 2002). In contrast, rare disruptions offer no previous experience that parallels them. The right counter-measure is yet to be identified. As such, the firm cannot draw ideas from its memory on how to tackle rare disruptions (Lampel et al. 2009). There are no existing plans for delegation or prioritization of tasks in addressing rare disruptions. Organization's personnel have no clear-cut way to approach the disruption.

Previous research shows that reliable information about the extent of disruption can improve the overall performance of a company (Li et al. 2017). This is particularly important for facing rare disruptions. Given the extensive ambiguity of rare supply chain disruptions, inclusion and involvement of others can lead to better decisions. Careful assessment of rare disruptions seems necessary because the firm needs to compensate for its lack of understanding of the intricacies of the disruption. Careful assessment helps surface the nuances associated with a rare disruption so as to better prioritize tasks and to place resources where necessary.

The above suggests that a focus towards a more careful review of the ramifications of decisions may prove to be more effective in the face of rare disruptions. This suggests that leader adaptiveness can be effective with rising rarity of supply chain disruptions.

4 Methodology

4.1 Sample and Data Collection

The data was gathered through a mixture of primary and secondary data sources. Primary data was collected to measure leadership competencies during supply chain disruptions from manufacturers using an online Qualtrics survey. Secondary data was obtained through COMPUSTAT and used to measure industry related variables and firm performance used as controls. Three follow-ups netted useful survey responses from a cross-section of 286 firms, resulting in a nearly 30% response rate. Missing data resulted in 35 responses being discarded.

4.2 Variables and Measures

The unit of analysis is firm response to supply chain disruptions. The supply chain, leadership, and operations literature were screened to identify relevant scales for the constructs used the study. For all constructs, multi-item 7-point Likert scale

(1-strongly disagree, 7–strongly agree) described in the following paragraphs were used.

Measurement of ADM was conducted using a three-item scale. The respondents were asked to evaluate their leader's adaptiveness by indicating how much they agree that their leader "suggests different angles," "seeks different views," and "suggests new ways." Characteristics of major supply chain disruptions were measured using three variables: unexpected, complicated, and enduring disruption.

Monitoring the performance of any production system should include both internal and external measure of performance (Stank, Crum, and Arango 1999). Thus, our operational damage scale consisted of seven items, including sales, access to technology, delivery reliability. In this context, we were interested in how the supply chain disruption negatively affected (directly and indirectly) the organization's response and recovery efforts. We asked respondents to evaluate the negative effect of the disruption, (7 point Likert 1-strongly disagree, 7–strongly agree). The reliability of the scale for the outcome variable (operational damage) was acceptable (Cronbach's alpha of 0.89), suggesting that operational damage can be considered as a unidimensional construct in the analyses.

Control Variables. We controlled for factors that could influence firm's operational damage in facing supply chain disruptions, as informed by prior literature on supply chain disruptions (Muffet-Willett and Kruse 2009; Sarros and Santora 2001). Statistical controls included firm size and financial performance, industry membership, the dynamism of firms' business context, the frequency of disruptions, and leadership characteristics. COMPUSTAT was used for financial data on public firms (fiscal years 2009, 2010, and 2011), while survey responses were used for private firms.

5 Analyses and Results

Multiple regression analysis was employed to test the proposed model. First, we explored the direct effects of ADM on operational damage. The results were found to be significant ($\beta = 0.121$, $p < 0.05$). They suggest that ADM is helpful in a leader's overall response to supply chain disruptions. However, in line with the argument for H1, ADM can be detrimental at extremely low or extremely high levels. At either extreme, ADM is associated with more operational damage from supply chain disruption. The summary of results is available in Table 2.

Second we addressed the effect of ADM on operational damage in the face of unexpected supply chain disruptions, suggesting that the effect of low-to-medium level ADM on limiting disruption damage becomes stronger with increased supply chain disruption unexpectedness. The results demonstrate significance ($\beta = 0.061$, $p < 0.05$). In the face of high unexpectedness of supply chain disruptions, limited ADM is more effective. Extensive ADM is more effective for supply chain disruptions with low unexpectedness. Here again, the subtleties of the resulting curvilinear relationship suggest that ADM is not as effective at extremely limited levels. Therefore,

Table 2 Multiple regression analysis—outcome variable: operational damage

	Model 0 controls		Model 1 SC drect effects		Model 2 unexpected SC disruption		Model 3 SC disruption complicatedness		Model 4 SC disruption rarity	
	β	p-value	β	p-value	β	p-value	β	p-value	β	p-value
Control variables[a]										
Size (sales)	−0.050	n/s	−0.050	n/s	−0.055	n/s	−0.047	n/s	−0.053	n/s
Environmental dynamism	0.335	0.001	0.335	0.001	0.313	0.001	0.302	0.002	0.337	0.006
Financial performance	−0.164	0.02	−0.164	0.02	−0.169	0.017	−0.169	0.019	−0.157	0.029
Frequency of disruptions	−0.020	n/s	−0.020	n/s	−0.012	n/s	−0.012	n/s	−0.082	n/s
Leader self-esteem	0.074	n/s	0.074	n/s	−0.081	n/s	−0.043	n/s	−0.019	n/s
Leader trusting personality	0.027	n/s	0.027	n/s	0.003	n/s	−0.069	n/s	0.061	n/s
Leader procrastination	−0.140	0.08	−0.140	n/s	−0.151	0.06	−0.148	0.059	−0.156	0.050
Baseline leadership traits										
Leader ADM			−1.317	0.001	1.298	n/s	0.344	n/s	−2.132	0.001
Leader ADM squared (**H1**)			**0.121**	**0.001**	- 0.185	n/s	−0.102	n/s	0.220	0.001
Disruption type (direct effect)										
Disruption unexpectedness					0.889	n/s				
Disruption complicatedness							0.578	n/s		
Disruption rarity									−0.652	n/s
Disruption type (interaction effects)										
Disruption unexpectedness[a] leader ADM					−0.519	0.039				

(continued)

Table 2 (continued)

	Model 0 controls		Model 1 SC drect effects		Model 2 unexpected SC disruption		Model 3 SC disruption complicatedness		Model 4 SC disruption rarity	
	β	p-value	β	p-value	β	p-value	β	p-value	β	p-value
Disruption unexpectedness[a] leader ADM squared **(H2)**					**0.061**	**0.018**				
Disruption complicatedness[a] leader ADM							−0.360	0.092		
Disruption complicatedness[a] leader ADM squared **(H3)**							**0.048**	**0.042**		
Disruption rarity[a] leader ADM									0.459	0.080
Disruption rarity[a] leader ADM squared **(H4)**									**−0.056**	**0.045**
Intercept	4.909		7.304		2.991		5.103		8.621	
R^2	0.072		0.132		0.166		0.173		0.163	
F-value	1.351	0.119	2.343	0.004	2.527	0.001	2.601	0.001	2.324	0.002

[a] A total of eight industry categories were modeled. Results are excluded for parsimony

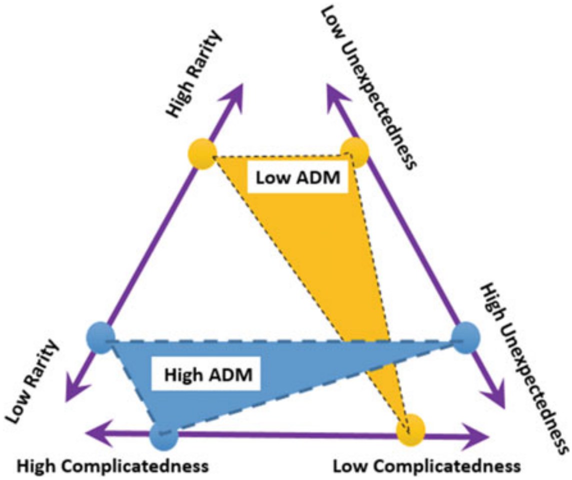

Fig. 1 Triangular model of adaptive decision making in facing supply chain disruptions

decisive decision-making may be more optimal for supply chains caught off-guard by a highly unexpected disruption.

Third, we tested the relationship between ADM and operational damage when moderated by supply chain disruption complicatedness. The results were significant ($\beta = 0.048$, $p < 0.05$), but not supported. The results suggest that more complicated supply chain disruptions limit the effectiveness of ADM. The effectiveness of extensive ADM, meanwhile, is reduced. The curvilinear nature of the results indicates that ADM is particularly ineffective at extremely low levels. Figure 3 shows the relationship between ADM and operational damage moderated by complicatedness. Therefore, limited ADM in the face of complicated supply chain disruptions is advised, making decisive decision-making the preferable leadership approach under such circumstances (Table 3).

Finally, we examined the role of rarity on ADM and operational damage from supply chain disruptions. The results showed significance ($\beta = -0.056$, $p < 0.05$). As related to the unfamiliarity of supply chain disruptions, use of limited ADM leads to lower operational damage in the face of familiar duration disruptions (Fig. 4). This argues for decisive action being taken to limit operational damage when the disruption is familiar. However, in the face of rare disruptions, use of extensive ADM leads to lowering of operational damage, suggesting that prudent leadership may be the more preferable approach. The relationship between ADM and operational damage is graphically depicted on Fig. 1.

Table 3 Summary of results

Hypothesis	Result	Implications
H1: Leader ADM carries a u-shaped relationship with operational damage from supply chain disruptions such that moderate level of ADM is associated with lower damage as compared to limited and extensive levels of ADM	Supported ($\beta = 0.121$, $p < 0.05$)	Findings suggest moderation is the best policy for leaders facing SC disruptions. Leaders that avoid extremes—be they in hasty decisiveness or cautious prudence—seem to help their organizations minimize the detrimental effects of SC disruptions
H2: Unexpected disruptions moderate the curvilinear association between leader ADM and SC disruption damage such that, with rising SC disruption unexpectedness, low—to-moderate levels of ADM lower the SC disruption damage	Supported ($\beta = 0.061$, $p < 0.05$)	The fact that unexpectedness, complicatedness, and rarity of SC disruption require variations on leadership emphasis is a manifest to the multifaceted and multidimensional characteristic of SC disruptions. Each SC disruption has the potential to be a uniquely unusual event such that the leader would need to customize the recognition, response and recovery efforts
H3: Complicated disruptions moderate the curvilinear association between leader ADM and damage from SC disruptions such that, with rising SC disruption complicatedness, moderate to high levels of ADM become more effective in minimizing the SC disruption damage	Supported ($\beta = 0.048$, $p < 0.05$)	
H4: Rare disruptions moderate the curvilinear association between leader ADM and damage from SC disruptions such that, with rising SC disruption rarity, moderate to high levels of ADM become more effective in minimizing the SC disruption damage	Supported ($\beta = -0.056$, $p < 0.05$	

5.1 Robustness Tests for Inverted U-Shaped Relationships

In order to address the validity of inverted U-shaped relationship between ADM and operational damage, several measures were taken. First, following previous studies, all continuous variables were mean centered to minimize multicollinearity as well as provide robustness for a U-shaped curve (Aiken and West 1991).

Additionally, we employed an approach suggested by Wales et al. to further assess the validity of the inverted-U shaped relationship between ADM and operational damage (Wales et al. 2013; Lind and Mehlum 2010). Without these tests, it is challenging to determine whether the extreme point (or the inflection point) is within the bounds of the data. First, we begin with a Wald test to assess the joint significance of the direct and squared terms of logistics integration. The results confirmed that both terms are jointly statistically significant [$F(2, 249) = 3.65$; $Prob > F = 0.001$]. Then, the Sasabuchi test was used to estimate whether the effect of ADM on operational is increasing at low values of ADM and the effect of ADM on operational damage is decreasing at high values of ADM. It is essential to examine slopes at these bounds to confirm that the inverted U-shaped relationship is representative of the data and not a statistical artifact. Overall test of presence of a U-shaped relationship shows significance (t-value = 2.07; $P <= 0.05$). Furthermore, significant values of lower and upper bound slopes indicate the presence of a U-shaped relationship (Lower bound slope = −0.717; t-value = −2.65; $P < 0.001$; Upper bound slope = 0.375; t-value = 2.07; $P < 0.05$). Finally, to validate that the extreme point of the curve is within the upper and lower bounds of ADM, Fieller approach was applied. If the confidence intervals are within the bounds of the low and high values of ADM, it offers support for the presence of a U-shaped relationship in the data. The estimated extreme point is 4.94, which is positioned within the upper and lower bounds of ADM (95% Fieller interval for extreme point: [4.17; 6.63]).

6 Discussion

In this study, we assessed the impact of leadership traits that can induce a ripple effect during supply chain disruptions. We consider ADM as a continuum spanning both high and low levels of adaptiveness. Results of the study confirmed our primary hypotheses that a moderate level of ADM is optimal in relationto operational damage from the ripple effects in supply chain disruptions. When faced with rare disruptions, higher ADM is particularly effective. However, low ADM is more effective in the face of unexpected and complicated disruptions.

6.1 Empirical and Theoretical Contributions

Recent research supply chain management and crisis has recognized supply disruption management as an important area of research (Schoenherr et al. 2012). The true test of a supply chain leader is during challenging times. At no time is this better manifest than during supply chain disruptions, when the inter-organizational dynamics are further complicated by the time-pressures, ambiguities and high stakes associated with the disruption (Dooley and Lichtenstein 2008). Such situations amplify decision-making behavior and associated ramifications.

Our findings suggest that moderation is the best policy for leaders facing supply chain disruptions. Leaders that avoid extremes—be they in hasty decisiveness or cautious prudence—seem to help their organizations minimize the detrimental effects of supply chain disruptions. Moderation, leadership that simultaneously considers the need for quick and effective alongside thoughtful consideration for the potential ramification of their actions across the supply chain, seems most effective in the face of supply chain disruptions. These findings fall in line with that from a few studies in similar contexts (e.g., Van Wart and Kapucu 2011). Related to supply chains, Williams et al. (2002) find that neither autocratic nor participative leadership styles are more effective than the other. Instead, leaders whose key approach is adaptable are shown to be effective.

A second contribution of this paper is in highlighting the unique characteristics of supply chain disruptions. As we noted earlier, literature on crisis leadership has historically been dominated by research on community and humanitarian related disasters (e.g., Patton 2015; Quarantelli 1997). While insightful, results from these studies may not be fully compatible with the intricacies of supply chain disruptions, nor with the possible leadership styles necessary to address them. The fact that unexpectedness, complicatedness, and duration of supply chain disruption require variations on leadership emphasis is a manifest to the multifaceted and multidimensional characteristic of supply chain disruptions. Each supply chain disruption has the potential to be a uniquely unusual event such that the leader would need to customize the recognition, response, and recovery efforts to reduce the ripple effect. This further supports the idea that ADM be matched to the type of supply chain disruption being dealt with to help minimize damage from the ripple effect.

Leadership traits tend to be thought of in terms of positive capabilities, or ones that allow the individual to promote better decisions even in the face of uncertainty (Simpson et al. 2002). However, there are potential downsides to any particular trait that is being considered. Our findings suggest that it is the responsibility of the leader in charge at "ground zero" of the supply chain disruption to adapt and improvise when responding to a supply chain disruption. The goal is to reduce the ripple in the downstream supply chain. Relatedly, we contribute to the literature on leadership in the face of complicated settings. Leadership, by its nature, is a complicated activity (Hunt 2004). This study is one of few empirical examinations that allows for a test of some of the central ideas developed by the paradox perspective (Denison et al. 1995). Our findings support the general implication of the paradox perspective in that more effective leaders generally display a more complicated and varied set of behaviors.

Finally, critiques of leadership theories highlight the shortcomings of the literature by focusing primarily on charismatic and other vision-laden leaderships. Yukl (2005) notes the importance of highlighting the task and strategic-oriented behaviors of leaders. Hunt (2004), who has extensively chronicled leadership, explains: "When between one-third and one-half of recent scholarly leadership articles are devoted to transformational leadership… one wonders whatever happened to plain, unadorned leadership directed toward task completion" (p. 1524). Moreover, missing from many leadership studies is sufficient specification of situational variables and facilitating conditions. Our study contributes to the leadership field of study by offering insights on the potential significance of considering adaptive leadership. This is particularly impactful for supply chain management, which can be extremely dynamic and turbulent.

6.2 Practical Implications

Our contribution to practice is in detailing how the intricate nature of supply chain disruptions creates thought-provoking challenges for leadership. As of late, many organizations have emphasized how they should prepare for and minimize the ripple effect of risks due to supply chain disruptions. However, the manner in which actual supply chain disruptions are to be handled is not as prominent of a topic within the supply chain management literature. Moving beyond the preparatory and risk mitigating stages of disruption management, this study offers explanation on how outstanding supply chain management leadership in the face of supply chain disruptions may decide and direct the organization through and past the danger introduced.

The findings above are particularly important to supply chain management leaders, as it is likely that many managers would have inclinations towards one particular style over another. It is increasingly clear that supply chains established during more stable times need to be reshaped for operation in an era of increased volatility. Supply chain leaders should be able to synthesize external and internal data and rapidly take action to minimize the impact of a disruption (Culp 2013). Each leader, perhaps even innately, has a preference towards being decisive or prudent. As Devitt and Borodzicz (2008) note, “Leaders managing crises under stressful situations are likely to revert to the style which they are most comfortable.” In fact, the urge to leverage the most comfortable approaches become stronger as the challenge posed by the crises increases in intensity (Deveitt and Borodzicz 2008). As evidenced here, this can be detrimental in the face of supply chain disruptions, which requires blending different leadership styles. For example, in 2012 the auto industry was rocked by a shortage of a specialty resin because the key supplier experienced a devastating explosion in its plant. It took the supplier six months to restart production, during which time the downstream production facilities of Ford and other major automakers were severely disrupted. If Ford supply managers were adaptive and decisive, they would have detected the risk exposure and associated production bottleneck and proactively worked with the supplier to fast-track its plans to bring online a new plant (Simchi-Levi et al. 2014). The challenge for most leaders is to behave confidently in uncertain times, yet do so with as much information and intelligence as they can generate.

One of the contributions of particular note from this study for managers is the notion of leadership under complicated supply chain disruptions. Contrary to findings from studies outside of the supply chain context (e.g., Strange and Mumford 2002) we find that leaders demonstrating prudent decision making do indeed perform better with regards to minimizing operational damage. The ability of a leader to adapt to a changing and complicated environment is a key foundation of crisis leadership in supply chain management. For example, supply managers' adaptability (achieved in this case by adjusting workforce skills and processes) allowed Toyota to quickly restore the supply of brake-fluid-proportioning valves (P-valves) after a major disruption (Simchi-Levi et al. 2014). Far too often are examples of crisis leaders that foreclose on options, cutting off or ignoring points of information when making vital decisions. This is undesirable, especially as crisis decision making requires an ability to think quickly and rationally, as well as to act. The consequence of muddled thinking or ignoring key situational factors can result in further disaster.

6.3 Future Research and Limitations

This study explored leadership approaches related to ADM in response to varying types of disruptions. The results of this study need to be considered alongside their limitations. We recognize the limitations of empirically based studies. For example, the responses garnered from this research were from managers working for Italian-based organizations. While these managers were spread across 25 multi-national companies with international supply chains that may be from numerous countries, future research should look at a broader array of countries.

While past research in SCM has focused extensively on overarching strategic aspects of the discipline (Giunipero and Eltantawy 2004), more recent research has called for attention to be paid to the "people" dimensions that contribute to supply chain functions (Wieland et al. 2016). To date, little research has examined the differences between leadership in supply chains, versus in other management contexts. We would echo the words of Thornton et al. (2016), who points out that "Without a savvy leader, the needs of supply chain management may be overlooked because they have no advocate to push their orientation within the firm." As supply chain managers continue to assume executive roles in the upper echelons of the corporate hierarchy, pointing to the increasing strategic importance of supply chain management (Wagner and Kemmerling 2015), we would argue for the need for future studies examining aspects of leadership within supply chain management.

Another direction for future research is considering whether moderation policy for leaders facing SC disruptions can affect SC efficiency. Previous research highlighted that various SCM decisions are rooted in the efficiency thoughts and resilience is frequently considered as a trade-off with the efficiency (Ivanov and Dolgui 2018). While leaders that avoid extremes may improve SC resilience, they might also decrease SC efficiency since the decision-making speed decreases. Ivanov and Dolgui (2018) offer several opportunities for future exploration, time-to-recover being among those areas needing more attention. For example, the relationship between lead time extensions and efficiency within the SC resilience context is fertile ground for future analysis. Simulation experiments, but also, observational techniques could be useful methods for examining such relationships.

Since there is no universal, ideal prescription of management response to supply chain disasters, another important consideration is that each disruption can have a notably different set of characteristics and therefore a uniquely designed combination of countermeasures to address them. For example, cultural aspects may be a factor, as certain cultures and communities celebrate decisive assertiveness and dominant styles of leadership. Others yearn for more modest servant leaders if they are willing to tolerate leaders at all. Societal and organizational expectations of leaders vary enormously from setting to setting, according to the requirements of context. In virtually every society and setting, we require leaders to be alternately collaborative and competitive.

The findings from this study represent the first known effort examining ADM to various SC disruptions. Given the noted variability of disruptions, opportunities for future research might include an examination of more specific disruption types common to supply chain management. These could include stock-outs, product recalls, and others, which can have disastrous effects that ripple throughout the supply chain. Also, while this study measured leadership via a survey in combination with archival financial measures, future work may utilize other methods. For example, the deductive case-based analysis might be particularly useful for delving more deeply into contextual factors impacting leadership and ADM. Future researchers might also want to look at leadership and ADM across the various stages of response to a disruption, i.e., prevention, mitigation, response, and recovery (Shaheen et al. 2018). Additionally, the regulatory concerns of certain countries might partially impact the speed of a response. Leadership under conditions where the public-private partnership has an extensive role may be of importance to managers coping with SC disruptions.

7 Conclusion

It only takes an instant for a smoothly running supply chain to be stricken by disaster. In these critical moments, the right leadership approach can impact the level of turmoil the organization, and connected supply chain stakeholders must suffer through. Such inter-organizational exchanges drive the right level of ADM, in terms of decisive speed versus methodical prudence. Using paradox and leadership theories, this research revealed how different forms of ADM impacts the extent of operational damage under various types of SC disruptions. While prior research tends to describe quick responding, visionary leaders as ideal in crises situations, our research demonstrates that in the face of different SC disruptions, leadership is indeed paradoxical. Clearly, our research demonstrates the importance of leadership for the supply chain research and practitioner communities.

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A Model of an Integrated Analytics Decision Support System for Situational Proactive Control of Recovery Processes in Service-Modularized Supply Chain

Dmitry Ivanov and Boris Sokolov

Abstract In the supply chain (SC) recovery process, a disruptive event, planning of the recovery control policy and implementation of this policy are distributed in time and subject to SC structural and parametrical dynamics. In other words, environment, SC structure and its operational parameters may change in the period between the planning of the recovery control policy and its implementation. As such, situational proactive control with combined use of simulation-optimization and analytics is proposed in the paper to improve processes of transition between a disrupted and a restored SC state. Implementation of situational proactive control can reduce investments in robustness and increase resilience by obviating the time traps in transition process control problems. This chapter develops a model of a decision support system for situational proactive control of SC recovery processes based on a combination of optimization and analytics techniques. More specifically, three dynamic models are developed and integrated with each other, i.e. a model of SC material flow control, a model of SC recovery control and a model of SC recovery control adjustment. The given models are developed within a cyber-physical SC framework based on the service modularization approach.

1 Introduction

Supply chain (SC) vulnerability and disruption management have become a prominent research domain over the last two decades. Literature differentiates preparedness and recovery decisions (Sheffi 2005; Ivanov 2017; Dolgui et al. 2018; Ivanov 2018;

D. Ivanov (✉)
School of Economics and Law, Department of Business and Economics, Berlin School of Economics and Law, 10825 Berlin, Germany
e-mail: divanov@hwr-berlin.de

B. Sokolov
Saint Petersburg Institute for Informatics and Automation of the RAS (SPIIRAS), V.O. 14 Line, 39, 199178 St. Petersburg, Russia
e-mail: sokol@iias.spb.su

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Yoon et al. 2018). Recovery processes usually follow the disruption and are deployed on the basis of proactive contingency plans and a recovery forecast (Tomlin 2006; Ho et al. 2015; Pavlov et al. 2018; Macdonald et al. 2018).

The existing decision support systems utilize the power of optimization and simulation techniques to support decision-makers in protecting the SC using optimal contingency plans such as risk mitigation inventory, capacity reservations, backup sourcing and combinations thereof (Gupta et al. 2015; Behzadi et al. 2017; Ivanov et al. 2017a, b, c; Sawik 2017; He et al. 2018; Ivanov 2019; Pavlov et al. 2019). In addition, recovery process simulation has recently been introduced in research (Ivanov et al. 2013, 2014a, b, 2016c, 2018b; Schmitt et al. 2017; Scheibe and Blackhurst 2018).

A disruptive event, planning of the recovery control policy and implementation of this policy are distributed in time and subject to SC structural and parametrical dynamics during a SC recovery process (Xia et al. 2004; Shao and Dong 2012; Sheffi 2015; Ivanov 2018). In other words, the environment, SC structures and operational parameters may change in the period between the planning of the recovery control policy and its implementation. This fact represents a gap in current research which mostly relies on recovery models based on recovery forecasting. The missing incorporation of real-time data about process execution in the recovery control deployment models reduces their value and efficiency. There are only a few works on recovery process scheduling (Ivanov et al. 2018a).

At the same time, recent studies have provided evidence of the technical applicability and effectiveness of such techniques by using SC event management techniques (Meyer et al. 2014; Sommerfeld et al. 2018). T&T systems and feedback control can be supported by RFID technology (Dolgui and Proth, 2010) and SC event management systems. Both RFID and SC event management systems can be used to effectively communicate disruptions to the other tiers and to help revise initial processes and schedules, respectively (Dolgui and Proth 2010; Zelbst et al. 2012). A critical issue in this area is detecting disruptions and their scope in real time. Embedding SC visualization and identification technology is crucial for its successful application in practice (Meyer et al. 2014). However, those studies are rather context-specific and did not provide a model of an integrated proactive-reactive decision support system for situational proactive control of SC recovery processes.

As such, situational proactive control with combined use of simulation-optimization and analytics is proposed in the paper to improve the transition processes between disrupted and restored SC states. Implementation of situational proactive control can reduce investments in robustness and increase resilience by obviating transition process control problems. This paper develops a model of an integrated proactive-reactive decision support system for situational proactive control of SC recovery processes based on combination of optimization and analytics techniques. More specifically, three dynamic models of a service-analytics decision support system for supply chain recovery control are developed and integrated with each other, i.e. a model of SC material flow control, a model of SC recovery control and a model of SC recovery control adjustment. The given models are developed within a cyber-physical SC framework based on service-oriented approach.

The rest of this study is organized as follows. Section 2 presents the problem of situational proactive control. The decision support framework is shown in Sect. 3. Section 4 is devoted to mathematical models of recovery control. The paper is concluded in Sect. 5 with a summary of the findings and a description of limitations and future research avenues.

2 Problem of Situational Proactive Control

The SC recovery process includes some events which start with the disruption and are continued into planning of the recovery control policy (e.g. based on a contingency plan), and the implementation of this policy through its deployment and control (Fig. 1).

It can be observed in Fig. 1 that the aforementioned events are distributed in time. In this time, the SC is subject to structural and parametrical dynamics. In other words, the environment, SC structures and operational parameters may change in the period between start of the planning of the recovery control policy and its implementation. The recovery process is planned at the point of time "start of recovery planning" subject to the deployment at the point of time "start of recovery implementation" considering as inputs the SC structure at the point of time "start of recovery planning", the internal parameters in this structure (e.g. available capacity and inventory), the external parameters (e.g. demand) and the forecasted states of those inputs at the point of time "start of recovery implementation". More specifically, the time gap between the events "start of recovery planning" and "start of recovery implementation" is responsible for the situation in which the actual SC structure and the internal and external parameters may be quite different compared to those forecasted. As such, new methods are needed to obviate the time traps in transition process control problems (Dunke et al. 2018).

As such, the incorporation of real-time data about process execution in recovery control deployment models is necessary to increase their value and efficiency. Such an incorporation is needed both for data updating and the adjustment of the recovery control policy during its planning and realization.

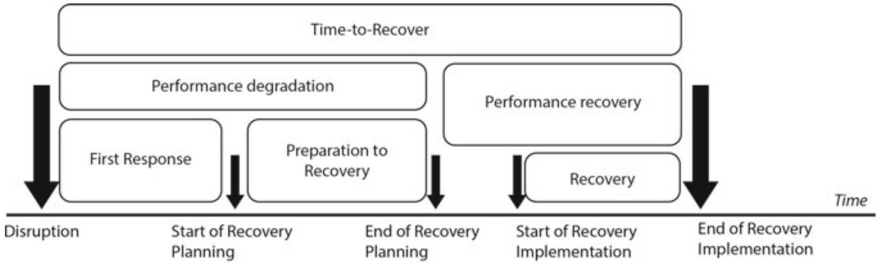

Fig. 1 Supply chain recovery process

3 Cyber-Physical SC Framework and Decision Support System Concept

Success in SC competition become more and more dependent on analytics algorithms in combination with optimization and simulation modelling. Initially intended for process automation, business analytics techniques now disrupt markets and business models and have had a significant impact on the development of SCM. As such, new disruptive SC business models will arise where SCs are understood not as rigid physical systems with a fixed and static allocation of some processes to some firms (Ivanov et al. 2019; Panetto et al. 2019). Instead, different physical firms will offer services of supply, manufacturing, logistics and sales which will result in the dynamic allocation of processes and dynamic SC structures (Fig. 2).

A new generation of simulation and optimization models extends decision support systems (DSS) towards decision analysis, modelling, control and learning systems (DAMCLS). Recent literature documented the possibility of modelling such integrated service-material flow SCs (Ivanov et al. 2014c; Yang et al. 2017) and service modularization in the SC (Giannakis et al. 2018).

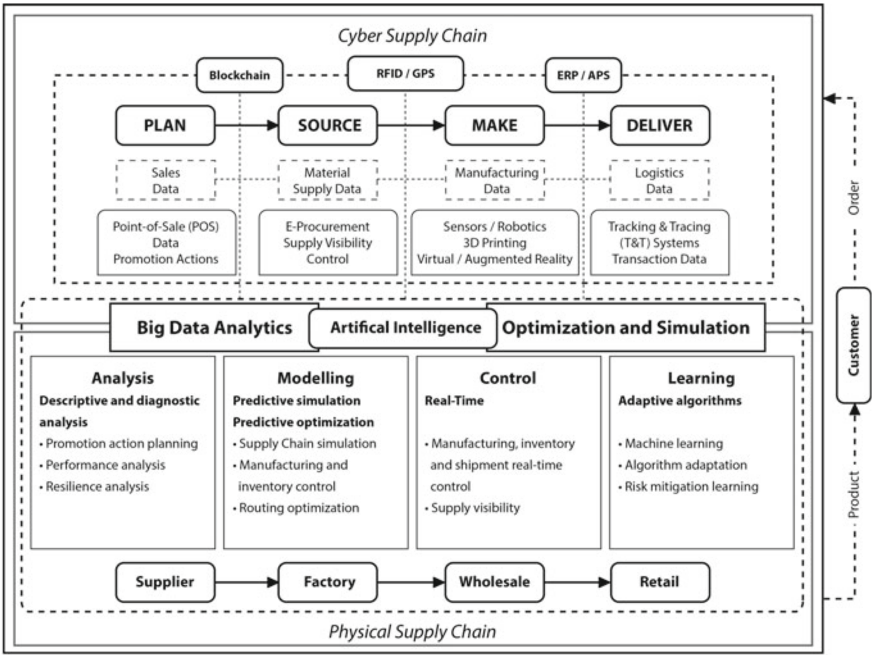

Fig. 2 Cyber-physical SC framework based on a service modularization approach

4 Model of Decision Support System

Recall Sect. 2 and the three kinds of models that need to be developed and integrated, i.e. a model of SC material flow control, a model of SC recovery control and a model of SC recovery control adjustment. The given models are developed within a cyber-physical SC framework based on a service-oriented approach, as described in Sect. 3.

The SC is modelled as a networked, controlled system described through a *dynamic* interpretation of the service execution (Ivanov and Sokolov 2013; Ivanov et al. 2016a, b). Three joint models of process control are proposed. Control model (M1) is first used to describe the schedule of the material flows control process, and then another control model (M2) is used to describe the recovery process. Subsequently, the model (M3) is introduced to describe the adjustment of the recovery process.

General assumptions and parameters

- Consider a set of customer orders A_{ν} ($\nu = 1, \ldots, S$).
- Denote $D_{\nu\chi}^{(o,j)}$ as services in the SC material flow process (marked as $^{(o)}$), where $\chi = 1, \ldots, \Gamma$ is the running index of the service. Services are logically arranged in the sequence in which they need to be executed to fulfil the customer order.
- Consider a set of SC elements (e.g. factories, warehouses) $M = \left\{M^{(j)},\ j \in N, N = 1, \ldots, n\right\}$ that can execute services.
- Denote $M_r^{(f,j)}$ as SC elements to be recovered.
- Denote $D_{\nu\chi}^{(f,j)}$ as services in the recovery process (marked as $^{(f)}$), each of which also belongs to order A_{ν}.
- $a_i^{(o)}$ and $a_i^{(f)}$ are the planned processing volumes of the services.
- Denote $\varepsilon(t)$ as an element of the matrix of time-spatial constraints ($\varepsilon(t) = 1$, if $t_0^k < t \le t_f^k$, $\varepsilon(t) = 0$ otherwise), where k are the numbers of time windows available for service execution.
- If a service is completed, a channel to the next stage appears. Denote the set of these vendor–buyer relations in the SC as $B = \{B^{(\mu)},\ \mu \in \bar{N})$, where the subscript η is used for the immediate product acceptor. If a relation exists, the flows $P^{(i,j)} = \left\{P_{<\chi,\rho>}^{(i,j)},\ \chi = 1, \ldots, s_i,\ \rho = 1, \ldots, p_i\right\}$. appear, where $\rho = 1,\ldots, p_i$ is the enumeration of flows.
- Denote $M_{\delta}^{(p,j)}$ as SC elements for the adjustment of the recovery policy.
- Denote $D_{rk}^{(p,j)}$ as services in the recovery adjustment process (marked as $^{(p)}$), where $r = 1, \ldots, R_j$ is the number of the recovery process and k is the index of a recovery adjustment service).
- Setup times are independent and included in the processing time.
- Costs are assumed to be a linear function of processed volumes.
- Denote $u_{\nu\chi\mu}^{(f,j)}$ as the actual intensity of service execution at $M_r^{(f,j)}$ with regard to the service $D_{\nu\chi}^{(o,j)}$ and $e_r^{(j)}$, $V_r^{(j)}$, $\Phi_r^{(j)}$ as the maximal processing intensity of the service $D_{\nu\chi}^{(f,j)}$ at $M_r^{(f,j)}$, maximal capacity of M_j and maximal productivity of $M_r^{(f,j)}$ before the recovery, correspondingly; $\bar{e}_r^{(j)}$, $\bar{V}_r^{(j)}$, $\bar{\Phi}_r^{(j)}$ are given variables

characterizing the same domains but after the recovery; $b_{r\delta}^{(k)}$ is the intensity of the service processing at $M_{\delta}^{(p,j)}$, which is required for the service $D_{rk}^{(p,j)}$ with regards to the recovery of $M_j^{(f)}$.

- Let t be the current instant of time, $T = (T_0,\ T_f]$ the recovery horizon (e.g. time-to-recover, cf Fig. 1) and T_0 (T_f) the start (end) instant of time for the recovery horizon, respectively.
- $\beta_{\nu\chi}^{(o,j)}(\tau)$ are given time functions for assessing the operated volume of the service $D_{\nu\chi}^{(o,j)}$ or penalties for non-fulfilment.
- $\alpha_{\nu\chi r}^{(f,j)}$ are penalty functions which are assumed to be known and characterize the time points when penalties increase because supply terms are broken.

In order to describe the execution of services, let us introduce the following *state variables*:

$x_{\nu\chi}^{(o,j)}$, $x_{\nu\chi}^{(f,j)}$ which characterize the fulfilment of the services $D_{\nu\chi}^{(o,j)}$,$D_{\nu\chi}^{(f,j)}$ in the order $A_{\nu}^{(o,j)}$ at M_j,

$x_r^{(f,j)}$ which characterizes the total employment time of $M_r^{(f,j)}$,

$x_{rk}^{(p,1)}(t)$ which characterizes the current state of $D_{rk}^{(p,j)}$ and

$x_r^{(p,2)}(t)$ which is an auxiliary variable characterizing the current state of the service processing. Its value is numerically equal to the time interval that has elapsed since the end of the recovery of $M_r^{(f,j)}$;

Decision variables and goals

Let us introduce the control variables:

$u_{\nu\chi\mu}^{(o,j)}(t)$ is a control that is equal to 1 if the service $D_{\nu\chi}^{(o,j)}$ is executed at M_j, otherwise $u_{\nu\chi\mu}^{(o,j)}(t) = 0$. $w_{\nu\chi\mu}^{(f,j)}$ is control variable that is equal to 1 if the service $D_{\nu\chi}^{(f,j)}$ is executed at $M_r^{(f,j)}$ and is equal 0 otherwise.

$\tilde{\nu}_{\nu\chi r}^{(f,j)}$ is an auxiliary control variable that is equal to 1 if the execution of service $D_{\nu\chi}^{(f,j)}$ has been fully completed and is equal 0 otherwise.

$\nu_{\chi r}^{(p,2)}(t)$ is secondary control variable that is equal to 1 at the instant of time t if a transition (i.e. recovery) from characteristics $(e_r^{(j)},\ V_r^{(j)}, \Phi_r^{(j)})$ to new ones $(\bar{e}_r^{(j)},\ \bar{V}_r^{(j)},\ \bar{\Phi}_r^{(j)})$ occurs; otherwise $\nu_{\chi r}^{(p,2)}(t) = 0$;

$\nu_{r\delta k}^{(p,1)}(t)$ is a control that is equal to 1 if the recovery service $D_{rk}^{(p,j)}$ for $M_r^{(f,j)}$ is executed at $M_{\delta}^{(p,j)}$; otherwise $\nu_{r\delta k}^{(p,2)}(t) = 0$;

$\nu_r^{(p,2)}(t)$ is an auxiliary control that is equal to 1 if the recovery process of $M_r^{(f,j)}$ is completed; otherwise $\nu_r^{(p,2)}(t) = 0$.

The *model* helps to coordinate three processes during the recovery period, i.e.

- an optimal process recovery,
- a SC material flow control under recovery during the recovery time and
- the recovery adjustment process.

Goals are measured by the order delivery times to customers and the volume of the orders delivered. These goals correspond to practical key performance indicators (KPI) of customer service level and delivery reliability. Customer service level is measured by a function of the actual delivery times. All the orders have to be completed by the time T_f. Otherwise, penalties for delivery breaks or backlog appear, subject to the known penalty functions $\alpha_{\nu\chi r}^{(f,j)}$ and $\beta_{i\eta\rho}(\tau)$, respectively. The reliability of delivery is measured by the volumes $x_{\nu\chi}^{(o,j)}$ of the delivered jobs subject to the planned volumes (i.e. the fullness of the order completing).

4.1 Mathematical Model of the Material Flow Control Process (Model M1)

The execution dynamics of services $D_{\mu}^{(i)}$ can be expressed as (1)

$$\frac{dx_{\nu\chi}^{(o,j)}}{dt} = \sum_{\mu=1}^{m_j} u_{\nu\chi\mu}^{(o,j)}, \tag{1}$$

The economic sense of (1) consists of the representation of the service execution dynamics in which process non-stationary and execution dynamics are reflected. The state variable $x(t)$ accumulates the executed volume of the considered service. The control actions are constrained as follows:

$$\sum_{\nu=1}^{n_j}\sum_{\chi=1}^{s_\nu} u_{\nu\chi\mu}^{(o,j)}(t) \le 1,\ \forall\mu; \sum_{\mu=1}^{m_j} u_{\nu\chi\mu}^{(o,j)}(t) \le 1,\ \forall\nu,\ \forall\chi; \tag{2}$$

$$\sum_{j=1}^{n} u_{\nu\chi\mu}^{(o,j)}[\sum_{\alpha\in\Gamma_{i\mu_1}^-} (a_{i\alpha}^{(o)} - x_{i\alpha}^{(o)}) + \prod_{\beta\in\Gamma_{i\mu_2}^-} (a_{i\beta}^{(o)} - x_{i\beta}^{(o)})] = 0 \tag{3}$$

$$\sum_{\mu=1}^{m_j} u_{\nu\chi\mu}^{(o,j)}[(a_{\nu(\chi-1)}^{(o,j)} - x_{\nu(\chi-1)}^{(o,j)}) + (a_{\nu\chi}^{(f,j)} - x_{\nu\chi}^{(f,j)})] = 0; \tag{4}$$

$$0 \le u_{\nu\chi\mu}^{(o,j)}(t) \le 1,\ \forall\nu,\ \forall\chi,\ \forall\mu; \tag{5}$$

$$u_{\nu\chi\mu}^{(o,j)}(t) \in \{0, 1\}, \tag{6}$$

where $\Gamma_{i\mu_1}^-$, $\Gamma_{i\mu_2}^-$ are the sets of service numbers which immediately precede a service, subject to completion of all the predecessor services or at least one of these services, respectively. Equation (2) shows that only one service can be executed at a SC element at a time. Constraint (3) brings the natural time logic into the model and determines the precedence relations. Constraint (4) determines the possibility of the delivery of the product ρ-flow to the η-customer. Constraints (5)–(6) reflect the intensity of service processing.

According to Eq. (6), the control contains the values of the *Boolean variables*. In order to assess the results of order execution, we define the following initial and end conditions:

$$x_{\nu\chi}^{(o,j)}(T_0^{(j)}) \in 0; \tag{7}$$

$$x_{\nu\chi}^{(o,j)}(T_f^{(j)}) = a_{\nu\chi}^{(o,j)}, \ \forall\nu, \ \forall\chi. \tag{8}$$

The constraints (7) reflect that, in the beginning, the volume of executed services is equal to zero (if a certain volume of orders is to be transferred from the previous planning period to the beginning of the current planning period, then this should be reflected in (7)). The conditions (8) reflect the desired end state. The right parts of Eq. (8) are predetermined at the planning stage subject to the volumes (i.e. lot-sizes) of each order.

According to the problem statement, let us introduce the following performance indicators:

$$J_1^{(o,j)} = \sum_{\nu=1}^{n_j}\sum_{\chi=1}^{s_\nu}\sum_{\mu=1}^{m_j}\int_{t_o^{(j)}}^{t_f^{(j)}} \beta_{\nu\chi}^{(o,j)}(\tau)u_{\nu\chi\mu}^{(o,j)}(\tau)d\tau; \tag{9}$$

$$J_2^{(o,j)} = \frac{1}{2}\sum_{\nu=1}^{n_j}\sum_{\chi=1}^{s_\nu}(a_{\nu\chi}^{(o,j)} - x_{\nu\chi}^{(o,j)}(t_f^{(j)}))^2. \tag{10}$$

The indicator J_1 (9) refers to penalties for breaking delivery terms. The goal indicator J_2 (10) characterizes the accuracy of the end conditions' accomplishment, i.e. the service level.

Corollary 1 Constraints (10) ensure that all orders are fully completed, i.e. the planned service level can be reached.

Proof Analysis of constraints (3) shows that control $\mathbf{u}(t)$ switches on only when the necessary predecessor services have been executed. $\sum_{\mu=1}^{m_j} u_{\nu\chi\mu}^{(o,j)}[(a_{\nu(\chi-1)}^{(o,j)} - x_{\nu(\chi-1)}^{(o,j)}) = 0$ guarantees the total processing of the predecessor services and $\sum_{\mu=1}^{m_j}(a_{\nu\chi}^{(f,j)} - x_{\nu\chi}^{(f,j)})] = 0$ of the current services. Herewith, constraints (3) determine the possibility of delivery to the customer $\bar{B}^{(\eta)}$ according to the product flow $P_{<s_i,\rho>}^{(j,\eta)}$ with the use of $M^{(j)}$. The proof is complete.

4.2 Mathematical Model of the Recovery Control Process (Model M2)

Let us describe the execution of services in the recovery process as follows:

$$\frac{dx_{\nu\chi}^{(f,j)}}{dt} = \sum_{r=1}^{R_j} u_{\nu\chi r}^{(f,j)}; \tag{11}$$

$$\frac{dx_{r}^{(f,j)}}{dt} = \sum_{\nu=1}^{n_j} \sum_{\chi=1}^{s_j} w_{\nu\chi r}^{(f,j)}; \tag{12}$$

$$\frac{dx_{r}^{(f,j)}}{dt} = \tilde{\nu}_{\nu\chi r}^{(f,j)}. \tag{13}$$

The control actions are constrained as follows:

$$0 \le u_{\nu\chi r}^{(f,j)}(t) \le [e_{\nu\chi r}(1 - \nu_r^{(p,2)}) + \bar{e}_{\nu\chi r}\nu_r^{(p,2)}]w_{\nu\chi r}^{(f,j)}; \tag{14}$$

$$\sum_{\nu=1}^{n_j} \sum_{\chi=1}^{s_\nu} V_{\nu\chi}^{(j)} w_{\nu\chi r}^{(f,j)} \le V_r^{(j)}(1 - \nu_r^{(p,2)}) + \bar{V}_r^{(j)}\nu_r^{(p,2)}; \tag{15}$$

$$\sum_{\nu=1}^{n_j} \sum_{\chi=1}^{s_\nu} u_{\nu\chi r}^{(f,j)}(t) \le \Phi_r^{(j)}(1 - \nu_r^{(p,2)}) + \bar{\Phi}_r^{(j)}\nu_r^{(p,2)}; \tag{16}$$

$$\tilde{\nu}_{\nu s_\nu}^{(f,j)}(a_{\nu s_\nu}^{(f,j)} - x_{\nu s_\nu}^{(f,j)}) = 0; \tag{17}$$

$$\sum_{r=1}^{R_j} w_{\nu\chi r}^{(f,j)}(a_{\nu(\chi-1)}^{(f,j)} - x_{\nu(\chi-1)}^{(f,j)}) = 0; \tag{18}$$

$$\sum_{r=1}^{R_j} w_{\nu\chi r}^{(f,j)}(t) \le 1, \ \forall\chi, \ \forall\nu; \tag{19}$$

$$0 \le w_{\nu\chi r}^{(f,j)}(t) \le 1. \tag{20}$$

Constraints (14)–(16) reflect the possibilities of service processing with regards to $M_r^{(f,j)}$ before and after recovery. Constraint (14) describes the joint functioning of the SC process to be changed and the recovery process. Constraints (17) and (18) determine the processing consequence of the services $D_{\nu\chi}^{(f,j)}$, $D_{\nu(\chi-1)}^{(f,j)}$ subject to the corresponding services $D_{\nu\chi}^{(o,j)}$, $D_{\nu(\chi-1)}^{(o,j)}$ of the material flow control process. Constraints (19) and (20) imply that at the given instant of time the processing of the service $D_{\nu\chi}^{(f,j)}$ can be executed only at $M_r^{(f,j)}$.

Boundary conditions (21)–(24) specify the values of variables $x_{\nu\chi}^{(f,j)}$, $x_r^{(f,j)}$ at the beginning and the end of the planning period $t_0^{(j)}$ и $t_f^{(j)}$ and can be written as follows:

$$x_{\nu\chi}^{(f,j)}(t_0^{(j)}) = 1; \tag{21}$$

$$x_r^{(f,j)}(t_0^{(j)}) = 0; \tag{22}$$

$$x_{\nu\chi}^{(f,j)}(t_f^{(j)}) = a_{\nu\chi}^{(f,j)}; \tag{23}$$

$$x_r^{(f,j)}(t_f^{(j)}) \in R^1. \tag{24}$$

Their meaning is similar to those in the model M1. The performance indicators are defined in the form of Eqs. (25)–(28):

$$J_1^{(f,j)} = \sum_{r=1}^{R_{j-1}} \sum_{r_1=r+1}^{R_j} \int_{t_o^{(j)}}^{t_f^{(j)}} (x_r^{(f,j)}(\tau) - x_{r_1}^{(f,j)}(\tau))^2 d\tau; \tag{25}$$

$$J_2^{(f,j)} = \sum_{\nu=1}^{n_j} \sum_{\chi=1}^{s_\nu} \sum_{r=1}^{R_j} \int_{t_o^{(j)}}^{t_f^{(j)}} \alpha_{\nu\chi r}^{(f,j)}(\tau) w_{\nu\chi r}^{(f,j)}(\tau) d\tau; \tag{26}$$

$$J_3^{(f,j)} = \frac{1}{2} \sum_{\nu=1}^{n_j} \sum_{\chi=1}^{s_\nu} (a_{\nu\chi}^{(f,j)}(\tau) - x_{\nu\chi}^{(f,j)}(t_f^{(j)}))^2; \tag{27}$$

$$J_4^{(f,j)} = \sum_{r=1}^{R_j} (T^{(j)} - x_r^{(f,j)}(t_f^{(j)}))^2; \tag{28}$$

Indicator (25) estimates the equal recovery volumes at different SC elements. Indicator (26) characterizes the accuracy of the end conditions' accomplishment, i.e. the service level. Indicator (27) refers to penalties for breaking delivery terms or any other penalties due to disruptions, i.e. the delivery reliability. Indicator (28) estimates the total processing of the orders affected by recovery.

4.3 Mathematical Model of the Adjustment of Recovery Control Process (M3)

The model presented in this subsection is similar to the models M1 and M2. This model describes the recovery process adjustment based on feedback information from RFID, sensors and T&T systems concerning changes in the SC and the environment. The mathematical model of recovery control can be presented as (29)–(30):

$$\frac{dx_{rk}^{(p,1)}}{dt} = \sum_{\delta=1}^{\Delta j} b_{r\delta k} \nu_{r\delta k}^{(p,1)}; \tag{29}$$

$$\frac{dx_r^{(p,2)}}{dt} = \nu_r^{(p,2)}. \tag{30}$$

The control actions are constrained as follows:

$$\sum_{r=1}^{R_j} \nu_{r\delta k}^{(p,1)}(t) \le c_{\delta j}^{(p,1)},\ \forall\delta,\ \forall k; \tag{31}$$

$$\sum_{\delta=1}^{\Delta j} \nu_{r\delta k}^{(p,1)}(t) \le 1,\ \forall\delta,\ \forall k,\ k = 1, \ldots, K_j^{(r)}; \tag{32}$$

$$\sum_{\delta=1}^{\Delta j} \nu_{r\delta k}^{(p,1)}(a_{r(k-1)}^{(p,1)} - x_{r(k-1)}^{(p,1)}) = 0; \tag{33}$$

$$\nu_r^{(p,2)}(a_{rK_j}^{(p,1)} - x_{rK_j}^{(p,1)}) = 0; \tag{34}$$

$$0 \le \nu_{r\delta k}^{(p,1)}(t) \le 1; 0 \le \nu_r^{(p,2)}(t) \le 1 \tag{35}$$

Constraints (31) reflect the possibilities of the performing recovery services $D_{rk}^{(p,j)}$ subject to the recovery of $M_r^{(f,j)}$. Constraints (32) set the requirement that the recovery service $D_{rk}^{(p,j)}$ can be performed only by one of $M_\delta^{(p,j)}$ available for the recovery. Constraints (33) determine the prioritizing of the services $D_{rk}^{(p,j)}$ and $D_{r(k-1)}^{(p,j)}$, associated with recovery of $M_r^{(f,j)}$. Constraints (34) define the end time of the recovery process of $M_r^{(f,j)}$. Constraints (35) set the domain of control actions $\nu_{r\delta k}^{(p,1)}(t)$ and $\nu_r^{(p,2)}(t)$ possible values. The end conditions are identical to those in model M2. The performance indicator is defined as (36):

$$J_1^{(p,1)} = \sum_{\delta=1}^{\Delta j}\sum_{r=1}^{R_\nu}\sum_{k=1}^{K_j}\left[\left(\int_{t_0^{(j)}}^{t_f^{(j)}} \left(\lambda_1 c_{r\delta k}^{(p,j)}(\tau) + \lambda_2 \beta_{rk}^{(p,j)}(\tau)\right)\nu_{r\delta k}^{(p,1)} d\tau\right) + \lambda_3 \frac{1}{2}\left(a_{rk}^{(p,1)} - x_{rk}^{(p,1)}\right)^2\right]; \tag{36}$$

where $c_{r\delta k}^{(p,j)}(\tau)$ are the costs of recovery and λ are the weight coefficients. Indicator (36) estimates the total processing quality of services $D_{\nu\chi}^{(f,j)}$. This indicator also enables estimation of total recovery cost, ongoing service of the modernized process, and total penalty for the schedule violation within the process recovery. These values can be calculated using the first component of indicator (36). The terminal (second) component of indicator (36) estimates the accuracy of the confirmation for the end conditions.

The recovery control process can now be formulated as the following problem of optimal program control (OPC): this is necessary to find an allowable control $\mathbf{u}(t), t \in (T_0,\ T_f]$ that ensures the vector constraint functions $\mathbf{q}^{(1)}(\mathbf{x}, \mathbf{u}) = \mathbf{0}$, $\mathbf{q}^{(2)}(\mathbf{x}, \mathbf{u}) \le \mathbf{0}$ (2)–(6), (14)–(20) and (31)–(35) are met for the model governed by (1), (11)–(13) and

(29)–(30) and guides the dynamic system (i.e. the SC) $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}, t)$ from the initial state to the specified final state. In terms of OPC, the program control of services execution is simultaneously the optimal recovery process. The formulated model is a linear, non-stationary, finite-dimensional controlled differential system with the convex area of admissible control. Note that this is a standard OPC problem; see (Lee and Markus 1967). This model is linear in the state and control variables, and the objective is linear. The transfer of non-linearity to the constraint ensures convexity and allows the use of interval constraints. For such kind of models, both sufficient and necessary optimality conditions have been proven (Dolgui et al. 2019).

It can be observed that the elaborated multi-level modelling complex can be applied for investigation and solution of different problem domains in the analysis and synthesis of SCs with regard to different, interlinked processes. The integration and coordination of the models is ensured by the following basic components:

- M2 influences the M1 model through the constraints (3). A service $D_{\nu\chi}^{(o,j)}$ in the unchanged process can start only after completing the previous service $D_{\nu(\chi-1)}^{(o,j)}$ in this process and the service $D_{\nu\chi}^{(f,j)}$ in the coordinated process;
- M3 influences M2 through Eqs. (14)–(16).
- The M1 model influences the M2 and M3 models through the conjunctive variables by the OPC problem solution with the help of the local cut method (Ivanov and Sokolov 2013).

The conducted investigations of the proposed models show that the use of the goal indicators (9)–(10), (25)–(28) and (36) makes it possible to model other factors with regard to SC effectiveness and efficiency. For example, with the use of the $c_{r\delta k}^{(p,j)}(\tau)$, the following can be explicitly reflected:

- Changes in the costs of SC recovery regarding SC evolution in dynamics; and
- Changes in total SC costs regarding the mutual influences of interlinked processes.

The elaborated models can also be applied to simulate different scenarios of recovery and the corresponding impact on SC performance. The analytical optimality properties of the model presented as well as the efficient computational algorithm have been previously presented and proven in the studies (Ivanov and Sokolov 2013; Ivanov et al. 2016a, b; Ivanov et al. 2018a). We omit their detailed presentation in this paper.

5 Conclusions

During the SC recovery process, a disruptive event, planning of the recovery control policy and implementation of this policy are distributed in time and subject to SC structural and parametrical dynamics. In other words, the environment, SC structures and operational parameters may change in the period between the planning of the recovery control policy and its implementation.

As such, situational proactive control with combined use of simulation-optimization and analytics has been proposed in the paper to improve the transition processes from a disrupted to a restored SC state. Implementing situational proactive control reduces investments in robustness and increases resilience by obviating the transition process control problems. This paper developed a model for an integrated proactive-reactive decision support system for situational proactive control of SC recovery processes based on a combination of optimization and analytics techniques. More specifically, three dynamic models were developed and integrated with each other, i.e. a model of SC material flow control, a model of SC recovery control and a model of SC recovery control adjustment. The given models are developed within a cyber-physical SC framework based on a service-oriented approach.

Advantages of the proposed approach are evident in two areas. On the one hand, continuous optimization is a convenient engineering tool to model service-oriented, cyber-physical SCs since the services and their accumulation over time can be easily described with the help of continuous state and control variables. On the other hand, dynamic description of the SC recovery process with the help of optimal control enables the incorporation of these results into an axiomatic of feedback control which uses the same methodological principles.

Some limitations of this study and future research can be considered in light of the technical integration of data analytics into the framework and the models developed. The models themselves need to be adapted for individual applications for which specific algorithms need to be developed, analytically analyzed, and practically implemented.

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Bullwhip Effect of Multiple Products with Interdependent Product Demands

Srinivasan Raghunathan, Christopher S. Tang and Xiaohang Yue

Abstract The bullwhip effect has been studied extensively by researchers using analytical and empirical models based on a single product. We extend the current theory to provide insights for a firm that manufactures multiple products in a single product category with interdependent demand streams. We find that interdependency between demand streams plays a critical role in determining the existence and magnitude of the bullwhip effect. More importantly, we show that interdependency impacts whether the firm should manage ordering and inventory decisions at the category level or at the product level, and whether the bullwhip effect measure computed at the category level is informative or not.

1 Introduction

Risk management in supply chains has become one of the most important topics in research and practice over the last decades. Several books (Handfield and McCormack 2008; Kouvelis and Dong 2011; Waters 2011; Gurnani et al. 2012; Sodhi and Tang 2012; Heckmann 2016; Khojasteh 2017; Ivanov 2018) and review articles (Klibi et al. 2010; Simangunsong et al. 2012; Ho et al. 2015; Fahimnia et al. 2015; Gupta et al. 2016) provide insightful overview and introduction to different aspects of this important field. The risks in a supply chain can be categorized into two types: disruption risk and operational risk.

S. Raghunathan (✉)
School of Management, The University of Texas at Dallas, Richardson, TX 75083, USA
e-mail: sraghu@utdallas.edu

C. S. Tang
UCLA Anderson School, Los Angeles, CA 90095, USA
e-mail: chris.tang@anderson.ucla.edu

X. Yue
Lubar School of Business, The University of Wisconsin-Milwaukee, Milwaukee, WI 53201, USA
e-mail: xyue@uwm.edu

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Recent literature and management practices provide evidence that accounting for risk is essential to provide practically relevant problem statements and decision-oriented solutions. Recent literature suggests that firms should consider both operational risks and disruption risks (Chopra et al. 2007) because these risks impact supply chain performance such as sales, stock return, service level, and costs, as evidenced from disruptions caused by incidents such as 2011 earthquake in Japan, 2011 floods in Thailand, and fire in the Phillips Semiconductor plant in New Mexico. Also, some researchers (e.g., Hendricks and Singhal 2005) have quantified the negative effects of supply chain disruption through empirical analysis and found 33–40% lower stock returns relative to their benchmarks over a 3-year time period that started 1 year before and ended 2 years after a disruption. Disruption risk represents a new challenge for supply chain managers who face the “ripple effect” (Ivanov et al. 2014a, b, 2017; Ivanov 2017; Dolgui et al. 2018). The ripple effect deals with structural disruptions in the supply chain, while the bullwhip effect deals with parametrical deviations in the supply chain.

The bullwhip effect examines weeks/daily demand and lead time fluctuations as primary drivers of the changes in the supply chain. It occurs at the parametric level and it can be mitigated so that the operations can be restored on a short-term basis. In recent years, the research community has started to investigate severe supply chain disruptions caused by natural disasters, political conflicts, terrorism, maritime piracy, economic crises, destroying of information system or transportation infrastructure failures. Some researchers (Ivanov 2018) refer to these severe natural and man-made disasters as the ripple effect in the supply chain where changes in the supply chain occur at the structural level and recovery may take mid and long-term periods with significant impact on output performance such as annual revenues.

Despite the difference between the ripple effect and the bullwhip effect, there is a linkage between them. Although we focus on how to mitigate the impact of the bullwhip effect of multiple products in a single product category with interdependent product demand streams in this chapter, our model and analysis can be used to examine the ripple effect if we view different products as country-specific products. Then, as the demand for a country-specific product is disrupted due to an economic crisis occurred in one country, the implication of this disruption can affect the demand for other products associated with other countries especially when the world economies are connected. From this vantage point, our bullwhip effect can be interpreted at a “higher” level so that the net effect is akin to the ripple effect. For this reason, we shall focus our discussion on the bullwhip effect in the remaining of this chapter, even though the result can be interpreted as the ripple effect in the context of a supply chain that produces country-specific products where each of the products is subject to uncertain disruptions arising from different counties.

In the bullwhip effect literature, the seminal work of Lee et al. (1997) examined different drivers of the bullwhip effect—i.e., the amplification of variance of demand as it propagates upstream through the supply chain. Lee et al. employed the autoregressive model of order one (AR (1)) in their analysis of bullwhip effect of a single product. Subsequent papers examined bullwhip effect using a variety of demand models, forecasting methods, and inventory policies, but they focused primarily in the single product setting (e.g., Graves 1999; Chen et al. 2000; Aviv 2003; Zhang 2004a; Miyaoka and Hausman 2004; Zhang 2004b; Gilbert 2005; Gaur et al. 2005; Chen and Lee 2009).[1] Empirical results have been mixed about the prevalence of bullwhip effect. Using firm-level data, Bray and Mendelson (2012) found that two-thirds of the publicly traded firms exhibit bullwhip effect, but using industry-level data, Cachon et al. (2007) found no significant bullwhip effect in many industries. Chen and Lee (2012) analytically showed that time and product aggregation can mask the bullwhip effect, while Bray and Mendelson reached similar conclusions using empirical data. The current theory of supply chain bullwhip effect has been developed using single product models. Chen and Lee considered multiple products to examine the impact of product aggregation, but do not model or analyze interdependency among individual product demand streams. In this work, we extend the current theory to provide new insights for a firm that manufacturers multiple products with interdependent demands in a product category.

The motivation for this work stems from product proliferation commonly observed in most industries. Product proliferation occurs when a firm introduces multiple variants or brands of the same core product. The dramatic increase in product variety over the last three decades in numerous product categories has been well documented by Cox and Alm (1998) and Aichner and Colletti (2013). A large product variety is observed also among contract manufacturers in industries such as electronics and automobiles, who supply components to multiple original equipment manufacturers. Product proliferation poses operational challenges to firms for a variety of reasons. For instance, because the different product variants within a product category are (imperfect) substitutes of each other, their demands tend to be interdependent in the sense they are not only contemporaneously correlated in a given time period but also serially correlated across time periods. The contemporaneous correlation is natural because these are variants of the same product. The serial correlation across different products arises because of consumer-driven factors and firm-driven factors. For example, the well-known variety seeking behavior of some consumers results in those consumers switching the product variant they buy over time (for example, switching from Kellogg's Corn Flakes in one week to Rice Krispies in the following week). Furthermore, firms may promote different product variants at different time periods which can also contribute to serial correlation (for example, distributing coupons for Corn Flakes in one month and for Rice Krispies in the following month). On the operational side, while some firms manage forecasting, production, ordering, and inventory of these products at the individual product level, some others manage them at the product category level. Though these aspects capture the essence of many current real-world scenarios, they have not been adequately addressed in the extant bullwhip effect literature.[2]

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[1] See Wang and Disney (2016) for a comprehensive review of the bullwhip effect literature.

[2] There is extensive literature on aggregate and individual product-level forecasting, commonly known as top-down and bottom-up forecasting, in the operations management literature (e.g., Sbrana and Silvestrini 2013, Chen and Blue 2010 are some recent studies that compare the forecast accuracy of top-down and bottom-up approaches).

We employ a vector autoregressive model of order one (VAR(1)) that captures the interdependency among product demands across periods using cross-correlation coefficient and interdependency within a period using contemporaneous (or spatial) correlation coefficient, in addition to the within product demand dependency using autocorrelation coefficient.[3] VAR(1) model is a natural extension of the widely used AR(1) model to model demands of multiple products, and has been studied and applied in a variety of multiproduct demand forecasting contexts (Box and Tiao 1977; Tiao and Box 1981; Tiao and Tsay 1983; Chen and Blue 2010; Sbrana and Silvestrini 2013).[4] In this chapter, we first derive the bullwhip effect formula by assuming that the firm manages the ordering and inventory decisions at the product level and use the formula to obtain the impacts of key model parameters. The well-known result that an increase in the autocorrelation coefficient amplifies the bullwhip effect (Lee et al. 1997) continued to hold in the VAR(1) model, but more importantly, the result extends to the cross-correlation coefficient. The impact of contemporaneous correlation and number of products on the bullwhip effect depend critically on whether the cross-correlation is positive or negative. When the cross-correlation is negative (positive), we show that an increase in contemporaneous correlation decreases (increases) the bullwhip effect, and an increase in the number of products increases (decreases) the bullwhip effect. That is, demand pooling and negative contemporaneous correlation do not necessarily mitigate the product-level bullwhip effect.

Subsequently, we derive the bullwhip effect formula when the firm manages the ordering and inventory decision at the product category level. We show that category-level bullwhip effect is increasing in the autocorrelation, cross-correlation, contemporaneous correlation, and the number of firms. Therefore, the conventional intuitions about the impact of these factors on the bullwhip effect persist at the category-level bullwhip measure. Furthermore, we also show that the bullwhip effect when the firm manages at the category level is identical to the bullwhip effect that is computed (or measured) by aggregating the demand and order data for all products even though the ordering and inventory decisions are made at the individual product level. This result demonstrates that correct implications cannot be derived based on the aggregate bullwhip effect measure without knowledge about how the products are actually managed within the firm.

Finally, we compare the product level and category-level bullwhip effects. Whether the category-level bullwhip effect is greater than or smaller than the product-level bullwhip effect depends critically on the cross-correlation coefficient—the product-level bullwhip effect is smaller (larger) than the category-level bullwhip effect when the cross-correlation coefficient is highly positive (negative). Therefore,

[3] This work is based on Raghunathan et al. (2017). All proofs of propositions are available in Raghunathan et al. (2017).

[4] While we do not have firm-level data to test whether the VAR(1) model fits brand demand streams, an examination of the data contained in the Compustat database shows that the VAR(1) model provides a statistically significant fit for the cost of goods sold (a widely used proxy for demand in the bullwhip effect literature) of firms within an industry. Furthermore, Chen and Blue (2010) gave an example of a semiconductor manufacturer where the VAR(1) model is appropriate to model the demand data of two product variants.

for a multiproduct firm, from the bullwhip effect point of view, the cross-correlation plays a vital role in the firm's choice regarding category-level verses product-level management of ordering and inventory decisions. Furthermore, the cross-correlation also plays a role in determining whether the bullwhip effect measured using aggregate data masks or exaggerates the underlying bullwhip effect if the firm adopts product-level management.

2 The Model

We consider a manufacturer who produces and sells $n \geq 2$ products in a product category. The demand for product i in period t takes on the following form:

$$D_{it} = d + \rho D_{i(t-1)} + \gamma \sum_{j=1}^{n} \frac{D_{j(t-1)}}{n} + \varepsilon_{it} \tag{1}$$

where D_{it} is product i's demand in period t, $\overline{D}_{(t-1)} = \sum_{j=1}^{n} D_{j(t-1)}$ is the product category's demand in period t-1, ρ is the autocorrelation coefficient, γ is the cross-correlation coefficient, ε_{it} is the error term which is identically normally distributed with mean zero and variance σ^2 for all i and t, ε_{it} for a given i is independent across time, and the contemporaneous correlation coefficient between ε_{it} and ε_{jt} is $\omega, \quad \forall i \neq j$. Of course, -1/($n$-1) < ω < 1 to ensure variance positivity. Thus, the demand streams for the products can be expressed as the following VAR(1) process:

$$\begin{bmatrix} D_{1t} \\ D_{2t} \\ \vdots \\ D_{nt} \end{bmatrix} = \begin{bmatrix} d \\ d \\ \vdots \\ d \end{bmatrix} + \begin{bmatrix} \rho + (\gamma/n) & \gamma/n & \cdots & \gamma/n \\ \gamma/n & \rho + (\gamma/n) & \cdots & \gamma/n \\ \vdots & \gamma/n & \ddots & \gamma/n \\ \gamma/n & \gamma/n & \cdots & \rho + (\gamma/n) \end{bmatrix} \begin{bmatrix} D_{1(t-1)} \\ D_{2(t-1)} \\ \vdots \\ D_{n(t-1)} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{nt} \end{bmatrix}. \tag{2}$$

The manufacturer procures the raw materials required for production from a supplier. Without loss of generality, we assume that each unit of a product requires one unit of raw material. We consider two potential replenishment strategies that the manufacturer could adopt. Under the *product-level* replenishment strategy, the ordering, replenishment, and inventory decisions are managed separately for each product, as if there is a separate upstream supply chain for each product. Under the *category-level* replenishment strategy, the decisions are made for the whole product category, as if there is a single upstream supply chain for all products combined. Regardless of the replenishment strategy used, we assume that the manufacturer adopts the optimal state-dependent base-stock policy to determine the order quantity (Lee et al. 1997; Chen et al. 2000).

The key aspects of the replenishment process are the following. Let L denote the replenishment lead time of raw materials, which we assume to be the same for all products. At the beginning of period t, the demands for all products in (t-1) are observed, and all orders made in period *t-L* are received from the supplier. Then, either an order z_{it} for product *i* (for a total of *n* orders) or a single order of $\overline{z}_t$ for the entire product category is placed with the supplier depending on the replenishment strategy used by the manufacturer. The production of products occurs during the period and demands for all products are realized and satisfied at the end of *t*. There is no system capacity constraint, no order batching, and free return of excess inventory. Inventory-related costs are proportional and are identical across products. Since the focus of this study is demand interdependency, we abstract away many operational details. For instance, we assume symmetric products to eliminate the impact of product-specific characteristics from our findings.

Finally, we impose the following *stationarity condition* to make the demand process covariance stationary.

Stationarity Assumption: $|\rho| < 1$ *and* $|\rho + \gamma| < 1$.

3 Derivation and Analysis of the Bullwhip Effect

Suppose the manufacturer uses the product-level replenishment strategy. Then, to compute the optimal base-stock level for a product, we need the expected value and variance of its demand over lead time *L*. This requires the forecasts, over the lead time, for not only the product's own demand but also the category demand. The joint demand process is used to perform minimum mean square error (MMSE) forecasting update.

The joint demand process is derived as follows. Using (1), we compute the category demand $\overline{D}_t$ to be the following.

$$\overline{D}_t = \sum_{i=1}^{n} D_{it} == nd + (\rho + \gamma)\overline{D}_{(t-1)} + \sum_{i=1}^{n} \varepsilon_{it} \tag{3}$$

Note that the category demand follows the AR(1) process. Now, we can express the firm demand and the category demand jointly as the following 2 × 2 VAR(1) process:

$$\begin{bmatrix} D_{it} - \mu_D \\ \overline{D}_t - n\mu_D \end{bmatrix} = \begin{bmatrix} \rho & \gamma/n \\ 0 & \rho + \gamma \end{bmatrix} \begin{bmatrix} D_{i(t-1)} - \mu_D \\ \overline{D}_{t-1} - n\mu_D \end{bmatrix} + \begin{bmatrix} \varepsilon_{it} \\ \sum_{i=1}^{n} \varepsilon_{it} \end{bmatrix}, \tag{4}$$

where $\mu_D = d/(1 - \rho - \gamma)$.

Let $\tau \geq 0$ be an integer, $\pi_k = \frac{(\rho+\gamma)^{k+1} - \rho^{k+1}}{\gamma}$ and $\Pi_\tau = \sum_{k=0}^{\tau} \pi_k$. The future demand for product *i* at period $(t + \tau)$, $D_{i(t+\tau)}$, can be expressed as a function of last observed product demand $D_{i(t-1)}$ and category demand $\overline{D}_{t-1}$, and future errors such as:

$$\begin{bmatrix} D_{i(t+\tau)} - \mu_D \\ \overline{D}_{t+\tau} - n\mu_D \end{bmatrix} = \begin{bmatrix} \rho^{\tau+1} & \rho\pi_\tau \\ 0 & (\rho+\gamma)^{\tau+1} \end{bmatrix} \begin{bmatrix} D_{i(t-1)} - \mu_D \\ \overline{D}_{t-1} - n\mu_D \end{bmatrix} + \sum_{k=0}^{\tau} \begin{bmatrix} \rho^{\tau-k} & (\gamma/n)\pi_{\tau-k-1} \\ 0 & (\rho+\gamma)^{\tau-k} \end{bmatrix} \begin{bmatrix} \varepsilon_{i(t+k)} \\ \sum_{i=1}^{n} \varepsilon_{i(t+k)} \end{bmatrix}$$

The optimal MMSE τ-period-ahead forecast is given by the conditional expectation of future demand $D_{t+\tau}$ given $D_{i(t-1)}$ and $\bar{D}_{t-1}$. The above joint demand system yields the following MMSE forecasting equations:

$$E\left(D_{i(t+\tau)} | D_{i(t-1)}, \overline{D}_{(t-1)}\right) = \mu_D + \rho^{\tau+1}\left(D_{i(t-1)} - \mu_D\right) + (\gamma/n)\pi_\tau\left(\overline{D}_{t-1} - n\mu_D\right) \tag{5}$$

The lead time demand forecast can then be obtained from summing the τ-period-ahead forecasts such as

$$\begin{aligned} E\left[\left(\sum_{\tau=0}^{L} D_{i(t+\tau)}\right) \middle| D_{i(t-1)}, \overline{D}_{(t-1)}\right] &= \sum_{\tau=0}^{L} E\left(D_{i(t+\tau)} | D_{i(t-1)}, \overline{D}_{(t-1)}\right) \\ &= n\mu_D + \rho\left(\frac{1-\rho^{L+1}}{1-\rho}\right)\left(D_{i(t-1)} - \mu_D\right) \\ &\quad + (\gamma/n)\Pi_L\left(\overline{D}_{t-1} - n\mu_D\right). \end{aligned}$$

So, the optimal base-stock level for product i for period t, S_{it}^*, is given by

$$\begin{aligned} S_{it}^* =& E\left[\left(\sum_{\tau=0}^{L} D_{i(t+\tau)}\right) \middle| D_{i(t-1)}, \overline{D}_{(t-1)}\right] + K\sqrt{\mathrm{Var}\left(\sum_{\tau=0}^{L} D_{i(t+\tau)} | D_{i(t-1)}, \overline{D}_{(t-1)}\right)} \\ =& n\mu_D + \rho\left(\frac{1-\rho^{L+1}}{1-\rho}\right)\left(D_{i(t-1)} - \mu_D\right) + (\gamma/n)\Pi_L\left(\overline{D}_{t-1} - n\mu_D\right) \\ &+ K\sqrt{\mathrm{Var}\left(\sum_{\tau=0}^{L} D_{i(t+\tau)} | D_{i(t-1)}, \overline{D}_{(t-1)}\right)} \end{aligned}$$

where K represents the service-level coefficient. Therefore, the optimal order quantity z_{it}^* is given by

$$\begin{aligned} z_{it}^* &= S_{it}^* - S_{i(t-1)}^* + D_{i(t-1)} \\ &= \rho\left(\frac{1-\rho^{L+1}}{1-\rho}\right)\left(D_{i(t-1)} - D_{i(t-2)}\right) + (\gamma/n)\Pi_L\left(\overline{D}_{t-1} - \overline{D}_{t-2}\right) + D_{i(t-1)} \end{aligned} \tag{6}$$

Using the variances of z_{it}^{*} and D_{it}, we can compute the formula for the bullwhip effect associated with product i. Lemmas 1 and 2 provided in the appendix derives these variances. The bullwhip effect is commonly measured according to either the (unconditional) variance of order quantity minus variance of demand, which we refer to as the *bullwhip difference*, or according to the (unconditional) variance of order quantity divided by variance of demand, which we refer to as *bullwhip ratio*. Since the upstream supply chain costs (e.g., inventory holding costs) are proportional to the square root of the order variance for a given demand model (Chen and Lee 2012), bullwhip difference measure is useful when absolute costs associated with the bullwhip are desired. On the other hand, the ratio measure is useful when percentage costs associated with the bullwhip effect are desired. We examine the bullwhip difference in detail first, followed by an examination of the bullwhip ratio.

3.1 Product-Level Bullwhip Effect: Bullwhip Difference

Define the following for notational convenience and expositional clarity.

$$\theta = \left(1 - \frac{1}{n}\right)(1 - \omega);$$

$$M(\lambda) = \frac{2\lambda\left(1 - \lambda^{L+1}\right)\left(1 - \lambda^{L+2}\right)}{(1 - \lambda)\left(1 - \lambda^{2}\right)}\sigma^{2}$$

Proposition 1 *The product-level bullwhip difference is given by*

$$BWE_{diff}^{product} = Var\left(z_{it}^{*}\right) - Var(D_{it}) = \theta M(\rho) + (1 - \theta)M(\rho + \gamma) \tag{7}$$

Equation (7) is a generalization of the bullwhip difference derived by Lee et al. (Equation (3.5)) for a single product AR(1) demand model. If $\gamma = 0$, Eq. (7) reduces to Lee et al.'s equation. We note that the product-level bullwhip difference is a convex linear combination of $M(\rho)$ and $M(\rho + \gamma)$. $M(\lambda)$ is the bullwhip difference in the case of an AR(1) demand stream with autocorrelation coefficient λ. Since the VAR(1) demand model we examine can be viewed as a linear combination of two AR(1) models—one with an autocorrelation coefficient of $\rho + \gamma$ representing the category demand and the other with an autocorrelation coefficient of γ representing the own demand—one could interpret $M(\rho)$ and $M(\rho + \gamma)$ as the bullwhip contribution of the product's own demand stream and that of the category demand stream, respectively. The parameter θ indicates the relative influence of the product's own demand stream vis-à-vis that of the category demand stream in determining a product's bullwhip, reflecting the differential effects of these two streams on a product's demand. Clearly, an increase in n or a decrease in ω increases the relative influence of the firm's own demand process on the bullwhip difference. When n increases or ω decreases, the variance of the category demand per product decreases because of the increase in the demand pooling effect, reducing the relative influence of the category demand on the product's bullwhip effect. When n approaches infinity, the influence of category demand stream and interdependency on a product's bullwhip vanishes.

Equation (7) reveals that a positive autocorrelation coefficient is not sufficient to ensure that bullwhip effect exists; bullwhip exists only when $\frac{M(\rho)}{M(\rho+\gamma)} > \left(1 - \frac{1}{\theta}\right)$. A set of sufficient conditions for the product-level bullwhip effect to exist are $\rho > 0$ and $\rho + \gamma > 0$. These conditions represent an extension of Lee et al. who show that a positive autocorrelation coefficient is sufficient for the existence of bullwhip effect in the single product case.

Proposition 2 *Suppose $\rho,\ \rho+\gamma > 0$. Then, (i) $BWE_{diff}^{product}$ is increasing in ρ, (ii) $BWE_{diff}^{product}$ is increasing in γ, (iii) $BWE_{diff}^{product}$ is decreasing in n if and only if $\gamma > 0$, and (iv) $BWE_{diff}^{product}$ is increasing in ω if and only if $\gamma > 0$.*

Proposition 2(i) generalizes the well-known impact of autocorrelation on the bullwhip difference in the single product scenario to the multiproduct scenario with interdependent demands—an increase in autocorrelation amplifies the firm-level bullwhip difference in both models, assuming bullwhip effect exists. The result that an increase in cross-correlation also amplifies the product-level bullwhip difference is new to the literature. Interestingly, an increase in the number of products does not always decrease the product-level bullwhip difference. One effect of an increase in the number of products is that it decreases the variance of the category demand because of demand pooling, and one would expect this effect to decrease the product's bullwhip difference. However, we find that an increase in the number of products has an opposing effect also on a product's bullwhip difference in our context of interdependent demands—an increase in the number of products decreases the influence of category demand and increases the influence of product's own demand in the product's bullwhip. Whether the former effect or the latter effect dominates depends on whether $M(\rho) < M(\rho+\gamma)$. Only when $\gamma > 0$, $M(\rho) < M(\rho+\gamma)$, implying that the sign of cross-correlation can fundamentally alter the impact of number of products on a product's bullwhip effect. The explanation for the impact of ω on the product-level bullwhip difference stated as Proposition 2(iv) is analogous to the explanation regarding the impact of n. In essence, the conventional intuition that a decrease in contemporaneous correlation or an increase in number of products enhances the demand pooling effect and reduces variance of the category demand, and hence has a mitigating effect on the bullwhip difference does not hold if the cross-correlation is negative.

3.2 Category-Level Bullwhip Difference: Impact of Product Aggregation

Recent research on bullwhip effect has shown that measuring the bullwhip effect using aggregate data instead of individual product-level data generally masks the underlying bullwhip effect (Chen and Lee 2012). This study assumes that ordering decisions are made separately for each product, but the bullwhip effect measurement is done using aggregate data. In our context, product aggregation can be viewed from two perspectives. The first perspective is the one used by the prior literature, i.e., the manufacturer uses product-level replenishment strategy but the measurement of bullwhip effect is made using aggregate data. The other perspective is that the manufacturer uses category-level replenishment strategy and the measurement is also done using category-level data. The distinction between these two perspectives is important because the implications that can be drawn from the measured bullwhip are very different under the two perspectives. Under the first perspective, any incorrect implication we draw about the underlying bullwhip effect is attributed solely to the measurement problem. On the contrary, under the second perspective, the implications relate to the underlying replenishment strategy used by the manufacturer.

If the manufacturer uses product-level replenishment strategy, using (6), we obtain the total order quantity as

$$\begin{aligned}\sum_{i=1}^{n} z_{it}^{*} &= \sum_{i=1}^{n}\Bigg[\rho\left(\frac{1-\rho^{L+1}}{1-\rho}\right)\left(D_{i(t-1)}-D_{i(t-2)}\right)\\ &\qquad + (\gamma/n)\Pi_L\left(\overline{D}_{t-1}-\overline{D}_{t-2}\right)+D_{i(t-1)}\Bigg]\\ &= \frac{(\rho+\gamma)\left(1-(\rho+\gamma)^{L+1}\right)}{1-(\rho+\gamma)}\left(\overline{D}_{t-1}-\overline{D}_{t-2}\right)+\overline{D}_{t-1}.\end{aligned}$$

Hence, the bullwhip difference measured using the aggregate data is computed as $Var\left(\sum_{i=1}^{n} z_{it}^{*}\right) - Var\left(\overline{D}_{it}\right)$.

On the other hand, if the manufacturer uses category-level replenishment strategy, the bullwhip difference is computed using the variance of the order quantity for the category, which is now determined using the optimal base-stock level for the whole category, and the variance of the category demand. Since the category demand follows an AR(1) process (recall Eq. (3)), we can compute the bullwhip difference using Eq. (3.5) of Lee et al. In the following result, we show that regardless of the replenishment strategy used, the category-level bullwhip difference is given by the following result.

Proposition 3 *Under both product-level replenishment and category-level replenishment strategies, the category-level bullwhip difference is given by*

$$BWE_{diff}^{catgeory} = (1-\theta)n^2 M(\rho+\gamma) \tag{8}$$

The finding that category-level bullwhip difference is the same regardless of the replenishment strategy used demonstrates that appropriate implications cannot be derived based on the category-level bullwhip difference without knowledge about how the products are managed within the firm. Specifically, if the manufacturer uses category-level replenishment strategy, then the category-level bullwhip difference is informative in the sense it reveals the true underlying bullwhip effect; on the other hand, if the manufacturer uses product-level replenishment strategy, then the category-level bullwhip difference is uninformative in the sense it may not reveal the true underlying bullwhip effect. It is easy to verify that if $\rho + \gamma > 0$, then category-level bullwhip effect exists.

Proposition 4 *Suppose $\rho + \gamma > 0$. Then, (i) $BWE_{diff}^{catgeory}$ is increasing in ρ, (ii) $BWE_{diff}^{catgeory}$ is increasing in γ, (iii) $BWE_{diff}^{catgeory}$ is increasing in n, and (iv) $BWE_{diff}^{catgeory}$ is increasing in ω.*

Proposition 4 is not surprising when we recognize that the variance of the category demand is increasing in all the parameters stated in the proposition. More importantly, contrasting Proposition 4 with Proposition 2 reveals that the counterintuitive impacts of n and ω on the product-level bullwhip effect when cross-correlation is negative are reversed at the category level. This result suggests that the impact of interdependency on the bullwhip difference is nontrivial and depends critically on the replenishment strategy used.

A key question is how product aggregation affects the bullwhip difference. To see the impact of aggregation, we compare the total bullwhip difference for all the products combined under the two replenishment strategies. Thus, we compare $BWE_{diff}^{catgeory}$ with $n * BWE_{diff}^{product}$ since $BWE_{diff}^{product}$ is identical for each of the n products.

Proposition 5 $BWE_{diff}^{catgeory} < n * BWE_{diff}^{product}$ *if and only if* $\frac{M(\rho)}{M(\rho+\gamma)} > 1 + \frac{n\omega}{1-\omega}$.

Clearly, the category-level bullwhip difference can be higher or lower than the product-level bullwhip difference. If the category-level bullwhip difference is smaller (larger) than the product-level bullwhip difference, and the manufacturer uses the product-level replenishment strategy, then aggregation masks (exaggerates) the underlying bullwhip difference. If the category-level bullwhip difference is smaller (larger) than the product-level bullwhip difference, then using the category-level replenishment strategy rather than the product-level replenishment strategy mitigates (amplifies) the true bullwhip effect.

Figure 1 illustrates Proposition 5 assuming that bullwhip exists both at the product and category levels. In figure, the unshaded regions represent the parameter space where either the stationarity assumption does not hold or the bullwhip does not exist at the category level. Figure 1 reveals that the total bullwhip difference is likely to be smaller at the category level than product level when n is high, ω is negative, and γ is not too high. On the other hand, the total bullwhip difference is likely to be smaller

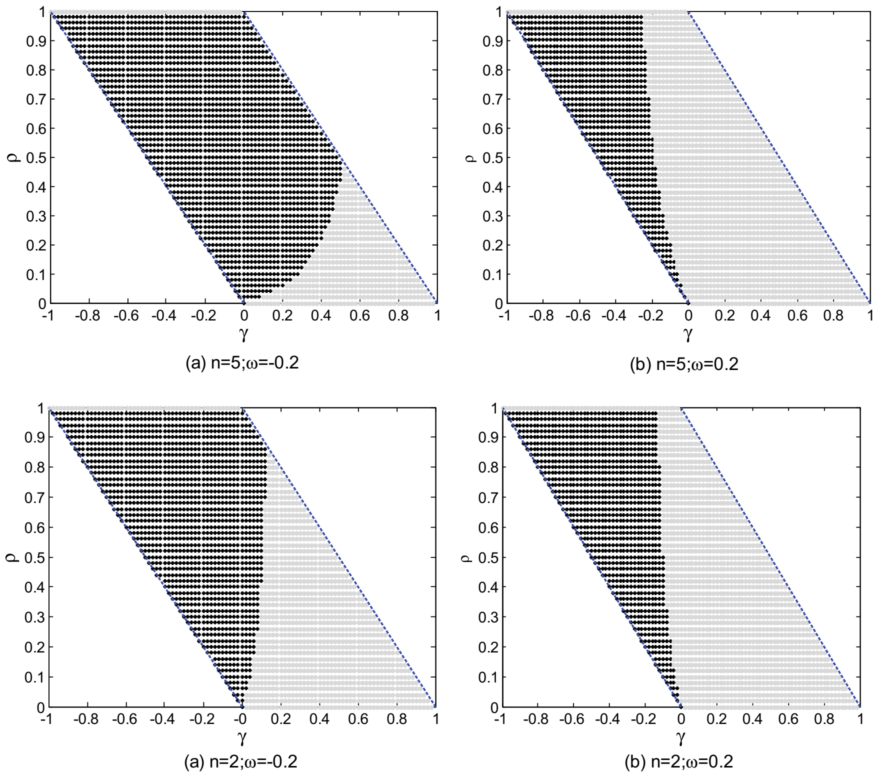

Fig. 1 Comparison of Product-level and Category-level Bullwhip Difference (Notes: $L = 2$. $\sigma^2 = 1$. Shaded region is the relevant and feasible region of comparison (i.e., $0 < \rho < 1$ and $0 < \rho + \gamma < 1$). $BWE_{diff}^{catgeory} \leq n * BWE_{diff}^{product}$ in the darkly shaded region. $BWE_{diff}^{catgeory} > n * BWE_{diff}^{product}$ in the lightly shaded region.)

at the product level than category level when n is high, ω is positive, and γ is not too low.

3.3 Bullwhip Ratio

Bullwhip ratio is useful when cost implications of bullwhip effect are analyzed on a percentage basis, as mentioned in the previous section. Moreover, the bullwhip ratio is independent of the demand error variance σ^2, thus normalizing the effect of inherent demand variability on the bullwhip effect.

Proposition 6 *(i) The product-level bullwhip ratio is given by* $BWE_{ratio}^{product} = \frac{Var\left(z_{it}^{*}\right)}{Var(D_{it})} = 1 + \frac{\theta M(\rho)/\sigma^2 + (1-\theta)M(\rho+\gamma)/\sigma^2}{\left(\frac{\theta}{(1-\rho^2)} + \frac{(1-\theta)}{\left(1-(\rho+\gamma)^2\right)}\right)}$. *(ii) The category-level bullwhip ratio is given by* $BWE_{ratio}^{category} = \frac{Var\left(\sum_{i=1}^{n} z_{it}^{*}\right)}{Var\left(\overline{D}_{it}\right)} = 1 + \left(1 - (\rho+\gamma)^2\right)M(\rho+\gamma)/\sigma^2$.

Note that $M(.)/\sigma^2$ is independent of σ^2. We find that the impacts of model parameters on the bullwhip ratio, both at product level and at category level, are non-monotonic. Specifically, we find that for $x \in \{\rho, \gamma, n, \omega\}$, $\frac{\partial BWE_{ratio}^{product}}{\partial x} > 0$ if and only if $BWE_{ratio}^{product} < \left(\frac{\partial Var\left(z_{it}^{*}\right)}{\partial x}\right) / \left(\frac{\partial Var(D_{it})}{\partial x}\right)$. Similarly, for $x \in \{\rho, \gamma\}$, $\frac{\partial BWE_{ratio}^{category}}{\partial x} > 0$ if and only if $BWE_{ratio}^{category} < \left(\frac{\partial Var\left(\sum_{i=1}^{n} z_{it}^{*}\right)}{\partial x}\right) / \left(\frac{\partial Var\left(\overline{D}_{it}\right)}{\partial x}\right)$. This finding suggests that if the rate of increase in demand variance is significantly higher than the rate of increase in order variance with respect to a parameter, then the bullwhip ratio is likely to be decreasing in that parameter. This result is somewhat similar to Proposition 9 of Chen and Lee (2012) which shows that bullwhip ratio approaches one (i.e., bullwhip ratio is masked) as number of products aggregated approaches infinity if the ratio of the order variance to the demand variance approaches zero.

Proposition 7 $BWE_{ratio}^{catgeory} < BWE_{ratio}^{product}$ *if and only if* $\frac{M(\rho)}{M(\rho+\gamma)} > \frac{1-(\rho+\gamma)^2}{1-\rho^2}$.

Proposition 7 is qualitatively similar to Proposition 5. Specifically, it reveals that aggregation does not necessarily mask (or mitigate) the bullwhip ratio nor exaggerate (or amplify) the bullwhip ratio, as found for the case of bullwhip difference. Furthermore, $\frac{M(\rho)}{M(\rho+\gamma)}$ needs to be sufficiently large for masking or mitigation to occur under both ratio and difference measures of bullwhip effect. In contrast to bullwhip difference, n and ω do not affect the impact of aggregation on bullwhip ratio. Figure 2 illustrates Proposition 7. We find that the category-level bullwhip ratio is smaller (larger) than the product-level bullwhip ratio in most of the parameter space where γ is negative (positive).

(Notes: $L = 2$. $\sigma^2 = 1$. Shaded region is the relevant and feasible region of comparison (i.e., $0 < \rho < 1$ and $0 < \rho + \gamma < 1$). $BWE_{ratio}^{catgeory} < n * BWE_{ratio}^{product}$ in the darkly shaded region. $BWE_{ratio}^{catgeory} > n * BWE_{ratio}^{product}$ in the lightly shaded region.)

4 Managerial Implications and Conclusion

Our findings have significant implications for academics as well as practitioners. From an academic research perspective, our findings reveal that the impact of the demand interdependency on the bullwhip effect is non-trivial and it can be counterintuitive. The findings are important because, on one hand, they cannot be obtained or

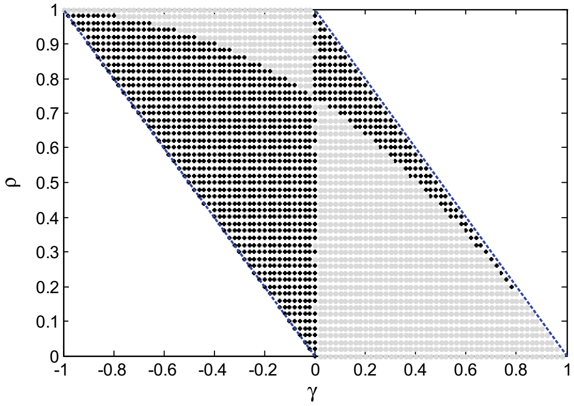

Fig. 2 Comparison of Product-level and Category-level Bullwhip Ratio

inferred through an analysis of single product demand models or multiproduct models with independent demand streams, but, on the other hand, many real-world supply chains manage interdependent products. Furthermore, managing products with interdependent demands as one category is a natural and widely practiced strategy in modern supply chains. However, the extant bullwhip effect literature has examined aggregation solely from a measurement perspective. The multiproduct demand model presented in this chapter provides preliminary insights into the impacts of category management practice on the bullwhip effect. Further examination of multiproduct supply chains seems warranted to obtain a much richer and more complete understanding of the bullwhip phenomenon in modern supply chains.

From a practitioner perspective, our findings imply that category-level replenishment is not always better than product-level replenishment from a bullwhip effect standpoint, despite the benefits demand pooling associated with category management may offer. The nature of the demand interdependency across product demands (i.e., the sign and the magnitude of the cross-correlation coefficient) determines whether category-level management is better than product-level management. In general, a negative cross-correlation tends to favor the category-level management. Furthermore, the implications practitioners should draw and bullwhip management strategies they should choose to adopt based on bullwhip estimates depend not only on the level at which the bullwhip is measured but also how the replenishment decisions are made within the firm. Measuring the bullwhip effect at the product category level is informative only if the firm manages the ordering process at the category level and is uninformative if the firm manages the replenishment process at the product level.

The findings also have implications to firms' other strategies related to the different brands or product variants to the extent the nature of cross-correlation is the result of these strategies. For instance, suppose brand-level promotion induces a negative cross-correlation between demand streams. Then, our results suggest that category-level replenishment process is likely to be better than brand-level replenishment process from a bullwhip perspective. In this case, applying a uniform marketing and replenishment strategies regarding the level at which products are managed could be sub-optimal.

Finally, this chapter provides potentially new insights into the reasons for the observation of mixed results regarding the presence of bullwhip effect at the firm and industry levels. For instance, Cachon et al. (2007) reported that bullwhip effect is noticeably absent in the US economy as a whole. Subsequently, many researchers have attributed data aggregation as an explanation for this finding (Chen and Lee 2012; Bray and Nicholson 2012). We suspect that products of firms within the same industry will likely have interdependent demand streams because they are likely to be competing or complementary products. Therefore, we hypothesize that such interdependencies could be an important contributing factor for the mixed results. An empirical study that tests this hypothesis will be a valuable complement to our study.

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Performance Impact Analysis of Disruption Propagations in the Supply Chain

Dmitry Ivanov, Alexander Pavlov and Boris Sokolov

Abstract Despite a wealth of literature on disruption considerations in the supply chain (SC), a method for quantification of the ripple effect that describes disruption propagation in the SC has not yet been developed. In addition, there are only a few studies that incorporate recovery into the performance impact assessment. This chapter develops a method to quantify the ripple effect in the SC with recovery policy considerations. We study a four-stage SC over time and consider both performance impact assessment and recovery decisions. The performance impact index developed is used to compare sales (revenue) in different SC designs to measure the estimated annual magnitude of the ripple effect. First, we compute optimal SC replanning for two disruption scenarios. Second, we estimate the performance impact of disruptions for six proactive SC designs. Finally, we compare the performance impact index of different SC designs and draw conclusions about the ripple effect in these SC designs along with recommendations for the selection of a proactive strategy. The performance impact index developed can be used to analyze how different markets are exposed to the ripple effect and how to compare different SC designs according to their resilience to severe disruptions.

1 Introduction

Systemic approaches to risk management in the supply chain (SC) became a visible research topic over the past decade. Fires, explosions, tsunami, and strikes at production plants, distribution centers, and transportation channels are typical disruptions

D. Ivanov (✉)
Berlin School of Economics and Law, Supply Chain Management, Badensche Str. 50, 10825 Berlin, Germany
e-mail: divanov@hwr-berlin.de

A. Pavlov · B. Sokolov
Saint Petersburg Institute for Informatics and Automation of the RAS (SPIIRAS), V.O. 14 line, 39, 199178 St. Petersburg, Russia
e-mail: sokol@iias.spb.su

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in supply chains (SC). The ripple effect in the SC occurs if a disruption cannot be localized and cascades downstream impacting SC performance (Ivanov et al. 2014a). Methodical elaborations on the evaluation and understanding of low-frequency-high-impact disruptions are, therefore, vital for understanding and further development of network-based supply concepts (Tomlin 2006; Stecke and Kumar 2009; Liberatore et al. 2012; Sawik 2016; Ivanov and Rozhkov 2017).

It has been extensively documented in literature that severe disruptions may ripple quickly through global SCs and cause losses in SC performance that can be measured by such KPIs (key performance indicators) as revenues, sales, service level, and total profits (Schmitt and Singh 2012; Simchi-Levi et al. 2015; Snyder et al. 2016; Schmitt et al. 2017; Ivanov 2018). Such risks are a new challenge for research and industry who face the *ripple effect* that arises from vulnerability, instability, and disruptions in SCs (Liberatore et al. 2012; Ivanov et al. 2014a, b; Ho et al. 2015; Ivanov et al. 2017a, b, c). As an opposite to the well-known bullwhip effect that considers high-frequency-low-impact *operational risks*, the ripple effect describes low-frequency-high-impact *disruptive risks* (Ivanov et al. 2014a; Simchi-Levi et al. 2015; Sokolov et al. 2016; Snyder et al. 2016; Han and Shin 2016, Ivanov et al. 2017b; Sawik 2017; Cavalcantea et al. 2019; Hosseini et al. 2019a, b).

Recent studies have extensively considered disruption risks in light of the impact of disruption propagation (Wilson 2007; Lim et al. 2013; Ivanov et al. 2013, 2014b; Paul et al. 2014; Ivanov 2017). Previous studies also suggested several measures for quantifying disruption risks (Zobel 2011; Basole and Bellamy 2014; Han and Shin 2016; Lin et al. 2017). However, single-stage disruptions have mostly been considered. Disruption propagation has been ignored and a method for ripple effect quantification has not yet been developed. In addition, there are only a few studies that incorporate the recovery stage into the performance impact assessment. We are not aware of any published research that considers ripple effect quantification with SC recovery considerations.

The objective of this study is to quantify the ripple effect in the SC with recovery considerations. The remainder of this paper is organized as follows. Section 2 analyzes recent literature. Section 3 considers the methodology and modeling approach. Section 4 is devoted to the model presentation and experimental calculation. Section 5 considers the performance impact assessment and managerial insights. The paper concludes by summarizing the most important findings and outlining future research needs.

2 Literature Review

We structure the literature review according to performance impact assessment techniques and engineering methodologies to model severe SC disruptions. Two engineering methodologies—optimization and simulation—dominate studies on SC performance impact assessment in light of severe disruptions (Blackhurst et al. 2018; Ivanov 2019; Pavlov et al. 2019; He et al. 2018; Talluri et al. 2013; Käki et al. 2015; Hosseini and Barker 2016; Dolgui et al. 2019; Ojha et al. 2018; Pavlov et al. 2018).

Petri nets have been applied to analyze disruption propagation through the SC and to evaluate the performance impact of disruptions (Wu et al. 2007). They allow the study of how changes disseminate through a SC and calculate the impact of the attributes by determining the states that are reachable from a given initial marking in a SC. Wilson (2007) considered transportation disruptions in a multistage SC in order to reveal the ripple effect's impact on fulfilment rate and inventory fluctuations. The findings suggest that transportation disruptions between the Tier-1 supplier and the warehouse have the greatest performance impact.

Tuncel and Alpan (2010) extended the body of knowledge by incorporating multiple disruption scenarios (disruptions in demand, transportation, and quality). In addition, this study also considers recovery actions and the performance impact of such mitigation strategies. Carvalho et al. (2012) presented a simulation study for a four-stage automotive SC. Focusing on the research question of how different recovery strategies influence SC performance in the event of disruptions, the authors analyzed two recovery strategies and six disruption scenarios. The scenarios differ in terms of presence or absence of a disturbance and presence or absence of a mitigation strategy. The performance impact was analyzed according to the lead time ratio and total SC costs.

Ivanov et al. (2014b) used a hybrid optimization-control model for simulation of SC recovery policies for multiple disruptions in different periods in a multistage SC. The developed approach allows simultaneous performance impact analysis of SC disruptions and recovery policies simulation. Basole and Bellamy (2014) used the measure "number of healthy nodes" to quantify the level of risk diffusion as the relation of the number of healthy nodes at time t to the network size.

With regards to robustness and resilience analysis, Nair and Vidal (2011) studied SC robustness against disruptions using graph-theoretical topology analysis. They studied twenty SCs which were subjected to random demand. The performances of the SCs were evaluated by considering varying probabilities of the random failures of nodes and targeted attacks on nodes. Furthermore, the analysis of the study also included the severity of these disruptions by considering the downtime of affected nodes. The results were obtained using multi-agent simulation. Furthermore, the authors went into detail on the impact of SC structural design on robustness in the presence of both demand and disruption uncertainty.

Zhao et al. (2011) quantified network connectivity and accessibility with the help of the largest connect component and average and maximum path length. Zobel (2011) computed predicted resilience assuming a sudden onset disruption and linear recovery behavior. Zobel (2014) extended to more generalized case considering nonlinearity and average loss per time unit.

Simchi-Levi et al. (2015) developed a risk-exposure index for the case of an automotive SC. The index computation is based on two models—time-to-recovery and time-to-survive—in order to the assess performance impact of a disruption in the SC. Raj et al. (2015) analyzed SC resilience based on a survival model to represent a time period from the system failure to operate to the time the system returns to its function (i.e., recovery). The input to the model is a failure event; the output of the model is the recovery time. The model allows a quantitative measurement of SC resilience in terms of recovery time.

Sokolov et al. (2016) quantified the ripple effect in the SC with the help of selected indicators from graph theory and developed a static model for performance impact assessment of disruption propagation in a distribution network. Han and Shin (2016) evaluated the structural robustness of the SC in random networks and compared this with the likelihood of network disruption resulting from random risk.

Ivanov et al. (2016) extended the performance impact assessment and SC plan reconfiguration with consideration of the duration of disruptions and the costs of recovery. They analyzed seven proactive SC structures, computed recovery policies to re-direct material flows in the case of two disruption scenarios, and assessed the performance impact for both service level and costs with the help of a SC (re)planning model containing elements of control theory and linear programming. This study reveals the impact of different parametrical and structural resilience measures on SC service level and efficiency. In the current paper, we use the basic model and the proactive strategies for SC design in Sect. 4 in order to analyze the performance impact of the ripple effect in Sect. 5.

The reliability of a multistage SC is evaluated by Lin et al. (2017) as the probability that market demand, and therefore sufficient commodity delivery, can be met by the SC through multiple stations of transit within the appropriate time frame. In this study, system reliability acts as the delivery performance index and is assessed by the number of minimal paths. Ivanov et al. (2018) developed a control-theoretic method to assess SC resilience with the consideration of recovery policies using attainable sets.

From the given literature, it can be observed that the scope of SC rippling and its impact on economic performance depends both on robustness reserves (e.g., redundancies like inventory or capacity buffers), flexibility in products and processes, disruption duration, and the speed and scale of recovery measures. Despite significant advancements in this research field, ripple effect assessment with SC recovery considerations is still an under-researched area and presents a promising field for future research.

3 Problem Statement and Research Methodology

We study a four-stage SC over time and consider both performance impact assessment and recovery decisions. The SCD comprises Tier 2 suppliers, Tier 1 suppliers, assembly plants, and markets. The disruptions and recovery policies are considered as given scenarios, the production and transportation quantities are the decision variables, and SC sales (revenue) is the KPI for measuring the estimated annual magnitude of the ripple effect.

The optimization model is developed to replan SC flows to maximize SC sales. The model aims to find the aggregate product flows to be moved from suppliers through the intermediate stages to the markets subject to revenue maximization (i.e., lost sales minimization) under (i) constrained capacities and processing rates, (ii) SC disruptions, and (iii) SC recovery for a multi-period case.

The modeling approach is the optimization-based simulation that allows simultaneous re-computing of the material flows in a multistage SC after a disruption and a comparison of the performance impact of different SCDs. Based on the optimization results, the performance impact of disruptions is computed.

For the computation of performance impact, we suggest introducing an index of performance impact (PI) that represents the relation between the planned KPI in a disruption-free mode and the real KPI in the disruption case (Eq. 1):

$$PI = \frac{KPI_{plan}}{KPI_{disruption}} \tag{1}$$

Such an index can be computed for each i-node in the SC, $i = 1,\ldots N$. Subsequently, we can compute a product of the i-PIs in order to calculate the overall PI in the SC (Eq. 2):

$$PI_{general} = \prod_{i=1}^{N} PI \tag{2}$$

The organization of the rest of this manuscript is as follows. First, we compute optimal SC replanning for two disruption scenarios and KPI. In order to make the PI analysis more depictive, we restrict ourselves to the analysis of estimated annual magnitude in terms of the revenue at markets. Second, we perform the first step for six proactive strategies in SC design. Finally, we compare the PI of seven SC designs (i.e., the initial SC design and six proactive strategies) and draw conclusions on the ripple effect in these SC designs along with recommendations on the proactive strategy.

4 Mathematical Model

The SC design model can be represented as follows (Table 1).

Objective function

$$J_{\chi 2} = \sum_{\rho=1}^{p} \lambda_{\rho} \sum_{i=1}^{n_{\chi}} \sum_{k=1}^{L_{\chi}} g^{-}_{\chi i \rho k}; \tag{3}$$

The objective function describes throughput maximization (i.e., sales indicator).

Constraints:

Table 1 Supply chain design formalization

Notation	Meaning
Structure	
$X_\chi(t) = \{A_{\chi i}(t), i \in N_\chi\}$	Set of nodes in the SC design in the χ disruption scenario at the point of time *t,* where *N* is the set of node numbers
$E_\chi(t) = \{e_{\chi ij}(t) \in \{0, 1\}, \quad i, j \in N_\chi\}$	Set of arcs in the SC design in the χ disruption scenario
Parameters	
$W_\chi(t) = \{w_{\chi ij\rho}(t), \quad i, j \in N_\chi, \ \rho \in P\}$	Set of operational characteristics for the production, transportation (if $i \neq j$) or processing at warehouse (if $i = j$) in the χ disruption scenario
$V_{\chi i}(t)$	Maximum warehouse throughput capacity at the node $A_{\chi i}$
$\omega_{\chi ij\rho}(t)$	Maximum transportation channel throughput capacity for the commodity ρ between $A_{\chi i}$ and $A_{\chi j}$
$\psi_{\chi i\rho}(t)$	Maximum inbound throughput capacity for the commodity ρ in $A_{\chi i}$
$\phi_{\chi i\rho}(t)$	Maximum outbound throughput capacity for the commodity ρ in $A_{\chi i}$
$I_{\chi k}$	Total ordered quantity from all suppliers in the period number *k*
γ_ρ	Importance of the commodity ρ
λ_ρ	Urgency of the commodity ρ
$\varepsilon_{ij}(t)$	Preset matrix time function of time-spatial constraints; we have $\varepsilon_{ij}(t) = 1$, if the channel between A_i and A_j is available and not disrupted within the given period of time, and $\varepsilon_{ij}(t) = 0$, otherwise
Indexes	
$k = \{1, 2, \ldots, L_\chi\}$	A number of the planning period in the planning horizon $T = (t_0, t_f]$
$T = (t_0, t_f]$	Planning horizon
$\rho \in P = \{1, 2, \ldots, p\}$	A number of the commodity in the SC
Decision Variables	
$x_{\chi ij\rho k}$	Amount of commodity ρ transmitted from $A_{\chi i}$ to $A_{\chi j}$ and received at $A_{\chi j}$ at time interval number *k*
$y_{\chi j\rho k}$	Amount of commodity ρ to be stored at the warehouse $A_{\chi i}$ at time interval number *k*
$g_{\chi j\rho k}$	Amount of commodity ρ to be delivered to $A_{\chi j}$ at time interval *k*
$z_{\chi j\rho k}$	Amount of commodity ρ at $A_{\chi j}$ to be returned (as caused by the missing capacity of SC nodes and channels) at time interval number *k*

$$I_{\chi i\rho k} + y_{\chi i\rho(k-1)} + \sum_{j\in N^{-}_{\chi ik}} \omega_{\chi ji\rho k}\cdot u_{\chi ji\rho k} + \phi^{+}_{\chi i\rho k}\cdot \vartheta^{+}_{\chi i\rho k} =$$

$$= \phi^{-}_{\chi i\rho k}\cdot \vartheta^{-}_{\chi i\rho k} + \sum_{j\in N^{+}_{\chi ik}} \omega_{\chi ij\rho k}\cdot u_{\chi ij\rho k} + y_{\chi i\rho k)} + z_{\chi i\rho k} \quad (4)$$

$$(\sum_{j\in N^{+}_{\chi ik}} x_{\chi ij\rho k} - \sum_{j\in N^{-}_{\chi ik}} x_{\chi ji\rho k}) + (y_{\chi i\rho k)} - y_{\chi i\rho(k-1)}) + (g^{-}_{\chi i\rho k} - g^{+}_{\chi i\rho k}) + z_{\chi i\rho k} = I_{\chi i\rho k} \quad (5)$$

$$0 \le x_{\chi ij\rho k} \le \omega_{\chi ij\rho k}\cdot(t_k - t_{k-1}), 0 \le \sum_{\rho=1}^{p} y_{\chi i\rho k)} \le V_{\chi i}, 0 \le g^{-}_{\chi i\rho k} \le \phi^{-}_{\chi i\rho k}\cdot(t_k - t_{k-1}),$$

$$0 \le g^{+}_{\chi i\rho k} \le \phi^{+}_{\chi i\rho k}\cdot(t_k - t_{k-1}), z_{\chi i\rho k} \ge 0. \quad (6)$$

Equations (4) and (5) describe the flow balances of the product ρ subject to the node $A_{\chi i}$ and ensure that the sum of the outgoing flow (subscript (-)), inventory, and return flow should equal the incoming flow (subscript (+)). Equation (6) contains capacity and nonnegativity constraints.

5 Experimental Results

We consider a four-stage SC in the automotive industry. Two Tier 2 suppliers deliver speedometers to a Tier 1supplier that supplies two assembly plants with cockpits. The assembly plants deliver cars to one of two markets. SC structural elements can become fully or partially unavailable for a certain period of time. This capacity reduction may have performance impact on sales in the markets.

For computational experiments, the following data set was used (Table 2).

In the first scenario, which we call "optimistic", a disruption at assembly plant #2 happens in the second period and destroys the capacity of this plant 100%. This disruption lasts two periods. In period #4, the capacity of this production plant is recovered 100%. In addition, in period #3 a fire at the Tier 2 supplier #1 happens that makes deliveries from this supplier to the Tier 1 supplier in period #3 impossible. In the next period, deliveries can run in normal mode again. Finally, due to strikes at a railway company in periods #4 and #6, the transportation channels between the assembly plant #1 and market #1 and between the Tier 2 supplier #2 and the Tier 1 supplier become unavailable, respectively (see Fig. 1).

In Fig. 1, the following parameters are represented:

- Tier 2 supplier #1: node #1
- Tier 2 supplier #2: node #2
- Tier 1 supplier: node #3
- Assembly plant #1: node #5
- Assembly plant #2: node #6
- Market #1: node #8
- Market #2: node #9

Table 2 Input data

Parameter	Value
Number of periods	6
Demand distribution over six periods	*Market 1:* 250-240-230-240-250-240 *Market 2*: 220-210-200-210-220-210
Delivery quantity to Tier 1 supplier	*From* supplier #1: 400 units in each period *From* supplier #2: 100 units in each period
Maximum processing throughput capacities at plants	*Tier 1 supplier:* 550 units a period Assembly plants: 300 units a period each
Maximum transportation throughput capacity	Channel Tier 2 supplier #1 to the Tier 1 supplier: 500 units a period, Channel Tier 2 supplier #2 to the Tier 1 supplier: 150 units a period, Channel Tier 1 supplier to the assembly plant #1: 300 units a period, Channel Tier 1 supplier to the assembly plant #2: 250 units a period, Channel assembly plant #1 to the market #1: 280 units a period, Channel assembly plant #2 to the market #2: 240 units a period,
Maximum warehouse storage capacities	Tier 2 supplier #1: 150 units per period Tier 2 supplier #2: 70 units per period Tier 1 supplier: 250 units per period Assembly plant #1: 100 units a period Assembly plant #2: 100 units a period Market #1: 50 units a period Market #2: 50 units a period
Price of the final product. $	*65*
Bill-of-material factor	*1:1, i.e., one speedometer is needed for one cockpit, and one cockpit is needed for one car*

Maximum processing throughput capacities are marked in rectangles, maximum transportation throughput capacities are presented on the arcs, and maximum storage capacities are depicted in triangles. The disruptions are marked red. In Fig. 2, the so-called “pessimistic scenario” is shown.

The following alternative proactive strategies for SC design can be considered:

1. Increase in the flexibility of supplier #2 so that it delivers, under normal conditions, 100 units in each period and can extend the quantity to 400 units if needed
2. New backup supplier is introduced at the Tier 1 stage
3. A backup assembly plant is introduced
4. Multiple sourcing strategy with alternative transportation channels
5. Increase in warehouse storage and processing capacity
6. Increase in transportation channel throughput capacity

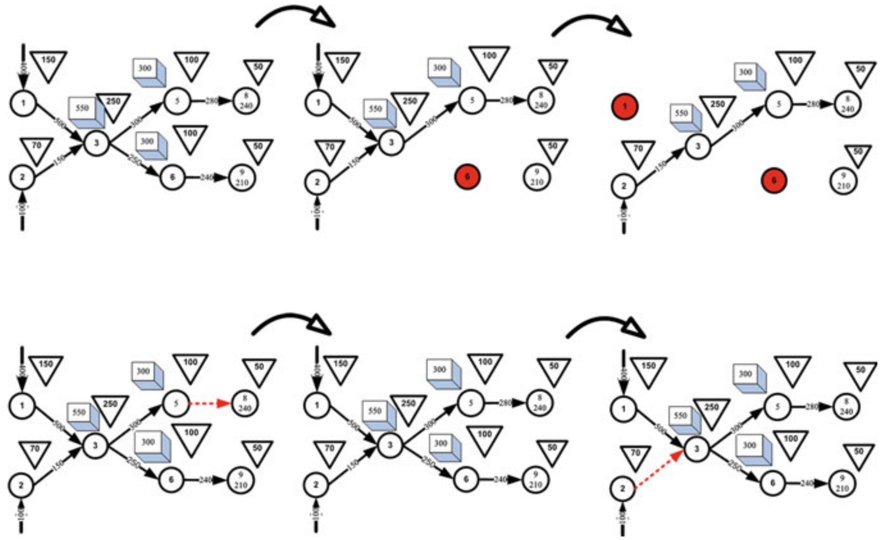

Fig. 1 "Optimistic" disruption scenario

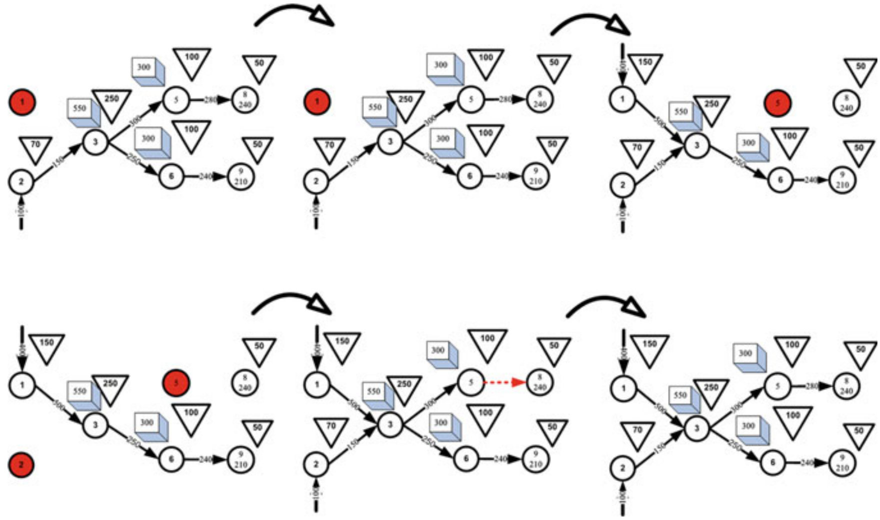

Fig. 2 "Pessimistic" disruption scenario

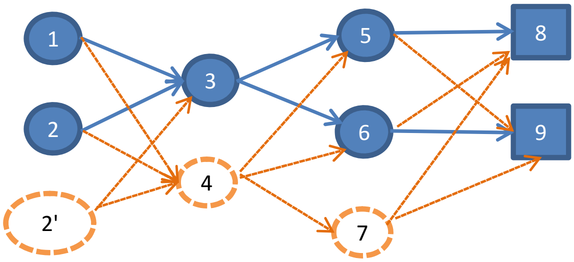

Fig. 3 Possible extensions to SC structure (Ivanov et al. 2016)

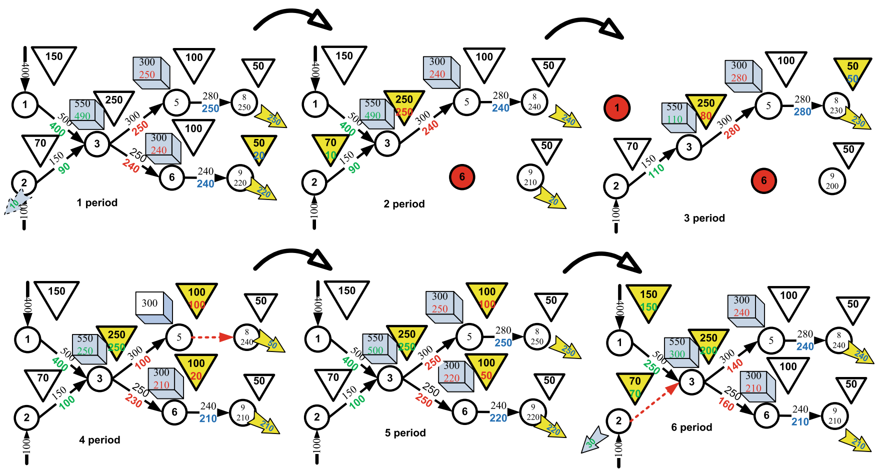

Fig. 4 Replanning results for optimistic scenario

The summary of these measures is shown in Fig. 3.

In regard to the processing and transportation throughput capacity of new SC design elements, we assume the following: throughput capacity of new transportation channels is 120% of the processing throughput capacity of the outgoing node; processing capacity at node #4 is 250 units in each period, and processing capacity at node #7 is 150 units in each period.

In Fig. 4, the result of optimal replanning for the initial SC design (cf. Figures 1 and 2) subject to the given data set (cf. Table 2) is presented.

In Fig. 3, the production and shipment quantities of the speedometers, cockpits, and cars are depicted and marked green, red, and blue, respectively. The yellow triangles show the storage capacities and their actual utilization. The grey rectangles depict the manufacturing maximum and used processing capacity, respectively. The numbers on the arcs represent the maximum transportation capacities and their actual utilization. The red nodes and channels are disrupted. The yellow arrows at nodes #8 and #9 depict the delivered quantity of goods at the markets.

Table 3 Performance impact of different proactive policies in optimistic scenario

№	Performance indicators	SC designs in optimistic scenario						
		Initial	Proactive SC designs					
			1	2	3	4	5	6
1	Revenue in the disruption scenario	139100	140075	140530	139100	139100	140985	142610
2	Maximum revenue in disruption-free scenario	176800	176800	176800	176800	176800	176800	176800
3	Value of lost sales	**37700**	**36725**	**36270**	**37700**	**37700**	**35815**	**34190**

Table 4 Performance impact of different proactive policies in pessimistic scenario

№	Performance indicators	SC designs in optimistic scenario						
		Initial	Proactive SC designs					
			1	2	3	4	5	6
1	Revenue in the disruption scenario	83200	83200	83200	85800	88400	85800	88400
2	Maximum revenue in disruption-free scenario	176800	176800	176800	176800	176800	176800	176800
3	Value of lost sales	**93600**	**93600**	**93600**	**91000**	**88400**	**91000**	**88400**

In Tables 3 and 4 and Figs. 5 and 6, the planning results are summarized for two scenarios.

It can be observed from Tables 3 and 4 and Figs. 5 and 6 that structural changes significantly impact SC performance. The highest revenue of $140,985 in the optimistic scenario can be achieved if we apply the SC design according to proactive strategy #5, i.e., an increase in warehouse storage and processing capacity is needed.

The highest revenue of $85,800 in the pessimistic scenario can be achieved if we apply the SC design according to proactive strategies #4 and #6, i.e., introduction of alternative transportation channels or/and increase in transportation capacity of the existing channels. To make a final decision, the costs of these proactive measures need to be analyzed.

Further, it can be observed that lost sales are much higher in the "pessimistic" scenario. Such a scenario comparison allows the drawing of conclusions on the performance impact of disruptions at different parts in the SC. For example, the Tier 2 supplier #1 (node #1), the production plant #1 (node #5), and the transportation channel between the node #5 and node #8 need to be considered as critical ele-

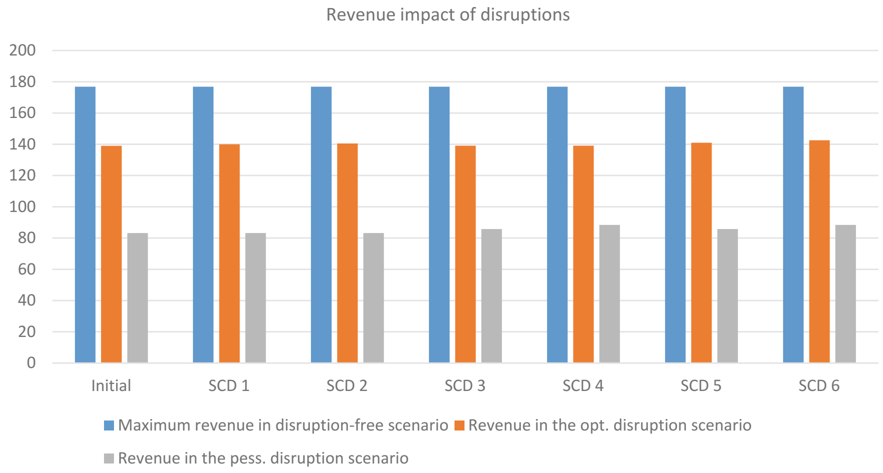

Fig. 5 Revenue impact of disruptions

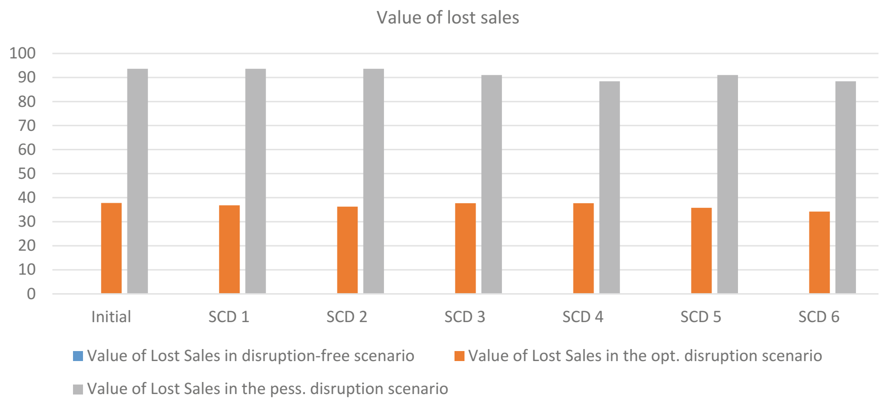

Fig. 6 Lost sales impact of disruptions

ments in the SC design. According to the study of Simchi-Levi et al. (2015), dual sourcing policies, risk-sharing contracts, and continuous capacity monitoring can be recommended for these SC elements.

6 Performance Impact of the Ripple Effect and Managerial Insights

Now, we use the computation results from Sect. 4 and compute the PI index using Eqs. 1 and 2. The diagrams with the computational results for seven SC design for

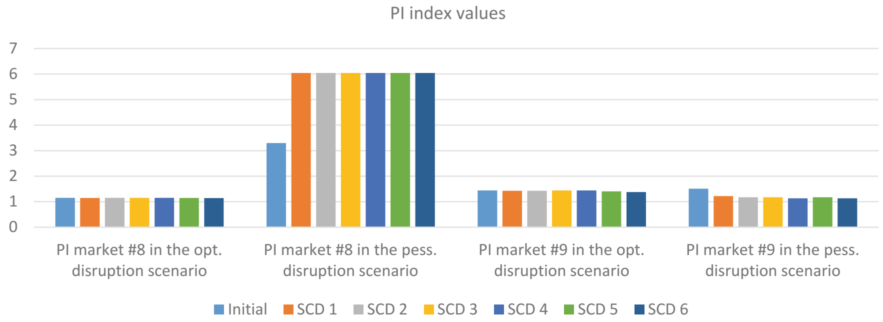

Fig. 7 PI computation for individual markets

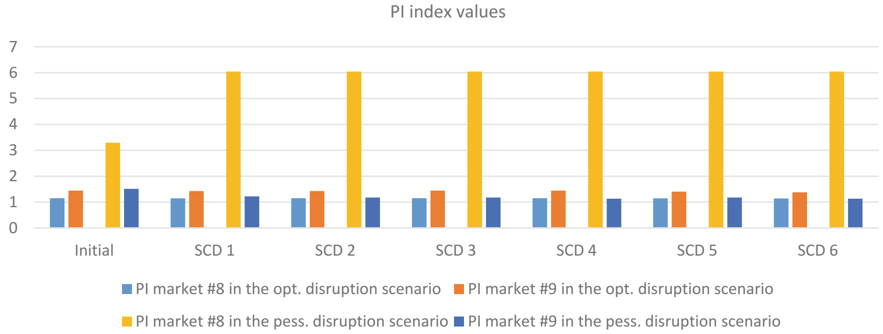

Fig. 8 PI computation for individual markets and different SC designs

both scenarios can be found in an online supplement. First, we compute PI for two markets individually using Eq. 1. In the next step, we aggregate these partial PI to general PI using Eq. 2. We consider SC sales (revenue) as the KPI for measuring the estimated annual magnitude of the ripple effect. To make the analysis more depictive, we restrict ourselves to the PI consideration at the markets without PI analysis at the intermediate stage in the SC. This is an admissible restriction since the revenue KPI is directly related to the market stage in the SC. The results of PI computation are shown in Table 5.

Let us present these results graphically and analyze their managerial implications (Figs. 7, 8 and 9).

Table 5 and Figs. 7, 8 and 9 can be used as a dashboard for SC design comparison in regard to the ripple effect. The results can also help to analyze the disruption impact at different markets individually in order to derive recommendations for securing supplier and customer satisfaction. For the given data set it can be observed that the SC for market #2 (node #9) is much more resilient and was less exposed to the ripple effect compared to market #1 (node #8). In both scenarios, the PI in regard to market #2 (node #9) does not exceed 1.51 while the maximum PI in regard to market #1 (node #8) is 6.04.

Table 5 PI computation results

	Initial	SCD 1	SCD 2	SCD 3	SCD 4	SCD 5	SCD 6
Maximum revenue market #8 in disruption-free scenario	94250	94250	94250	94250	94250	94250	94250
Revenue market #8 in the opt. disruption scenario	81900	82225	82470	81900	81900	82225	82470
PI market #8 in the opt. disruption scenario	**1,150794**	**1,146245**	**1,150794**	**1,150794**	**1,150794**	**1,146245**	**1,14284**
Revenue market #8 in the pess. disruption scenario	28600	15600	15600	15600	15600	15600	15600
PI market #8 in the pess. disruption scenario	**3,295455**	**6,041667**	**6,041667**	**6,041667**	**6,041667**	**6,041667**	**6,041667**
Maximum revenue market #9 in disruption-free scenario	82550	82550	82550	82550	82550	82550	82550
Revenue market #9 in the opt. disruption scenario	57200	57850	57850	57200	57200	58760	59930
PI market #9 in the opt. disruption scenario	**1,443182**	**1,426966**	**1,426966**	**1,443182**	**1,443182**	**1,404867**	**1,37744**
Revenue market #9 in the pess. disruption scenario	54600	67600	67600	70200	72800	70200	72800
PI market #9 in the pess. disruption scenario	**1,511905**	**1,221154**	**1,175926**	**1,175926**	**1,133929**	**1,175926**	**1,133929**

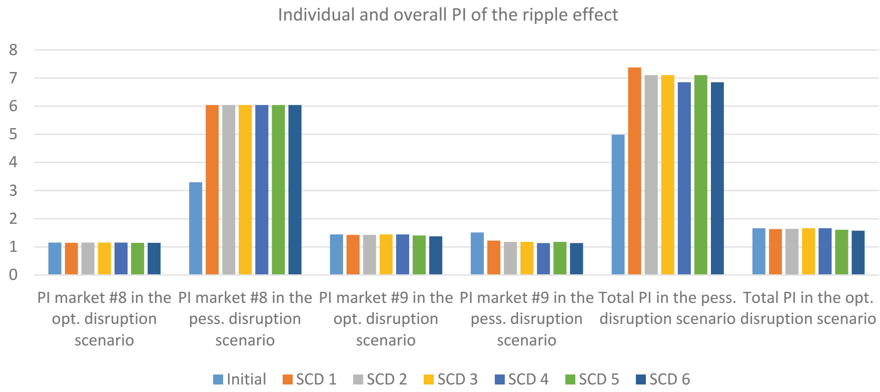

Fig. 9 Comparison of individual and total PI computation

In the case of the optimistic scenario, the lowest ripple effect can be observed in SC design #6 both at the market #1 (node #8) and at the market #2 (node #9), PI = 1.14284 and PI = 1.3744, respectively. In the case of the pessimistic scenario, the lowest ripple effect can be observed in the initial SC design at market #1 (node #8, PI = 3.295455), while at market #2 (node #9), minimum PI = 1.133929 for SC designs #4 and #6.

In total cumulative PI in the optimistic scenario, a large gap between the minimum PI (i.e., initial SCD) and PI for other SC designs can be observed in Fig. 9. At the same time, the total PI values in the pessimistic scenario are very close to each other with a small advantage for SC design #6.

Therefore, PI computation supports the results of the optimization model described in Sect. 4. For the considered example, it becomes obvious that market #1 (node #8) is highly exposed to the ripple effect in the negative scenario while market #2 (node #9) shows disruption-resistance and performs in the pessimistic scenario even better than in the optimistic one.

In the joint analysis of two markets, the initial SC design can be recommended since it exhibits the lowest ripple effect. At market #8, risk-sharing contracts can be recommended with the customers. In addition, storage capacity extensions and a higher safety stocks can be applied in this market.

7 Conclusions

The experiments with the optimization model and PI index analysis depict how disruption risks may result in the ripple effect and structure dynamics in the SC. From the developed model and experiments, it can be observed how the scope of the rippling and its performance impact depend on the SC design structure.

The results of this study are twofold. First, with the help of the developed approach, severe disruptions in the SC can be modeled subject to temporary unavailability of some SC elements and their recovery. Second, a method to compare SC designs with a performance impact assessment of the ripple effect has been developed.

The developed method of ripple effect evaluation helps to analyze effective ways to recover and reallocate resources and flows in the SC and to select a resilient SC design. As such, the model can be used by SC risk specialists to analyze the performance impact of different resilience and recovery actions and adjust mitigation and recovery policies with regard to critical SC design elements and SC planning parameters.

In the future, PI computation can be extended in regard to multiple objectives. In addition, PI can be evaluated individually at each SC echelon. Finally, markets can be modeled as heterogeneous entities allowing for competitive elements.

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Ripple Effect Analysis of Two-Stage Supply Chain Using Probabilistic Graphical Model

Seyedmohsen Hosseini and MD Sarder

Abstract Supply chain disruptions are increasingly caused by growing global supply sourcing, complexity, and interconnectedness of supply chains (SCs). A key challenge in the context of supply chain disruption management is to control and monitor the ripple effect of SCs. The ripple effect occurs when the impact of disruption cannot be localized and propagates throughout the SC. Like the bullwhip effect, the ripple effect can negatively impact performance both upstream and downstream of SC entities. This work proposes a new methodology, based on a probabilistic graphical model, to analyze the ripple effect in a two-stage SC. The probabilistic graphical model developed is capable of capturing disruption propagation that can transfer from upstream suppliers to downstream end customer in an SC.

1 Introduction

In recent years, supply chains (SCs) have become more susceptible to a variety of disruptions, such as natural disasters, human-made accidents, malevolent attacks, labor strikes, and common failures due to the complexity, globalization, and interdependencies of supply networks. There are dozens of examples that show the vulnerability of SCs and the need for resilience planning in the supply chain management (SCM). For example, Toyota, the world's biggest-selling automaker, halted its production for several days in the aftermath of the Japanese earthquakes and tsunami that occurred in 2011. Honda also suspended its motorcycle production near the quake city of Kumamoto in southern Japan for a week. Other automakers, such as Nissan, were also forced to halt their production for at least several days: this imposes huge

S. Hosseini (✉)
Industrial Engineering Technology, University of Southern Mississippi, Long Beach, MS, USA
e-mail: mohsen.hosseini@usm.edu

M. Sarder
Department of Engineering Technologies, Bowling Green State University, Bowling Green, OH, USA
e-mail: msarder@bgsu.edu

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disruption costs. The impact of this natural disaster was not limited only to Japanese automakers, but also negatively affected giant electronic companies. For example, Sony was unable to continue the production of image sensors at one of its production firms in Kummamoto due to structural and equipment damage. Many other semiconductor manufacturers had to stop their production, because of the physical damage to their manufacturing firms (Fortune 2016). In addition to domestic manufactures, international automakers who received auto parts from Japanese suppliers were also impacted by the Japanese earthquake and tsunami. Research also shows that there were nearly as many disruptions in tiers two and three of the SC as in tier one, but three-quarters of companies had no visibility into tier two or beyond (Churchill 2018). Matthew Grmwade, head of automotive at JLT, stated that new research shows that automakers are not only facing serious challenges in terms of the growing number of disruptive events to the SC industry, but in the diversity of these events as well.

Modern automotive SCs are vast, highly complex operations. It is impossible to quickly and precisely assess affected ports, airports, and road networks to establish the extent of possible disruption. As such, pre- and post-disruption resilience strategies are required for complex supply networks. A comprehensive review of pre and post-disaster resilience strategies can be found in (Hosseini et al. 2016; Hosseini and Al Khaled 2016).

A key challenge in the context of supply chain risk management (SCRM) is how to control the effect of disruption and its propagation through the SC. The ripple effect occurs when the effect of disruption cannot be localized and its impact propagates upstream and downstream through an SC. Although much research has been conducted to measure disruption impact on suppliers, manufacturing firms, and distribution centers, the ripple effect has not been studied enough. The incentive of this chapter is to model and analyze the impact of the ripple effect using a probabilistic graphical model (PGM). PGM is capable of capturing disruption propagation that can transfer from upstream suppliers to downstream end customer in an SC.

2 Literature Review

Although SC disruption has been studied by many scholars (Ivanov 2009; Ivanov and Sokolov 2012; Ivanov et al. 2013; Ivanov et al. 2014a, b; Ivanov et al. 2015; Bode and Wagner 2015; Ivanov 2016; Ivanov et al. 2016a, b, c, d; Ivanov et al. 2017a, b; Ivanov et al. 2016a, b, c; Luangkesorn et al. 2016; Kondo 2018; He et al. 2018; Behdani and Srinivasan 2017; Guo and Gen 2018; Ivanov 2018a, b; Dolgui et al. 2017; Ivanov and Dolgui 2018; Cavalcantea et al. 2019; Hosseini et al. 2019a, b), the ripple effect of disruption throughout an SC still merits more attention. Ivanov (2018b) developed a discrete-event simulation model to simulate disruption propagation in multistage SC with consideration of capacity disruptions. Ivanov et al. (2018) investigated the ripple effect on digital manufacturing and Industry 4.0. The authors examined the relationship between big data analytics, additive manufacturing, Industry 4.0, and SC disruption risks; and how digitalization contributes to enhancing ripple effect control. Ivanov et al. (2014a, b) developed a framework to quantify the ripple effect using control theory. The proposed framework also includes the following states: (i) measuring the ripple effect using control theory, (ii) mitigating uncertainty at the planning state, (iii) monitoring process execution, (iv) response of process execution in case of disruptions, and (v) recovery and minimizing the long-term impact of disruptions. Ivanov et al. (2013) developed a multi-objective optimization model for multi-commodity production distribution of a multistage centralized network. The authors studied the impact of different disturbances on distribution execution. Ivanov et al. (2016d) studied different recovery policies in the presence of the ripple effect in a time-critical SC. The results of their studies propose optimal proactive and reactive strategies to tackle the ripple effect from the perspectives of flexibility and resilience. Ivanov et al. (2015) examined integrated SC planning with multiple products, suppliers, transit nodes, and customers in a multi-period mode. The authors quantified the ripple effect on SC planning decisions by using dynamic optimal control theory. The interval of structure constancy has been used in their work to model the ripple effect. Sokolov et al. (2016) measured the ripple effect in SCs from a structural point of view. The authors proposed a multi-criteria approach based on integrating the static and dynamic structure of an SC using optimal control theory and an AHP approach.

Levner and Ptuskin (2018) presented optimization models based on entropy theory to quantify the ripple effect on SC systems. The proposed entropy-based optimization model was used to evaluate the economic loss imposed on SCs by natural disaster leading to ripple effect. The main advantage of their entropy-based methodology is that it simplifies the hierarchal tree model of the SC, while preserving information about risk.

Ivanov (2018a, b) studied the behavior of production-ordering systems with disruption consideration and recovery strategies in the post-disruption period, and the influence of severe disruptions on a production and distribution network design. The author developed a discrete-event simulation model using *anyLogistix* software. The author found that SC behavioral changes caused by disruption could result in delayed orders. Additionally, the author found that isolated distribution networks could be subject to more severe decreases in performance in the event of SC disruptions.

3 Theory of Probabilistic Graphical Models

PGM, also known as a Bayesian network, is structured based on Bayes' theorem and graph theory. PGM is a powerful technology, which can handle risk assessment problems that involve uncertainty. PGM is capable of combining both historical data and expert knowledge to describe causality relationships between a target variable and causal factors. PGM has been used in different disciplines as a decision-making tool to manage uncertainty and provide risk assessment. The application of PGM in SCRM and resilience can be found in (Hosseini and Barker 2016a, b; Hosseini et al. 2016b; Hosseini 2016; Hosseini and Sarder 2019).

A PGM is a directed acyclic graph with a set of nodes (variables) and a set of arcs. The relationship between the nodes can be expressed in terms of joint probability distribution using a conditional probability. A PGM can be mathematically represented by a graph G, $G = (V, E)$, where $V = \{Y_1, Y_2, \ldots, Y_n\}$ is a set of nodes and $E = \{< Y_1, Y_2 >, < Y_1, Y_3 >, \ldots, < Y_i, Y_j >\}$ is a set of arcs. Y_i is node i or random variable i, $< Y_i, Y_j > \in E$ represents the dependency or causal relationship between Y_i and Y_j. If there is an outgoing arc from node Y_i to Y_j, $Y_i \rightarrow Y_j$, then Y_j is called the parent node of Y_i and Y_i is the child of node Y_j. The directed arcs encode the conditional probability that exists between Y_i and Y_j. According to the chain rule, the joint probability distribution of all nodes (variables) can be written as the product of the conditional probability of each node (variable):

$$P(Y_1, Y_2, \ldots, Y_n) = \prod_{i=1}^{n} P(Y_i | Y_1, Y_2, \ldots, Y_{i-1}) \tag{1}$$

where n is the number of variables (nodes) in PGM, $i = 1, 2, \ldots, n$. By assuming that the marginal probability distribution of node Y_i is conditioned on the probability of its parent nodes set $\pi(Y_i)$, where

$\pi(Y_i) \subseteq \{Y_1, Y_2, \ldots, Y_{i-1}\}$, Eq. (1) can be rewritten as follows:

$$P(Y_1, Y_2, \ldots, Y_n) = \prod_{i=1}^{n} P(Y_i | \pi(Y_i)) \tag{2}$$

where n represents the number of nodes in PGM, $i = 1, 2, \ldots, n$. An illustrative example of PGM with five nodes $Y_1, Y_2, \ldots, Y_5$ and a set of arcs is represented in Fig. 1. In this example, Y_1 and Y_2 are root nodes as they do not have parents, Y_5 is leaf node, as it does not have any children, and Y_3 and Y_4 are both intermediate nodes as they have both parent and child nodes. The joint probability distribution of this PGM can be written as follows:

$$P(Y_1, Y_2, Y_3, Y_4, Y_5) = P(Y_1)P(Y_2)P(Y_3|Y_1)P(Y_4|Y_2, Y_3)P(Y_5|Y_4) \tag{3}$$

The marginal distribution of each node can be calculated based on full joint probability distribution. For example, the probability distribution of Y_3 is calculated using a marginalization technique, as shown in Eq. (4):

$$P(Y_3) = \sum_{Y_1, Y_2, Y_4, Y_5} (Y_1)P(Y_2)P(Y_3|Y_1)P(Y_4|Y_2, Y_3)P(Y_5|Y_4) \tag{4}$$

The probability of Y_3 can be further rewritten, as shown in Eq. (5), using a local marginalization technique.

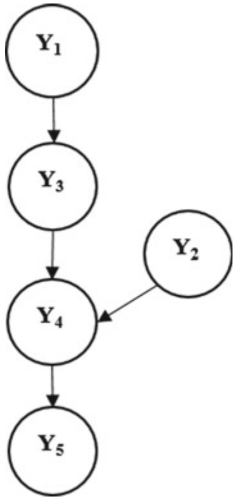

Fig. 1 An illustrative example of PGM with five nodes

$$P(Y_3) = \left(\sum_{Y_1} P(Y_1)P(Y_3|Y_1)\left(\sum_{Y_4}\left(\sum_{Y_2} P(Y_4|Y_2, Y_3)P(Y_2)\left(\sum_{Y_5} P(Y_5|Y_4)\right)\right)\right)\right) \quad (5)$$

4 Ripple Effect Analysis

This section aims to simulate and analyze the ripple effect on a two-stage SC. To do so, we use causal inference to model ripple effect and disruption propagation. In PGM, we can enter all evidence, such as supplier disruption, and use propagation to update the marginal probabilities of all unobserved variables, such as the manufacturer. This can yield an exceptionally powerful method of analysis to measure the impact of supplier disruption on manufacturers. To perform inference analysis, we first enter an observation, in this case that supplier is disrupted, and propagate the impact of that observation on the entire SC using a Dynamic Discretization algorithm (DDA). See Fenton and Neil (2013) for an overview of the DDA method.

Let us consider a two-stage SC with four suppliers and two manufacturers, as represented in Fig. 2. The prior probability of suppliers and marginal probability distributions of manufacturers are also shown in Fig. 3. To demonstrate, the prior probability of supplier 1 being operational or disrupted is 90 and 10%, while this probability for supplier 2 is 85 and 15%, respectively. The probability that manufacturer 1 is operational or disrupted is 85 and 15%, respectively.

To analyze the ripple effect of supplier disruption on manufacturers, we made an observation for each supplier. We set the probability of each supplier to be fully disrupted (1005) and propagated the impact of that observation on manufacturers

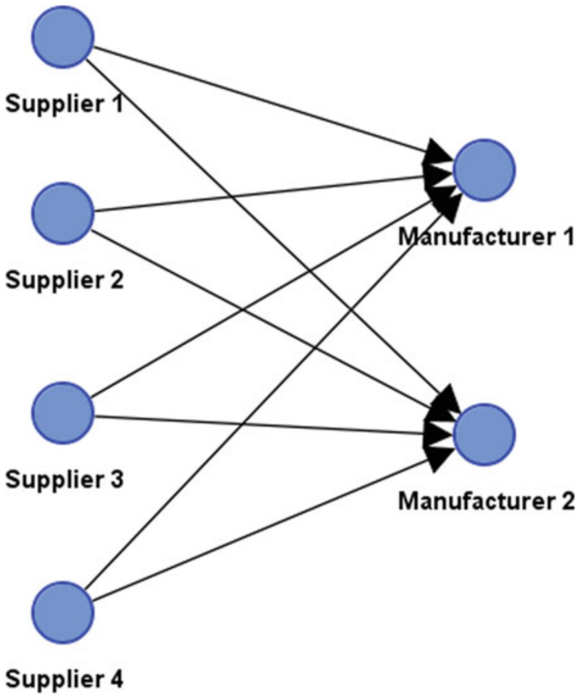

Fig. 2 A PGM with four suppliers and two manufacturers

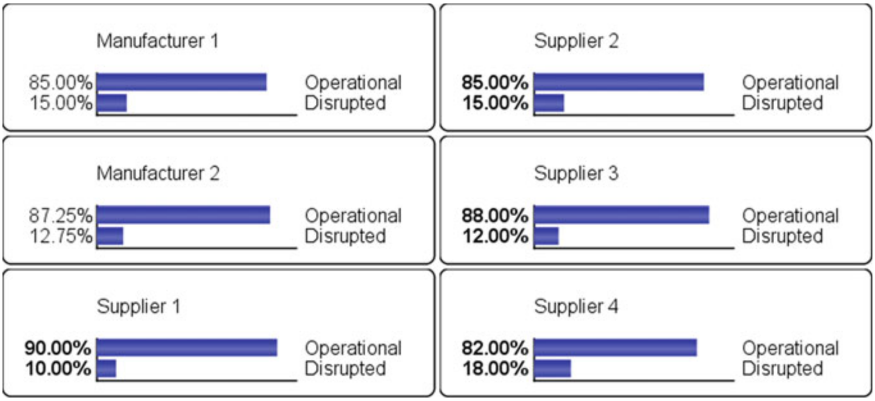

Fig. 3 Prior probabilities of suppliers and marginal distribution probabilities of manufacturers

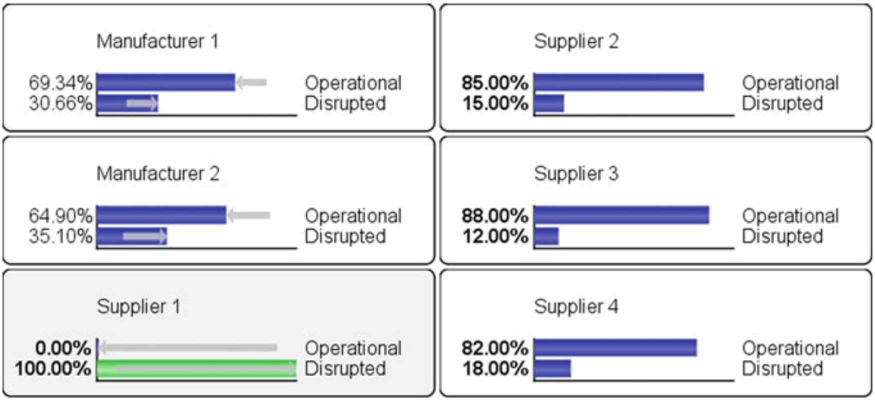

Fig. 4 Marginal distribution probability of manufactures when supplier 1 is fully disrupted

using DDA by updating the marginal distribution probability of the manufacturer variables. It is clear that when we make an observation for suppliers by setting the probability of disruption to 100%, the disruption probability of the manufacturers will increase. The ripple effect of a supplier disruption on a manufacturer can be quantified as the marginal probability disruption of that manufacturer under prior inference analysis and the marginal probability of that manufacturer after inference analysis, when the prior disruption probability of the supplier is set to 100%. For example, we performed inference analysis of supplier 1 by making an observation that this supplier was fully disrupted (probability of disrupted state of supplier 1 = 100%).

Figure 4 represents the inference analysis of supplier 1, where supplier 1 is assumed to be fully disrupted. As shown in Fig. 4, the disruption probability of manufacturers 1 and 2 increases to 30.66 and 35.10%, respectively. It is notable that the disruption probability of manufacturers 1 and 2 in the base model is 15 and 12.75%, respectively.

The results of inference analysis of disruption at supplier 2 on manufacturers are shown in Fig. 5. From the inference analysis illustrated in Fig. 5, it is evident that the disruption probability of manufacturers 1 and 2 increase to 41 and 31.14%, respectively. Table 1 lists the disruption probabilities of both manufacturers when each supplier is fully disrupted. Notably, supplier 2 has the highest disruption impact on manufacturer 1 (by 22.23%), while supplier 1 has the highest disruption impact on manufacturer 2 (by 23.35%).

The marginal distribution probability of manufacturers 1 and 2 when supplier 3 is fully disrupted is shown in Fig. 6.

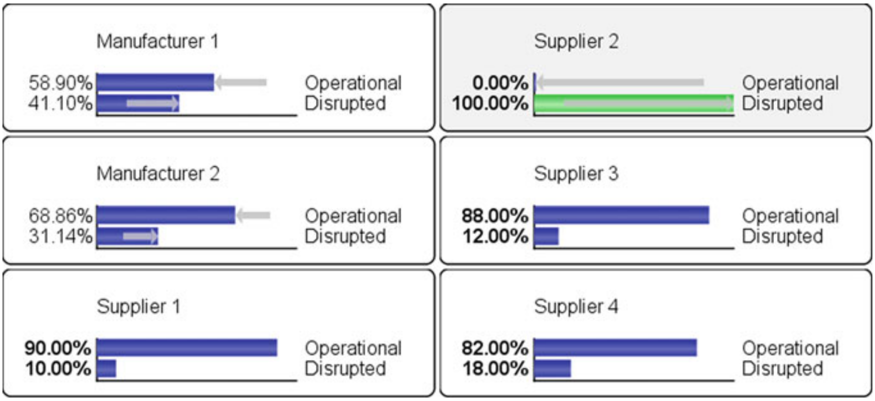

Fig. 5 Marginal distribution probability of manufacturers when supplier 2 is fully disrupted

Table 1 Comparison between base model and inference model of manufacturers given disruption of different suppliers

Supplier 1			
Base model		Inference model	
Manufacturer 1	Manufacturer 2	Manufacturer 1	Manufacturer 2
15%	12.75%	30.66%	35.10%
Supplier 2			
Base model		Inference model	
Manufacturer 1	Manufacturer 2	Manufacturer 1	Manufacturer 2
15%	12.75%	41.10%	31.14%
Supplier 3			
Base model		Inference model	
Manufacturer 1	Manufacturer 2	Manufacturer 1	Manufacturer 2
15%	12.75%	37.23%	26.84%
Supplier 4			
Base model		Inference model	
Manufacturer 1	Manufacturer 2	Manufacturer 1	Manufacturer 2
15%	12.75%	36.34%	31.31%

5 Conclusions

SC managers face continuous challenge from a growing number of disruptive events due to global sourcing, interconnected SC structures, and SC structural complexity. Disruption management in SCs has become a critical issue in the context of SCM. A key issue in SC disruption management is to analyze and manage the propagation impact of disrupted suppliers on downstream SC entities. In reality, the disruption of

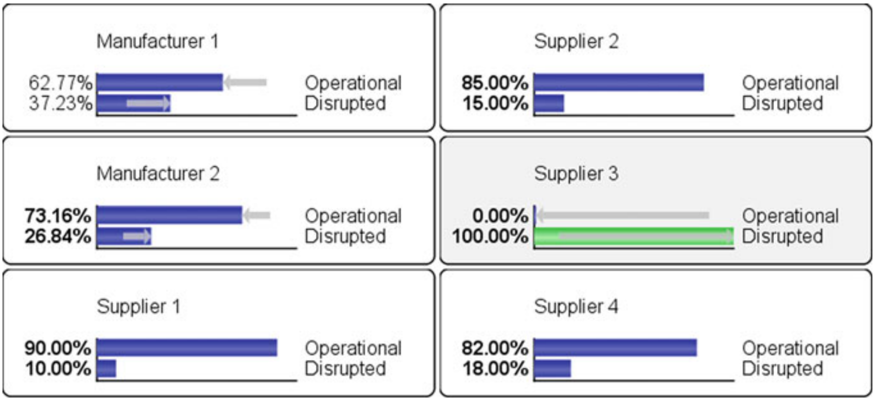

Fig. 6 Marginal distribution probability of manufacturers when supplier 3 is fully disrupted

a supplier may propagate through the SC and negatively impact other entities, such as manufacturers, distributors, and retailers. It is important to identify those suppliers whose disruption could potentially have a higher disruption impact on other entities, particularly manufacturers. In this study, propagation analysis of suppliers in a two-stage SC is studied using inference analysis. Inference analysis in a PGM with four suppliers and two manufacturers has been performed to identify which supplier has the highest disruption propagation impact on manufacturers. By identifying and fortifying critical suppliers, the chance of continuous operations during and in the aftermath of disruption can be increased significantly.

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Entropy-Based Analysis and Quantification of Supply Chain Recoverability

Dmitry Ivanov

Abstract The problem of designing resilient supply chains at the semantic network level is considered. The entropy method is used to show the interrelations between supply chain design and recoverability. Easy-to-compute quantitative measures are proposed to estimate supply chain recoverability. For the first time, entropy-based supply chain analysis is brought into correspondence with supply chain structural recoverability and flexibility considerations downstream the supply chain. An exact and a heuristic computation algorithm are suggested and illustrated. The developed approach and recoverability measure can be used to select a resilient supply chain design in terms of potential recoverability.

1 Introduction

Designing the resilient supply chains has become a crucial research avenue over the last decade. In essence, the main research thread is to identify supply chain structures, which are robust and/or recoverable in the event of severe disruptions such as facility breakdowns, strikes, supplier bankruptcies, or financial crises. Significant research advancements have been achieved in this area at the semantic network level, design, planning, and control levels (Martel and Klibi 2016; Mistree et al. 2017; Ivanov 2018). While design, planning, and control levels deal with both structural parameters (i.e., the facility locations and connections in between them) and operational parameters (i.e., demand, capacity, and lead time, to name a few), the semantic network level considers the structural domain only. The target of the analysis at the semantic network level is to identify major interdependencies between the network graph forms and the supply chain robustness, flexibility, adaptability, and resilience (Zobel 2014; Ivanov 2017; Giannoccaro et al. 2017; Ivanov et al. 2017a, b; Dolgui et al. 2018).

D. Ivanov (✉)
Department of Business and Economics, Berlin School of Economics and Law, 10825 Berlin, Germany
e-mail: divanov@hwr-berlin.de

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Linking supply chain complexity and disruption risk resistance has become more and more important (Nair and Vidal 2011; Scheibe and Blackhurts 2018; Levner and Ptuskin 2018; Birkie et al. 2017; He et al. 2018). Blackhurts et al. (2005), Ho et al. (2015), Jain et al. (2017), Ivanov et al. (2017a) underline that global sourcing, product individualization, and cross-channel logistics strategies increase supply chain complexity. Scheibe and Blackhurst (2018) identified SC structure as one of three major drivers of disruption propagations in the SC. Complex networks become more vulnerable to sever disruptions, which change the supply chain structures and are involved with supply chain structural dynamics (Ivanov et al. 2010; Ivanov and Sokolov 2010; Mistree et al. 2017; Ivanov 2018). Moreover, the ripple effect in the supply chain complicates disruption management (Liberatore et al. 2012; Ivanov et al. 2014a, b; Ivanov 2017).

As an opposite to the well-known bullwhip effect that considers high-frequency-low-impact *operational risks*, the ripple effect studies low-frequency-high-impact *disruptive risks* (Ivanov et al. 2014a; Simchi-Levi et al. 2015; Aqlan and Lam 2015; Sokolov et al. 2016; Snyder et al. 2016; Han and Shin 2016; Sawik 2017). The ripple effect describes the impact of disruption propagation in the supply chain on structural dynamics and performance. Recent studies extensively considered disruption risks in light of the impact of disruption propagation (Wilson 2007; Ivanov et al. 2014b; Paul et al. 2014; Ivanov 2017; Scheibe and Blackhurst 2018; Levner and Ptuskin 2018; Ivanov 2019; Altay et al. 2018; Käki et al. 2015; Lücker and Seifert 2017). Previous studies also suggested several measures to quantify disruption risks (Zobel 2011; Basole and Bellamy 2014; Han and Shin 2016; Lin et al. 2017; Dolgui et al. 2019). However, single-stage disruption has mostly been considered, and disruption propagation in light of supply chain complexity has been neglected.

In addition, recoverability of the supply chain plays an important role in supply chain resilience and in mitigating the ripple effect. The disruption profile constituted in the work by Sheffi and Rice (2005) includes eight phases: preparation actions, the disruptive event, the first response, the initial impact, the full impact, the recovery preparations, and the recovery and long-term impact. That is why the recoverability is an important part of supply chain resilience. Ivanov et al. (2017b) revealed several major recovery policies in the supply chain. One of them is the backup sourcing and shipment activation in the event of disruption and the resulting structural changes in the supply chain. This study focuses on the said recovery policy and brings it into correspondence to supply chain complexity.

Complexity quantification can be achieved by means of "entropy" which was first introduced by Shannon and Weaver (1963) and applied to supply chain domain in the studies by Harremoës and Topsøe (2001), Isik (2010), Allesina et al. (2010), Ivanov and Arkhipov (2011a), Ivanov and Arkhipov (2011b), Yu and Xiao (2014), Yuming (2015), Levner and Ptuskin (2015, 2018).

Levner and Ptuskin (2018) addressed ripple effect analysis using entropy measure from the environmental risk perspective and underlined that it would be "more practicable to study the harmful impact of the environmental risks in more general framework," i.e., in combination with other risk types and classes (Quang and Hara 2018). This study closes the research gap described above and develops a quantitative entropy-based measure to analyze supply chain recoverability in event of facility disruptions. For the first time, entropy-based supply chain analysis will be brought into correspondence with supply chain structural recoverability and flexibility considerations downstream the supply chain. An exact and a heuristic computation algorithm will be suggested and illustrated.

The rest of this paper is structured as follows. Section 2 is devoted to literature analysis. The method for a recoverability potential assessment is presented in Sect. 3. The exact computation algorithm is presented and illustrated numerically in Sect. 4. Section 5 considers the heuristic method. Section 6 summarizes the outcomes of this study and discusses its limitations and future research avenues (Hosseini and Barker 2016).

2 State of the Art

2.1 Entropy-Based Studies

Harremoës and Topsøe (2001) developed an entropy-based approach to examining the vulnerability of supply network nodes using maximum entropy (Hosseini and Barker 2016). They tested the entropic approach on a real-world healthcare supply chain and successfully extracted the most dangerous risks in the supply chain. Isik (2010) applied the entropy concept to measure complexity associated with information and material flows.

Allesina et al. (2010) developed eight indexes based on entropy to measure the level of complexity in the supply chain by mapping the exchanges of goods between the different actors in the network. The impact of possible modifications of the supply chain structure can be evaluated using these tools, providing an evaluation of the different structural dynamics scenarios. Ivanov and Arkhipov (2011a) and Ivanov and Arkhipov (2011b) applied the entropy model to the analysis of supply chain adaptation potential. They considered supply chains in virtual enterprises which are formed through the dynamic selection of partners from a pool of available suppliers (the so-called structural–functional reserve) in the supply chain. They also developed some modifications in regard to real-scale supply chain structures.

Yu and Xiao (2014) used the entropy principles for evaluation, analysis, and data processing in problems related to supply chain resilience and risk management. Levner and Ptuskin (2015, 2018) applied the entropy concept to identify vulnerable supply chain nodes and to measure the impact of environmental risks, respectively. The study by Yuming (2015) explored supply chain flexibility from the dimensions of resources and time when the supply chain is coordinated. Resource allocation with the entropy concept in the event of supply chain coordination was proposed. The entropy-based analysis allows estimation of resource output elasticity and time output elasticity. The paper also proposed a method of measuring supply chain flexibility by integrating resource flexibility and time flexibility. Levner and Ptuskin (2018) addressed the ripple effect analysis using entropy measure from the environmental risk perspective.

2.2 Related Studies to Quantify the Supply Chain Disruption Risk Resistance

In a study by Nair and Vidal (2011), 20 supply chains subject to random demand were analyzed using graph-theoretical topology analysis to study the robustness of those supply chains in the event of disruptions. In consideration of varying probabilities of the random failure of nodes during targeted attacks, the authors evaluated the performance of the supply chains. The assessment of severity of the disruptions included the downtime of the nodes affected. The conclusions of the study were based on multi-agent simulation, and the authors detailed the impact of the supply chain structural design on robustness when both demand and disruption were uncertain.

Assuming a sudden onset disruption and linear recovery behavior, Zobel (2011) estimated supply network resilience, while Zobel (2014) extended the study to a general case which accounted for nonlinearity and average loss per unit time. Using the largest connected component and average and minimum path length, Zhao et al. (2011) quantified network connectivity and accessibility. On the other hand, Basole and Bellamy (2014) quantified the level of risk diffusion as the number of functioning nodes at time t relative to the size of the network using the "number of healthy nodes" as a measure. In the study by Simchi-Levi et al. (2015), a risk exposure index was developed for an automotive supply chain. The index was computed using two models, time to recovery and time to survive, and the impact of a disruption on the supply chain's performance was then assessed.

Using a survival model to illustrate the time from when a system failed to the time when it resumed functioning (i.e., recovery), supply chain resilience was analyzed in the study by Raj et al. (2015). The input to the model was the event of failure, while the output was recovery time, which allowed the resilience of the supply chain to be measured in terms of recovery time. Using several indicators from graph theory, Sokolov et al. (2016) developed a model to assess and quantify, using connectivity, reachability, complexity, and centralization as metrics, the performance impact of the ripple effect in a distribution network.

Considering supply chain structural dynamics in a multistage network with cross-docking terminals, the study by Ivanov et al. (2016) presented a method of quantification for the financial impact of disruptions on the supply chain, and then recommended the use of hybrid optimal control, a linear programming model which considers several structural constancy intervals. The supply chain structure remained stable between these intervals, while structural changes occurred during the transition to the next structural constancy interval. The authors modeled the structural dynamics of the supply chain with optimal control, and performed optimization between intervals with a linear programming model with two-side constraints.

In random networks, the study by Han and Shin (2016) evaluated the structural robustness of the supply chain and compared this robustness to the random risk of network disruption. Lin et al. (2017) assessed the reliability of a multistage supply chain using the probability that market demand can be met if multiple stations of transit are used with the appropriate time frame, where system reliability, acting as the delivery performance index, is assessed by the number of minimal paths. Pavlov et al. (2018) developed a hybrid fuzzy-probabilistic approach to supply chain resilience estimation with structural dynamics and ripple effect consideration. The genome method was applied with the objective of including the structural properties of the supply chain design into resilience assessment. A supply chain design resilience index was developed that can be used as a method of comparing different supply chain designs regarding the resilience both to disruption propagation and with recovery consideration. Moreover, the developed approach allows the identification of groups of critical suppliers whose failure interrupts the supply chain operation.

3 Method to Quantify Supply Chain Recoverability

We apply the method of network adaptation potential analysis (Ivanov and Arkhipov 2011a; Ivanov and Arkhipov 2011b). The supply chains are functionally and structurally complex and are multistage systems. A recovery policy in the supply chain is formed through dynamic selection of backup sources and paths in the network which results in a higher number of possible alternative recovery trajectories. The realization of such alternative recovery strategies allows a flexible reaction to the disrupted supply chain's structural changes. Thus, even at the planning stage, the supply chain design should be considered "branchy".

The introduction of alternative recovery structures into the supply chain results in different levels of structural complexity. The assessment of this structural characteristic can be intuitively related to the quantity and variety of supply chain recovery trajectories, the quantity of polytypic actions, the variety of logical connections between them, the existence of "branching" or structure decoupling points, and the possibility of choosing between alternative variants of supply chain recoverability. In this paper, the approach to the above-described assessment issue, called supply chain recoverability potential, will be considered.

The recoverability potential concept can be formulated as follows. The recoverability potential is the supply chain's structural property which is characterized by the decoupling or branching degree of the supply chain recovery policy and the possibility to adapt to a real execution environment.

Quantitative estimation of recoverability potential serves for the analysis of the determination of a number of elements in the supply chain design, their variety, and the interrelations between them with regard to the potential ability of a supply chain to survive in the presence of disruption, i.e., to have at least one undisrupted path to the end stage in the supply chain, e.g., customers or markets.

4 Exact Method

4.1 Computational Method

Taking into account the semantic affinity of complexity, uncertainty, and recoverability, the measure of a complex system state's relative variety, i.e., the entropy is suggested for the quantitative estimation of the supply chain's recoverability potential. Assume that the supply chain network structure is designed and can be divided into t layers, i.e., supplier, factories, and retailers. It is possible to choose between n_t supply chain elements within each t-layer. The probability p of choosing any path in the supply chain network is equal. Recovery paths are designed according to the set system of logic links according to the recovery policies. Then network structure complexity, as a measure of subject possibilities and equivalent to a variety of choices of alternative sets, can be estimated with the indicator known as entropy H of a complex system:

$$H = -\sum_{i=1}^{N} p_i \ln p_i \tag{1}$$

where p_i is the probability of i-state of system or in our case, the selection probability of i-recovery trajectory, $i = 1, 2, \ldots, N$. First, in order to compute the entropy index H, the probabilities of each recovery path in the supply chain should be determined, and, second, the logarithm of this probability should be found. This will be explained in more detail further in the paper using a numerical example (see Fig. 1).

As the entropy assessment of supply chain complexity is performed as a basis for the estimation of further recoverability potential, any of the log bases can be used. We use the natural (normal) *ln* because it is the most convenient way to compute experiments in entropy as shown in Shannon and Weaver (1963).

It is not difficult to compute the index of network entropy when the network is set up and the hypothesis about the choice of equally probable operations at each planning stage is accepted. As a result, an estimation can be received that indirectly characterizes the network recoverability potential. Let us present a simple example (see Fig. 1).

Let a supply chain design have the structure presented in Fig. 1. The downstream supply chain design includes three layers: a cross-docking hub, two distribution centers, and five retailers. For this type of the network, the entropy index is H = 1.6 according to Eq. (1). There are two options to transit from the first layer (i.e., the hub) to the second layer (i.e., the distribution centers). Therefore, the probability of each path selection in between the first and second layers is 0.5. In considering the upper node of the second layer, there are three alternative links to reach the third layer, i.e., the retailers. Therefore, the probability of each path selection from this node to the retailers at the third layer will be approximately 0.33. Hence, the selection probability of each of the three alternative ways through the upper node of the second layer is

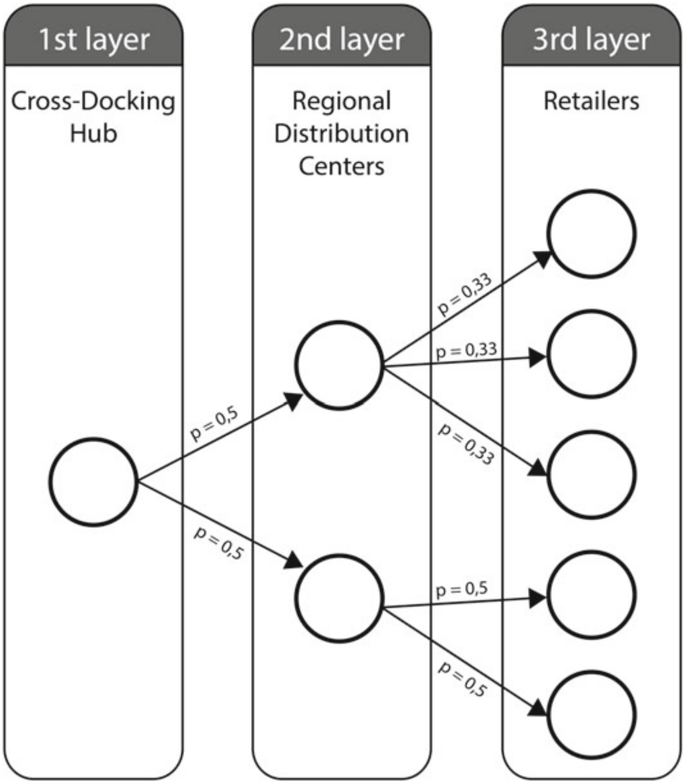

Fig. 1 Example of the supply chain design structure

$p = 0.5 * 0.33 = 0.165$. Now, the logarithm from this probability can be taken: ln $0.165 = -1.8$. We get $0.165 * (-1.8) = -0.3$. As three alternative links exist, $-0.3 \times 3 = -0.9$. Analogously, in considering the bottom node of the second layer, there are two alternative links to reach the third layer. Therefore, the probability for each will be 0.5. Hence, the selection probability of each of the two ways through the bottom node of the second layer is $p = 0.5 * 0.5 = 0.25$. Now, the logarithm from this probability can be taken: $\ln 0.25 = -1.39$. We get $0.25 * (-1.39) = -0.35$. As two alternative links exist, we then consider $H = -(-0.35 \times 2) = 0.7$. The sum H of the two nodes in the first stage is, therefore, $0.9 + 0.70 = 1.6$.

The maximum recoverability value for a network with a set number of supply chain elements at each stage will obviously be achieved when all the variants of transitions from i-operation elements to $(i + 1)$-operation elements are admissible and equally probable, i.e., in the case of a complete bipartite graph (see Fig. 2). For this case, we will have $H^{max} = 2.3$.

In analyzing a real supply chain, it is useful to have relative (normal) estimations $H^{(o)} = H/H^{max}$ as well as absolute estimations of a variety level (entropy) H. For

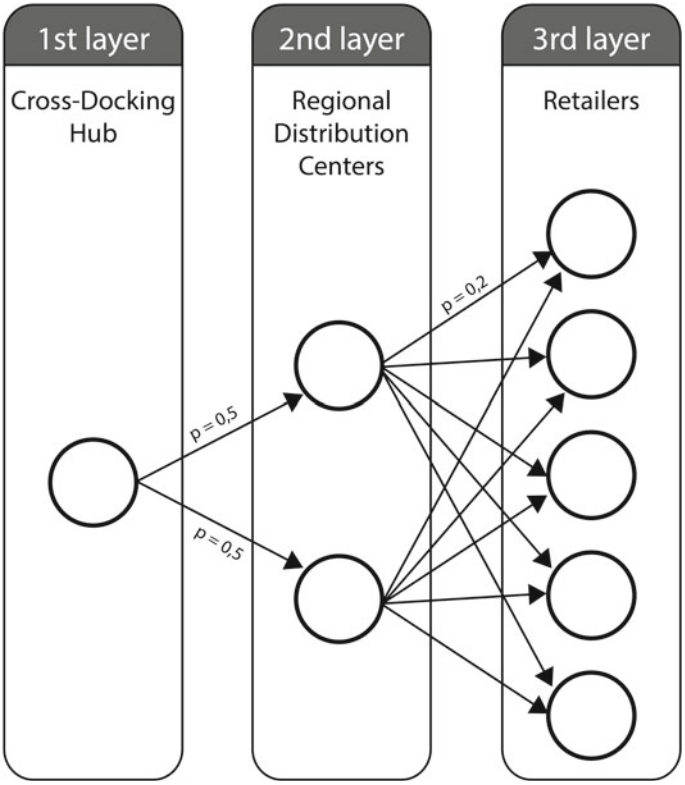

Fig. 2 Supply chain design structure as a complete bipartite graph

the network in Fig. 1, the relative estimation of entropy is $H^{(o)} = 1.6/2.30 = 0.7$. Absolute estimations allow us to compare supply chain design structures that differ in the quantity of the supply chain stages, the quantity of elements at different stages, and a variety of links between elements. Relative estimations characterize, in essence, the degree of affinity between the variety of links in a concrete supply chain to the maximum value.

However, index (1) does not reflect one important requirement for the supply chain structural recoverability, i.e., the maintenance of a high service level and the required higher recoverability due to higher flexibility downstream in the supply chain, which is important for supply chain adaptation possibilities on the customer side. Let us introduce another supply chain structure, but with the same number of elements and links (see Fig. 3).

The entropy index for both supply chain design structures presented in Figs. 2 and 3 are identical and equal $H = 2.30$. At the same time, these two structures essentially differ, because the recovery path selection variety changes in different ways while moving downstream in the network.

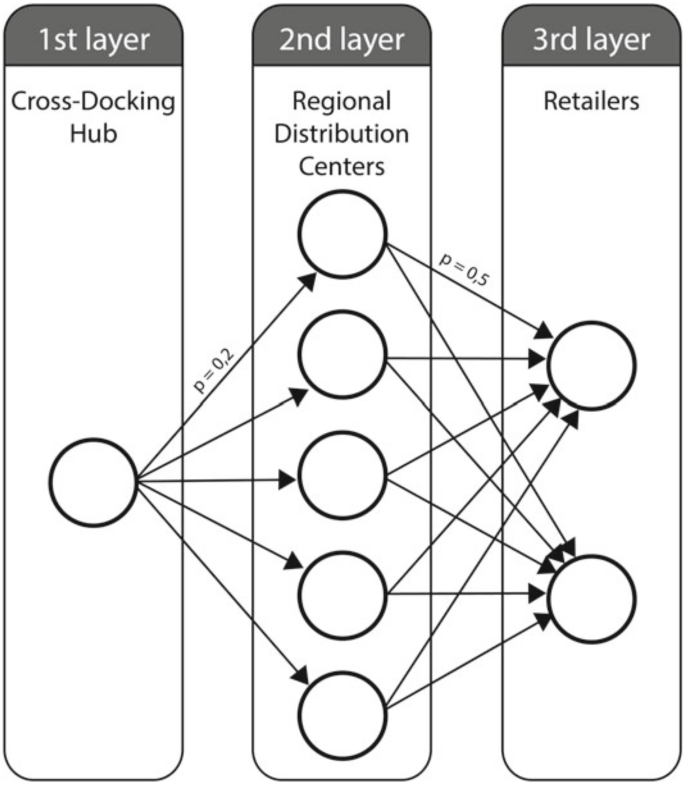

Fig. 3 Modified supply chain design structure

An extended recoverability estimation can be concluded after several transformations of Eq. (1) by presenting the i-trajectory selection probability as the multiplication of its unit probabilities $p_i = p_{i1}$ x p_{i2} x …..x p_{iT}. Equation (1) will be transformed as shown in Eq. (2):

$$
\begin{gathered}
H = -\sum_{i=1}^{N} p_{i1}xp_{i2}x\ldots xp_{iT}\ln(p_{i1}xp_{i2}\ldots xp_{iT}) = \\
\sum_{i=1}^{N} p_{i1}xp_{i2}x\ldots xp_{iT}\ln(p_{i1}xp_{i2}\ldots xp_{iT}) = \\
\sum_{i=1}^{N}\left(\prod_{\substack{k=0\\k\neq t}}^{T-1} p_{ik}xp_{il}\ln p_{il} + \prod_{\substack{k=0\\k\neq t}}^{T-1} p_{ik}xp_{i2}\ln p_{i2} + \ldots + \prod_{\substack{k=0\\k\neq t}}^{T-1} p_{ik}xp_{ik}\ln p_{ik}\right) = \\
\sum_{i=1}^{N}\sum_{t=0}^{T-1}\left(\prod_{k=0} p_{ik}\right)x(p_{it}\ln p_{it})
\end{gathered}
\tag{2}
$$

It can be observed in Eq. (2) that the supply chain recovery variety is expressed through the probabilities of a trajectory unit selection. This allows us to introduce weights which reflect the subjective considerations of the selection variety value at each interval of structural constancy. We will designate these weights as w_t and consider them normal, that is, $0 \le w_t \le 1$, $\sum w_t = 1$. Let us name the obtained estimation *the supply chain-weighted variety* (the weighted entropy) and denote it as H_w (Eq. 3):

$$H_W = -\sum_{i=1}^{N}\sum_{t=0}^{T-1} w_t \left(\prod_{\substack{k=0 \\ k\neq t}}^{T-1} p_{ik}\right) x(p_{it}\ln p_{it}) = -\sum_{i=1}^{N}\prod_{t=0}^{T-1} p_{it}\sum_{t=0}^{T-1} w_t \ln p_{it} \tag{3}$$

The index of weighted variety (Eq. 4) can also be called the supply chain absolute recoverability potential: we denote it as A and $A = H_w$.

For a supply chain design with the maximum value of weighted entropy (i.e., the supply chain network structure with initial functionality and the maximum number of equally probable recovery paths), Eq. (3) becomes simpler (Eq. 4):

$$H_w^{max} = -\sum_{t=0}^{T-1} w_t \ln p_{it} \tag{4}$$

Let us consider the following estimation as the indicator of the supply chain relative recoverability (Eq. 5):

$$A^{(0)} = \frac{H_w}{H_w^{max}} \tag{5}$$

The recoverability potential index is sensitive to changes in the supply chain node structure, the allocation of these knots within intervals of structural constancy, and the variety of recovery path selection.

4.2 Numerical Example

To illustrate the proposed technique, we use the supply chain design structures shown in Figs. 1, 2, and 3. The corresponding values of the necessary estimations of network variety and recoverability potential are shown in Table 1. The weights w_t are considered in direct proportion to the t layer number (i.e., the layers downstream in the supply chain and closer to the customers get higher weights subject to the requirement of a higher service level).

It can be observed that the recoverability potential $A^{(0)}$ of the supply chain design structures shown in Figs. 2 and 3 is equal and is greater compared to that of structure 1a. In addition, the indicator H_w shows a higher responsiveness and agility in

Table 1 Examples of supply chain variety and adaptation potential estimations for different network structures

Supply chain design structure	Variety estimations, H, (H^{max})	Weighted variety estimation (absolute recoverability potential), $A = H_w$	Maximum estimation of weighted variety, H_w^{max}	Relative recoverability potential estimation, $A^{(o)}$
Figure 1	1.6; (2.30)	0.94	1.31	0.72
Figure 2	2.30; (2.30)	1.31	1.31	1.00
Figure 3	2.30; (2.30)	0.99	0.99	1.00

the structure as shown in Fig. 2 (see Eqs. 3–5). The higher value of the indicator H_w indicates that supply chain recoverability increases downstream in the supply chain, that is, the variety of recovery paths increases downstream in the supply chain and extends flexibility and responsiveness in the parts of the supply chain near the customers.

The final selection of the supply chain design with recoverability considerations should be performed on the basis of economic efficiency and recoverability potential indicators. In addition, if a supply chain design structure is economically preferable, but lacks the recoverability in event of severe structural disruptions, additional links can be introduced in the supply chain to increase the flexibility. For example, technology standardization at production plants can be performed so that each of them would be able to produce different (or at least two) product families.

5 Heuristic Method

Equations (1)–(5) are rather simple and can be easily applied in software. However, in the case of complex network models, technical computation difficulties may arise since the number of trajectories in the network can become astronomical. In addition, individual trajectory selection probabilities in complex networks are rather small and, as it is known, arithmetical calculations with small values can lead to serious errors. This is why it is suggested to carry out the recoverability adaptation potential calculations on the basis of network model decomposition.

The analysis of various supply chain design structures shows that the operations within a supply chain layer often does not influence other operational blocks. Such a situation occurs when all the possible links between the elements of adjacent supply chain layers exist. Let us show several examples. We analyze a supply chain design structure as illustrated in Fig. 4.

The selection of a node at one supply chain layer into the recovery path does not influence the probability of selecting any node in the subsequent layer into the

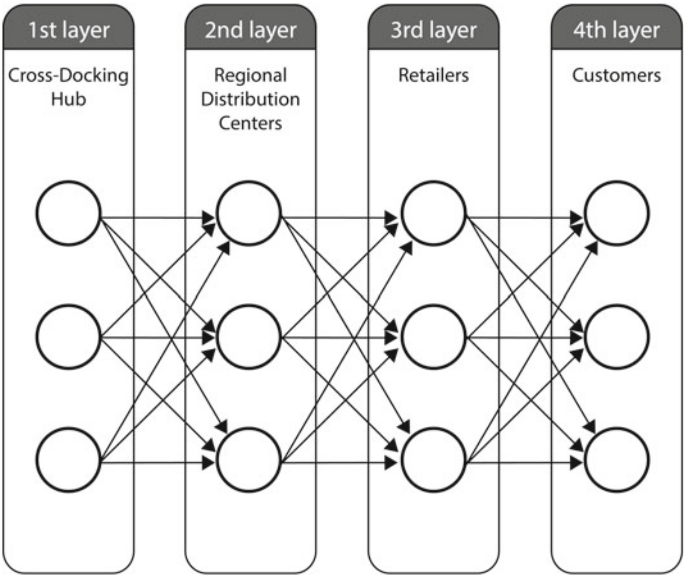

Fig. 4 Example of a four-layer supply chain

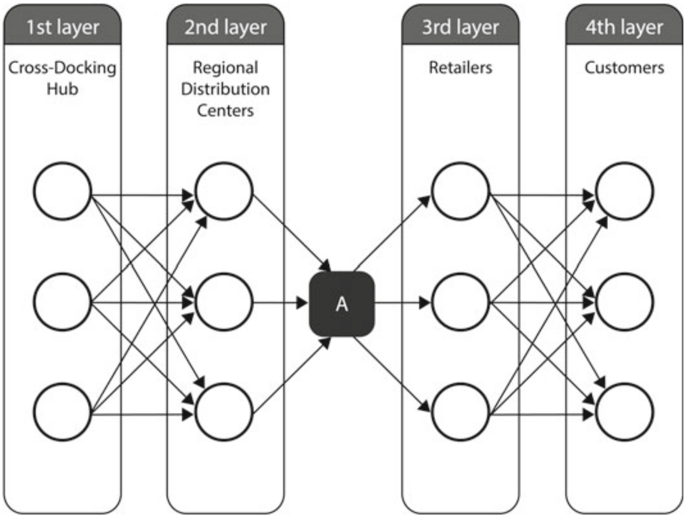

Fig. 5 Example of a four-layer supply chain with auxiliary element *A*

same recovery path. In this case, the auxiliary "dividing" block can be introduced between the layers, which include one element that divides the supply chain into two fragments (Fig. 5).

The recoverability adaptation potential estimation is then approximately equal to the fragment potential sum. For supply chain designs that have the maximum number of links, this equality is exact, and it is possible to present this formally. The auxiliary action A in Fig. 5 divides the supply chain into two fragments, I, II. The supply chain and its fragment recoverability potentials are as follows: $H_{max} = lnN = 4.394$, $\mathrm{H_I} = ln9 = 2.197$, and $H_{II} = ln9 = 2.197$. We can observe that the equation $H_{max} = H_I + H_{II}$ holds true. When the recoverability potentials of the fragments are different, an approximation should take place. The analysis of different supply chain structures showed that computational accuracy with network model decomposition is sufficient to carry out a real data analysis. Hence, it can be concluded that the recoverability adaptation potential estimation of supply chain design structure fragments can be used to simplify practical computations.

6 Conclusion

The problem of designing resilient supply chains at the semantic network level has been considered in this study. The entropy method was used to reveal the interrelations between supply chain design and recoverability. An entropy-based quantitative measure has been suggested to estimate supply chain recoverability. For the first time, the entropy-based supply chain analysis is brought into correspondence with supply chain structural dynamics. An exact and a heuristic computation algorithm are suggested and illustrated. The developed approach and recoverability measure can be used to select a resilient supply chain design.

Advantages of the developed method are the simplicity of recoverability index computations as well as the numerous applications to real-life problems due to the higher abstraction level of the model developed. The nodes in the network can be considered suppliers, logistics, production companies, or even a production line resource allowing almost any level of abstraction in the analysis.

In terms of the limitations of this study, it should be noted that homogenous goods downstream in the supply chain have been considered. The bill-of-material considerations in the upstream supply chain would make it necessary to adapt this concept. Regarding the absolute and relative recoverability potential estimation, it should be noted that the relative estimations with the maximum variety of links are identical and equal to 1, no matter how many stages the supply chain has. This limits the application possibilities to a certain extent, but nevertheless, they still retain an analytical role, supplementing absolute adaptation potential estimations. The proposed supply chain adaptation potential indicators can be used as criteria for selecting supply chain design structures at the configuration stage with consideration of severe disruption risks and supply chain structural dynamics. Future research can include the introduction of bill-of-material considerations and case-study applications of the developed method to reveal specific aspects relevant for different industries and services.

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New Measures of Vulnerability Within Supply Networks: A Comparison of Industries

James P. Minas, N. C. Simpson and Ta-Wei (Daniel) Kao

Abstract Modern supply chains have become increasingly complex and interconnected, raising concerns as to the potential loss of system-wide resilience. One distinct element of supply chain risk is the potential for detrimental material to propagate through the supply chain undetected, eventually exposing unsuspecting consumers to defective products. In this chapter, based on methods inspired by epidemiology, we propose new measures for quantifying this risk. We then apply these measures to real-life supply networks from eight industries to compare their relative levels of risk across a 17-year time horizon. Our results indicate that while in aggregate supply chain risk has increased overtime, both the level and sources of risk differ markedly by industry.

1 Introduction

Recent history has witnessed the growth of complex supply chain networks, creating a web of supply-related partnerships that spans almost all regions of our planet. Managing risk across these emergent systems begins with effective means of measuring and expressing potential threats therein. The purpose of this study is to develop better measures for the comparative assessment of supply chain risk, using methods inspired by epidemiology. Once formulated, we apply these measures to authentic supply chain network structures from various industries across a 17-year timeline. Whole industries are found to vary in their structural vulnerability to the random

J. P. Minas (✉)
Ithaca College, Ithaca, USA
e-mail: jminas@ithaca.edu

N. C. Simpson
University at Buffalo (SUNY), Buffalo, USA

T.-W. Kao
University of Michigan-Dearborn, Dearborn, USA

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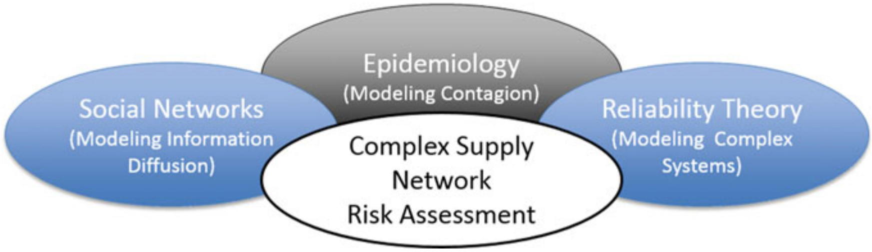

Fig. 1 Three domains contributing to the development of new measures for complex supply network analysis

malignancy of a single network member, although complexity is clearly on the rise throughout. We begin this exploration with greater detail of the motivation of the study, including a brief review of related literature.

1.1 Motivation

Biological models of contagion offer insight into the spread of disruption across complex environments, and will provide the greatest motivation for the new measures presented here. However, the allegory of contagion in the context of supply chains highlights the broader phenomenon of *diffusion*, and thus there are several related domains that indirectly inform this project, as pictured in Fig. 1. For example, both the propagation of risk across a complex supply network and the underlying risk of disease exposure are related to the older framework of reliability theory. In the disruptive context, the outcome of interest is the probability of 'success' of the disruption (as opposed to success of the system), yet the underlying structure of quantifiable risk spreading across points of contact is suggestive of reliability modeling. Similarly, information diffusion through social networks, such as *Twitter* posts and reposts during Hurricane Sandy (Yoo et al. 2016), evokes both the dynamics of diffusion across a connected population and the broader context of collective behavior.

In supply chain management, partnerships effectively create populations at risk of cascading disruption, which spreads in a fashion evocative of both information diffusion and epidemics. We examine eight such populations, arrayed in what we call *industry ego networks*, each being a combined set of all companies within a given industry (the egos), and every other company in any industry with which an ego company has at least one direct or indirect supply relationship. Much of the extant literature examining authentic supply chain structure focuses on one particular industry exclusively such as automotive retailing (Dong et al. 2015) or automotive manufacturer (Choi and Hong 2002). Generalizing findings such as these in the future will partially depend on better understanding of how supply chain structure

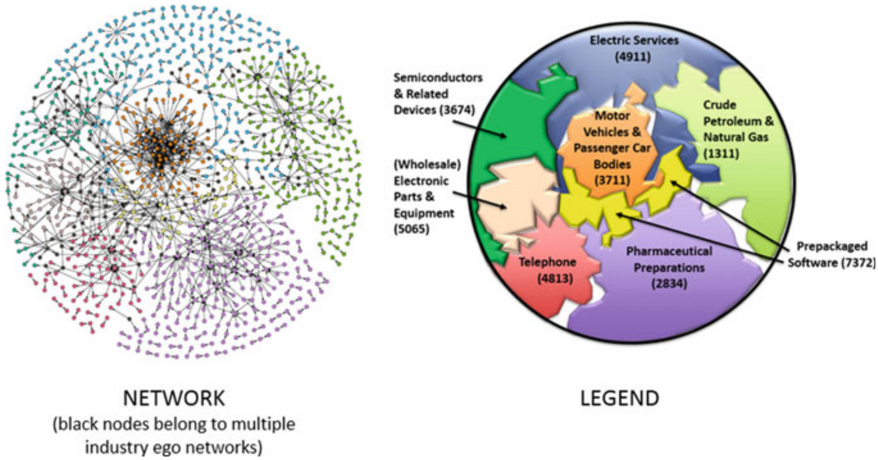

Fig. 2 The eight industry ego networks of 2014

may vary between industries, and thus the choice of eight such settings in this study. Figure 2 displays the combined membership of all eight industry ego networks as they appeared in the year 2014.

1.2 Related Literature

Network science offers a theoretical lens to study supply chains as complex networks, where entities exhibit adaptive action in response to changes in other entities and the whole network (Choi et al. 2001; Pathak et al. 2007). Studies adopting this lens have related network structure through a variety of measures to a range of outcomes in a variety of industries. Earlier investigations often focus on links between network structure and firm performance in a positive sense, particularly as determinants of innovation. For instance, Ahuja (2000) examines the international chemical industry and finds that both direct and indirect ties in collaboration networks have positive impacts on innovation, but structural holes have the opposite effect. Grewal et al. (2006) examine relationships among projects and find structural embeddedness has a strong and significant effect on project success. Phelps (2010) find that ego network density strengthens the influence of technological diversity. Bellamy et al. (2014) focus on supply alliance networks in the electronics industry and show centrality has a significant effect on a focal firm's innovation output, while network efficiency reinforces the relationship between supply network accessibility and innovation output. Using data from biopharmaceutical firms, Mazzola et al. (2015) find that a firm's eigenvector centrality and structural holes impose opposite effects on new product development, while their interaction with open innovation flow is a positive influence. Carnovale and Yeniyurt (2014) show that betweenness centralities of both focal firm and partners have significant effects on new manufacturing joint venture formation. In 2015, they identify the effects of ego network structures on ego network innovation (Carnovale and Yeniyurt 2015). Kim (2017) show the interconnections among direct major customers have a negative impact on a supplier's profitability. Recently, De Stefano and Montes-Sancho (2018) find that positional embeddedness of partners engaged in environmental R&D cooperation enhances the influence of that cooperation on product performance.

A complex network perspective also allows for a holistic assessment of determinants of supply chain disruption (Basole and Bellamy 2014b; Dolgui et al. 2018), although work with this focus is somewhat more recent. Basole and Bellamy (2014a) use visualization techniques to create graphical representations of the electronic industry's supply chain network. The network visualizations are then used to identify and analyze disruption risk sources, characterized by a variety of measures including traditional social network constructs such as betweenness centrality. Kim et al. (2015) compare four fundamental supply network structures and show that node (facility) and arc (transportation) level disruptions do not necessarily create network level disruptions. Sokolov et al. (2016) consider structural network measures together with dynamic performance measures in their multi-criteria model for the design of resilient supply chains. Earlier models of financial risk diffusion, analogous to the epidemiology-inspired approach presented in this chapter, include Gai and Kapadia's (2010) analytical model of contagious default in financial networks and Battison et al. (2007) model of bankruptcy propagation in production networks. Use of epidemiology-type diffusion models in supply chain management includes agent-based simulation models applied to theoretical small-world and scale-free topologies (Basole and Bellamy's 2014b) and to the electronic industry's supply chain network (Basole et al. 2016). However, both these studies differ from our work in that they calculate the health state of the entire network while we are concerned with the probability of a defect or disruption reaching the consumer level. Our study also differs from this previous work in that we consider authentic supply chain networks from multiple industries over multiple years, thus allowing for a comparative analysis of risk between industries overtime.

2 Epidemics in a Supply Chain Context

Biological epidemics provide an intriguing allegory for supply chain risk, as they embody the problem of complex patterns of contact enabling a detrimental condition to propagate. In this study, we explore the framework of the archetypical SIR model in epidemiology, as it might assist in characterizing risk exposure in supply networks. The origins of the SIR model are widely attributed to the early work of Kermack and McKendrick (1927), and many of its derivatives in the setting of epidemiology are discussed in the review of Hethcote (2000). In this section, we first explore the basic SIR framework in the context of a supply network, and then formulate the related measures of risk exposure that we will apply to assess eight industries in Sect. 3.

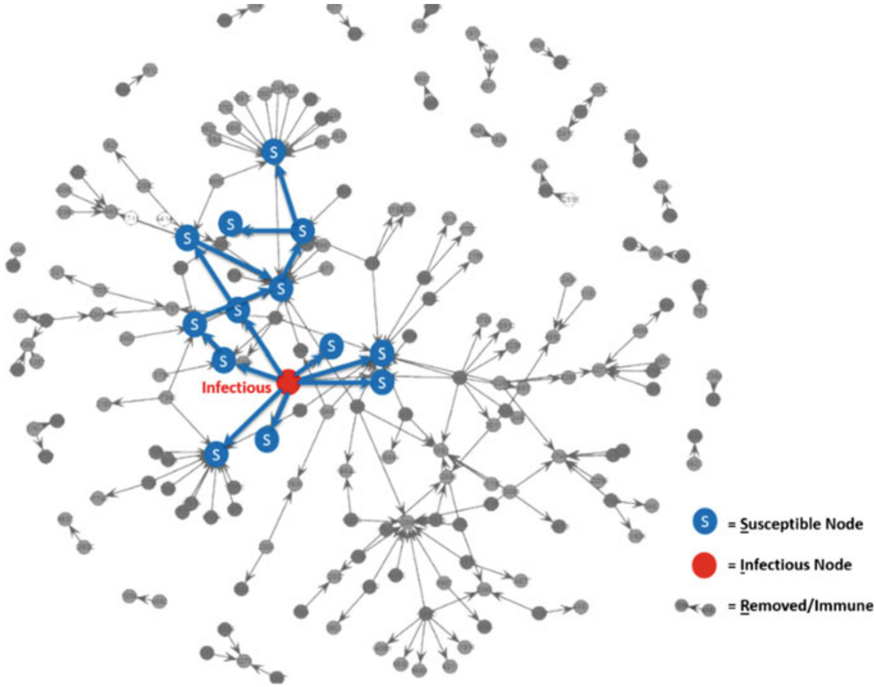

Fig. 3 An example of infectious versus susceptible and immune nodes in a supply network

2.1 The SIR Model

The SIR model is a compartmental model of epidemiology, dividing a population into three groups. In the SIR model, these compartments are those individuals who are susceptible (S) to a disease, those who are currently infected with that disease (I) and those who have recovered and now immune, or removed in the sense that they have died from the disease (R). Two important framework parameters are β, the probability of an individual of susceptible status (S) contracting the disease upon exposure to an infected individual, and Υ, the transition rate of an individual from infected status (I) to that of recovered/removed (R). The three categories are illustrated in context of directed supply network in Fig. 3.

While biological infection provides an intuitive analogy when modeling how suppliers may transmit disruption to buyers, it is important to note some differences in the two cases. In epidemiology, the SIR framework is predominantly dynamic in nature, as it attempts to predict how many people would be members of each category throughout the timeline of a potential epidemic. Supply chain ‘contagion’ does follow epidemiology in the sense that disruption moves in ‘waves’, where the first wave represents the progression of defective material from a source to any stage directly downstream, and subsequent waves represent these undetected flaws traveling farther down the supply chain. Indeed, any firm or stage downstream of a defective source is the equivalent of susceptible, and the probability β, the risk of infection, is analogous to the risk of Type II errors on behalf of a susceptible buyer's inbound and outbound quality control programs. However, supply chain analysis departs from epidemiology on the issue of outcome of interest. In the case of epidemiology, focus is on the growth and decline of the categories within a given interval of time, particularly the risk that the infectious category may grow at a rate that crests in a network-wide epidemic. In the case of supply chain risk analysis, the focus shifts to the purpose of the supply chain, its ultimate product, and market. In this context, the issue of how much of the network 'population' is infected is not as salient as the risk that the infection penetrates a subset of network nodes, those nodes that release the detrimental material to inflict harm on unsuspecting consumers. Logically adapting the SIR model to this shift in the domain is discussed next.

2.2 Formulating the SIR Framework in the Context of Supply Chains

Consider an industry that sells output to consumers, supported by supply chains of major partners who may or may not belong to that same industry. The consolidated set of the industry members (or ego nodes) and their respective upstream supply chains are known as the *industry ego network* in this study, as described earlier in Sect. 1. In this context, the model relies on two environmental parameters:

Let β_{ij} = the probability of detrimental material from supplier *i* being incorporated into the output of buyer *j*.
Let Ω_{i} = the probability that firm *i* will spontaneously create material detrimental to the supply chain.

β_{ij} is the 'infection rate' between firms *i* and *j*. This rate represents the risk of a Type II error in the buyer *i*'s inbound quality control program, allowing transmission of detrimental material from upstream. Ω_{i} refers to the origin of detriment, analogous to the probability that firm *i* is 'patient zero', or the source of an outbreak. To express the network's general vulnerability, information on network structure is introduced next:

Let {Z} be the set of all ego nodes, or industry members whose output is sent directly to consumers.
Let $\{S_{\mathrm{i}}\}$ be the set of suppliers of firm *i*.
Let e_{i} = the risk that firm i's output is detrimental. e_{i} is calculated by:

$$e_i = 1 - \left((1 - \Omega_i) \prod_{\forall j \in \{S_i\}} (1 - \beta_{ij} e_j) \right)$$

Conceptually, e_i is the most elemental construct in this study, and its calculation is evocative of system reliability: the probability that firm i's output is detrimental is the complement of the joint probability that firm i did not spontaneously produce detrimental material nor did it unknowing assimilate detrimental material from one or more of its suppliers. Risk element e_i is then used in building several broader expressions of risk:

Let $CTL =$ *the consumer threat level*, a measure of the risk that detrimental material will reach the industry's consumer market. CTL is calculated by:

$$CTL = 1 - \prod_{\forall j \in \{Z\}} (1 - e_j)$$

Let $CTL(k) =$ *the consumer threat level posed by firm k,* or a measure of the risk that detrimental material will reach the industry's consumer market given that $\Omega_k = 1$ and $\Omega_j = 0$ for all $\forall j \neq i$

Finally, we define Mean CTL as a summary measure of network vulnerability, calculated by averaging the values of $CTL(k)$ for all firms k in the industry network.

2.3 Interpreting the SIR-Related CTL Measures

Figure 4 illustrates the distinction between ego versus non-ego susceptible nodes in the case of two different infectious nodes within Fig. 3 network. Figure 4 also illustrates that, in the case of any given node, the consumer threat level of a node may be readily apparent, as in the case of node j; or considerably less transparent, as in the case of node k. In the case of node j, assuming all connections bear the same risk of successful transmission β =5%, then $CLT(j) = 1-(1-\beta)^3$ =14.3%. Making the same assumption for node k, $\mathrm{CLT}(k) = 1- ((1-\beta)^6 *(1-((1-(1-\beta^3)^2)\ \beta^2))^2) =$ 26.5%.

Up until this point, we have explained the risk under study as a passage of defective material through successive stages of a supply chain, as this application is the most suggestive of the spread of disease. It should be noted, however, that these constructs have an equally useful alternate interpretation: measures of the risk of visible supply chain disruption. In this interpretation, Ω_i is defined as the probability of complete failure of firm i as a supplier, and β_{ij} is the risk that firm j cannot switch suppliers or implement any contingency plan before it fails to meet its obligations due to the outage at firm i. Measure e_i becomes the combined risk that firm i will fail in its role in the supply chain for any reason and *CLT(i)* expresses the likelihood the consumer will witness an outage at the downstream end of the supply chain, given firm i does fail. It should also be noted that these expressions can be interpreted as explicit probabilities provided that ego-level firms have no connections amongst each other, consistent with the illustration in Fig. 4. This is not a confining assumption, in that it is reasonable to expect that ego-level firms, marketing the supply network's ultimate

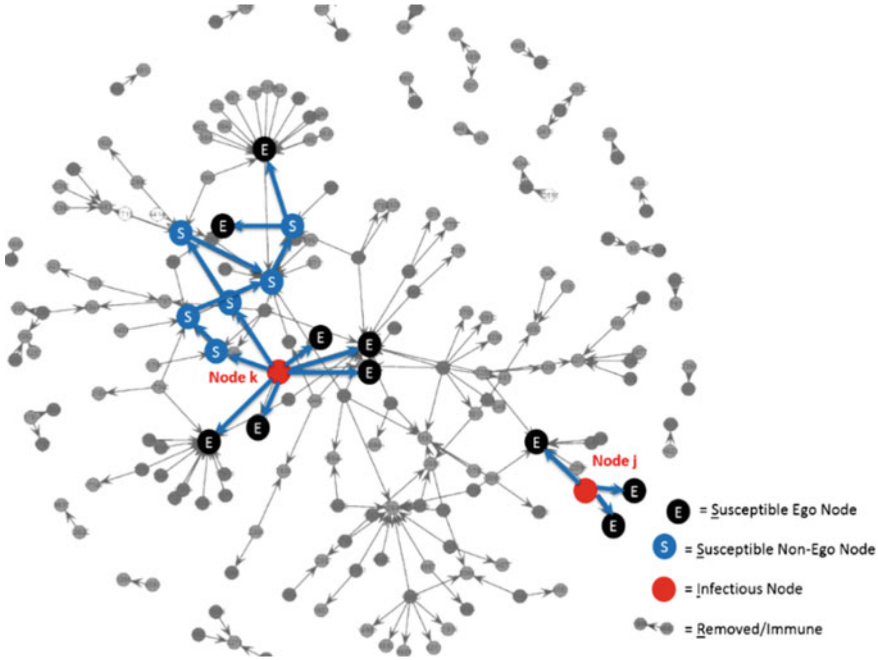

Fig. 4 An example of infectious nodes j and k with associated susceptible ego and non-ego nodes

product to the consumer, are most likely to be commercial rivals. However, this does depend on how the ego-level industry is defined in the data, and in the event of one or more supply relationships within downstream industry, these measures become upper bounds on the exact risk. Employing the model in this fashion is similar to use of the PERT methodology, which has been providing convenient lower bounds on project deadline risk since its debut in Miller (1962).

3 Measuring Consumer Threat Level Across Eight Industries

3.1 Data and Methodology

To demonstrate our proposed measures in the context of authentic supply chain networks, our data source consists of major supply partnerships reported under Financial Accounting Standard (FAS) 131, which requires every publicly traded supplier in the US to report any firm accounting for at least 10% of its sales. Over 76,000 1-year relationships reported between 1998 and 2014 were retrieved from *Compustat* and manually cleaned and supplemented with the four-digit SIC code for each of the

18,000 + companies cited. From this, eight industry ego networks were extracted for each year of the 1998–2014 timeline, resulting in a total of $8*17 = 136$ networks. This process begins by selecting a particular four-digit SIC code as the ego industry, and extracting all firms within an annual data set identified by that code, creating set $\{Z\}$ as discussed in the previous section. The ego network is then generated from this set by retrieving all suppliers of $\{Z\}$, and then all suppliers of those suppliers, continuing until no additional direct or indirect supply relationships can be detected in the data. The union of these eight subgraphs in 2014 was presented earlier in Fig. 2, as the upstream supply networks of the eight industries contain some connections across the subgraphs. In contrast, Fig. 5 illustrates the same eight subgraphs as true ego networks, with node color delineating supply tier within the subgraph. It is apparent from Fig. 5 alone that the nature of supply chain structure varies dramatically between industries. The largest industry network in terms of population is Electric Services (SIC: 4911), but this same industry conspicuously lacks a significant 'main component', the largest interconnected portion of the network graph. In contrast, Pharmaceutical Preparations (SIC: 2834) provides the second largest ego industry network but with a prominent main component. While Motor Vehicles and Passenger Car Bodies (SIC: 3711) provides an ego network that is unremarkable in population size, it is dramatically dense, having by far the highest ratio of connections to nodes.

Upon extraction of all 136 ego networks as 'edge files', delineating the supply network structure as a set of paired connections, each file was evaluated for the risk measures described in Sect. 2, programmed in VBA in conjunction with Microsoft Excel.

3.2 Results and Discussion

Table 1 provides both the *Mean Consumer Threat Level (Mean CTL)* and the *Maximum Consumer Threat Level (Max CTL(k))* for each industry at three points along the timeline, calculated with a uniform infection level parameter (β) of 0.05 for all linkages.

Across the observations in Table 1, all industries except for Prepackaged Software (SIC: 7372) have a *Mean CTL* greater than 0.05, the value of the original parameter β. Since *Mean CTL* represents average risk of consumer level exposure to disruption and β is the probability of disruption spreading one stage downstream from a supplier to a buyer, this result indicates that seven of the eight industries possess supply chain network structures that *propagate risk* with respect to their downstream ego nodes. Figures 6 and 7 illustrate the variation in *Mean CTL* and *Max CTL(k)* in 2014. While the majority of industries have *Mean CTL* values in the 0.06–0.069 range, the notable exception is Motor Vehicles & Passenger Car Bodies (SIC: 3711) with a *Mean CTL* of 0.143, more than double that of the next highest industry. This elevated *Mean CTL* is a result of how densely interconnected the Motor Vehicles & Passenger Car Bodies supply network is, creating multiple paths from a problematic supplier to the consumer level.

Table 1 Consumer Threat Level (*CTL*) measures at infection level parameter $\beta = 0.05$

	1998 Mean CTL	1998 Max CTL(k)	2007 Mean CTL	2007 Max CTL(k)	2014 Mean CTL	2014 Max CTL(k)
Crude Petroleum and Natural Gas (1311)	0.048	0.143	0.064	0.371	0.068	0.370
Telephone Communications (4813)	0.066	0.462	0.050	0.185	0.060	0.265
Pharmaceutical Preparations (2834)	0.066	0.190	0.071	0.265	0.069	0.384
Motor Vehicles & Passenger Car Bodies (3711)	0.074	0.265	0.101	0.346	0.143	0.774
Electric Services (4911)	0.060	0.265	0.062	0.302	0.065	0.302
Electronic Parts & Equipment (5065)	0.052	0.098	0.043	0.098	0.051	0.098
Prepackaged Software (7372)	0.047	0.143	0.055	0.143	0.043	0.185
Semiconductors & Related Devices (3674)	0.057	0.185	0.058	0.370	0.066	0.462

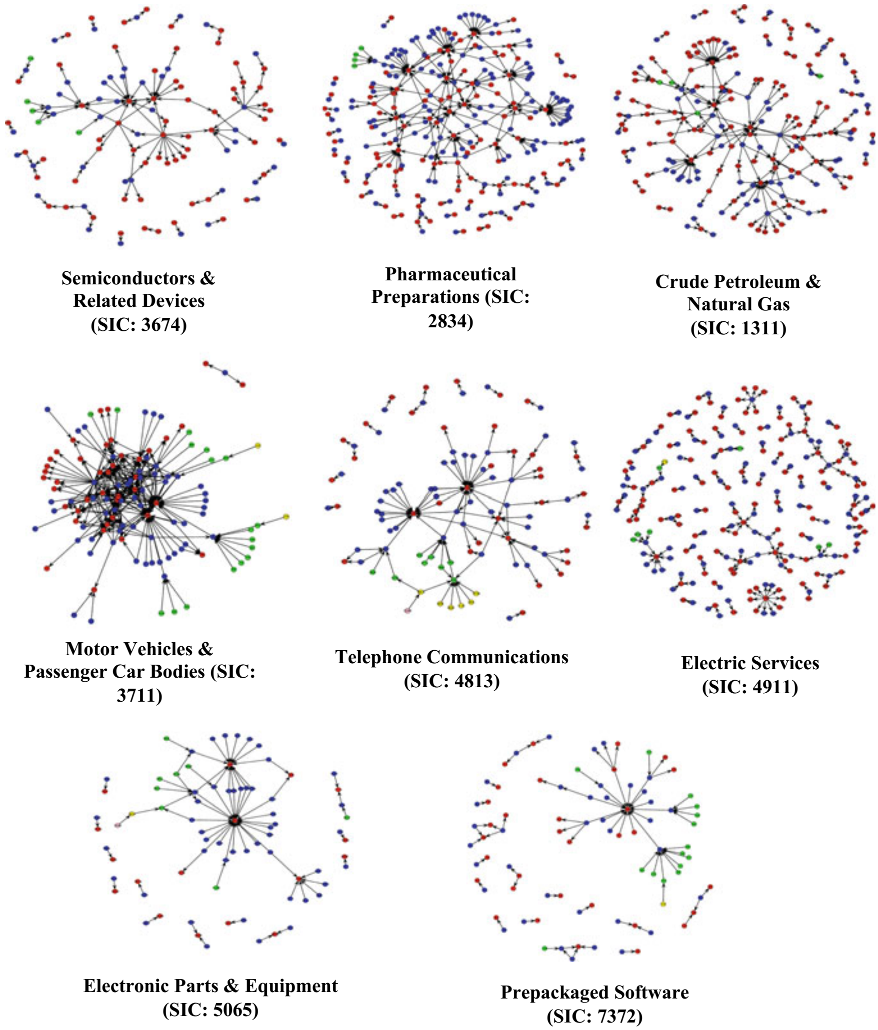

Fig. 5 Gallery of eight industry ego networks from 2014. Ego nodes appear in red

It can be seen in Table 1 and Fig. 7 that the 2014 *Max CTL(k)* varies widely by industry, with values ranging from 0.098 to 0.774. Again, the industry with the highest *Max CTL(k)* is Motor Vehicles & Passenger Car Bodies, where the measure can be interpreted as a 5% chance of defective material being transmitted across any link in the network yields an approximately 77% risk that such material from firm *k,* Tenneco Inc., reaches the consumer level unimpeded. This extremely high *CTL(k)* is a function of Tenneco Inc.'s position in the supply chain network, where it supplies multiple buyers, as highlighted in Fig. 8. At the other end of the spectrum, Electronic Parts & Equipment (5065) and Prepackaged Software (SIC: 7372) have

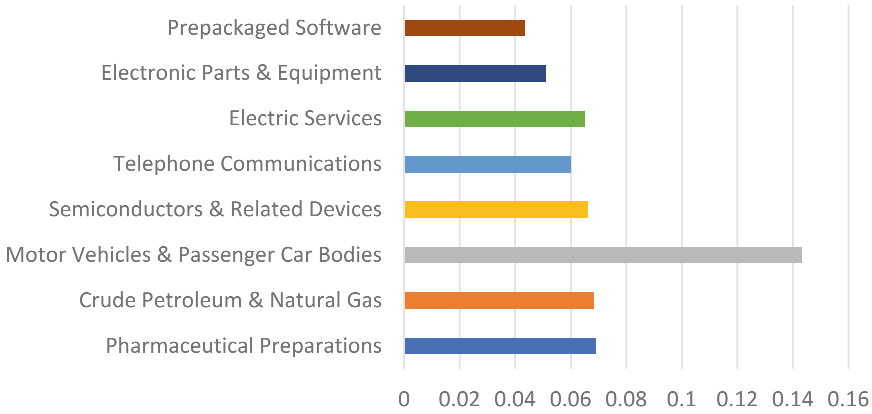

Fig. 6 2014 Mean Consumer Threat Level (*Mean CTL*) by Industry for $\beta = 0.05$

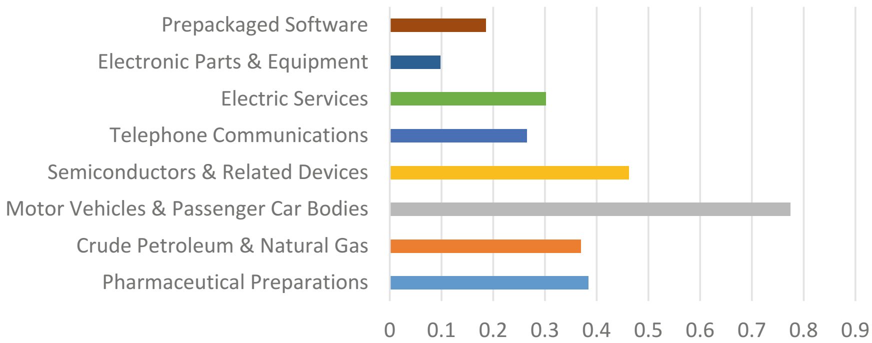

Fig. 7 2014 Maximum Consumer Threat Level (*Max CTL (k)*) by Industry for $\beta = 0.05$

both the lowest *Mean CTL* and *Max CTL(k)*. These conditions are not owed to the relatively small size of these networks, as seen in Fig. 5, but rather to the dominance of *structural holes* throughout the underlying network structure, where the exclusive nature of most supply relationships produces chains of dependencies without the interconnections needed to propagate risk from one source.

Figure 9 illustrates the *Mean CTL* time series in terms of the mean of all eight industries, flanked by the data specific to the industries with the highest and lowest levels of this measure. It is apparent from the Fig. 9 industry aggregate that *Mean CTL* has increased between 1998 and 2014, rising from its lowest levels in 2001. However, this trend is not uniform across all industries. Motor Vehicles & Passenger Car Bodies reflects this trend, but at a much steeper rate of increase, almost doubling *Mean CTL* over the 17-year time horizon, largely on the momentum of a trend that starts in 2004. In contrast, Prepackaged Software (SIC: 7372) posts a slight decrease in *Mean CTL* across the same timeline, and is the only industry with a *Mean CTL* less then β throughout most of that interval, indicating that this industry's network

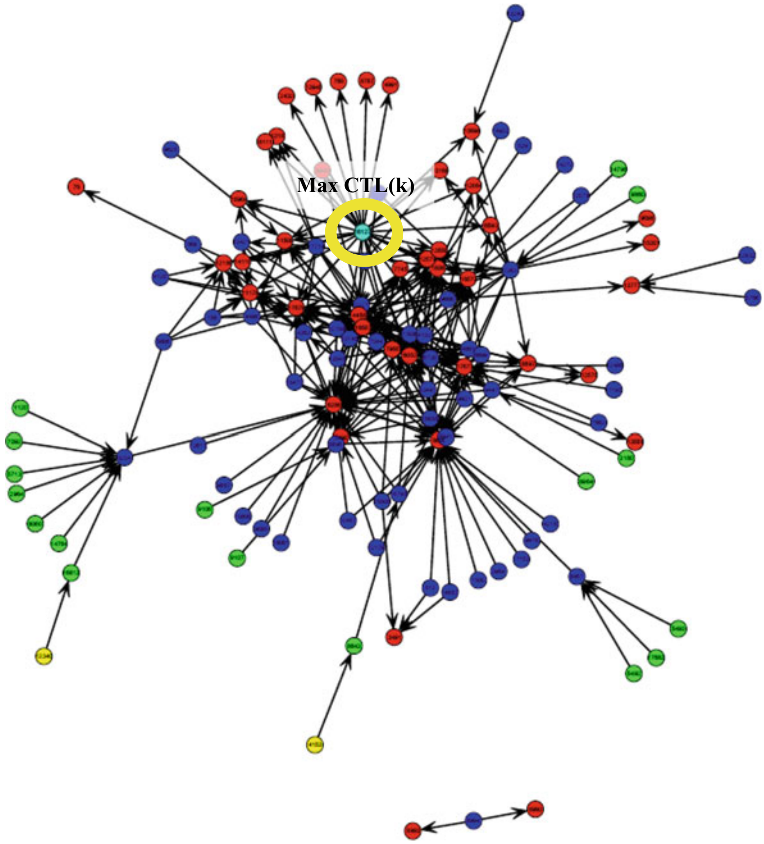

Fig. 8 Motor Vehicles & Passenger Car Bodies (SIC: 3711) in 2014 with the *Max CTL(k)* firm highlighted. Ego nodes appear in red

structure mitigates the risk of disruption proceeding to the ego level, as opposed to propagating it. However, it should not be assumed that high values of *CTL* are the only measures that reflect risk in this context. The firm *k* associated with *Max CTL(k)* can be interpreted as a supply network's most vulnerable point, in terms of protecting its end product. Table 2 provides both the identity and the industry of that specific threat, year by year, for the Prepackaged Software industry.

Although Prepackaged Software generally measured the lowest for *Mean* and *Max CTL(k),* throughout the timeline, Table 2 displays the irony that this industry had the highest annual 'churn' in both the exact location of that threat in the network and in the supporting industry it represents. This issue of churn in the identity of firm *k* of *Max CTL(k)* has important implications for the ego industry, in that low churn implies the location of this vulnerability is more predictable from year to year, and thus protective measures against this structural weakness in the supply network might be developed and moved into place. An example of low churn is, in

Table 2 Identity and industry of node with Maximum Consumer Threat Level (*Max CTL(k))* within Prepackaged Software (7372) industry ego supply network

Year	Company name	Industry	CTL(i) @ β = 0.05
1998	Rainmaker Systems Inc	Computer Programming, Data Processing, and Other Computer-Related Services	0.143
1999	Aquantive Inc	Advertising	0.098
2000	Data Return Corp	Computer-Integrated Systems Design	0.185
2001	Securelogic Corp	Prepackaged Software	0.098
2002	Moduslink Global Solutions	Computer Programming, Data Processing, and Other Computer-Related Services	0.098
2003	Nvidia Corp	Semiconductors and Related Devices	0.098
2004	Nvidia Corp	Semiconductors and Related Devices	0.098
2005	Akamai Technologies Inc	Computer Programming, Data Processing, and Other Computer-Related Services	0.050
2006	Digital River Inc	Computers and Computer Peripheral Equipment and Software	0.143
2007	Digital River Inc	Computers and Computer Peripheral Equipment and Software	0.143
2008	Digital River Inc	Computers and Computer Peripheral Equipment and Software	0.143
2009	Digital River Inc	Computers and Computer Peripheral Equipment and Software	0.265
2010	Seagate Technology PLC	Computer Storage Devices	0.143
2011	American Assets Trust Inc	Real Estate Investment Trusts	0.143
2012	Seagate Technology PLC	Computer Storage Devices	0.143
2013	Rally Software Dev Corp	Prepackaged Software	0.226
2014	Kilroy Realty Corp	Real Estate Investment Trusts	0.185

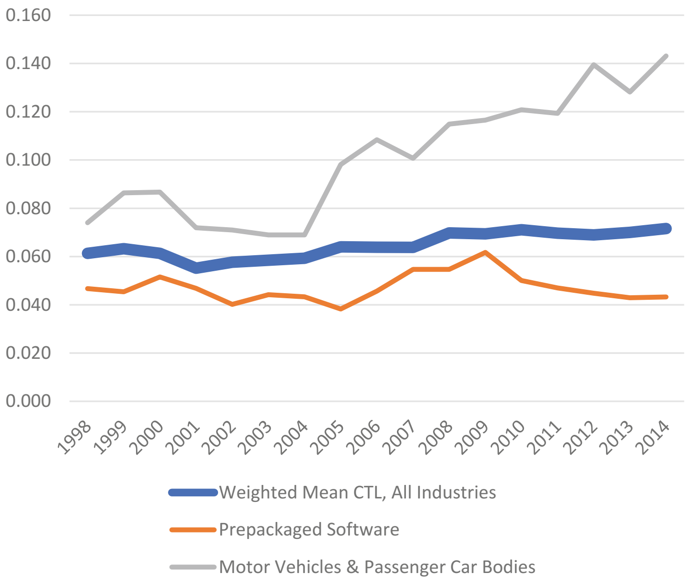

Fig. 9 Timeline of Mean Consumer Threat Level (*Mean CTL*) for $\beta = 0.05$, 1998–2014

fact, the Motor Vehicles & Passenger Car Bodies industry, where the designation of *Max CTL(k)* has been shared between six companies in 17 years, almost invariably from the closely related Motor Vehicle Parts and Accessories (SIC: 3714) industry. Further, the maximum threat arises from the same supplier, Tenneco Inc., for the last 6 years of the timeline and from one other firm, Dura Automotive Systems, for 6 of the 9 years from 1998 to 2007. In contrast, Table 2 shows how concurrently the spikes in Prepackaged Software's otherwise low CTL levels are inflicted by twice as many different firms, whose origins switch between nine different industries. This phenomenon where the highest risk firm in the Prepackaged Software industry is a ‘moving target’ suggests challenges for identifying and managing sources of risk when compared to the more static case of the Motor Vehicles & Passenger Car Bodies industry.

In the context of network evolution, *Mean CTL* and *Max CTL(k)* can provide additional insight into supply network vulnerability when considered jointly. Figure 10 provides a scatterplot of each year in the Motor Vehicles & Passenger Car Bodies timeline, where *Mean CTL* and *Max CTL(k)* provide the x and y coordinate. The resulting pattern reveals that while Motor Vehicles & Passenger Car Bodies has experienced distinct growth in *Mean CTL* over this time period, its *Max CTL(k)* levels behave quite differently. Rather, *Max CTL(k)* level is stable from 1998 to 2007, exhibits a sharp increase in 2008, and the restabilizes at a higher level for 2009–2014.

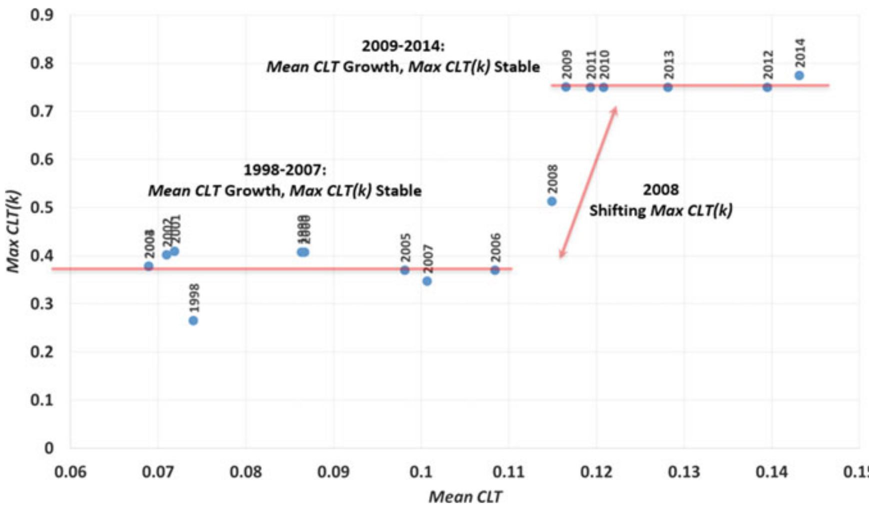

Fig. 10 *Mean* versus *Max CLT(k)* for the Motor Vehicles & Passenger Car Bodies (3711) Industry Ego Supply Network, 1998–2014

This analysis suggests further opportunity for investigation of this industry structure, particularly in 2007–2009, as this stepwise increase is unlikely to be the result of random force. Indeed, the time period of the transition suggests economic recession, and inspection of the data suggests a marked increase in the focal industry's dependence on fewer but more broadly shared suppliers after this period.

It should be noted that not all industry ego networks exhibit a reaction to economic recessionary periods. Figure 11 provides contrast, where a similar scatterplot of the Crude Petroleum and Natural Gas industry (SIC:1311) exhibits steady simultaneous increases in both *Mean CTL* and *Max CTL(k)* over the 17-year horizon, with no visible disturbances associated with the time period around 2008. Crude Petroleum and Natural Gas have the distinction of being one of only three industry ego networks in the data set that experienced substantive growth in size, increasing 76% between 1998 and 2014. However, this condition is not likely a determinant of the pattern produced in Fig. 11, in that the two other industries with similar growth patterns, Electronic Parts & Equipment (93% growth in size) and Prepackaged Software (112%) share yet a third pattern of no distinct trends in either *Mean CTL* or *Max CTL(k)* over the same 17-year period. This further underscores the need to better understand the structural differences between industries to further understanding of how to better protect their supply chains.

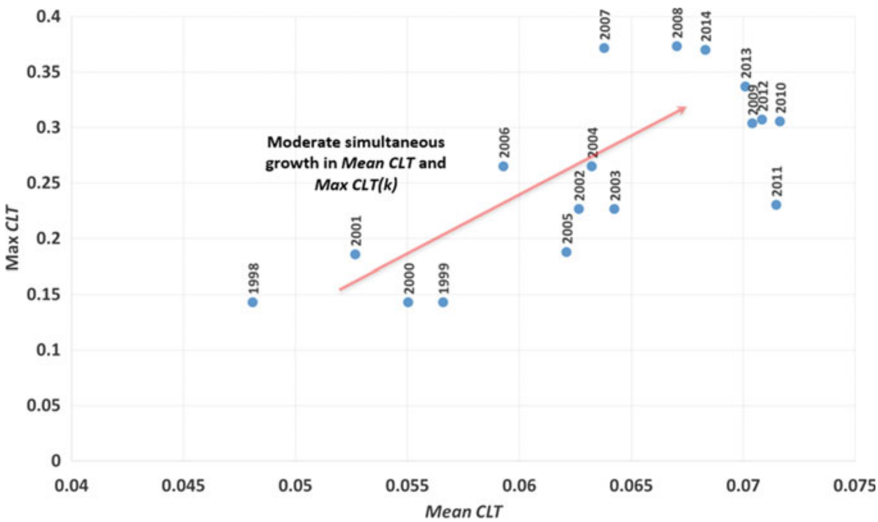

Fig. 11 *Mean* versus *Max CLT(k)* for the Crude Petroleum and Natural Gas (1311) Industry Ego Supply Network, 1998–2014

4 Summary and Conclusions

In this chapter, we consider how supply chain network structure contributes to defect or disruption propagation. Given that in recent years supply chains have grown in both size and complexity, it is critical that we are able to understand and manage the resultant risks. Our proposed measure *Consumer Threat Level (CTL)* is a novel approach to quantifying the risk of defective material reaching the consumer market. *CTL* is a function of supply chain relationships and can be calculated as a firm-level measure, that is, the risk of consumer exposure to detrimental material from a given firm. Alternately *Mean CTL* can be calculated and used as a summary measure of a given supply chain network's vulnerability. We applied our *CTL* metrics to authentic supply chain networks from eight industries across a 17-year time horizon, which provided a series of insights summarized in Table 3.

The results of our empirical investigation indicate that overall the risk of consumer exposure to defects or disruptions as measured by *CTL* has increased overtime. However, both risk levels and sources of risk differ markedly by industry, with the most dramatic increases in risk seen in the Motor Vehicles & Passenger Car Bodies industry. Our method for quantifying this consumer level risk is an important contribution in that it allows for objective comparison of relative risk between firms and between industries, as well as measurement of changes in risk overtime. However, the underlying reasons for differences in and evolution of supply chain network structures and resultant consumer threat levels remain open questions that merit further inquiry.

Table 3 Summary of insights and corresponding managerial implications

Observations from this study	Managerial implications
Supply chain vulnerability, as revealed by *CTL* measurement, is not uniform across industries	Best practices in risk mitigation are likely to vary between industries. Practices should not be transferred between industries with the expectation of similar results
Mean CTL is higher than the baseline risk of 'infection', β, for most industries	Supply chain partnerships are trending toward the sharing of suppliers between downstream firms, often indirectly through one or more intervening tiers. This sharing between downstream rivals may pose risks beyond those discussed here
When assessing an industry ego network, *Max CTL(k)* is typically several times greater than *Mean CTL*	It is not uncommon for a supply network to have a particularly vulnerable area, centered around one firm more deeply ingrained in partnerships throughout. Maintaining awareness of this location is vital for all downstream planners, and the measures discussed here offer a convenient means of monitoring such
Industries with more favorable *CTL* measures do not necessarily possess a stable source of *Max CTL(k)*	The most vulnerable area of a supply network will shift dynamically if its partnerships are likewise changing through time. In some industries, the greatest risk may not be from the absolute size of potential threat, but from an inability to anticipate the source. Stable partnerships through time mitigate this difficulty throughout any network

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Disruption Tails and Revival Policies in the Supply Chain

Dmitry Ivanov and Maxim Rozhkov

Abstract We study capacity disruption and recovery policy impacts on supply chain (SC) performance. Discrete event simulation methodology is used for analysis with real company data and real disruptions. Two novel findings are shown. First, disruption-driven changes in SC behaviour may result in backlog and delayed orders, the accumulation of which in the post-disruption period we call 'disruption tails'. A transition of these residues into the post-disruption period causes the post-disruption SC instability, resulting in further delivery delays and non-recovery of SC performance. Second, a smooth transition from the contingency policy through a special 'revival policy' to the normal operation mode allows the negative effects of the disruption tails to be partially mitigated. These results suggest three managerial insights. First, contingency policies need to be applied during the disruption period to avoid disruption tails. Second, recovery policies need to be extended towards an integrated consideration of both disruption and the post-disruption periods. Third, revival policies need to be developed for the transition from the contingency to the disruption-free operation mode. A revival policy intends to mitigate the negative impact of the disruption tails and stabilize the SC control policies and performance. The experimental results suggest the revival policy should be included in the SC resilience framework if the performance cannot be recovered fully after the capacity recovery.

D. Ivanov (✉)
Department of Business and Economics, Berlin School of Economics and Law, Supply Chain Management, 10825 Berlin, Germany
e-mail: divanov@hwr-berlin.de

M. Rozhkov
X5 Retail Group, Moscow, Russia
e-mail: max-over@yandex.ru

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1 Introduction

Disruptions in supply chain (SC) capacities may happen at both production factories and at logistics facilities, such as distribution centres (DC) (Snyder and Daskin 2005; Tang 2006; Klibi et al. 2010; Simangunsong et al. 2012; Simchi-Levi et al. 2015; Gunasekaran et al. 2015; Sokolov et al. 2016; Tukamuhabwa et al. 2015; Spiegler et al. 2016; Kamalahmadi and Mellat-Parast 2016; Fahimnia et al. 2016; Jain et al. 2017; Rezapour et al. 2017; Ivanov 2018a; Dolgui et al. 2018; Ivanov et al. 2019). Disruption risks can be caused by natural or man-made catastrophes, political crises, strikes or legal disputes. These disruptions are rarely localized at the disrupted node and frequently propagate in the SC causing the ripple effect (Liberatore et al. 2012; Ivanov et al. 2014a, b; Han and Shin 2016; Scheibe and Blackhurst 2018; Ivanov 2018a, b, Namdar et al. 2018; Levner and Ptuskin 2017; Dolgui et al. 2018; Ivanov et al. 2019; Ivanov and Dolgui 2018).

In regard to the disruption risks, resilient production backup and contingency inventory control policies became a visible research avenue over the last decade (Snyder and Daskin 2005; Tomlin 2006; Song and Zipkin 2009; Yang et al. 2009; Ivanov et al. 2010; Federgruen and Yang 2011; Atan and Snyder 2012; Lim et al. 2012; Kouvelis and Li 2012; Schmitt and Singh 2012; Ivanov and Sokolov 2013; Qi 2013; Kim and Tomlin 2013; Hishamuddin et al. 2013; Raj et al. 2015; Choi et al. 2016; Ivanov et al. 2016; Govindan et al. 2016; Sawik 2017; Mizgier 2017; Schmitt et al. 2017; Dubey et al. 2017; Namdar et al. 2018; Sawik 2018; He et al. 2018; Dolgui et al. 2019; Pavlov et al. 2019). Despite significant progress in theoretical studies and empirical principles to manage severe disruptions in the SC at proactive and reactive stages, recent literature has usually assumed an immediate transition to a normal operation mode at the time of capacity recovery. Moreover, a full system stabilization after the capacity recovery has typically been assumed without considering any residual effects such as delayed orders and backlogs accumulated over the destabilized system states during the disruption time.

This study closes the research gap described above with the objective of revealing the dependencies between SC disruptions, contingency policies and transition to the post-disruption operation mode. First, the analysis is conducted in regard to disruption-driven changes in SC behaviour resulting in delayed orders and backlogs, the accumulation of which can be considered ‘disruption tails’. The influence of these tails during the post-disruption time in the course of transition into the normal operation mode is investigated. A comparison of SC operation with and without contingency policy is performed to compare the impact of disruption tails on SC operational and financial performance. Second, a comparison of SC operational and financial performance between an immediate deactivation of the contingency plans and installation of the normal operation policies after capacity recovery and usage of the revival policy is studied. These experiments aim at providing managerial insights on the application of contingency production and inventory control policies during the disruption period and revival policies during the transition time to normal operation after capacity recovery.

The rest of this study is organized as follows. Section 2 describes recent literature on recovery policies in the SC and simulation studies on SC disruptions. Section 3 is devoted to case study presentation and research methodology description. Experimental settings with production and distribution disruptions are the focus of Sects. 4 and 5, respectively. Section 6 concludes the paper by summarizing the most important insights, limitations of this study and future research avenues.

2 State of the Art

2.1 *Recovery Policies in the Supply Chain*

SC resilience has been a prominent research topic for the last 10 years. *Proactive* and *reactive* resiliency policies have been developed with the aim of protecting the SC from disruption before it happens, and ensuring mitigation of the disruption after it happens (Ho et al. 2015; Snyder et al. 2016; Ivanov 2017). Given the nature of this study, this literature analysis is focused on contingency inventory control policies and backup sourcing when used during the recovery phase.

Assigning customers to disruption-prone locations to minimize total SC costs, Snyder and Daskin (2005) optimized SC design. To analyse the dynamic effects of inventory buffers when suppliers are unreliable, Federgruen and Yang (2011) created a general periodic review model. To capture the trade-off between inventory policies and disruption risks for an unreliable, dual sourcing supply network, Iakovou et al. (2010) studied a single period stochastic inventory model for both capacitated and incapacitated cases, and evaluated different contingency strategies. In a study by Shao and Dong (2012), an assemble-to-order system with a backup source is analysed. This system offers on-time delivery and a policy in which customers are compensated for waiting in each period of disruption. The results of the study imply that at the start of an SC disruption a backup source strategy is preferable, while a compensation strategy is preferable as time goes on. In the specific example considered, a dynamic mixed strategy with customer choices is better than a backup sourcing strategy. The manufacturer's decision regarding which reactive strategy to choose is determined according to backup costs and customer sensitivity.

Considering supplier capacity constraints, Costantino et al. (2012) created an agile reconfiguration approach to resilient SC design. Using diagraph modelling and integer linear programming, this approach optimizes SC design. In the study by Benyoucef et al. (2013), SC design is considered in the case of unreliable suppliers, subject to minimization of fixed location, inventory and safety stock costs at distribution centres, and ordering and transportation costs throughout the SC. Ivanov et al. (2013) combined linear programming and optimal program control in a model that included SC reconfiguration as a reaction to disruptions.

Hu et al. (2013) studied the incentives, whether *ex ante* (prior to disruption) or *ex post* (after disruption), which drive a supplier's investment in capacity restoration.

According to their findings, the *ex ante* commitment is weakly preferred by both the buyer and the supplier when the buyer provides incentives. According to Kim and Tomlin (2013), if recovery capacity is the only option, then firms, in a decentralized setting, overinvest in capacity, which results in higher system availability at a higher cost. Yet, when it is possible to invest in both, then firms tend to underinvest in preventing failure and overinvest in recovery capacity.

In the study by Qi (2013), a continuous review inventory model including random disruptions for the main supplier was developed. Considering transportation disruption, Hishamuddin et al. (2013) showed a recovery model of a two-echelon serial SC, which allowed the determination of optimal ordering and production quantities during the recovery period. This minimized total costs.

Considering structural dynamics, Ivanov et al. (2014b) constructed a multi-period, multi-commodity SC model, the formulation of which distributes static as well as dynamic parameters between the linear programming and control models. In the study by Ivanov et al. (2016), an approach for analysing several proactive SC structures, determining recovery policies to redirect material flows in two disruption scenarios, and measuring the performance impact on service levels and costs was developed. Dupont et al. (2017) applied a mixed-integer linear programming method to develop a model for helping an SC manager to select a supplier portfolio with disruption risk considerations. Their study allows consideration of the risk sensitivity (i.e. risk aversion and loss aversion) of the SC manager in the modelling process.

While the Dupont et al. study (2017) considers deterministic demand, Sawik (2013) developed a stochastic programming model for supplier selection and order allocation in light of disruption risks, and conceptualized a portfolio approach to SC disruption management (Sawik 2017). Sawik's works also consider an SC manager's risk sensitivity. Khalili et al. (2017) analysed integrated production–distribution planning in the SC considering excessive capacities at the production plants, backup routes for shipments and pre-positioning of emergency inventory in distribution centres. They also proposed a new indicator for optimizing the SC resilience level based on restoration of lost capacities.

Amiri-Aref et al. (2018) studied a multi-period location-inventory optimization problem in a multi-echelon SC characterized by uncertain demand and a multi-sourcing. The authors integrated inventory planning decisions made under a reorder point order-up-to-level (s, S) policy, with the location-allocation design decisions to cope with demand uncertainty. A two-stage stochastic mathematical model that maximizes the total expected supply chain network profit is proposed. The results show the efficiency of the linear approximation of the (s, S) policy at the strategic level to produce robust design solutions under uncertainty. Further insights from this study underline the sensitivity of the design solution to the demand type and the impact of the inventory holding costs and backorder costs, especially under non-stationary processes.

2.2 Simulation Studies in Supply Chain Disruptions

Considering severe SC disruptions for resilience analysis and using discrete event simulation, Carvalho et al. (2012) analysed the behaviour of an SC in four stages considering several recovery strategies and the performance of the SC during disruption. The scenarios the authors studied were different in terms of whether or not there was a disturbance and whether or not a mitigation strategy was in place. The ARENA-based simulation model they developed provided for the determination of lead time rations and total SC costs. In the study by Schmitt and Singh (2012), disruption risk was measured by using 'weeks of recovery' as a proxy for the amplification of disruption. The scenarios developed were both proactive and reactive and satisfied demand by making use of another network location, obtaining material or transport from other sources or routes and retaining inventory reserves along the whole SC. Utilizing the duration and likelihood of closure in a completely observed, exogenous Markov chain model, Lewis et al. (2013) studied risks of disruption at ports of entry. The periodic review inventory control model that the authors developed implies that in the scenarios developed operating margins could either decrease 10% as a result of relatively long port of entry closures or, without contingency plans, be eliminated entirely. In addition, anticipated holding and penalty costs could increase by 20% when port of entry utilization is expected to increase.

In a four-stage SC created in the software any Logistix, Ivanov et al. (2017a, b, c) used simulation to study the SC's dynamic behaviour and the impact of disruptions on performance. The authors observed the ripple effect as well as studied proactive and reactive strategies. The results of the study imply that disruptions upstream more often lead to the ripple effect when there is a single source policy in place, and safety stock should be increased at facilities downstream from elements of the SC that are risky. In addition, ripple effect propagation towards the customers is decreased when inventory levels are higher in the downstream SC. However, increasing safety stock at disruption-risky facilities must be carefully considered, since when disruption-risky facilities cannot perform outbound operations then this will not effectively decrease the ripple effect. This study also pointed out that the ripple effect impacts service level and order fulfilment more than the duration of the disruption, which indicates that dual sourcing at the bottlenecks of SCs, as well as large inventory holdings downstream from facilities that are disruption risky are of greater importance than quick investments in fast recovery.

A multi-stage SC with suppliers, factory, distribution centres and customers was studied by Ivanov (2017b). As in previous studies, the findings show a time lag between the start of recovery and the impact of that recovery on the closing of the service-level gap: proactive SC policies must account for the duration of disruptions. Using AnyLogic, Ivanov and Rozhkov (2017) analysed how capacity disruptions impact the performance of policies for ordering and production in a real-life retail SC with considerations of product perishability. The findings of the study imply that SC managers should consider the effects of 'postponed redundancy' when they design resilient SCs. The effect is concerned with how redundant production ordering system behaviour during the period of disruption impacts the production ordering system post-disruption. Redundant behaviour during the disruption period might include redundant production or deliveries which are downstream from the affected part of the SC, or redundant order allocations for upstream facilities which are disrupted. In addition, the authors created and tested a coordinated SC production ordering contingency policy in and after the disruption in order to decrease the negative effects of 'postponed redundancy'.

Schmitt et al. (2017) investigated adjustments in order policies in the framework of a four-stage assembly SC. Simulation experiments revealed that longer lasting impacts occur from disruptions at echelons close to ultimate consumption. Moreover, the results show that expediting inventories in the disrupted mode can trigger unintended bullwhip effects, and hurt rather than help overall performance. As an alternative, dynamic order-up-to policies perform more promisingly as an adaptive mitigation tool. Trucco et al. (2017) analysed an Italian FMCG supply chain and simulated its resilience in AnyLogic. The results suggest that it is important to develop coordinated control strategies in the event of severe supply chain disruptions. These results are in line with the insights provided in the study by Schmitt et al. (2017), Ivanov and Rozhkov (2017) and Ivanov (2019).

3 Case Study Description and Methodology

3.1 Case Studies

Two case studies are considered in this paper in regard to both production and distribution capacity disruptions that occurred in reality and for which the authors observed real company operational policies and performance.

3.1.1 Production Capacity Disruption

An FMCG company, which produces juices and beverages in Russian contracted and proprietary plants, is the first case study (Ivanov and Rozhkov 2017). The data of the company, covering a period from 2013–2015, was gathered in 2016. The data is primarily concerned with the plants the company owned and the plants which it subcontracted. This includes real and forecasted demand data, collected from internal company report, as well as inventory, production and shipment control data were obtained by observing the management information system in a joint analysis with factory and DC department managers.

The study concerns part of the FMCG SC. It is a two-stage SC with five DCs and one factory. This factory delivers the product 'juice', which has an average shelf life of 270–360 days, to the DCs. Product perishability is a key factor of the SC. Demand forecasts are the basis for ordering at the DCs, and the inventory policy is (Q, s, r).

The inventory level y is forecasted for n periods at each period r. Subject to minimum reorder quantity Q, a new order, size O_r, with a planned delivery period $r + n$ is placed when y is less than reorder point s. The planning is made for $n+m-1$ periods when production is only possible for each m period. For all customers, shipments follow a first expired first out (FEFO) policy.

Decreases in safety stock and increases in the frequency of transportation are the typical results of the limits of product perishability. Subject to minimum service level, with a targeted service level of 98.5%, the SC planning accounts for the risk of writing off products. The other constraints on shelf life are taken from contract agreements with major food retail companies which operate in Russia (ranging from 62 to 70%). By considering the risk of production capacity disruption, safety stock may be increased. The factory's production capacity is subject to random disruptions. Disruptions of production capacity occurred often in 2015 and 2016, which caused interruptions of deliveries from plants to DCs. These interruptions lasted anywhere from 2 days to 3 weeks.

The primary focus of this study is how disruptions of production capacity impact SC performance, accounting for a two-component demand structure and limited expiration dates. A discrete event simulation model was developed in AnyLogic to show the SC dynamics and ascertain reorder, production, and shipment numbers and times from the DCs to the factory. Each shipment, disruption and recovery is modelled as an event, while information exchange between DCs and the factory are obtained from state charts and messages. In Appendix 1, the mathematical formulation of this model can be found.

The planning algorithms account for the fact that the stock deteriorates and the batch, which is ready to ship now, might be unusable in a few weeks. A week is the basic time unit. It is assumed that plans are made each week. However, several parameters are measured in days. Heuristics were developed, tried out and implemented for daily use with the help of the analysts of the company's SC. As is common for the food industry, the demand model is subject to randomness and seasonal factors, which according to the company's data cause demand variations of 50% within the planning horizon. When demand rises or falls by 20%, it is possible to have long term, 4-week duration demand changes. It is possible to describe both factors of demand variation according to uniform or triangular distribution. Along with an aggregation of historic demand from 60 periods, uniform distribution was used in the study experiments. The ordering policy is similar to an economic lot scheduling model's basic planning process (Wagner and Whitin 1958). Differences include remaining shelf life, based on Nahmia's (1980) mathematical approach, and consideration of the demand structure. In the simulation model, demand non-stationarity is an individual function, and 13 periods constitute the model year. The seasonal demand coefficient k is defined using a basic demand level for each period r. The planning of production was found on a discrete event simulation approach: when a DC's inventory reaches reorder point, then another production order is made. The size of the order is a multiple of the minimum lot size, and cannot be cancelled. The planning of production accounts for lead time from factory to DC. When a batch's computed production period is met, then orders enter the queues in the system. This applies to all products. If an order remains in the queues longer than the DC's planning horizon, then the order goes out of the system, but this does not result in lost order costs. If the waiting time constraint is reached, then the order is moved to the production module. The start times of processing are based on the production week computed. Schedule smoothing, or early production, is not allowed.

The setups of production utilize time and cost containment. Simultaneously, infrequent setups can cause delivery delays and increased variability in lead times. In the model, setups are controlled in planned and disrupted modes. Without capacity disruption, the planned mode uses lot-size-based planning. This means that if five orders for one product, each for 10,000 product units, are in waiting in the queue with a minimum lot size of 40,000 units, then four of the five orders will be batched and produced together as one lot. After this, the setup which was planned will be completed.

When there is a capacity shortage as a result, e.g. of a demand peak or disruption, then flexible setup rules are followed. The queue size, parameter QC, is monitored. The inventory of raw material in the system of production has no limit. First, in the sequence, the allocated order O_r or O_r is sent forward in the queue μ_r. The time for manufacture t_m is calculated on the basis of a function of order quantity O_r and production capacity K.

At the end, the analysis of SC resilience is made according to random disruptions which cause a decrease of 50% in production capacity (cf. Eq. 2). In the model, disruptions are random events. Normal distribution governs the intervals between disruptions t_{dp} and their duration t_{ds}. This hypothetical assumption of normal distribution for the occurrence of disruption and recovery period is in part proved by real data.

3.1.2 Distribution Capacity Disruption

The second case study is based on another company that produces non-perishable products for four regional markets. Without loss of generality, a fragment of the SC considered comprises three production plants and four regional distribution centres (DCs) (Fig. 1).

The DC in region 1 crashed due to construction quality problems. A huge amount of inventory was destroyed. At the day of the DC disruption, the experts estimate that the reconstruction of the DC will take about 4 months.

The following data (but not limited to) has been collected at the company:

- SC design: locations of SC elements (factories and DCs) and links in between them.
- Demand in the markets and its uncertainty.
- Parameters of SC elements (e.g. production capacities, throughputs, prices and costs).
- Operating policies of SC elements (e.g. inventory control policy, production control policy, shipment control policy and sourcing control policy).

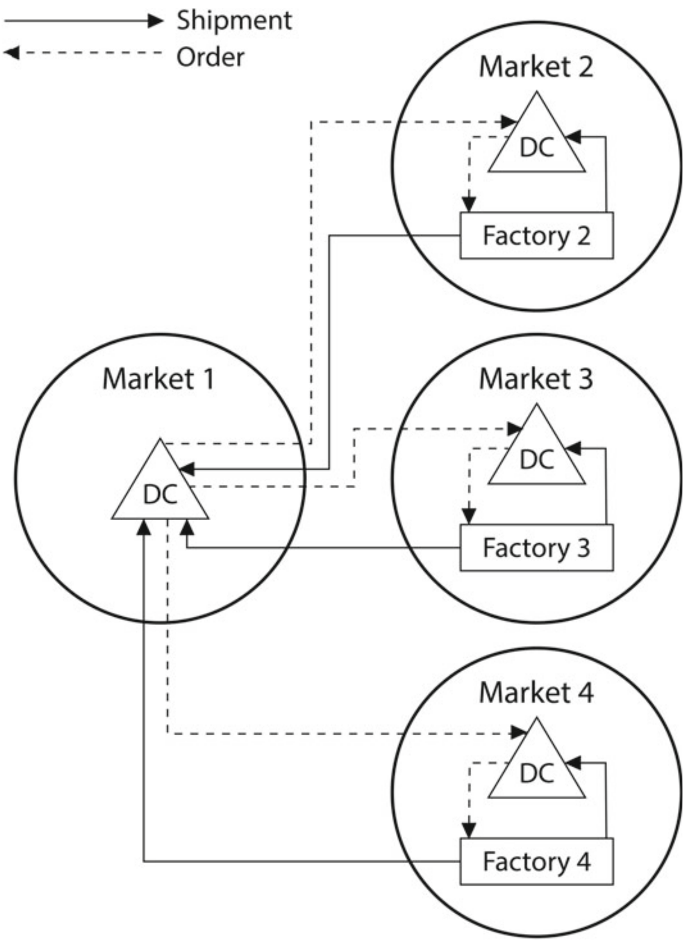


Fig. 1 Supply chain design structure

This data was observed for a period of 3 years. Moreover, we observed the actual sales and service-level data following the disruption at the DC described. A drastic decrease was observed in both sales and service-level dynamics.

The following control algorithms are implemented in the simulation model. Demand in the markets is considered as an aggregated, normally distributed demand of all customers in this region characterized by a seasonal component subject to four periods. Weekly order placements from the markets to the DCs are considered.

A continuous review system is applied at the DCs. Backordering is allowed so that no orders can be lost. For simplification, an average lead time from DC to the market is considered: it is assumed that all customers within the region can be reached during this lead time. According to demand generation algorithms, orders are placed at the DCs. Subject to inventory-on-hand, safety stock, lead times, reorder point, and the target inventory, shipments to the markets and replenishment from the factories is controlled.

A transportation order aggregation period of 5 days with the less-than-truckload (LTL) control policy has been considered. Transportation time has been considered as a normally distributed value. (cf. Table A2 in Appendix 2). Each factory is considered as a single-stage continuous production system with fixed production time and no setups. Production capacity is limited by the unit production time. For example, a production time of 0.4 days for m^3 means maximum daily capacity of 2.5 m^3 at a factory. Without loss of generality, no further batching rules are considered. Multiple sourcing control with the preference 'closest location' is used. The algorithm decides where to source the demand from the paths 'Markets—DCs' and 'DCs—Factories' subject to closest facility location with available inventory.

A set of key performance indicators (KPI) has been established to analyse the simulation results. The expected lead time (ELT) service level is the ratio of orders delivered within the 'Expected lead time' to total orders. The expected lead time is a parameter that is set up for each market. It measures the time between the placement of an order at a DC and receiving the goods from the DC. Current backlog orders depict the currently unprocessed number of orders, i.e. the orders which were received but have not been shipped yet. It is updated on a daily basis when incoming orders are received, a new shipment is sent, incoming orders are lost, or an incoming shipment is processed (in accordance with processing time set for the facility). Delayed orders show statistics on the quantity of orders, which failed to arrive within the specified, expected lead time. The data is updated each time an order is delayed.

For the problem considered above, a discrete event simulation model and a network optimization model have been developed in anyLogistix (see Appendix 2). anyLogistix is a simulation and optimization tool developed by the AnyLogic Company. The optimization functionality of anyLogistix is implemented on the CPLEX basis in a network optimization module. Simulation functionality in anyLogistix is based on discrete event simulation with agents that can be used either in a standard setting or be customized in AnyLogic. anyLogistix allows a wide range of experiments in regard to facility location planning, multi-stage and multi-period SC design and planning, inventory control, transportation control and sourcing analysis in both deterministic and stochastic settings. Variation and comparison experiments can be performed. Modelling of the SC disruptions is implemented using events and state change diagrams.

3.2 Research Methodology

Because the problem statements concerning disruption propagation deal with time-dependent settings which include dynamic inventory control, transportation control, sourcing control and production control policies, the simulation methodology for the given problem domain has earned an important role in academic research (Ivanov 2017). In comparison to analytical closed-form analysis, simulation has the advantage that it can handle complex problem settings with situational behaviour changes in the system over time. This is inevitable in considering dynamic changes in SC organizational and parametrical structures (Ivanov et al. 2010).

In this study, we use discrete event simulation methods. For validation, the network optimization with and without disruption consideration has been performed in CPLEX using anyLogistix optimization and simulation software. The optimization experiments allowed a determination of the aggregate annual throughputs which are used for validation of the simulation results. The simulations in anyLogistix are run over the optimization results and include additional, time-dependent inventory, production, transportation and sourcing control policies which are difficult to implement at the network optimization level. In addition, *analytical computations* using standard inventory control models have been done. For *verification*, the following methods have been used: simulation run over network optimization results, output data analysis in the log files and testing with the help of deterministic demand and lead time data. Moreover, replications and a warming up time with some initial inventory have been applied for the *testing*. The disruptions have been scheduled in the middle of the simulation period in order to avoid the 'noise' of the simulation experiment start. Variation experiments to validate the simulation model have been performed. In particular, mean and standard deviation of demand, safety stock and production capacity have been varied to confirm model robustness.

The first stage of the experiments contains production disruption analysis with a focus on contingency inventory control policy impacts. The second part of the experiments addresses DC disruptions focusing on analysis of survival policy impacts.

At both stages mentioned above, the analysis is conducted in regard to disruption-driven changes in SC behaviour resulting in delayed orders and backlogs the accumulation of which can be considered 'disruption tails'. The influence of these tails at the time of post-disruption in the course of transition into the normal operation mode is investigated. A comparison of SC operations with and without contingency policy will be made to compare the impact of disruption tails on SC performance. A comparison of SC performance between an immediate deactivation of the contingency plans and installation of the normal operation policies after the capacity recovery and usage of the revival policy will be performed. These experiments aim at providing managerial insights on the application of contingency production and inventory control policies during the disruption period and revival policies at the transition time to normal operation after capacity recovery.

The contingency plan includes the installation of additional links in the SC which lead from the factories directly to the market 1. This implies a longer lead time (cf. Table A2 in Appendix).

The revival policy includes the contingency plan and additional elements such as:

- backup contractors,
- capacity flexibility (capacities of own plant in region 1) and
- using capacity of other own plants in neighbourhood countries.

that are activated during the disruption period to support the contingency plan actions. The details of revival policy activation will be given in Sect. 5.

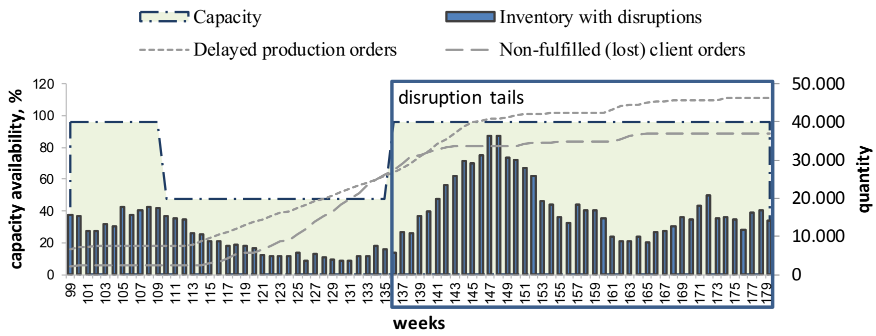


Fig. 2 Dynamics of customer order fulfilment

4 Production Disruptions Experiments

4.1 No Contingency Inventory Control Policy

In Fig. 2, the simulated dynamics of customer order fulfilment is presented subject to the model and data in Appendix 1.

In period #110, the disruption begins and continues for 26 weeks, and then 30 weeks of a recovery period follow. The DC's inventory is accessible through period #117, because immediately before the disruption period a delivery was completed from the factory to the DC. Because 50% of the capacity remains operable, we know that in periods #120 and #122, two small deliveries from the factory to the DC were made. Higher inventory costs result from several delayed production orders being shipped to the DC after the capacity recovery. Following this, the intensity of the order allocations changes again. The result of the high inventory levels is that write risks are increased and the system attempts to allocate fewer order for production. Penalties may occur if deliveries are delayed, e.g. inventory becomes zero in period #165. This indicates lost sales. This in turn shows that *both product shortages and write-off risks are caused by production capacity disruptions.*

Given the higher inventory costs caused by the shipment of the delayed production orders, write-off risks are increased and the system tries to allocate fewer production orders, as stated. These SC dynamics can be called '*postponed redundancy*'. This refers to how the production ordering system behaviour in the after-disruption period is impacted by redundant production ordering system behaviour during the disruption period (Ivanov and Rozhkov 2017). Examples of redundant SC behaviour during the disruption period might include redundant production or deliveries downstream from the disruption, or redundant order allocations made to facilities upstream from the disruption.

Following production capacity disruption and stabilization, the increases in lost orders rise significantly in several periods after capacity disruption. Nearly directly following production disruption, there is an increase in delayed orders. The period

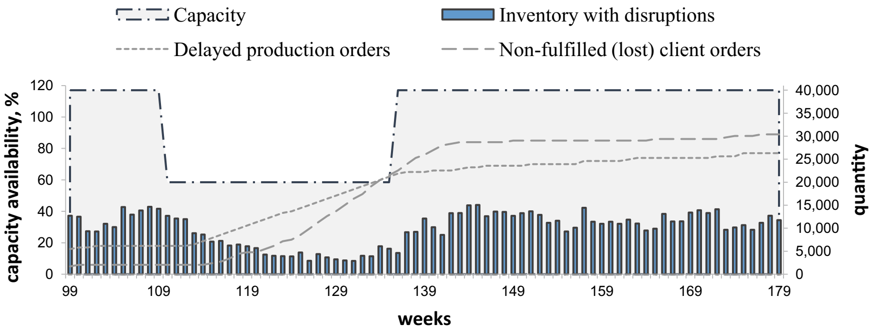


Fig. 3 Impact of waiting order cancellation

of stabilization, the start of which is closely connected to inventory reaching its maximum level in the SC, lasts longer for lost than delayed orders.

The SC's average inventory does not fall to zero during disruption because the factory remains capable of operating at 50% production capacity. A peak in inventory, related to disruption tails, occurs following the recovery of capacity. As a result, we understand *that when there are increases in delayed orders while there are stabilized service levels, then there will be a significant increase in inventory in the SC soon after.*

4.2 Contingency Inventory Control Policy

Measures can be taken to mitigate increases in inventory while the SC recovers. Particularly, it is recommended to cancel each waiting production order in the period of capacity recovery. Essentially, the orders which are waiting in the queue in the recovery period have a delay of at least one period. However, those orders which are allocated should remain. The results of this hypothesis simulation are shown in Fig. 3.

By making a comparison of Figs. 2 and 3, we understand *that cancelling the waiting orders during the period of capacity recovery means that overstocking and write-off risks can be avoided.* The inventory level is not greater than disruption-free mode levels. As a result, we surmise *that the impact of disruption tails can be mitigated by a contingency production-inventory control policy, i.e. cancelling the waiting orders in the production-inventory system.*

5 Distribution Centre Disruption Experiments

Simulation experiments have been conducted subject to the following three settings:

- without the contingency policy,
- with the contingency policy that implies an installation of additional links in the SC from the factories to the market 1 (cf Fig. 1) (These links are activated immediately after the DC1 disruption and function until the DC1 recovery.),
- with the contingency and revival policy that includes such emergency sources as backup contractors, capacity flexibility (capacities of own plant in region 1) and using capacity of other own plants in neighbourhood countries.

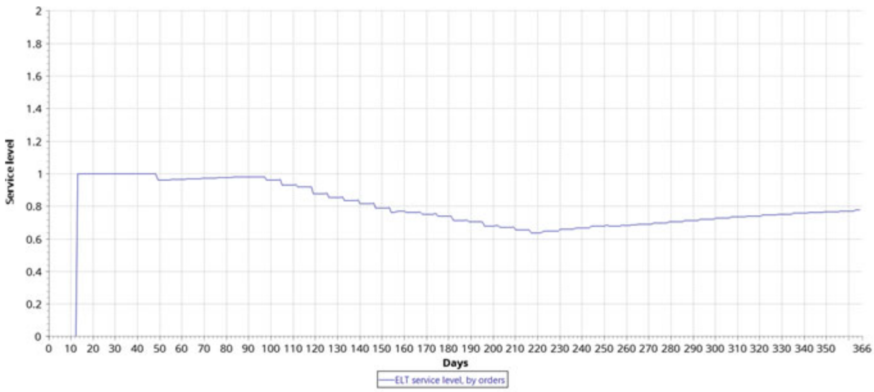
In line with the study by Ivanov (2017), we assume a time lag between the disruption, activating the contingency policy capacities and the first effects of these contingency policy operations. The emergency sources operate according to the following logic: no initial inventory is available; 2 days after the DC1 disruption, the emergency sources start producing for the market 1; first deliveries to the market 1 arrive in about 18–20 days after the disruption date.

The results are shown in Figs. 4 and 5.

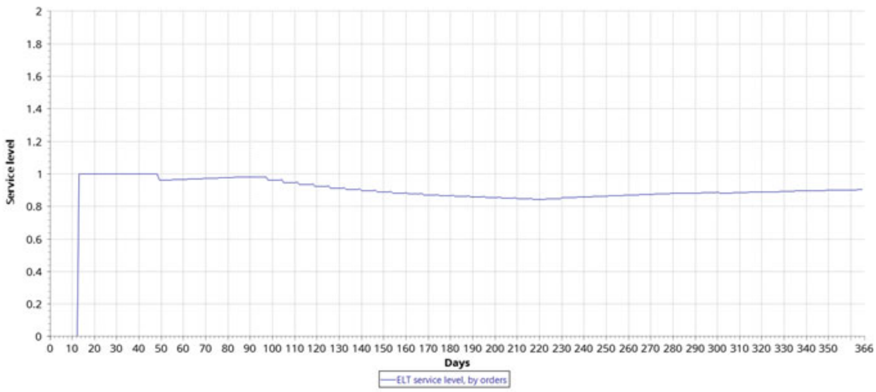
Figures 4 and 5 depict the dynamics of order fulfilment and service level (measured in orders; the diagram represents the average) following the disruption on day 91 and lasting until the DC1 recovery on day 213. The delayed and backlog orders can be observed in the cases without any contingency policy and with the contingency even in the post-disruption period representing the disruption tails. The revival policy helps to improve the service level and reduce the impacts of the disruption tail in terms of delayed and backlog orders in the post-recovery period.

When observing Figs. 4 and 5, an increase in service level, a reduction in the number of delayed orders during the disruption period and an elimination of delayed orders after the disruption recovery can be observed with a transition from the case without contingency policy, through the introduction of the contingency policy, to the usage of the revival policy. The revival policy allows stabilization of the order fulfilment dynamics resulting in a positive effect on service-level performance. The *delayed orders accumulated over the disruption period do not influence SC operations and performance since new contracting plants compensate for this with the help of additional production capacity. This allows the service level to recover faster as compared to the usage of recovery policy only* (Figs. 4 and 5). This observation provides the evidence of *disruption tail mitigation with the help of a revival policy based on a production capacity increase in the post-disruption period.* It indicates the necessity of considering not only contingency recovery policies, but also the *revival policies in the SC* which may align normal operation policy and deactivation of the contingency policies. The insights gained recommend inclusion of the revival policy in the SC resilience framework (Fig. 6).

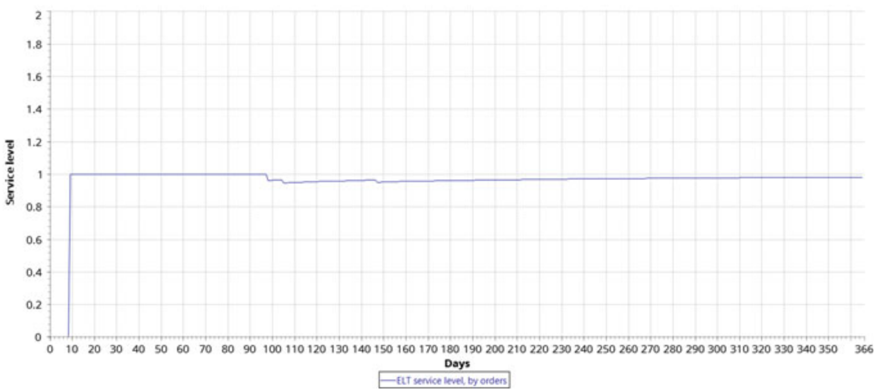
The disruption profile constituted in the work by Sheffi and Rice (2005) includes eight phases: preparation actions, the disruptive event, the first response, the initial impact, the full impact, the recovery preparations and the recovery and long-term



(a) service level dynamics without contingency and revival policy

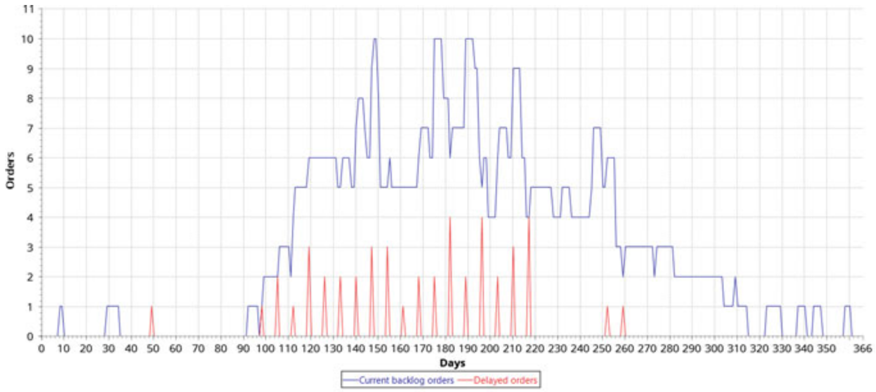


(b) service level dynamics with contingency policy

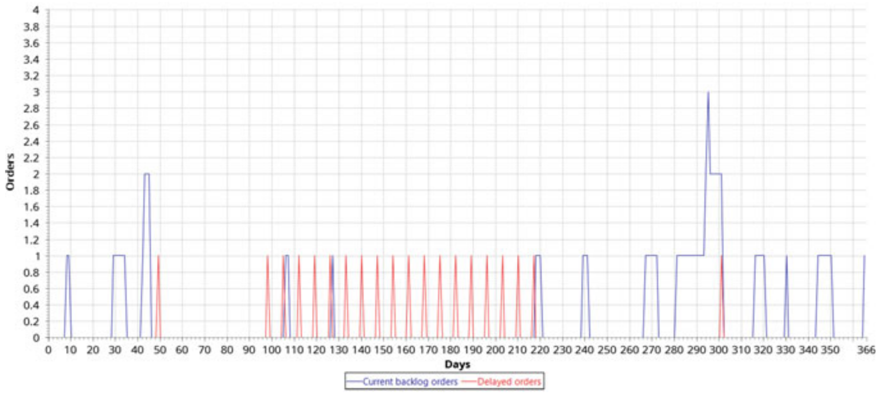


(c) service level dynamics with contingency and revival policy

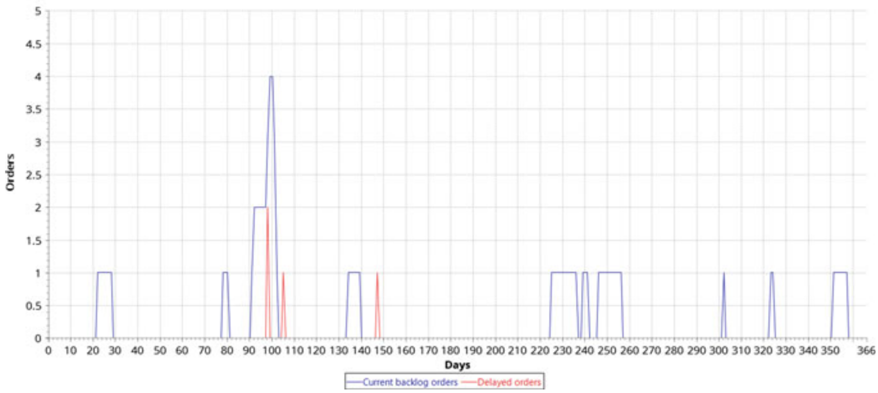
Fig. 4 Service-level dynamics. **a** service-level dynamics without contingency and revival policy **b** service-level dynamics with contingency policy **c** service-level dynamics with contingency and revival policy



(a) Order fulfillment dynamics without contingency and revival policy



(b) Order fulfillment dynamics with contingency policy



(c) Order fulfillment dynamics with contingency and revival policy

Fig. 5 Order fulfilment dynamics. **a** Order fulfilment dynamics without contingency and revival policy **b** Order fulfilment dynamics with contingency policy **c** Order fulfilment dynamics with contingency and revival policy

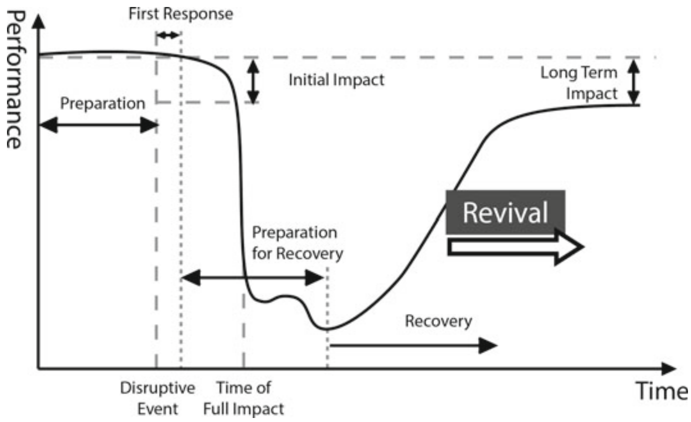


Fig. 6 Extended supply chain resilience framework (extended from Sheffi and Rice 2005)

impact. Our experimental results suggest including the revival policy into the SC resilience framework if the performance cannot be recovered fully after the capacity recovery. The revival policy extends the SC resilience framework at the stage of transition from recovery to post-disruption period. The rationale for inclusion of a revival policy into the SC resilience framework is the fact that an immediate transition from the contingency plan during the disruption and recovery period to the normal operation mode may be complicated by disruption tails. In addition, of the companies operated with forecasted recovery dates, the inertness of the decisions on activation and deactivation of contingency plans frequently leads to disruption tails. The disruption tails represent residue from the disruption period, such as backlog and delayed orders, which may influence SC operations and performance in the post-disruption mode. The revival policy intends to mitigate the negative impact of these disruption tails and stabilize the SC control policies and long-term performance impact.

6 Conclusion

Despite significant progress in theoretical studies and empirical principles for managing severe disruptions in the SC at proactive and reactive stages, recent literature has mostly assumed an immediate transition to a normal operation mode at the time of capacity recovery. Moreover, full system stabilization after capacity recovery has been assumed without considering any residue, such as delayed orders accumulated over the destabilized system states during the disruption time. The experiments performed allowed revelation of the *disruption tails,* which are the repercussions of the backlogs and delayed orders accumulated over the disruption period.

Post-disruption instability, i.e. the disruption tails in the SC has been observed in this study as a consequence of the production ordering behaviour during the disruption period. Disruption tails occur in two cases. The *first reason for disruption tails* is non-coordinated inventory and production control policies, i.e. if DCs and customers continue placing new orders even if the production capacity is disrupted. A transition of backlog and delayed order residues into the post-disruption period destabilizes the SC resulting in further delivery delays and non-recovery of the operational and financial SC performance. These orders are accumulated in the waiting lines of production systems and increase the delays and backlogs. After the capacity recovery, the production system needs to produce both the backlog and new incoming orders. If the recovered production capacity is lower than the total of the backlog and new incoming orders, this results in new delays and backlogs. If the recovered production capacity is sufficient to cover both the total of the backlog and new incoming orders, this results into disproportionally high delivery quantities at the DCs. In turn, the DCs stop ordering because of the high inventory, and this results in some periods having new shortages. The *second reason for disruption tails* is the inertness of the decisions on activation and deactivation of contingency plans. An immediate deactivation of the contingency plans and installation of the normal operation policies after capacity recovery in the presence of the delayed orders and backlogs also results in the destabilization of inventory and production systems and in the new delayed orders and backlogs.

Two case studies with different settings, perishable and non-perishable products, and different data sets have been considered and the experiments with both case studies confirmed the disruption tails existence. With the results gained, this study closes the research gap described above with the objective of revealing the dependencies between SC disruptions, contingency policies and transition to the post-disruption operation mode.

The results obtained suggest two managerial insights. First, contingency production and inventory control policies need to be applied during the disruption period. Moreover, recovery policies should not be limited to the disruption period only, they should also consider the post-disruption period. Second, special actions need to be developed for the transition time from the contingency plan to the disruption-free operation mode. We call these actions ‘revival policy’. The experimental results argue in favour of revival policies to mitigate the impact of the disruption tails. Moreover, a revival policy extends the SC resilience framework at the stage of transition from recovery to post-disruption period.

We provide examples of contingency policies for production factory and DC disruptions as well as for the revival SC policy. Disruption tails can be reduced by applying a contingency policy during the disruption time when the production control system cancels excessive DC orders waiting in the production system queues because of disrupted manufacturing capacities. Alternatively, the DCs need to adjust their ordering policy subject to the reduced production capacity to avoid long waiting times and the resulting delayed orders, backlogs, service-level reductions and the production-inventory control system destabilization after the capacity recovery. As an example of the revival policy, an increase in SC production capacity has been suggested by means of contracting additional plants prior to normal contingency recovery policy deactivation. This allows avoidance of the disruption tails in the post-disruption period.

Concerning the limitations of this study, the contextual insights gained experimentally need to be pointed out. Further research might include analysis of other industries and datasets. Moreover, analytical studies are needed to provide more generalizable theoretical results and practical recommendations, i.e. in the area of recovery policies with the post-disruption period considerations.

Appendix 1. Mathematical Model for Section 4

Indices

α	Priority customer index
β	Non-priority customer index
f	Actual demand index
r	Period index, $r \in [1; T])$
ST	Standard deviation index
l	Trend variation index
i, j	Products 1 and 2, respectively
g	Distribution centre number, $g \in [1; G])$
z	DC order index $n \in [1; N]$, where N is total number of DC orders
ω	Current forecasting period, $\omega \in [r; r + LT + m - 1]$
w	Index of products with expired date
h	Index of setups at the factory, $h \in [1; Nch]$
ds	Disrupted
ch	Setup

Parameters

T	Number of planning periods in planning horizon
G	Number of DCs
d	Basis demand in a r-period, in units
k	Seasonal demand coefficient in a r-period
δ^{ST}	Demand standard deviation r-period
δ^{l}	Demand trend parameter for the length of r-periods
d_{fr}	Actual demand in a r-period, in units
ν	Priority customer rate
s	Reorder point, in units
Q	Minimum reorder quantity, in units
LT	Lead time, in periods
m	Frequency of batch setups in the factory, in periods
p_{α}	Minimum requirement on the rest product freshness for α-customers
K	Maximum production capacity per period, in units
B	Minimum batch size, in units
QC	Maximum production order queue length, in orders
t_{ch}	Setup time
t_{dp}	Disruption time
t_{ds}	Disruption duration, in periods
ξ	Capacity reduction coefficient, in units
c_{h}	Unit inventory holding costs per period, in $
c_{tr}	Unit transportation costs per delivery, in $
c_{fix}	Fixed production costs, in $ per capacity unit
c_{ch}	Setup costs, in $
p	Unit price, in $
u	Penalty for non-delivered products, in $
SL_{min}	Minimum service level, %
η	Shelf life

Variables

O	Order quantity from DC to factory, in units
F	Production date for a z-batch, period
H	Total holding costs
T	Total transportation costs
W	Total write-off costs
U	Total penalty costs
M	Total manufacturing costs
TC	Total costs
μ	Processing queue length, in units
t_m	Production time for a batch, in periods
y	Inventory in a r-period

Objective function

$$\begin{aligned}
&\min TC = H + T + W + U + M = \\
&\underbrace{}_{Total\ supply\ chain\ costs} \\
&= H = \sum_{r=1}^{1200}\sum_{g=1}^{5} c_h \cdot y_{ir}^{g} + \sum_{r=1}^{1200}\sum_{g=1}^{5} c_h \cdot y_{jr}^{g} + \\
&Total\ inventory\ holding\ costs \\
&+T = \sum_{n=1}^{N^i}\sum_{g=1}^{5} c_{tr} \cdot L^g * O_{in}^{g} + \sum_{n=1}^{N^j}\sum_{g=1}^{5} c_{tr} \cdot LT^g \cdot O_{jn}^{g} + \\
&Total\ transportation\ costs \\
&+W = \sum\nolimits_{r=1}^{1200}\sum\nolimits_{g=1}^{5} p \cdot y_{wir}^{g} + \sum\nolimits_{r=1}^{1200}\sum\nolimits_{g=1}^{5} p \cdot y_{wjr}^{g} + \\
&Total\ write-off\ costs \\
&+U = \sum\nolimits_{r=1}^{1200}\sum\nolimits_{g=1}^{5} u_{ir}^{g} + \sum\nolimits_{r=1}^{1200}\sum\nolimits_{g=1}^{5} u_{jr}^{g} + \\
&Total\ penalty\ costs \\
&+M = \sum\nolimits_{h=1}^{N_{ch}^{i}} c_{ch+} \sum\nolimits_{r=1}^{1200} c_{fix} \cdot K \\
&Total\ manufacturing\ costs
\end{aligned} \tag{1}$$

Constraints

$$K_{ds} = K \cdot \xi \tag{2}$$

$$\forall SL_g \geq SLmin \tag{3}$$

$$\mu_{jr} > QC_1 \tag{4}$$

$$\mu_{jr} - \mu_{ir} > QC_2 \tag{5}$$

$$O_i \geq B_i \tag{6}$$

$$s_{i,j} \in int \tag{7}$$

$$s_{i,j} \geq 0 \tag{8}$$

Two-stage, multi-period SC planning with multiple constraints on production capacity, setups, shipments and inventory control is the object under investigation. A two-product system with independent seasonal stochastic demand with high variability is analysed. The planning horizon is 7 weeks. Production planning decisions include inventory dynamics at the DC. We consider both product availability and 'freshness' level requirements in service levels although customers are segmented according to their freshness requirements.

The fixed parameters include minimum order size and inventory level at DCs, minimum production batch size, queue size limits, setup time, production capacity, wastage, inventory holding, production, setup and transportation costs. Also included are the mean demand and its standard deviation, shelf life and freshness threshold, production order allocation interval, penalties, mean and standard deviation of time duration and interval of capacity breakdown, and the remaining capacity percentage after the disruption.

Production constraints include minimum lot size, maximum capacity and setup time. Inventory constraints are comprised of minimum inventory levels (i.e. reorder point expressed in days of supply availability) and minimum order size. Outbound deliveries from distribution centres follow the FEFO rule. A continuous review system with fixed order quantity and pull production strategy is considered.

The objective is to minimize total system costs while maintaining the required service level. Total costs are computed as a sum of total holding costs, transportation costs, write-off costs, penalty costs and manufacturing costs (Eq. 1). Unit inventory holding costs c_h and transportation costs c_{tr} are used to compute total costs. In a case of inventory with expired date y_w, write-off costs increase proportionally to the purchasing prices p. If the customer order size exceeds the inventory at DC, a penalty u is applied. Manufacturing costs depend on the number of setup and fixed costs for capacity units, c_{fix}.

Service level is calculated as a ratio of products shipped divided by products ordered with no backlogging within model period. SC performance is therefore measured with the help of total costs and service level. Total cost metrics are comprised of inventory holding costs at the DCs, write-off costs, transportation costs, production costs and penalties. Holding costs are computed subject to interest rates. Write-off costs are computed based on the product costs. Transportation costs depend on the distance, order quantity and shipment tariff. Production costs include fixed equipment-related costs (proportional to the capacity units) and setup costs. Penalties are applied if the order size from the key customer exceeds the available delivery quantity. Service level is computed as a ratio of the delivered and ordered products.

According to Eq. (2), production capacity can be reduced by a disruption coefficient ξ. By default, the following parameters are used: mean interval is 100 periods and mean duration of disruption is 20 periods. Standard deviations are 50 and 10 periods, respectively. At the end of the disruption period, the capacity K returns to normal.

Equation (3) sets the constraint on minimum service level. In the considered practical case, 98.5% has been used as the reference value for minimum service level. Equations (4) and (5) define maximum queue lengths in the production system. According to Eq. (6), production quantity can equal or exceed minimum batch size. Equations (4)–(6) define the rules for production setups. Equations (7) and (8) are binary and non-negativity constraints on the reorder point for products i and j.

Empirical data revealed the average weekly demand of 2,500 units. The basic demand in the model is 2,541 units multiplied by the seasonal factor. The period demand d_r is therefore defined according to Eq. (9).

$$d_r = k * d \tag{9}$$

The actual demand d_{fr} may vary in a period with a standard deviation δ_r^{ST} subject to uniform distribution. Additionally, period demand may be corrected by a trend δ_r^l of demand increase or decrease for the length of four periods. Therefore, actual period demand d_{fr} is generated according to Eq. (10):

$$d_{fr} = d_r * \delta_r^{ST} * \delta_r^l \tag{10}$$

Demand is divided into two customer groups, i.e. α customers have higher priority than β customers. Demand share of α customers is defined by parameter ν according to Eq. (11).

$$d_{fr\alpha} = d_{fr} * \nu \; ; d_{fr\beta} = d_{fr} * (1 - \nu) \tag{11}$$

DC operations are modelled using a multi-agent approach. We considered a set Z of production batches that are sorted upwards according to production dates F_z Parameters ρ_α and ρ_β. Then, we defined the minimum requirements for the rest shelf life for both customer groups. Let us consider current forecasting period ω ($\omega \in [r; r + n + m - 1]$) in order to define the general outbound delivery planning algorithm for key customers and each period as follows:

$$
\begin{aligned}
& for z_i \in Z \\
& if F_{z_i} > \omega - \rho_\alpha * \eta \\
& if z_i > d_{\omega\alpha} \\
& z_i = z_i - d_{\omega\alpha}
\end{aligned}
$$

Table A1 Input data

Parameters	Parameter value
Minimum days of supply	14
Minimum order size in product units	10,000
Rolling planning horizon, in periods	7
Minimum period between production order allocations, in periods	1
Production capacity, product units per period	40,000
Minimum reorder quantity	10,000
Lead time, in periods	2–3
Maximum production capacity per period, in units	40,000
Minimum batch size, in units	20,000
Setup time, periods	0.08
Setup costs per period, in $	7,500
Mean of the interval between capacity disruptions, in periods	100
Standard deviation of the interval between capacity disruptions, in periods	50
Mean of disruption duration, in periods	20
Capacity reduction coefficient, in %	50
Minimum service level, %	98.5
Shelf life, in periods	36

$$
\begin{aligned}
&d_{\omega\alpha} = 0 \\
&else \\
&d_{\omega\alpha} = d_{\omega a} - z_i \\
&else \\
&next.
\end{aligned}
$$

The algorithm described above allows for consideration of both inventory dynamics and expected shelf life of future deliveries.

The experiments have been performed on the following parameter setting (Table A1).

Appendix 2. Mathematical Model for Section 5

Indices

f	Actual demand index
α	α-service level
r	Period index, $r \in [1; T])$
ST	Standard deviation index
λ	Market number, $\lambda \in [1; \Lambda]$
i	Production facility number, $i \in [1; H]$
j	Distribution centre number, $j \in [1; G])$
t	Running time index
T	Length of the planning horizon

Parameters

T	Number of planning periods in planning horizon
G	Number of DCs
H	Number of factories
Λ	Number of markets
D	Mean weekly demand in a r-period, in units
q	Mean basis demand, in units
k	Seasonal demand coefficient in a r-period
δ^{ST}	Weekly demand standard deviation in a r-period
K	Maximum production capacity per day, in units
B	Maximum storage capacity at the DCs per day, in units
L^{in}	Maximum inbound processing capacity at the DCs per day, in units
L^{out}	Maximum outbound processing capacity at the DCs per day, in units
ξ	Capacity reduction coefficient, in units
c_h	Unit inventory holding costs per day, in $
c_{tr}	Unit transportation costs per delivery, in $
c_{fix}	Fixed site costs, in $ per day
c_{man}	Own manufacturing costs, in $ per unit
c_{sub}	Subcontracting manufacturing costs, in $ per unit
c_{in}	Inbound processing costs, in $ per unit
c_{out}	Outbound processing costs, in $ per unit
c_{down}	Penalty for demand non-fulfilment, in $ per unit
p	Unit price, in $

Variables

P	Production quantity at the factory, in units per day
S	Selling quantity in the markets, in units
X^{in}	Processed inbound quantity at the DC, in units per day
X^{out}	Processed outbound quantity at the DC, in units per day
Q	Shipment quantities in between the factory, DC, and the markets, in units per day
H	Total inventory holding costs, in \$
T	Total transportation costs, in \$
W	Total processing costs, in \$
F	Total fixed costs, in \$
M	Total manufacturing costs, in \$
U	Total penalty for delayed delivery, in \$
TC	Total costs, in \$
y	Inventory in a r-period, in units
d	Distance, in km (computed based on real routes)

Objective function

$$max Profit = Revenue - TC = (p \cdot S) - (H + T + W + U + M + F), \quad (1)$$

where

$$H = \sum_{t=1}^{T} \sum_{j=1}^{G} c_h \cdot y_{jt}^{g}$$

$$Total\ inventory\ holding\ costs$$

$$T = \sum_{j=1}^{G} \sum_{i=1}^{N} c_{tr} \cdot d_{ij} \cdot Q_{ij} + \sum_{i=1}^{N} \sum_{\lambda=1}^{\Lambda} c_{tr} \cdot d_{\lambda i} \cdot Q_{i\lambda}$$

$$Total\ transportation\ costs$$

$$W = \sum_{j=1}^{G} (c_{in} + c_{out})$$

$$Total\ processing\ costs$$

$$F = \sum_{j=1}^{G} c_{fix} + \sum_{i=1}^{N} c_{fix}$$

$$Total\ fixed\ costs$$

Table A2 Experimental settings

Parameter	Values
Mean basis weekly demand in the market 1, in m^3	6,000
Mean basis weekly demand in the markets 2–4, in m^3	4,000
Number of periods	4
Period length, in months	3
Seasonal demand coefficients for four periods	1.00–1.25–0.75–1.0
Standard deviation of weekly demand, in m^3	25% from the mean
Expected lead time in the markets, in days	7
Lead time in between two SC stages within a region, in days	1
Mean lead time in between two SC stages from different regions, in days	5
Standard deviation lead time in between two SC stages from different regions, in days	2
Reorder point at the DC1, the factories and emergency plants, in m^3	10,000
Target inventory level at the DC1, the factories and emergency plants, in m^3	20,000
Safety stock at the DC1, in m^3	6,000
Reorder point at the DCs 2–4, in m^3	7,000
Target inventory level at the DCs 2–4, in m^3	14,000
Initial inventory at the DCs 2–4 and factories, in m^3	10,000
Initial inventory at the DC1, in m^3	20,000
Production time for product unit, in days, in m^3	0.001
Maximum production capacity at own factory, in m^3 per period	90,000
Maximum production capacity at emergency sources, in m^3 per period	10,000
Recovery time after a disruption, in months	4
Time between the disruption and activating the contingency policy such as subcontractor, milk producer capacity and own factories abroad, in days	20
Mean lead time to the market 1 in the disruption period, in days	8
Standard deviation lead time to the market 1 in the disruption period, in days	2

$$F = \sum_{i=1}^{N} c_{sub} \cdot P_i + \sum_{i=1}^{N} c_{man} \cdot P_i$$

$$Total\, manufacturing\, costs$$

$$U = \sum_{\lambda=1}^{\Lambda} c_{down}$$

$$Total\ penalty\ costs$$

Demand constraints

$$Q_{j\lambda t} \geq d_{t\lambda}$$

$$D_r = k \cdot q_\lambda$$

$$D_{fr} = D_r \cdot \sigma_r^{ST}$$

Shipment constraints

$$Q_{ijt} \leq X_t^{out}$$

$$Q_{\lambda jt} \leq y_{jt}$$

Capacity constraints

$$P_{it} \leq K_{it} \cdot \xi$$

Constraints on inventory holding and processing at the DCs

$$y_j \leq B_j \cdot \xi$$

$$X_{t+1}^{out} \leq L^{out}$$

$$X_{t+1}^{in} \leq L^{in}$$

The experiments have been performed with the following parameters (Table A2).

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Managing Disruptions and the Ripple Effect in Digital Supply Chains: Empirical Case Studies

Ajay Das, Simone Gottlieb and Dmitry Ivanov

Abstract This chapter studies the impact of accelerating digitalization on supply chain risk management. The interrelationships between digital technologies and supply chain disruption risk are analyzed using multiple case studies from various industries. The empirical analysis guided a conceptual framework based on extant theory and specific hypotheses. The chapter concludes with a discussion of research opportunities for future study. In particular, the discussion involves perspectives and future transformations that can be expected in the transition toward cyber-physical supply chains.

1 Introduction

To keep pace with current trends, companies and supply chains develop products and processes that meet new requirements in terms of productivity, sustainability, competitiveness, and risk management. Digitalization strategies and technologies are being increasingly identified, evaluated, tested, and applied to meet such requirements. Disruptive innovations such as Blockchain, Industry 4.0, and additive manufacturing catalyze the development of new paradigms, principles, and models in supply chain management (SCM) (Ivanov et al. 2013; Ivanov 2017). The Internet of Things (IoT), cyber-physical systems, and smart, connected products, facilitate the development of digital supply chains (SC) and smart operations (Fazili et al. 2017; Liao et al. 2017; Ivanov et al. 2016; Ivanov and Dolgui 2019; Panetto et al. 2019; Dolgui et al. 2019a, 2019b; Ivanov et al. 2018; Qu et al. 2017; Strozzi et al.

A. Das
Narendra Paul Loomba Department of Management, Zicklin School of Business, CUNY-Baruch, One Bernard Baruch Way, New York, NY 10010, USA
e-mail: ajay.das@baruch.cuny.edu

S. Gottlieb · D. Ivanov (✉)
Department of Business and Economics, Berlin School of Economics and Law, 10825 Berlin, Germany
e-mail: divanov@hwr-berlin.de

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2017; Tran-Dang et al. 2017; Yang et al. 2017; Rossit et al. 2018; Saberi et al. 2018). Recent surveys by Addo-Tenkorang and Helo (2016), Gunasekaran et al. (2016, 2017, 2018), Nguyen et al. (2018), Moghaddam and Nof (2018), Choi et al. (2018), and Ben-Daya et al. (2018) proposed classifications of different digital technologies, and discussed potential impacts on SCM. Such digital technologies include big data analytics, advanced manufacturing technologies with sensors, decentralized agent-driven control, advanced robotics, augmented reality, advanced tracking and tracing technologies, and additive manufacturing.

While the individual technology contributing elements (e.g., robots, sensors, RFID—radio frequency identification, agents, modular factories, etc.) are not really new, they are becoming more practical, and companies are becoming more receptive to their adoption. In addition, attempts to interconnect and integrate such local solutions, using current advances in data processing technologies, can be observed in practice. Digitalization demands change in existing operations. As such, it calls for new principles and models to support SC risk management (SCRM) in the future (Ivanov 2018a, b; Ivanov et al. 2017).

The investigation of the interrelations between digital technology and SC risks is still at a preliminary stage, and requires new conceptual frameworks and taxonomies (Schlüter et al. 2017; Ivanov et al. 2019). Papadopoulos et al. (2017) pointed out that data analytics can help in improving SC risk management and disaster resistance. Choi and Lambert (2017) and Choi et al. (2017) provided evidence of how data analytics can be used to improve resilience of SC operations by utilizing firms' databases and large volumes of data to predict risks, assess vulnerability, and enhance their SCs. Simchi-Levi et al. (2015) presented a data-driven system to analyze supplier exposure in the automotive sector. Ivanov et al. (2019) showed that data analytics can be used at the planning stage to identify supplier risk exposure and can help at the reactive stage to monitor and identify disruptions. They proposed a framework of integrated cyber-physical SC simulation and optimization and related this framework to system-cybernetics principles. Their result echo those in the study by Choi (2018) that presented a new practical perspective on how big data related technologies can be used for global SCs with a systems of systems(SoS) mind-set. Baryannis et al. (2018) summarized recent AI applications to SC risk management and shoed some future research directions in risk identification, assessment, and response. Priore et al. (2018) applied machine learning to the dynamic selection of replenishment policies according to SC environmental dynamics.

This chapter seeks to move the discussion forward and develop a framework for a detailed analysis of SC digital technology and disruption risk effects (Ivanov et al. 2014a, b; Sokolov et al. 2016; Dolgui et al. 2018; Pavlov et al. 2018) using a multiple case study methodology (Blackhurst et al. 2011).

2 Empirical Analysis

This section develops hypotheses regarding the mutual interrelations of digital SC and the ripple effect, and analyzes these empirically. The first set of hypotheses (H1–H3) focuses on disruption risks in SCM assuming that supplier disruptions are more likely to occur than other risks. The ripple and bullwhip effects are typical manifestations to be analyzed within this hypothesis set. Causes of disruption, disruption management experience and risk mitigation methods, and disruption recovery are therefore examined in hypotheses H1, H2, and H3.

Hypotheses H4 and H5 are developed to explore the application of digital technologies in practice. The opportunities and benefits of digital technologies are often emphasized in literature. However, such are often surmised or anecdotal. Applications of digital technology may be different in reality and might be characterized by many challenges and obstacles.

The third set of hypotheses (H6–9) deals with the obvious gap in knowledge about the influence of digital technologies on SCRM. The contribution of digital technologies in creating a resilient SC in the pre- and post-disruption stages, their impact on SC efficiency, and the role of digital technologies to ripple effect control in SCRM are important research questions. The following hypothesis examines these questions:

- **Hypothesis H1**: Supplier disruptions have a higher likelihood of appearance, relative to other types of disruptions.
- **Hypothesis H2**: Disruptions have a serious impact on a large part of the SC.
- **Hypothesis H3**: Flexible SC networks are associated with successful SCRM.
- **Hypothesis H4**: SCRM opportunities and potential benefits become visible through the use of digital technologies.
- **Hypothesis H5**: Obstacles to implementation and data security concerns are the most likely impediments to the use of digital technologies.
- **Hypothesis H6**: Digital technologies contribute to SC resilience by improving risk mitigation capabilities at the pre-disruption stage.
- **Hypothesis H7**: Digital technologies contribute to SC resilience by improving disruption recovery capabilities at the post-disruption stage.
- **Hypothesis H8**: Digital technologies in SCRM are associated with SC efficiency.
- **Hypothesis H9**: Digital technologies contribute to ripple effect control in SCRM.

The above hypotheses emerge in a conceptual framework that broadly examines the impact of digital technologies on SCRM. Figure 1 organizes the SCM factors, disruption risks, and digital technologies into a suggested framework. The generic framework refined and validated during the course of this study, intends to provide managerial guidance for the creation of successful SCRM through the use of digital technologies.

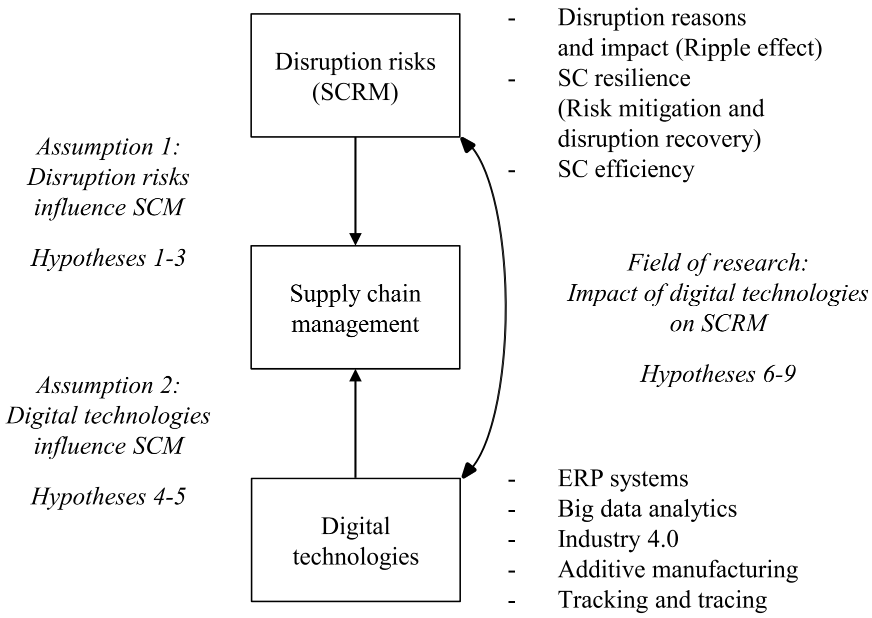

Fig. 1 Conceptual framework

3 Case Studies

3.1 Sample Selection

The interviewed persons in this research were key decision-makers in their firms' SCRM and have extensive experience in dealing with disruptions. The data were collected through semi-structured interviews in order to achieve a certain degree of comparability, and at the same time ensure an unimpeded flow of narration. This method combines the flexibility of an open interview with the focus of a structured survey. Open-ended questions were used to collect qualitative text data, offering participants opportunity to elaborate and contextualize their experiences with risk management. Structured questions provided ranking options. Interview questions were formulated based on identified gaps in the literature and resultant hypotheses. The collected information analyzed in the context of the hypotheses and the conceptual framework (Fig. 1).

Experts in SCRM were approached via email and asked to share their experiences through a developed questionnaire provided in English (cf. Appendix). A total of nine completed questionnaires were collected within a period of 4 months. Data confidentiality and respondent anonymity were assured and implemented. The first phase of data collection therefore obtained preliminary but detailed knowledge through filled out questionnaires. The second phase of data collection obtained secondary data from public databases to triangulate the interview data. Follow-up phone interviews were then conducted to gain more in-depth knowledge.

Construct validity was pursued using a variety of approaches. The research and interview questions were elaborated in exchange with academics. The result of the first interviews was discussed in order to adjust the interview questions where necessary. Support for internal validity was provided by the triangulation process together with comparisons with existing literature. External validity was examined using a multiple case study approach. Support for both internal and external validities materialized from the comparative case studies. Each case had been carefully selected to meet either similarity or variance goals, subsequently investigated with within-case and cross-case analyses. In addition, a tested and refined interview protocol (questionnaire) provided added reliability. To further ensure a high degree of reliability and traceability of the data, additional questions were asked by telephone in the second phase of the interview, duly transcribed into text format.

The data analysis was conducted by analyzing the individual cases and comparing them with one another. As part of the within-case analysis, each case or respective company, and the related data were analyzed individually. In the cross-case analysis, the questionnaire responses were reviewed across the entire sample. Cases were compared to identify similarities and differences. The aim was to find recurring patterns and make qualitative statements.

3.2 Cases

Nine case studies from medium-sized to large companies from various industries were created based on the in-depth interviews. A majority of the companies are from the automotive and semiconductor industry, as these industries, in particular, are expected to have an SC network also in high-risk areas such as Japan, which is frequently affected by extreme nature events. The other case studies are from the climate systems, food retail, rail vehicles drive systems, and consulting industry (Tables 1, 2, and 3).

Case A (Food Industry)

The food retail SC consists of up to three echelons. The hypermarket branch has one federal distribution center, which is controlled by the hypermarket. Each of the 93 hypermarkets has a bakery and salad shop. On the second SC stage there are two federal distribution centers, which are shared with and controlled by the supermarkets. The regional distribution network consists of six distribution centers, also controlled by the supermarkets. The federal distribution centers specialize in dry, fresh, and frozen products as well as fruit and vegetable products. Regional distribution centers, on the other hand, have the entire product range. Three types of warehouse processing are applied: cross-docking (the goods are pre-packed by the vendor, no longer stored, but processed directly and delivered to the customer), pick-by-line, and picking.

Table 1 Overview of investigated companies

Case	Industry	Main product	Country	Company's size (Employees)	Company sales (2017)
A	Food retail	Food	Russia	>500	16–18 Billion Euro as a retail group 1.6–1.8 Billion Euro as a hypermarket business branch
B	Semiconductor	Automotive, Power Management and Multimarket, Industrial Power Control, Chip Card and Security	Germany	>500	7 Billion Euro
C	Rail vehicles drive systems	Mechanical gears	Germany	50-500	50–100 Million Euro
D	Automotive supplier	Automotive electronics	Germany	>500	40, 5 Billion Euro
E	Aerospace, automotive, railway and engineering	Supply chain collaboration Sourcing, quality solutions and transport management Solutions	Germany	50–500	50 Million Euro
F	Semiconductor	Chips, wafer	Netherlands	>500	8 Billion Euro
G	Automotive supplier	Automotive electronics	Germany	>500	120 Million Euro
H	Automotive	Vehicles	Germany	>500	98 Billion Euro
I	Climate systems	Air conditioners, heat pumps, chillers	Netherlands	50-500	175–250 Million Euro

Table 2 Overview of interviewed experts

Case	Informant (Professional position)	Department	Years of experience	Specialization
A	Supply Chain Optimization Manager	Department of Supply Chain Optimization and Supplier Relationship	1, 5	Supply Chain Optimization, Analytics, Supply Chain Network Optimization
B	Head of Supply Chain Innovation	Supply Chain Innovation	>20	Principal Logistics Systems
C	Business Process Manager	Large Traction Drives Technologies	>7	Process Optimization
D	Risk and Process Manager	Risk and Allocation Management	7	Corporate Supply Chain Management and Risk & Allocation Management
E	Manager Consulting	Consulting	23	Automotive industry, IT Consulting, Supplier Portal Collaboration
F	Vice President and Business Unit Supply Chain and Operations Manager	Supply Chain Management	30	Global Operations Management Automotive
G	Processes and Tools Manager	Supply Chain Management	15	Processes and Tools Mexico
H	Risk Manager	Risk Management	20	Strategy Purchasing and Supplier Network, Risk Management, Crisis and Insolvency Management
I	Supply Chain Manager	Supply Chain Management	15	Supply Chain Optimization, Supply and Demand Planning

Table 3 Reasons for experienced disruptions

Disruption type	Causes for disruption
Supplier disruptions	Single sourcing
Production capacity disruptions	Production system inflexibility Low data visibility Missing buffers in capacity utilization Force majeure Single sourcing
Logistics disruptions	Force majeure Single sourcing
Demand disruptions	Missing buffers in capacity utilization Low data visibility No real-time monitoring Customers (first-tier) not knowing their demand because their customers (original equipment manufacturer) do not know their demand
Product/technology disruptions	Complex mix of product specification and changing customer requirements

Case B (Semiconductor industry)

The business processes in case B are based on the SCOR model: planning, sourcing, making, delivery, and return. The company strives for a self-optimized SC with a perfect mix of automated processes and human decision-making processes according to the roadmap being descriptive, diagnostic, predictive, and prescriptive. Operations vision and mission are communicated top-down throughout the operations community. Operations strategy is documented in various ways to reach all levels. High-level workshops every year and monthly board meetings ensure that all activities from lighthouse projects to projects and to tasks are aligned with the strategy. The SC has evolved from rigid patterns to a global and highly flexible supply network as the smart factory approach has improved the manufacturing flexibility realized through superior planning processes.

Case C (Rail vehicles drive systems industry)

The general European SC scope of the company C is component manufacturers, proprietary value creation, bogie manufacturer, and vehicle manufacturer. Approximately, ten main components are predominantly procured from Europe with one supplier per component. The main component "gearing" is usually manufactured at the company C's own site (other business segments). Components are then delivered to the bogie manufacturer. Some components are provided by the customer. The proprietary value creation of company C consists of assembly, testing, and completion. Bogie manufacturers and vehicle manufacturers may be identical or separate in terms of logistics or business.

Case D (Automotive supplier industry)

At the location surveyed, the group operates the world's largest production plant for automotive electronics. Products for eight different business units are manufactured there, from sensor systems and transmission controls to engine components. A total of around 360,000 units leave the plant every day, which supplies major German and international automobile manufacturers. The leading German automotive supplier group has 427 locations in 56 countries with a total of more than 3000 suppliers.

E (Aerospace, automotive, railway, engineering consulting industry)
Case E is an SC collaboration platform that connects companies with their business partners and assists their ERP systems. The dynamic corporate network connects 65,000 companies worldwide. Of these, 50,000 are suppliers who work with major customers. The platform enables a quick reaction to market changes and fluctuations and thus ensures the long-term success of the SC. The focus of company E is on the manufacturing industry and covers industry-specific requirements of the aerospace, automotive, railway, and engineering industries with consulting solutions.

Case F (Semiconductor industry)
Company F produces chips and wafers as automotive products for advanced driver assistance systems, vehicle networking, or safety applications, for example. The respondent of the semiconductor company limited the SC overview to the automotive business. There are nine internal factories for wafers and chips and about ten wafer foundry suppliers and ten chip suppliers. The number of material suppliers is estimated at over 100.

Case G (Automotive supplier industry)
The Group's site has one factory and one logistics center where electronics for the automotive industry are produced. The German plant from which the expert was interviewed has around 370 customers worldwide.

Case H (Automotive industry)
The Group has over 20 automotive plants worldwide. Most of the goods are procured via single and global sourcing from 5,000 suppliers. In addition, just-in-time and just-in-sequence delivery concepts are applied. The interviewed expert does not focus the SC overview on the own location, since the respondent is an SC risk manager for the entire German automotive group.

Case I (Climate system industry)
Company I, headquartered in the Netherlands, has three suppliers from Asia. Products are air conditioning systems, heat pumps, and chillers for the market of air conditioning solutions. There are five distribution centers in Europe, three of which serve several countries. High running models are delivered directly from Asia to all five distribution centers and low running models to the three main warehouses supplying all of Europe.

4 Evaluation

4.1 Disruption Causes, Concerns About Risks, and Experiences with Disruptions

In order to examine the situation of the individual cases, concerns about disruption risks in the SC are first surveyed. The two most commonly cited concerns were external and supplier risks. External risks, such as fire, floods at the site, severe weather affecting the power supply, political instability, the risk of terrorism, or earthquakes at the supplier were mentioned by the experts. In addition, there is a seasonal risk for company I, which serves the climate solutions market. When summer is not hot, a lot of stock goes unsold and ends up as overstocks, incurring costs. On the other hand, when the summer is unexpectedly warm, the company can face shortage. Five out of nine companies fear supplier disruptions due to changes in product quality or supplier insolvency. Beside external and supplier risks, underestimation of demand, logistics disruptions which occur on route to the site or to an external warehouse, and time risks, such as the failure of bottleneck machines, production capacity disruptions, and reliance on ocean freight were identified in the questionnaire responses. The companies' concerns are consistent with the categories identified in literature, though information disruption and the ripple effect were not explicitly mentioned.

All respondents had experienced supplier disruptions, production capacity disruptions, logistics disruptions, and demand disruption. In every case, there were supplier and production capacity disruptions with high to very high impact. Further disruptions were referenced in terms of force majeure, tax, and regulation. Single sourcing, missing buffers in capacity utilization, and low data visibility are the most frequent causes of disruptions. Respondent B added product and technology disruptions caused by a complex mix of product specifications and changing needs in customer product specifications.

Single sourcing, missing buffers in capacity utilization, and low data visibility are the most frequent causes for disruptions. Respondent B added product and technology disruptions caused by a complex mix of product specification and changing customer product specification needs.

4.2 Disruption Effects on Supply Chain Processes

In assessing the impact of one type of disruption on another, almost all respondents stated that an interruption in production capacity, and thus an interruption in delivery to the customer, was caused by disruptions to suppliers and demand. To gain more insight in empirical studies into measures to prevent the ripple and bullwhip effects, the participants were asked their opinion on the integration of suppliers into their risk management or on the establishment of a risk management system with their suppliers. The risk manager from company H explains: "We only look at the risks that affect our direct suppliers (first-tier), because the next supplier level (second-tier) is usually not known. It is not revealed by the first-tier supplier or it is disclosed, but not recorded in our system. In principle, we cannot afford to monitor all value-added levels on using our own resources. Our purchasing conditions also stipulate that first-tier suppliers must establish their own risk management. In addition, if we handled the risk management of our suppliers, then they would no longer be responsible suppliers would be taken out of their responsibility if we handled their risk management and suppliers were then no longer responsible for disruptions caused into our production."

The risk manager also emphasized that any disruption in the supply of components impedes the construction of a car, but not every component is equally critical. Risk management must therefore be oriented particularly toward supply-relevant components.

4.3 Risk Mitigation and Disruption Recovery Methods

In addition to the opinion on supplier integration in the company's own risk management, the methods used for risk mitigation and disruption recovery are identified. The participants were asked to describe a recent major SC disruption and how this disruptive event was managed. Table 4 presents the experiences according to the type of disruption.

The presentation of disruptions experienced supports hypothesis H1, as four out of nine companies were affected by supplier disruptions. In most cases, it seemed essential in terms of disruption recovery to have second-source suppliers or to be able to replace missing parts with similar parts.

As an SCRM strategy, company C aims to reduce its risk exposure and avoid repetition of previously experienced risks. However, general market risks can only be influenced to a limited extent. The SCRM process of company H is carried out by risk management and crisis management departments: "Our classic risk management comprises the evaluation of the probability of risk occurrence and possible damage potential. In addition, suppliers are evaluated both at the time of tender submission and on an ongoing basis. The crisis management department reacts actively to disruptions. Financial losses, such as insolvencies, are dealt with, or in the event of fire or flooding at the supplier, a task force team is sent into check fire protection conditions or earthquake safety. In the event of supplier interruptions, the replenishment times of the actual supplier and of other suppliers are assessed first. The crisis team then ranks the damages at the supplier and implements measures for the most severe damages. It is important to find the right balance between risk management and crisis management. You can invest a lot of money in risk management so that nothing happens, but at some point the marginal benefit will be small. Then it is better to have a good crisis management team, because something can always happen. But the right balance is gut feeling."

Despite multiple sourcing and checking material requirements on a daily basis, company D feels hardly able to protect itself against disruptions and a possible ripple

Table 4 Disruption experiences and recovery measures

Disruption type	Case	Examples	Disruption recovery measures
Demand disruption	A	*A federal distribution center for fresh and frozen product categories became stymied during high season mid-December. The results included 100% utilized warehouse space, queues of trucks, and delayed orders. Demand was much higher than planned. This led to a loss of service level and service level time KPIs, and increased costs*	*First, we assigned suppliers to ship to regional distribution centers if it was applicable* *Further recovery measures included temporal decentralization of suppliers (direct deliveries to hypermarkets instead of to the distribution center), the use of a discounter branch's distribution center for shipments of frozen products, and a review of the assortment matrix* *T Supply Chain Operations Director spent all of December in the distribution center until the situation stabilized, enabling faster management decisions and providing additional expertise*
	I	*Last year Portugal suffered an extreme heat wave and sales spiked heavily*	*We supplied products from all over Europe to Portugal to remedy the shortage*
External disruption	B	*In the third week of February 2015, three of the four production lines at the manufacturing plant of our supplier in Malaysia caught fire. Products for our plant were affected. This incident led to direct influence on the relationships between us, our supplier, and our customer. 30 Million Euro of our company's turnover was affected, together with around 50 products and 100 customers*	*We found a second-source supplier, used products from both suppliers, and got the disruption under control*
External disruption	F	*A year and half ago we had an earthquake at one of our wafer foundry suppliers*	*After being notified of the disruption, we inventoried the affected products and evaluated the effects on the supply chain (enough buffers yes/no, alternative supply/dual sourcing yes/no). After the conclusion, we worked with the supplier on the most critical cases without affecting the supply to the end customer*

(continued)

Table 4 (continued)

Disruption type	Case	Examples	Disruption recovery measures
Supplier disruption	C	*Bankruptcy of a second-source supplier*	*We qualified further potential suppliers as a recovery measure and expanded our second-source strategies*
	D	*Force majeure at supplier*	*We set up a task force team (purchasing, SCM, Business Units) as an interface to the plants and had meetings to solve the problem (tools for identifying the affected raw and customer part number on site). Return on capital was calculated within 12 h*
	G	*One supplier had problems in production; the second-source supplier could not deliver the material in time*	*We bought the same material from a distributor at a higher price*
	H	*Three weeks of production stoppage due to supply interruption at supplier*	*Missing parts were substituted with similar parts*

effect, as other suppliers can barely help with the shortage of special materials. The disruption recovery measures of company D in the event of a material shortage begin with an allocation process of limited resources from all other locations of the disturbed supplier and suppliers from the multiple sourcing strategies. The worst case scenario is to be dependent on a broker as a last resort.

The responses about risk mitigation methods and disruption recovery measures show that the focus is once again on dealing with supplier disruptions (H1) and that an established crisis management team is necessary.

In order to further investigate the SCRM measures of the cases surveyed, the participants were asked to describe what could have been done better in the event of a disruption. Company B's SC innovation manager, who experienced a fire at the supplier's production site, realized that a systematic SC incident management routine was missing and this led to nontransparent information exchange and miscommunications. The respondent learned that a company's roles and the human behavior of both the company and their suppliers in disruption risk management have a significant impact on final performance. The company has therefore implemented a formula for considering the performance of human behavior in its discrete event simulation model.

Further findings from the disruptions experienced are that (1) data accuracy in the systems used is absolutely essential for enabling quick reactions on the customer side (Case D), (2) coordination between different departments in large companies is difficult (Case G), and (3) the management of a higher safety stock level in a central warehouse is necessary to ensure a Europe-wide supply in case of material shortage (Case I). The empirical data confirm how important it is to communicate clearly within a company and to work closely with suppliers so that it is possible to react quickly and flexibly depending on the type of disruption and minimize its effects on overall SC performance. These findings reinforce hypothesis H3.

4.4 Chances of Digital Technologies in Supply Chain Management

To explore digital technologies as resilience and efficiency drivers in SCM, the participants were asked about the use of digital technologies in their company operations and support in case of disturbances. Digital technologies were evaluated in terms of utility on a scale from 1 (highest degree of utility) to 6 (lowest degree of utility), and in terms of cost of implementation, using a scale from 1 (very high costs) to 6 (very low costs). Table 5 provides an overview of digital technologies used by the participants. Empty fields in the table represent cases where respondents did not have knowledge of costs, or do not apply the technology.

BDA and ERP systems are used by all nine companies surveyed while trace and tracking systems were used by eight companies. These three technologies have high utility for the participants, but are also associated with medium to high costs. Indus-

Table 5 Digital technology application to SC disruption risk management

Case digital technology	A	B	C	D	E	F	G	H	I	Sum
Big data analytics	++	++	++	+++	++	++	++	+++	+++	9
Industry 4.0 applications		+		+++		++	++	+		5
Additive manufacturing technology		+		+++		+	+	++		5
Advanced T&T technologies	+++	++	+++	+++	++	+++	+++	++		8
ERP system	+++	++	+++	+++	+++	+++	+++	+++	+++	9

Ranking 1–2: (+++) high degree of utility; ranking 3–4: (++) medium degree of utility; ranking 5–6: (+) low degree of utility

Case digital technology	A	B	C	D	E	F	G	H	I	Sum
Big data analytics	++	++	++	+++	++	++	++	+++	+++	9
Additive manufacturing technology		+				+++	+++	++		4
Advandced T&T technologies	++	++	+++		++	+++	+	+		7
ERP system	+++	++	+++		+++	+	++	+++	+++	8

Ranking 1–2: (+++) high costs; ranking 3-4: (++) medium costs; ranking 5–6: (+) low costs

try 4.0 applications and additive manufacturing technology are only used by five companies. Apart from company D, which sees a very high utility in both applications, the other four companies evaluate these only with a medium to low degree of usefulness, and generally see medium to high costs in the application of Industry 4.0 applications and additive manufacturing technology. The interviewee from the semiconductor industry reported that an advanced planning system, advanced global detailed visibility, advanced detailed reporting, deep learning, simulation, and advanced communication tools are also used in company B. Apart from deep learning, the respondent evaluates the applications with high to very high utility, but also with medium to high implementation and usage costs. The manager in consulting, company E, highlighted the collaboration platform connecting customers with suppliers, noting significant benefits for cooperating partners and medium implementation and usage costs. Cited advantages include the optimization of production planning, support for operational demand processes, and transparency in the placing of transport orders—enabling timely intervention that led to the avoidance of risks and impending bottlenecks.

ERP systems, earlier mentioned as a common industry application, have also been identified by seven companies as the most supportive technology for disruption management. According to the respondents, ERP systems make it possible to redirect the material flow of suppliers, warn of bottlenecks, and gain insight into stock levels. ERP is also considered useful for SC analysis and mid-term demand planning.

The business process manager of the company C stated: "*ERP and trace and tracking systems support operational disruption management. Big data analytics are mainly used for strategic risk reduction by evaluating supplier performance (especially quality performance). The main purpose of digitalization is to optimize operational performance.*"

The widespread use and evaluation of very high utility of digital technologies certainly bring opportunities to implement them in SCRM. Analogous to findings in the literature, empirical data confirm hypothesis H4, the opportunities, and potential benefits of digital technologies.

4.5 Impact of Digital Technologies on Supply Chain Resilience

To answer the research question regarding digitalization's influence on SC's resilience, respondents reported on how digital technology supports, or could support, the process of risk mitigation and disruption recovery. Table 6 displays the summary of the individual results (ranked from 0: low to 10: high).

In particular, T&T and ERP systems, but also BDA and Industry 4.0 applications are seen to help increase SC resilience in the pre- and post-disruption phases, through real-time monitoring. Visibility and predictability in the SC are achieved primarily through BDA and ERP systems in both phases. ERP and also T&T systems provide participant E with a clear overview of the current system status and the effects of the management measures implemented. The ability to mitigate and resist risk is supported by BDA that improve the reliability of material supply and by Industry 4.0 applications, improving the reliability of production systems. The ability to recover from disruption is mainly driven by BDA, Industry 4.0 applications, and ERP systems. Rapid prototyping is also assessed as a factor increasing SC resilience in the post-disruption stage. The importance and popularity as well as the inflexibility of ERP systems in SCRM are once again emphasized by the following statement of the respondent F: "*Our ERP system (and the linked Advanced Planning Tool) is the most important tool. All necessary information can be found here. It would help if we could do a better scenario analysis (what-if analysis), but ERP systems are usually not built for it.*"

Besides the technologies used so far, respondent D would benefit from a risk pre-warning system in SCRM, so that they can react quickly to earthquakes, hurricanes, and capacity bottlenecks and form emergency teams.

Although individual answers do not provide fully conclusive results, it is notable that additive manufacturing was almost never mentioned. Interviewee H said that they do not know the technology well enough, but considers 3D printing to be inconceivable in risk management and unhelpful in automotive production. Possible advantages are the production of small batches, customer-specific components, or rare spare parts, but it might not be suitable for mass production, according to

Table 6 Influence of digital technology on SC resilience

Do these digital technologies help to increase SC resilience (risk mitigation at the pre-disruption stage) by improving the following:	BDA	Industry 4.0	Additive manufac-turing	T&T systems	ERP systems
Real-time monitoring	5	5	0	8	7
Visibility, predictability	7	5	0	5	7
Material supply reliability	8	5	0	5	6
Production capacity reliability	6	7	0	3	6
Do these digital technologies help to increase SC resilience (disruption recovery at the post-disruption stage) by improving the following:	**BDA**	**Industry 4.0**	**Additive manufac-turing**	**T&T systems**	**ERP**
Real-time monitoring	3	5	0	5	6
Visibility, predictability	5	5	1	5	6
Material supply reliability	5	4	1	3	6
Production capacity reliability	5	5	2	2	6

Ranking from 0 (low) to 10 (high)

the interviewee. The insights offered by the respondents show that hypotheses H6 and H7 are supported. However, some digital technologies are still inflexible and not yet mature, or companies have not yet had contact with additive manufacturing in a way that best supports their company's ability to minimize risks and recover from disruptions.

The insights offered by the respondents generally support hypotheses H6 and H7. However, some digital technologies are still immature and inflexible, or like additive manufacturing, not tried out or well understood.

4.6 Contribution of Digital Technologies to Ripple Effect Control in Supply Chain Disruption Risk Management

Since resilience contributes to ripple effect control, this section summarizes these findings and supplements them with an explicit questioning of the participants about their ripple control measures. BDA supports ripple effect control in both the pre- and post-interruption phases. Participants emphasized the visibility and predictability of SCs through data availability. Data enable better demand forecasting and reduce the risk of demand interruptions. Real-time coordination allows faster decision-making, which is critical for responding to disruptive events. According to the findings from the literature, respondents find advanced T&T systems in combination with ERP systems helpful for collecting real-time data. The possibility of real-time monitoring reduces time risks caused by delays in the SC processes and enables better emergency planning in the event of a malfunction.

The risk manager, company H, explains that BDA's data helped him to react more quickly when a plant caught fire. BDA informed him about the event one day earlier than the media and gave him a decisive time advantage over competitors in buying components from distributors before all products were sold out. The storm surge in Fukushima, 2011, was also mentioned by interviewee H. As a rule, other stages of the value chain are not known, but semiconductors that are not purchased directly are an exception. This allowed the risk manager to react to the storm surge at an early stage, to supply own suppliers with purchased products and thus to ensure the own automobile production. A possible ripple effect could be prevented in this way.

Participants were concerned about data security not only in relation to BDA. At this point, consulting manager (company E) emphasizes the advantages of the SC collaboration platform. The data exchange is outsourced on the platform and no access to the ERP systems of the customers and their suppliers is necessary. Data provided visualizes the current future demand, the current stock situation of the customer, and also simulates future shipments. According to the experiences of the respondent, the increased SC transparency reduces the risks of demand and supply interruptions as well as ripple effect risks and improves SC coordination and SC performance.

The ripple effect control and SC collaboration of company C are supported by ERP systems. Data availability enables preventive SCM and improved supplier selection. Suppliers are integrated into the ERP system through an interface that receives reports on the quality of suppliers. If the supplier is involved and identifies possible quality management deficiencies at an early stage, it is possible to reschedule production. In addition, the main suppliers are audited regularly. Risks and possible measures are jointly defined within the framework of process failure mode and effects analysis.

3D printing can assist companies in controlling the ripple effect through faster response to demand fluctuations and other disturbances, and by reducing adverse impacts through greater production flexibility and shorter lead times. However, additive manufacturing is not perceived as suitable for mass production in the empirical study. This perception may be due to the focus on large companies in the study that primarily produce in large batches. Empirical studies demonstrate the contribution of digital technologies to ripple effect control. Nevertheless, many participants were still concerned about data security.

5 Empirically Derived Contribution of Digital Technologies in Supply Chain Disruption Risk Management

The hypotheses tested by questionnaires and supplemented by theory allow the following qualitative statements to be derived. Empirical data from multiple case studies prove the literature-based hypotheses in the segment of disruption risks in SCM (Hypotheses H1-3) to be true. There is a clear focus on supplier disruptions in the experiences of the participants and their risk management measures. Effective collaboration with suppliers, transparent exchange of information, and consideration of the human behavior of all actors appear to be a key factor for successful risk management.

The second segment of hypotheses (H4–5) studied the influence of digital technologies on SCM. BDA, Industry 4.0 applications, additive manufacturing technology, T&T systems, and ERP systems were identified in the literature as main groups of digital applications and could also be confirmed by the experiences of the participants. Especially, BDA, ERP, and T&T systems appeared to be most useful. In literature, however, the utilization and popularity of ERP systems have been underestimated. In the empirical analysis, ERP systems have been rated as the most common and supportive application for dealing with disruptions. But it has also been discovered that ERP systems are not flexible enough when it comes to rapid data changes. The inflexibility of ERP systems could be a driving force behind the implementation of new technologies. In Industry 4.0 applications and additive manufacturing technology, though, it is primarily the high costs of investment and use that are seen as impediments. The cost factor and inestimable benefits discourage companies from acquiring new digital technologies, even when the potential for considerable gain exists. Another finding from empirical data is the companies need for trust, which is necessary for data exchange with external SC collaborators.

The impact of digital technologies on SCRM was analyzed in the third set of hypotheses (H6–9). Digital technologies help to create resilient SCs by increasing the ability to mitigate risks in the pre-disruption phase and recover from disruptions in the post-disruptions phase, and enhance SC efficiency and ripple effect control. Exploratory research confirmed the benefits of BDA, Industry 4.0 applications, T&T systems, and ERP systems. In particular, digital technologies enable better forecasting of disturbances, faster reaction to disruptive events, and improved SC collaboration. The uses, and more importantly, the advantages of additive manufacturing technology, which are highlighted in the literature in terms of simplifying production processes, attaining a competitive advantage or increasing production flexibility and speed, were hardly mentioned. Related reasons could be that companies have not yet had any contact with additive manufacturing technology, the technology does not fit their business, or established systems fear business and SC redesign.

6 Conclusions

The study's empirical analysis developing case studies from a series of interviews with experts from various industries formed a basis for developing a conceptual framework that integrates the various issues in digitalization in SCs. The examination suggests that while most companies would have had experiences with disruptions, supplier disruptions constitute the most severe and significant form of disruption. The focus on supplier disruptions was also reflected in the risk management measures and the digital technologies used for this purpose. BDA, advanced T&T technologies, and ERP systems are frequently used in the pre- and post-disruption phases.

Exploratory research has shown better forecasting of disturbances, faster response to disruptive events, and improved SC collaboration through digital technologies. ERP systems, BDA, T&T technologies, and Industry 4.0 applications, in particular, enable the collection of real-time data and thus guarantee a resilient and efficient SC as well as control of the ripple effect. However, the high costs for the implementation and use of new digital technologies support the popularity of widely used ERP systems despite their inflexibility. The high implementation costs, unsuitability for mass production, and the immense task of SC redesign discourage companies from 3D printing, despite published benefits. Other challenges identified in the multiple case study approaches are the need for standardized interfaces of digital technologies, the need to take into account the human behavior of all actors, and the need for trust between SC actors to enable efficient cooperation between SCs and transparent exchange of information. These aspects seem to be key factors for successful risk management, and should be actively considered by SC managers.

Appendix Hypotheses and Corresponding Interview Questions

Key element studied	Hypotheses and corresponding interview questions
Disruption risks in SCM	
Disruptions (Causes, concerns, experiences)	**H1**: Supplier disruptions have a higher likelihood of appearance
	What are the most important supply chain disruption risks that your company is concerned about? *Which disruption risks did your company experience in the past?* *What are the reasons for the disruptions experienced at your company?*
Disruption impacts (Ripple effect)	**H2**: Disruptions have a serious impact on a large part of the SC
	Identify/estimate impact of one type of disruption on another…e.g., supplier disruptions led to production capacity disruptions which led to …. *Which processes of your supply chain (e.g., outbound logistics) are mainly affected by disruptions and what KPIs (e.g., on-time delivery) do you use to measure the deviations caused by disruptions?*
Risk mitigation and disruption recovery	**H3**: Flexible SC networks are required for successful SCRM
	Please describe how a recent major supply chain disruption was managed. *Is there a disruption recovery process in your company? How it looks like?* *Have you experienced a supply chain disruption that could have been better managed? Please describe the situation and what you would do differently next time.*
Application of digital technologies in SCM	
Chances of digital technologies	**H4**: Chances become visible through the use of digital technologies to date

(continued)

(continued)

Key element studied	Hypotheses and corresponding interview questions
	Which of the following digital technologies do you use in your company's supply chain operations? *Which digital technology (if any) best supported your managing a disruptive event, and how?*
Challenges of digital technologies	**H5**: Challenges in the use of digital technologies are more likely to be associated with obstacles to implementation and data security concerns
	Which functionality in the digital technology was missing when you applied it to disruption mitigation and recovery? *Has digital technology hindered you from making a better decision in case of a disruptive event? Can you describe the situation and the obstacle of digital technology?*
Impact of digital technologies on SCRM	
Resilience by risk mitigation	**H6**: Digital technologies contribute to create resilient SCs by improving risk mitigation capabilities at the pre-disruption stage
	How digital technology does/could support your risk mitigation process? *Do digital technologies help to increase SC resilience at the pre-disruption stage?*
Resilience by disruption recovery	**H7**: Digital technologies contribute to create resilient SCs by improving disruption recovery capabilities at the post-disruption stage
	How digital technology does/could support your disruption recovery process? *Do digital technologies help to increase SC resilience at the post-disruption stage?*
Supply chain efficiency	**H8**: Applying digital technologies in SCRM increases SC efficiency
	Do digital technologies help to increase SC efficiency?
Ripple effect control	**H9**: Digital technologies contribute to ripple effect control in SCRM
	Via *additional questions by telephone*

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Resilience and Agility: The Crucial Properties of Humanitarian Supply Chain

Rameshwar Dubey

Abstract In this chapter, we theorize and test a model to study the impact of agility and resilience on humanitarian supply chain performance. Here, supply chain agility and supply chain resilience are explained based on existing literature. We have undertaken an extensive literature review to build up the theory and further tested the theory using confirmatory factor analysis (CFA). The multivariate statistical analyses suggest that supply chain agility is an important property of pre-disaster performance, and supply chain resilience is an important property of the post-disaster performance, in humanitarian supply chain network. The present study attempts to further existing literature, and outlines limitations and further research directions.

1 Introduction

In recent years, the field of humanitarian supply chain design has attracted burgeoning interest among academics and practitioners (Gunasekaran et al. 2018; Altay et al. 2018). Researchers have argued that the humanitarian supply chain may be guided by similar theories to the commercial supply chain but humanitarian logistics and supply chains require different approaches in order to manage (e.g., Oloruntoba and Gray 2006; Wassenhove 2006; Kovacs and Spen 2007). The design of the humanitarian supply chain is quite challenging as the impact of poor design is quite severe. The aims of the humanitarian supply chain design are to move efficiently and effectively different forms of food, medicines, and medical support to ensure quick recovery (Holguin-Veras et al. 2012). The high failure rate of the humanitarian supply chain network can be largely ascribed to the complexity in humanitarian supply chain. The number of disasters is increasing globally, as in the number of lives affected by disasters (Nagurney et al. 2011). Balcik and Beamon (2008) and Nagurney and Qiang (2009) pointed out that the number of disasters and catastrophic events has increased in last two decades and the impacts on human lives have also nearly dou-

R. Dubey (✉)
Montpellier Business School, 2300 Avenue Des Moulins, 34000 Montpellier, France
e-mail: r.dubey@montpellier-bs.com

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bled. However, although we can see a significant increase in the number of disasters and their impacts on human lives, there is acute shortfall in the relief provided by the various sectors that includes food, health, water and sanitation, shelter and non-food items, and economic recovery and infrastructure needs (Nagurney et al. 2011).

While there is rich body of literature on humanitarian supply chain network design (Maon et al. 2009; Nagurney et al. 2011; Vlachos et al. 2012; Bhattacharya et al. 2014), the extant literature has failed to reflect on the humanitarian supply chain network properties. Childs (2013) attempted to explain the behavior of humanitarian aid workers in assessing the level of risk using cultural theory. The current literature on the humanitarian supply chain is either focusing on overviews or applications of operational research tools in designing humanitarian supply chain networks. In the past, behavioral operations management theory has not been explored fully in explaining the complex nature of the disaster relief supply chain. Hence, in our present study, our aim is to develop a disaster relief supply chain network and further try to explain the properties of the humanitarian supply chain network using cultural theory, and further test the impact of these supply chain properties on humanitarian supply chain performance. The rest of the chapter is organized as follows. In second section, we have outlined the state of the art and develop our theoretical framework. Subsequent sections develop a research model based on this framework, describe the construct operationalization and data collection method, present the data analysis and the results of model testing, and discuss the findings and their theoretical and managerial implications. This paper concludes with directions for further research.

2 Theoretical Framework

The foundation of our theoretical framework (see Fig. 1) comprises two elements: supply chain network theory and cultural theory. In recent years, supply chain network theory (Halldorsson et al. 2007; Hearnshaw and Wilson 2013) has emerged as a powerful theory to explain supply chain network design (e.g., Braziotis et al. 2013; Dai et al. 2014). We argue that supply chain network theory will provide an explanation into the properties of the humanitarian supply chain network. We further argue that the cultural theory will offer interesting insights to explain the complex nature of the humanitarian supply chain network. Our theoretical framework is grounded in the proposition that supply chain network properties are under the moderating effect of organizational culture. In our present research, we have adopted the supply chain design principles of Melnyk et al. (2014). Here, our framework has included all three elements, i.e., (i) influencers, (ii) design decisions, and (iii) building blocks.

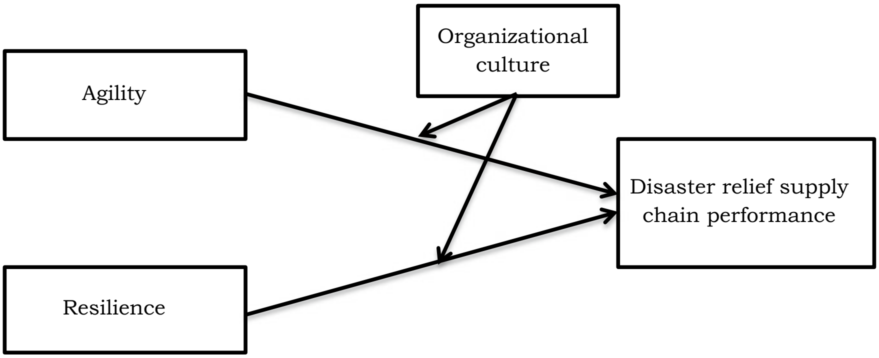

Fig. 1 Theoretical framework

2.1 Agility

Supply chain agility in recent years has attracted significant contributions; however, supply agility as a property of the supply chain network was popularized by Lee (2004). However, Christopher (2000) and Christopher and Towill (2001) attempted in their research to provide a theoretical foundation to explain an agile supply chain. Yusuf et al. (2004) further argue in their study how an agile supply chain can provide a competitive edge to the organization. However, Oloruntoba and Gray (2006) argue that agility in supply chain networks is crucial characteristics to move humanitarian aid to disaster-affected victims. The humanitarian supply chains are particularly short lived and quite unstable. Hence, in the absence of long-term planning, the humanitarian supply chains must possess speed and flexibility to respond to the disaster-affected victims with the necessary humanitarian aid, which includes health, food, water and sanitation, shelter and non-food items, and other infrastructure needs (Dubey and Gunasekaran 2016). There is a rich body of literature which has attempted to provide theoretical and functional definitions of the agile supply chain (e.g., Christopher 2000; Lee 2002, 2004; Swafford et al. 2006; Li et al. 2008, 2009; Dubey et al. 2018a, b; Aslam et al. 2018); however, in humanitarian supply chain literature the concept of agility is still underdeveloped. In the past, researchers have recognized the universal need for building agility in humanitarian supply chain networks (e.g., Trunick 2005; Wassenhove 2006; Kovacs and Spen 2007; Li et al. 2009; Holguin-Verras et al. 2012; Cozzolino et al. 2012). Sometimes, agility can be mistaken with other similar but different concepts, such as adaptability, flexibility, and resilience (Charles et al. 2010). Agility is the property of a supply chain network which enables the network to deal with and take advantage of uncertainties and volatilities, while adaptability is used for more profound medium-term changes. Flexibility, on the other hand, is the characteristic of "agility" that enables supply chain networks to deal with uncertainties and volatilities.

2.2 Resilience

Scholars have attempted to provide an overview of resilience and the use of the term in various contexts in the management literature (Bhamra et al. 2011; Ivanov et al. 2014, 2017, 2018; 2019; Ivanov and Dolgui 2018; Dolgui et al. 2018; Altay et al. 2018). Burnard and Bhamra (2011) attempted to develop a conceptual framework for organizational resilience and offered further research directions. Sheffi (2005) has attempted to offer another functional definition of supply chain resilience. Supply chain resilience has been defined as the property of a supply chain network which enables the supply chain network to regain its original configuration soon after the decay of disturbing forces that include earthquakes, floods, hurricanes and tropical storms, tornadoes, tsunamis, diseases, etc. Soon after a disaster, the resilience in the humanitarian or disaster relief supply chain will determine the return to a normalcy phase through collaboration among the various actors in the supply chain network (Boin et al. 2010; World Economic Forum 2013; Ivanov et al. 2013; Ivanov and Sokolov 2013). In recent years, Zobel (2011a) and Zobel and Khansa (2014) have attempted to define disaster resilience and provided a quantitative model to assess resilience in the disaster relief supply chain. Tierney and Bruneau (2007) proposed "The Resilience Triangle" (see Fig. 2) which helps to analyze how various supply chain strategies can reduce the size of the supply chain triangle. To further buttress our resilience triangle concept we reviewed some existing literature (Bruneau et al. 2003; Tierney and Bruneau 2007; Zobel 2011b). Bruneau et al. (2003) introduced the resilience triangle concept. To measure loss of resilience, Bruneau et al. (2003) introduced a mathematical equation to determine the loss of resilience as

$$\mathrm{R} = \int_{to}^{t} [100 - Q(t)]dt$$

Here, R = loss of resilience and Q (t) = quality of infrastructure as a function of time.

When any disaster, in any form strikes, the quality of the infrastructure decreases, as shown by dipping vertical line, and then is restored to normalcy as time passes (shown along horizontal axis). Bruneau et al. (2003) argued that in order to improve rapidity, the height of the triangle should be less [i.e., (to-t) → 0] or, in order to reduce the depth, the resistance property in the supply chain network needs to be built. This is termed as robustness and is one of the desired dimensions of resilience. In simple language, an attempt needs to be made to decrease the area measured by

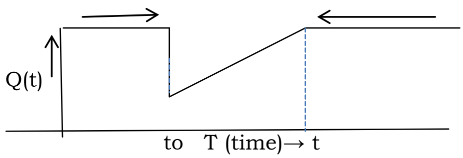

Fig. 2 Resilience triangle [Adapted from Bruneau et al. (2003)]

the triangle. This has been used in recent years to measure the resilience of physical infrastructure elements such as hospitals (Zobel 2011a). In our present research, we further use the modified TOSE resilience framework of Tierney and Bruneau (2007) that includes technical domain, organizational resilience, societal perspective, and economic resilience. Day (2014) attempted to explain the resilience property in a disaster relief supply chain using complexity theory and a systems resilience approach. Day (2014) identified three key elements in any resilient supply chain: (i) topology (path lengths, redundancies, clustering, etc.); (ii) entities (nongovernmental organizations, military, third-party logistics providers, government agencies, military, donors, media, etc.); and (iii) environment.

2.3 Organizational Culture

Mitra and Singhal (2008) have argued the importance of building integration in a supply chain network. Further, Braunscheidel et al. (2010a) have stressed the importance of organizational culture on supply chain integration. Cadden et al. (2013) further investigated the impact of culture on supply chain network design; however, studies on the influence of organizational culture on supply chain network design or any area of operations management are very limited (McDermott and Stock 1999). Ravasi and Schultz (2006) argued that organizational culture is a set of shared mental assumptions which guide the behavior of people in an organization. In our case, we try to extend the definition of Ravasi and Schultz (2006) to the supply chain network. We have attempted to extend Needle's (1994) definition that organizational culture is a set of values, beliefs, and principles of the humanitarian supply chain actors and is a product of history, service, types of employees, management styles, and national culture. Childs (2013) attempted to explain security strategies for humanitarian aid workers using cultural theory. Douglas (1999) proposed a four culture theory which is quite useful in explaining the behavior of disaster relief supply chain actors. Here, we argue that organizational culture may have a moderation effect on disaster relief supply chain network design and disaster relief supply chain performance. Furthermore, how culture moderation effects can influence the humanitarian supply chain performance during the pre-disaster and post-disaster phases is explored.

2.4 Pre-disaster and Post-disaster Phase Performance Measures

The United States Federal Emergency Management Agency (FEMA 2008) stated that even a highly developed nation, the United States, is prone to disasters that could be from chemicals, terrorist attacks, flood, etc. In response to a potential threat and the magnitude of the impact that can be caused by these possible sources of disasters, the US Congress passed the Disaster Mitigation Act in 2000 (United States Congress 2000). However, our aim is to understand how various bodies like FEMA have formulated a structure to improve the preparedness level and make the response action effective. It requires effort to pool the resources which includes identification of the warehouse location, sufficient support humanitarian aid workers with right kind of attitude and skill, sufficiently large quantity of humanitarian aids, availability of transport vehicles, and enough money to acquire any kind of resource when needed.

2.4.1 Pre-disaster Phase

The preparedness phase of the humanitarian supply chain network actors is critical to the pre-disaster performance. It enables a reduction in the number and severity of the disasters, through prevention and mitigation, as well as improved emergency response, through preparation and planning. We argue that prevention/mitigation and planning/preparedness may differ theoretically but sometimes there are significant overlaps which contribute to the ultimate goal of vulnerability reduction. Hence, for vulnerability reduction, policy development is a precursor to vulnerability assessment. We therefore argue that agility in the humanitarian supply chain network may prove to be highly beneficial in case of vulnerability reduction. We have argued in the preceding section that dynamic sensing, dynamic flexibility, and dynamic speed together constitute an agile humanitarian supply chain network. However, the resilience property in this phase is also important in building robustness in the humanitarian supply chain network. However, to make it simple, we propose to focus on the agility property in the pre-disaster phase. Oloruntoba and Gray (2006) have argued that agility in the humanitarian supply chain network enables preparation for disaster to be made and further mitigates the vulnerability. We have outlined our pre-disaster performance measures in Table 2.

2.4.2 Post-disaster Phase

The ***post-disaste*r** phase includes the short-term response, and the recovery and reconstruction phase in the long term. The recovery and reconstruction phase is the restoration of all aspects of the disaster's impact on a community, and the return of the local economy to some sense of normalcy. The recovery phase can be broken down into two periods. The short-term phase typically lasts from 6 months to at least a year. It involves the delivery of immediate services to victims in the form of medical aid, food, drinking water, building materials to construct damaged infrastructure, clothing, and other necessary materials. Communities must access and deploy a range of public and private resources to enable a long-term recovery. Abidi et al. (2013, 2014) have attempted to develop a framework for humanitarian supply chain performance measurement that can be used to measure pre-disaster and post-disaster performances in the humanitarian supply chain network. The performance measurement dimensions are income from the community, fundraising expenses per household, donor management, donations per households, federated income per households, stock managed by service agreements, donation-to-delivery to deliver, flexibility, cost-effectiveness, stock efficiency, cost recovery, percent of goods delivered, etc. (Abidi et al. 2014). We have outlined the modified items as per the context in India based on the pretesting in Table 2.

3 Research Model and Hypotheses Development

Based on our theoretical proposition, organizational culture moderation between supply chain agility, supply chain resilience, and disaster relief supply chain performance, we develop a research model, as shown in Fig. 3 and propose six research hypotheses.

3.1 Supply Chain Agility and Pre-disaster Performance

During a disaster, mostly due to the unavailability of the supply, emergency responses get affected and result in increased human suffering and loss of life. Hence, it can be argued that the effectiveness of the movement of humanitarian aid to disaster-affected

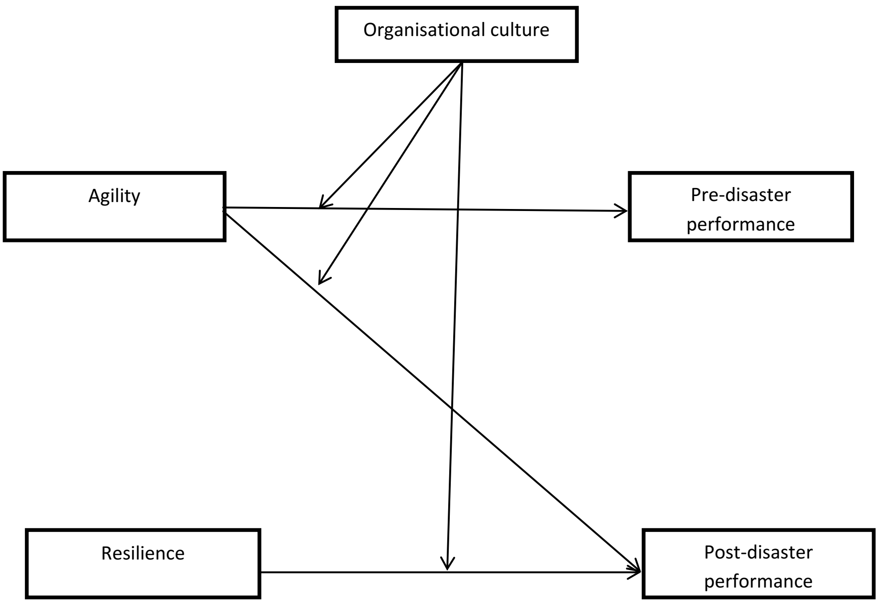

Fig. 3 Research model

victims, preparedness is vital. Duran et al. (2011) argued that in effective disaster responses, the agility in mobilizing the supplies and the effectiveness in distributing them is critical. However, the effectiveness of the responses is dependent on the amount of preparedness. Oloruntoba and Gray (2006) argued in their research that agility in humanitarian and disaster relief supply chain networks is a desired property, as emergency responses are short and quite unpredictable. We therefore hypothesize that:

H1: Agility in a disaster relief supply chain network has a positive impact on pre-disaster relief supply chain performance.

3.2 Supply Chain Agility and Post-disaster Relief Supply Chain

During the response phase, the agility in humanitarian and disaster relief supply chain network is essential for the successful distribution of humanitarian aid to the disaster-affected victims. The response time is critical to human life. Oloruntoba and Gray (2006) have argued the need for agility in humanitarian and disaster relief supply chain networks. Pettit and Beresford (2009) argued that right time, right place, right condition, and right quantity are essential features of humanitarian logistics. We therefore hypothesize:

H2: Agility in a disaster relief supply chain network has a positive impact on the post-disaster relief supply chain performance.

3.3 Moderating Effects of Organizational Culture

Study on interaction effects of organizational culture with humanitarian and disaster relief supply chain networks is underdeveloped (Richey 2009). Richey (2009) argued that the disaster relief supply chain literature is still at a nascent stage and there is an immense opportunity for empirical research. In the past, researchers from the general management community have theorized and demonstrated that organizational culture leads to adopting management practices consistent with the culture, and that these practices are associated with organizational performance. However, there is scant literature focusing on the impact of organizational culture in the operations and supply chain management literature (Braunscheidel et al. 2010b). In recent years, the organization culture and its interaction effect on the supply chain network have attracted significant contributions (e.g., Braunscheidel and Suresh 2009; Braunscheidel et al. 2010a; Cadden et al. 2013; Blome et al. 2013). We therefore argue that organizational culture has a significant moderation effect on supply chain network design. Based on the preceding discussion, we therefore hypothesize:

H3: Organizational culture has a moderating effect on the link connecting agility and pre-disaster performance.

H4: Organizational culture has a moderating effect on the link connecting agility and post-disaster performance.

H5: Organizational culture has a moderating effect on the link connecting resilience and post-disaster performance.

3.4 Resilience Supply Chain and Post-disaster Relief Supply Chain

The resilience property of a disaster relief supply chain has attracted significant contributions from researchers in recent years (e.g., Day 2014; Scholten et al. 2014; Zobel and Khansa 2014). Bruneau et al. (2003) have further argued that the resilience property has four dimensions which include robustness, redundancy, resourcefulness, and rapidity. However, they have further debated using the resilience triangle, that is, by improving robustness and rapidity, the resilience of the infrastructure can be improved. Hence, when disaster strikes, robustness in the humanitarian supply chain network mitigates severity and rapidity further helps to recover to the normalcy phase. Zobel (2011b) further argued that inherent social resilience, which is difficult to quantify has an important role to play during the post-disaster phase. We therefore argue that resilience in a disaster relief supply chain network is a prerequisite for a post-disaster relief supply chain network. Hence, we hypothesize:

H6: The resilience property in a disaster relief supply chain network has a positive impact on post-disaster relief supply chain performance.

4 Research Design

4.1 Operationalization of Constructs

We used a survey-based approach to test our model and research hypotheses. A questionnaire was developed by identifying relevant measures from an extensive literature review. The questionnaire is consolidated into two sections.

Section 1

This section includes the name of the organization and information on individuals such as gender, age, number of years of experience, and awareness related to humanitarian relief activities.

Section 2

This section includes questions related to agility, resilience, culture, and disaster performance measures. The questions are mixed, and both positively and negatively worded questions are used to avoid bias. The objective of this section is to gage the perception of the respondents, who are part of the humanitarian relief supply chain network. The respondents were asked to give a rating on a five-point Likert scale (i.e., 1 = strongly disagree, to 5 = strongly agree).

Some modifications were made in the existing constructs to make it suitable for the disaster relief supply chain network. Since target organizations are the entities or humanitarian supply chain actors which are part of disaster relief supply chain network (i.e., nongovernmental organizations, military, government agencies, transporters, local people, local police, donors, etc.), a panel consisting of experts in the disaster relief supply chain network examined the validity of the items. For the purpose of pretesting, 15 experts were identified from the databases of CILT India, the Asian Council of Logistics Management and the CII Institute of Logistics. A few changes to the scales were made in order to match the Indian context. Before consulting these experts, we checked the background of the experts. One is a senior member of the Asian Council of Logistics Management and CILT. Hence, the close association with these professional bodies has helped us to learn about their level of involvement in past and current involvement in disaster relief activities. Some experts are editorial board members of reputable journals like Journal of Humanitarian Logistics and Supply Chain Management and Humanitarian Logistics Association. We ensured that all the pretest candidates had the knowledge required to improve the quality of our measurement. All the exogenous and endogenous constructs are operationalized as shown in Table 1.

4.2 Data Collection

The structured questionnaire was e-mailed to senior members of the Asian Council of Logistics Management, which is an Indian-based professional society based in Kolkata, India, the CILT India, as well as the Indian Institute of Railway Logistics and Materials Management, senior police officers of Maharashtra, Uttar Pradesh, and Uttarakhand, reputable NGOs specially engaged in disaster management, logistics service providers who specialize in humanitarian logistics, government departments, and academicians engaged in the disaster or humanitarian logistics field. Over 1750 questionnaires were sent out of which 378 questionnaires were returned, and 319 questionnaires were found suitable for further analysis. After following up with respondents who did not respond to the earlier questionnaires, the number increased to 350, which represents a 20% response rate. The frequency distribution of the respondents is presented in Table 2. Information related to the number of male/female respondents, age of respondents, and the number of years of experience is not presented, as these variables are not considered in the proposed hypothesis formulation.

Table 1 Building blocks of research model and their items

Construct	References	Items
Agility in disaster relief supply chain network	Li et al. (2009)	• Dynamic sensing • Dynamic flexibility • Dynamic speed
Resilience in disaster relief supply chain network	Tierney and Bruneau (2007), Zobel and Khansa (2014)	• Robustness • Redundancy • Resourcefulness • Rapidity • Technical capabilities • Organizational resilience • Social dimensions which include population and local group which are either vulnerable or adaptable to disasters and hazards • Economic ability to build resources
Organizational culture	Detert et al. (2000)	• Truth and rationality among supply chain partners • Motivation toward humanitarian work • Cooperation • Commitment • Coordination • Responsibility • Orientation to work
Pre-disaster performance	Abidi et al. (2013, 2014)	• Availability of humanitarian aid • Right humanitarian aids • Right place • Right quantity • Right quality
Post-disaster performance	Abidi et al. (2013, 2014)	• Right time • Quick recovery • Time taken to regain its normal life • Life saved • Restoring communication • Reconstructing roads and bridges

Table 2 Responded questionnaires

Departments		Targeted respondents	Questionnaires received	%
Senior government officers of India		140	15	10.71
Maharashtra state police	Senior police officers	75	15	20
UP state police	Senior police officers	150	25	16.70
Uttarakhand state police	Senior police officers	50	15	30
Asian Council of Logistics Management	Senior members	75	50	66.67
CILT India	Fellows	25	20	80
	Chartered members	100	30	30
Indian Institute of Railway Logistics & Materials Management		150	30	20
Goonj NGO		250	50	20
Hope Foundation		175	25	14.29
Blue Dart	Senior managers	75	10	13.33
Corporate Disaster Resource Network (CDRN)—India		250	25	10
Indian Red Cross Society		220	30	13.64
Academicians who are engaged in research related to humanitarian supply chain		15	10	66.67
Total		1750	350	20

4.3 *Nonresponse Bias*

A nonresponse bias test is highly recommended by statisticians for survey data, regardless of the achieved response rate (e.g., Armstrong and Overton 1977; Barriball and While 1999). There are various available nonresponse bias methods or techniques with different strengths and limitations. The **Wave Analysis** technique is used in this study as it is (1) a widely used method, (2) inexpensive, (3) less time consuming, (4) low in data requirements, and (5) reasonable and coherent within the paper context.

It is also known as the linear extrapolation method (Armstrong and Overton 1977). In our study, there were two mailing periods:

Wave 1: E-mail the online questionnaire accompanied by an information and consent form and
Wave 2: Send a reminder to those who had not responded after 6 weeks.

The differences in the waves (wave 1 = initial respondents and wave 2 = late respondents) were analyzed. The statistical difference was estimated using the t-test, with a p-value of less than or equal to 0.05 being considered to be statistically significant. In this case, it was found that the responses from the two waves were not statistically significantly different from each other. It can therefore be concluded that nonresponse bias is not a major issue in the study.

5 Data Analyses and Results

5.1 Assumptions Test

The indicators checked for constant variance, outliers, and normality. It is important to check these properties, before one proceeds in evaluating the reliability and validity of the measurement items or elements. We have checked the Mahalanobis distances of the predicted variables to identify multivariate outliers (Cohen et al. 2013). It is a very conservative approach, but highly useful in checking the normal distribution of data (i.e., maximum magnitude of skewness and kurtosis. In our case, we found these values to be 1.139 and 1.261, respectively, well within the limits recommended by past researchers (univariate skewness < 2, kurtosis < 7) (Curran et al. 1996). The plots as well as the statistics both suggest that the deviances are not significant. We further checked multicollinearity using variance inflation factors (VIF). However, in our case, the VIFs were slightly higher than 10. We also tested the moderation effect, as the VIF tended to be high (see Baron and Kenny 1986). We used confirmatory factor analysis (CFA) to establish the construct validity (i.e., convergent validity and discriminant validity). We have presented the fit indices in the tabulated form as follows:

From Table 3, we can see our goodness of fit indices were well within specified limits (Hu and Bentler 1999; Hooper et al. 2008). From this, we can conclude that our research model (see Fig. 2) fits well with our collected data, using a structured questionnaire. To further check discriminant validity, we compared the squared correlation between two latent constructs to the average variance extracted (AVE) (Fornell and Larcker 1981). The split survey was adopted in our study to reduce the likelihood of common method bias; however, common method bias still occurs. In such a situation, we performed Harman's single-factor test as suggested by Podsakoff et al. (2003). We performed exploratory factor analysis by entering all the variables in SPSS 20.0. The variables were further reduced to six latent factors using principal

Table 3 Goodness of fit indices

Index	Observed value	Recommended value
Normed chi-square	1.73	$<2^a$
Root mean square error for approximation (RMSEA)	0.05	<0.08
Comparative fit index (CFI)	1.3	>0.9

([a]*Hooper et al.* (2008) *recommend a maximum value between 2 and 5. However, we have assumed a maximum cut-off limit as 2*)

component analysis (PCA) (varimax rotation). The Kaiser–Meyer–Olkin measure of sampling adequacy is 0.74. The extracted six latent factors had eigenvalues greater than 1.0, covering nearly 67% of the total variance. The first latent factor had nearly 21.1% of the total variance, thus we can conclude that common method bias is not a serious issue in our study.

The standard loadings were in all cases greater than 0.7 (see Table 4), with considerably higher t-values ($p < 0.01$), scale composite reliability greater than 0.7 and average variance extracted (AVE) greater than 0.5 (see Table 4). Therefore, we can assume that our constructs of the research model (see Fig. 2) possess convergent validity. From Table 5, we can see that the square root of the average variance extracted is found to be greater than the square of the correlation between any two constructs in a given column. This indicates that our constructs (see Fig. 2) possess discriminant validity.

5.2 *Hypotheses Tests*

The research hypotheses were tested using regression analysis. We used multiple regression analysis which may be regarded as a conservative method in comparison to the covariance-based approach or variance-based approach. In our case, we checked our assumptions and we found that regression analysis can be used for testing our research hypotheses. The hypotheses test results are presented in Table 6 as follows:

From Table 6, it can be seen that our six research hypotheses, which we identified to test our research model (see Fig. 2), are supported. The first hypothesis (H1), which we have theorized based on our extensive literature review, explains nearly 7.3% of the pre-disaster performance and the beta coefficient is 0.270 which is statistically significant at $p = 0.002$, and suggests that agility in a humanitarian supply chain network is a significant construct. The result of our statistical analysis has supported the claim of past researchers (e.g., Oloruntoba and Gray 2006; Duran et al. 2011).

Table 4 Overview of constructs and their items (factor loadings, composite reliability, average variance extracted, and Cronbach's alpha)

Constructs	Items	Factor loadings	Cronbach's alpha
Agility in disaster relief supply chain (X1) CR = 0.775 AVE = 0.535	Dynamic sensing	0.726	0.722
	Dynamic flexibility	0.722	0.731
	Dynamic speed	0.746	0.721
Resilience in disaster relief supply chain (X2) CR = 0.904 AVE = 0.612	Robustness	0.711	0.716
	Redundancy	0.759	0.711
	Resource fullness	0.731	0.764
	Rapidity	0.811	0.743
	Social dimensions	0.911	0.711
	Economic ability	0.756	0.734
Organizational culture (X3) CR = 0.807 AVE = 0.568	Truth and rationality toward partners	0.759	0.711
	Motivation	0.764	0.714
	Cooperation	0.763	0.754
	Commitment	0.745	0.789
	Coordination	0.789	0.719
	Responsibility	0.699	0.767
Pre-disaster performance (Y1) CR = 0.881 AVE = 0.712	Availability of humanitarian aid	0.821	0.714
	Right place	0.844	0.733
	Right quantity	0.866	0.798
Post-disaster performance (Y2) CR = 0.862 AVE = 0.557	Right time	0.703	0.728
	Quick recovery	0.660	0.720
	Life saved	0.745	0.732
	Time taken to regain its normal life	0.878	0.715
	Restoring communication	0.728	0.729

Note CR = $(\sum \lambda i)^2/((\sum \lambda i)^2 + \sum \varepsilon))$, where λi denotes standard factor loadings and ε denotes error

Table 5 Correlations among constructs

Constructs	X1	X2	X3	Y1	Y2
X1	**0.731**[a]				
X2	0.097[b]	**0.782**[a]			
X3	0.013[b]	0.202[b]	**0.754**[a]		
Y1	0.04[b]	0.371[b]	0.000[b]	**0.844**[a]	
Y2	0.098[b]	0.032[b]	0.053[b]	0.095[b]	**0.746**[a]

([a]represents $\sqrt{\text{AVE}}$ and [b](Coefficient of correlation)^2)

Table 6 Regression analysis output

Hypotheses	R^2	ß	t-statistic	Significance	Supported/not supported
H1: X1 → Y1	0.073	0.270	3.203	0.002	Supported
H2: X1 → Y2	0.034	0.173	2.136	0.035	Supported
H3: X1 * X3 → Y1	0.070	0.056	3.120	0.002	Supported
H4: X1 * X3 → Y2	0.071	0.045	3.146	0.002	Supported
H5: X2 * X3 → Y2	0.137	0.067	4.4543	0.000	Supported
H6: X2 → Y2	0.047	0.272	2.520	0.013	Supported

The second hypothesis (H2), which assumes that supply chain agility in a disaster relief supply chain network, has a positive impact on post-disaster relief performance. The link (X1 → Y2) explains nearly 3.4% of post-disaster performance and the beta coefficient is 0.035, which is statistically significant at 0.035. The findings suggest that though supply chain agility is an important property of the disaster relief supply chain network, for pre-disaster performance rather than post-disaster performance. The third, fourth, and fifth hypotheses results suggest that organizational culture has an important role to play. The magnitudes of R^2 and the beta coefficient were significantly improved due to the moderation effect of organizational culture. These results support the findings of (Braunscheidel and Suresh 2009; Braunscheidel et al. 2010b; Cadden et al. 2013). However, we believe that our findings are the first attempt to test the theory in a humanitarian supply chain network. The sixth hypothesis (H6) has been theorized based on our review of the extant literature. The statistical analyses indicate that our hypothesis is supported. The link (X2 → Y2) explains nearly 4.7% of the total post-disaster performance. The beta coefficient is 0.272 which is significant at $p = 0.013$. The result of our analysis is found to be consistent with (Day 2014).

5.3 *Discussion*

Our interest in investigating supply chain network theory and cultural theory in the context to humanitarian supply chain network was triggered by two facets of the supply chain design principle of Melnyk et al. (2014) and Day (2014) in contributions to the field of operations and supply chain management theory. The current literature on the humanitarian supply chain revolves around theory building. However, the literature focusing on theory testing is scant. The humanitarian supply chain is quite a complex field. Most of the time, partnerships are formed hastily, resulting in poor coordination and cooperation. This could explain the past failure of efforts in humanitarian supply chains. Tatham and Kovács (2010) attempted to offer a solution to hastily formed disaster relief supply chain networks through a swift trust mechanism. However, swift trust is one of the components of organizational culture and it may differ from case to case. In the absence of any empirical study, we therefore theorized our model based on commercial supply chain success and humanitarian supply chain existing theories. In this way, we have attempted to answer pressing calls, and the findings of our study have both theoretical and managerial implications.

5.3.1 Theoretical Contributions

By empirically validating a research model which we have derived through an extensive literature review, this study offers two unique contributions to the current literature of humanitarian supply chain networks. First, as a novel contribution, we tested the impact of cultural theory on humanitarian supply chain networks. In this way, we have attempted to test the supply chain design principle of Melnyk et al. (2014), all not an extension in the complete sense. Second, we have tested the existing theory in the context of humanitarian supply chain. In this way, we have tested the theory using survey methodology. We have recognized the pending calls of the supply chain and operations management researcher in the context of the humanitarian supply chain, which is still recognized as one of the nascent fields in operations and supply chain management.

5.3.2 Managerial Implications

Many of our findings offer guidance to NGOs, government agencies, transporters, local bodies, and the military. The moderating role of organization culture provides clear direction in that truth and rationality toward partners, motivation, cooperation, commitment coordination, and responsibility which have an important role to play in building effective humanitarian supply chain networks. Agility in a supply chain network which reflects building dynamic sensing, dynamic flexibility, and dynamic speed in a supply chain network can help to improve the preparedness level and further assist to mobilize the resources which are necessary in enhancing pre-disaster performance. Similarly, focusing on robustness, redundancy, resources, rapidity, social dimensions, and economic abilities in humanitarian supply chain networks will help to improve post-disaster performance. We recognize that the idea of offering multiple suggestions to stakeholders may be universally ill-advised because the present study is based on samples collected from one country only.

6 Conclusions

Drawing broadly on supply chain network theory, organizational culture and disaster relief supply chain performance, and the extant literature on the humanitarian supply chain, we have developed a research model and tested it empirically using a data survey instrument. The hypotheses were identified from our theoretical model (see Fig. 2) and tested statistically. The statistical analyses indicate that our model constructs possess construct validity, and the goodness of fit indices further indicates that our research model is sound. The hypothesis testing further confirmed that all our six hypotheses are well supported. The study further supports the extant literature and extends supply chain theory by empirically testing the research model.

6.1 Research Limitations

This study has its own limitations, as in other studies, but these limitations can further provide future research directions. Here, the confounding variables were not controlled. Second, the present analysis is based on cross-sectional data. The causality cannot be established based on cross-sectional data. Third, the present study has not investigated top management commitment. Hence, the outcome of the study could have been slightly different as top management commitment helps to translate the vision into execution.

6.2 Further Research Directions

Based on study limitations and the findings of our study, we have outlined further research opportunities, which can take the present study to the next level. The role of leadership or top management commitment can offer a new perspective to our research model (see Fig. 2). In the past, we have seen that most studies have either used a case study or grounded theory approach to build theory and have used extensive literature reviews, to build theory and to further test it empirically. However, from the methodological point of view, it is suggested that thorough integration of qualitative research techniques such as case research, action research, ethnographic studies, appreciative inquiry, etc., the theory can be built, and further, by using a structured questionnaire, the developed theory can be further tested using a large sample size. In this way, the current body of operations and supply chain literature can be extended.

Note: *This chapter has been prepared based on Altay et al.* (2018) *study. In this chapter, we present different perspectives to explain how agility and resilience are desired crucial properties of disaster relief operations. Hence, we recommend readers to read this chapter as well as Altay et al.* (2018) *to have a complete perspective.*

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Digital Supply Chain Twins: Managing the Ripple Effect, Resilience, and Disruption Risks by Data-Driven Optimization, Simulation, and Visibility

Dmitry Ivanov, Alexandre Dolgui, Ajay Das and Boris Sokolov

Abstract The quality of model-based decision-making support strongly depends on the data, its completeness, fullness, validity, consistency, and timely availability. These requirements on data are of a special importance in supply chain (SC) risk management for predicting disruptions and reacting to them. Digital technology, Industry 4.0, Blockchain, and real-time data analytics have a potential to achieve a new quality in decision-making support when managing severe disruptions, resilience, and the Ripple effect. A combination of simulation, optimization, and data analytics constitutes a digital twin: a new data-driven vision of managing the disruption risks in SC. A digital SC twin is a model that can represent the network state for any given moment in time and allow for complete end-to-end SC visibility to improve resilience and test contingency plans. This chapter proposes an SC risk analytics framework and explains the concept of digital SC twins. It analyses perspectives and future transformations to be expected in transition toward cyber-physical SCs. It demonstrates a vision of how digital technologies and smart operations can help integrate resilience and lean thinking into a *resileanness* framework "Low-Certainty-Need" (LCN) SC.

D. Ivanov (✉)
Department of Business and Economics, Berlin School of Economics and Law, 10825 Berlin, Germany
e-mail: divanov@hwr-berlin.de

A. Dolgui
IMT Atlantique, LS2N, CNRS, La Chantrerie, 4, rue Alfred Kastler, 44300 Nantes, France
e-mail: alexandre.dolgui@imt-atlantique.fr

A. Das
Narendra Paul Loomba Department of Management, Zicklin School of Business, CUNY-Baruch, One Bernard Baruch Way, New York, NY 10010, USA
e-mail: ajay.das@baruch.cuny.edu

B. Sokolov
Saint Petersburg Institute for Informatics and Automation of the RAS (SPIIRAS), V.O. 14 Line, 39 199178 St. Petersburg, Russia
e-mail: sokol@iias.spb.su

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1 Introduction

Digital technologies catalyze the development of new paradigms, principles, and models in supply chain management (SCM). The Internet of Things (IoT), cyber-physical systems, and smart, connected products, facilitate the development of digital supply chains (SC) and smart operations (Fazili et al. 2017; Liao et al. 2017; Qu et al. 2017; Strozzi et al. 2017; Tran-Dang et al. 2017; Yang et al. 2017; Minner et al. 2018; Panetto et al. 2019). Recent surveys by Addo-Tenkorang and Helo (2016), Oesterreich and Teuteberg (2016), Gunasekaran et al. (2016, 2017, 2018), Nguyen et al. (2018), Moghaddam and Nof (2018), Choi et al. (2018), Ben-Daya et al. (2018) proposed classifications of different digital technologies and discussed their potential impacts on SCM. Such digital technologies include big data analytics, advanced manufacturing technologies with sensors, decentralized agent-driven control, advanced robotics, augmented reality, advanced tracking and tracing technologies, and additive manufacturing.

The increasing interest in the digital data applications to SCM is not surprising. The quality of model-based decision-making support strongly depends on the data, its completeness, fullness, validity, consistency, and timely availability. These requirements on data are of a special importance in SC risk management for predicting disruptions and reacting to them (Ivanov 2018b). Digital technology, Industry 4.0, Blockchain, and real-time data analytics have a potential to achieve a new quality in decision-making support when managing severe disruptions, resilience, and the Ripple effect (Frazzon et al. 2018, Ivanov et al. 2017, 2019a).

A combination of simulation, optimization, and data analytics constitutes a digital twin: a new data-driven vision of managing the disruption risks in SC. A digital SC twin is a model that can represent the network state for any given moment in time and allow for complete end-to-end SC visibility to improve resilience and test contingency plans (Ivanov 2018c). This chapter proposes an SC risk analytics framework and explains the concept of digital SC twins. It analyses perspectives and future transformations to be expected in transition toward cyber-physical SCs. It demonstrates a vision of how digital technologies and smart operations can help integrate resilience and lean thinking into a *resileanness* framework "Low-Certainty-Need" (LCN) SC (Ivanov and Dolgui 2019).

The investigation of the interrelations between digital technology and SC risks is still at a preliminary the beginning stage of its development and requires new conceptual frameworks and taxonomies (Ivanov et al. 2019a). This chapter seeks to move the discussion forward and develop a framework for a detailed analysis of SC digital technology and disruption risk effects manifested at times in *structural dynamics* (Ivanov et al. 2010) and the *ripple effect* (Ivanov et al. 2014a, b, 2016; Sokolov et al. 2016; Elluru et al. 2017; Dolgui et al. 2018; Ivanov and Rozhkov 2017; Pavlov et al. 2018; He et al. 2018; Ivanov 2018a, b; Dolgui et al. 2019a; Pavlov et al. 2019). Despite initial efforts to unearth new insights about the impact of digital technologies on SC risks (Tupa et al. 2017; Ivanov et al. 2017; Papadopoulos et al. 2017; Schlüter et al. 2017; Ivanov et al. 2019a; Baryannis et al. 2018; Dolgui et al. 2019b, c; Dubey et al. 2019), the understanding of individual and interactive contributions on specific SC disruption risk management and ripple effects remains limited. This study closes this research gap by a combinatorial examination of the results gained from two isolated areas, i.e., the SC digitalization and managing the disruption risks in the SC. In particular, the focus of this chapter is directed on the data-driven decision-support systems to improve SC resilience and manage the ripple effect and disruption risks.

This chapter does not pretend to be encyclopedic and rather highlights the research that examines the relationships between SC digitalization and SC disruptions risks. The objective is to identify the perspectives of digital SC twins that can be leveraged to direct future research in exploring how digital technologies affect ripple effect and performance of the SCs, and how they can be used to manage the disruption risks and to improve resilience. More specifically, this study seeks to answer the following questions:

- What relationships exist between big data analytics, Industry 4.0, additive manufacturing, Blockchain, and advanced trace and tracking systems and SC disruption risks?
- How digitalization can contribute to enhancing ripple effect mitigation and analysis?;
- What digital technology-based extensions are needed in applications of quantitative analysis to ripple effect in the SC to emerge with digital supply chain twins?

2 Digital Supply Chain Technologies

Digitalization means using digitized data and digital technologies not only to improve processes, functions, and activities, but also to change processes to achieve a certain benefit. The objective is to enhance revenue streams and create new business opportunities (Hagberg et al. 2016). Digitalization of operations aims to improve production and SC capability and flexibility through real-time communication and intelligent, high-resolution data systems (Reddy et al. 2016). Digitalization is a continuing transformation toward a digital supply chain, and progressively changes most enterprise processes.

This section reviews recent literature in four elements identified in recent surveys on digitalization applications to SCM, i.e.,

- Big data analytics
- Industry 4.0
- Additive manufacturing
- Advanced tracking and tracing technologies, Blockchain.

In each of these groups, we describe the respective technology and its recent applications to SCM.

2.1 Big Data Analytics and Artificial Intelligence

Big data analytics (BDA) and artificial intelligence (AI) bring a completely new potential benefit to data-driven SC risk management. Big data has been characterized in the literature by 5Vs: volume, variety, velocity, veracity, and value (Wamba et al. 2015, 2017). Veracity and value are particularly important since data analysis shows the real value of big data.

Big data analytics (BDA) is based on knowledge extraction from vast amounts of data, facilitating data-driven decision-making. The more the data from the actual production process is recorded, the more important it becomes to evaluate this data volume with the help of BDA applications. ERP systems are generally not suited to this task. One challenge is that internal and external data from smart, networking products are frequently unstructured. The resulting solution is a repository that stores different data streams in their original formats. From there, the data can be reformatted and examined with descriptive, diagnostic, predictive, and prescriptive data analytics tools.

Descriptive analysis records the condition, the environment, and the functioning of the products. Diagnostic analysis analyses the reasons for reduced product performance or failure. Predictive analysis recognizes patterns that signal upcoming events. Prescriptive analytics identifies measures to solve issues and improve outcomes (Porter and Heppelmann 2015).

Analytics employs mathematical and statistical tools to collect, store, accumulate, and analyze big data volumes. The applications themselves are not new, but it is the combination with big data that brings new added value and competitive advantage. What is new is the rapid pace at which data can be captured in real time. This, in turn, extends the type and richness of data sets, and offers an unprecedented opportunity for investigation. Additionally, the nature of the investigation has changed. Technological tools are continuously supplied with data, and become more intelligent by using self-learning algorithms. For example, predictive analytics involves self-learning algorithms that identify and analyze relationships among variables, and develop outcomes such as buyer behavior forecasts. Active human involvement is not required in this process As a result, BDA becomes an active participant in the investigation process, and can create new knowledge about unknown or buried patterns and effects. Large-scale investigations detect such patterns, turning volume data into precise insights (Sanders 2016).

BDA has undoubtedly been the most elaborated area of digital technology application to SCM over the last decade. Johnson et al. (2016) and Simchi-Levi and Wu (2018) analyzed the application of BDA to retail. Nguyen et al. (2018) noted that optimization is the most popular approach in prescriptive analytics application to logistics and transportation area. Retailers strive to grow revenue, margins, and market share. Price optimization models calculate the variance of demand with price changes, and combine this information with relevant cost and inventory data to recommend prices that could maximize revenue and profits. BDA applications to SCM can also be seen in procurement processes, manufacturing shop floors, promotion actions in the omnichannel model, routing optimization, real-time traffic operation monitoring, and proactive safety management (Addo-Tenkorang and Helo 2016; Gunasekaran et al. 2016, 2017; Nguyen et al. 2018; Zhong et al. 2017). Nguyen et al. (2018) identified some additional areas where BDA can be applied to SCM in the near future. These areas include quality control in manufacturing, dynamic vehicle routing, in-transit inventory management in logistics/transportation, and order picking and inventory control systems in warehousing. Niesen et al. (2016) and Papadopoulos et al. (2017) observed that BDA can help improve SC risk management and disaster resistance. Baryannis et al. (2018) summarized recent AI applications to SC risk management and identified some future research directions in risk identification, assessment, and response. Priori et al. (2018) applied machine learning to the dynamic selection of replenishment policies according to SC environmental dynamics. Cavalcantea et al. (2019) developed a supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing.

2.2 Industry 4.0

The intelligent networking of machines and processes with the help of digital technologies is creating autonomous, Internet-linked, self-regulating production systems, popularly termed as Industry 4.0. Industry 4.0 seeks to visualize and predict the performance of processes, plants, SCs, and product properties on the basis of information available in real time (Ivanov et al. 2019b). For this purpose, smart sensors are applied to capture and communicate information and requirements comprehensively to any recipient in real time. Production models are implemented in the form of so-called cyber-physical production systems. Such cyber-physical production systems collect data via production-integrated sensors and measurement systems in real time, store and evaluate data, and interact actively with the physical, human, and digital world. Intra and external connectivity are provided by IoT via digital communication devices.

Industry 4.0 is a global phenomenon. There is no unique or circumscribed set of technologies or practices that define Industry 4.0. Most research considers factory concepts that share attributes of smart networking (Strozzi et al. 2017). The vision of Industry 4.0 is that the product to be manufactured carries all the relevant information about its production requirements. In addition, integrated production installations become self-organized through the collaboration of production machines, transport equipment, tools, and logistical components that can communicate with each other and exchange data via embedded systems. Digital technologies enable flexible decision-making by providing real-time data in all areas of the SC (Bonfour 2016, p.20). Digitalization and Industry 4.0 offers information and coordination based competitive advantage, generates new employment opportunities, and increases visibility and control in supply chains. However, it requires long-term commitment, and guarantees about data security (Porter and Heppelmann 2015).

Industrial robots are a part of Industry 4.0, found mainly in series production and warehousing applications. Robots perform high precision tasks independently as also support employees in their work, by handing over tools, for example. Their use accelerates, facilitates, and simplifies production activities. Unlike conventional industrial robots, which require time-consuming training, flexible robots learn quickly from people. They communicate with one another via the cloud, and support optimal production planning. In practice, however, questions still remain on several issues such as the ownership of cloud data among SC partners, or machine intercommunication protocols (Andelfinger and Hänisch 2017).

2.3 Additive Manufacturing

Additive manufacturing technology is a design-driven manufacturing process in which components are produced from material layers on the basis of 3D data sets and a virtual blueprint. "3D printing" is often used as a synonym. The use of different materials and the elimination of previously required special tools are an advantage. Furthermore, the rapid design and manufacturing process allows considerable time savings compared to conventional product development cycles (Zhang and Jung 2018, pp. 3–5). Great freedom of design, low material waste, and the feasibility of economically manufactured, individualized products make additive manufacturing attractive for many industries. The method is currently used primarily in rapid prototyping, but increasingly so in series production too (Li et al. 2017). Khajavi et al. (2014), Holmström and Gutowski (2017), Feldmann and Pumpe (2017), Li et al. (2017) described the applications of additive manufacturing to operations and SCM. Those applications reach from spare part logistics to redesigning global SC production and sourcing strategy. The core of additive manufacturing applications to SCM is the usage of 3D printers at different stages in the SC to increase manufacturing flexibility, achieve shorter lead times, increase product individualization, and reduce inventory. However, mass production volumes are not commercially possible yet.

2.4 Blockchain and Advanced Tracking and Tracing Technologies

Capturing and sharing information in real time is critical to detecting faults and their extent, as well as in planning SC recovery (Sheffi 2015). Tracking and tracing (T&T) systems aim at timely identification of deviations or danger of deviations in SCs, analysis of such deviations, alerts about disruptions that have occurred or may occur, and elaborating control actions to recover SC operability.

T&T systems combine with radio-frequency identification (RFID) and mobile devices to provide current information about process execution (Bearzotti et al. 2012). T&T systems and feedback control can be supported by RFID technology (Dolgui and Proth, 2010) and SC event management systems (Ivanov et al. 2013), effectively communicating disruptions to the SC tiers and helping revise initial schedules (Dolgui and Proth 2010; Zelbst et al. 2012). A critical issue is detecting disruptions and their scope in real time. Embedding SC visualization and identification technology is crucial for this, in practice.

In addition, emerging Blockchain applications in SCs promise enhanced scale and scope of T&T systems together with creation of information pipeline systems and SC finance applications (Hofmann et al. 2018). The central idea is to increase visibility and efficiency based on dispersed, tamper-proof, and verifiable record-keeping in the SC.

For example, IBM and Walmart are researching how to increase food SC safety control using Blockchain technology (IBM 2017). Recently, the applications of Blockchain technology have begun to revolutionize different aspects of SC and operations management for development of real time SC capabilities (Ivanov et al. 2019a; Kshetri 2018; Saberi et al. 2018). The central idea is to increase visibility and efficiency based on record-keeping in the SC. Blockchain applications to SCs become more and more important to enhance the scale and scope of digital processes along with creation of information pipeline systems and SC finance applications (Hofmann et al. 2018). A Blockchain is a decentralized database that exists as copies in a network of computers (Crosby et al. 2016). It is a chain of blocks, because the data and information stored is captured in blocks.

Regulatory processes (e.g., customs) can be expedited using Blockchain by improving confidence in documentations. This, in turn, can result in reductions in wastage, risk, and insurance premiums. The list of all transactions is stored as copies throughout all further evolvements on numerous computers (a network of even hundreds of computers).

These and further recent examples of Blockchain technology applications to SCs (Ivanov et al. 2019a; Saberi et al. 2018) support the new proposition that competition is not between the SCs, but rather between the information services and analytics algorithms behind the SCs. As such, SCs will no more be understood as a rigid physical system with a fixed and static allocation of some processes to some firms. Instead, different physical firms will offer services in supply, manufacturing, logistics, and sales which will result in the dynamic allocation of processes and dynamic SC structures forming a cyber-physical SC.

In practice, new cloud-based analytics platforms such as SupplyOn Industry 4.0 Sensor Clouds make it possible to control the SC in real time, and plan and adjust processes using up-to-date information. By simply clicking on a container type, the graphs indicate whether there has been a violation of the defined temperature or humidity limits along the time axis. The data analysis in this chart allows a quick identification of all orders where the lead time was exceeded, allowing for a quick identification of questionable transports.

Summarizing, the following SC digitalization framework can be presented (Fig. 1).

BDA, additive manufacturing, Industry 4.0, and advanced tracking and tracing technologies can be considered as digital enablers of the four major SC processes in the SCOR model, i.e., plan, source, make and deliver, respectively. A digital version of the SCOR model would therefore consist of digital planning, digital manufacturing,

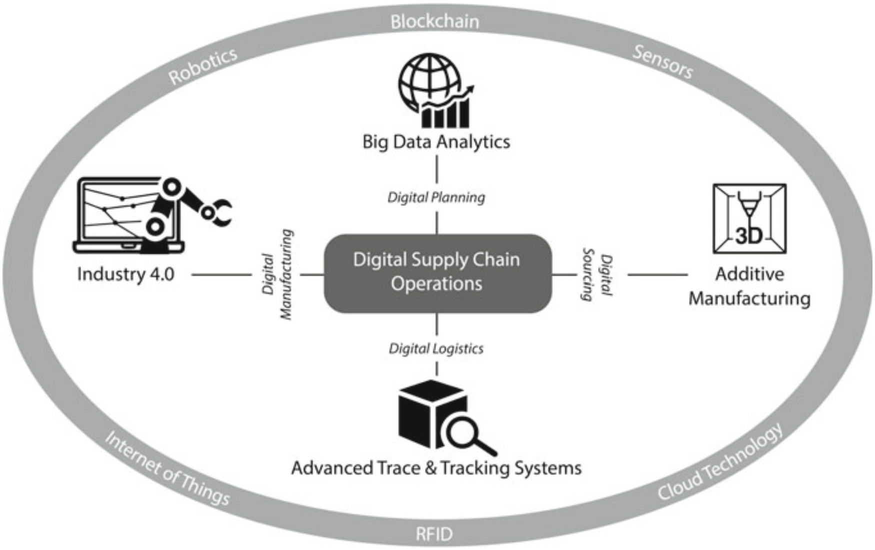

Fig. 1 Digitalization framework of supply chain risk management (Ivanov et al. 2019a)

digital sourcing, and digital logistics. IoT, cloud technology, robots, and sensors form the technical guts of a digital SC. This classification will be further used in the paper for analysis of digitalization impacts on severe SC risks and the ripple effect. For each of the areas, Fig. 1 suggests possible applications of digital technology with regards to SC disruption risks. For example, additive manufacturing can reduce supply risk by creating the opportunity to replace missing materials with the 3D printed components. BDA can be used at the planning stage to identify supplier risk exposure. T&T systems can help at the reactive stage to monitor and identify disruptions. At the same time, it needs to be noted that digital technologies may have multiple applications, which are not restricted to a particular SCOR process.

3 Impact of Digital Technologies on the Ripple Effect

3.1 Linking the Digital Supply Chain and Disruption Risks

Following the study by Ivanov et al. (2019a), Table 1 summarizes the major drivers of digital technology applications to SCM, the respective enablers, opportunities and challenges for SCM, as well as the impact on disruption risk management and the ripple effect

Table 1 Major digital technology applications to SCM and the impact on disruption risk management and ripple effect

Digitalization application to SCM	Enablers	Opportunities and benefits	Challenges in SCM	Impact on disruption risk management and ripple effect
Predictive analytics	Big data	Increase in promotion action quality Better demand forecasts Increase in supply chain visibility Better customer experience promotions	Data transparency and safety Coordination complexity increase in cross-channel logistics	Reduction in demand risks Reduction in information disruption risks and better quality of contingency plan activation Higher time risks because coordination complexity increases
Industry 4.0	IoT, smart products, robotics, augmented and virtual reality	Customized production system at the costs of mass production Individualized products and higher market flexibility Risk diversification Higher responsiveness Shorter lead times and better capacity utilization	Radical changes in SC and manufacturing process organization Reduction in number of SC layers New locations close to the markets Re-qualification of employees, redesign of facility layouts Data security Increase in design and control complexity	Higher information risks Higher exposure to external risks, including unauthorized access Reduction in time and demand risks
3D printing	Additive manufacturing	Flexibility increase, Product variety, Shorter lead time Efficiency increase in MRO inventory control		Reduction in demand risks Higher exposure to external risks Higher supply risks if disruption happens in the upstream SC since no intermediate inventory in between the stages
Advanced T&T technologies	RFID, sensors, Blockchain	Real-time identification Real-time material flow tracing Increase in data quality	Increase investments in ICT Data security	Reduction in information disruption risks and better quality of contingency plan activation Reductions in supply and time risks due to real-time coordination if activating contingency policies

Specifically, digitalization's impact on the ripple effect, that is, the magnitude and reach (upstream and downstream) of a disruption in a part of the SC is elaborated in Table 2.

It can be observed in Tables 1 and 2 that digitalization technologies generally have a positive impact on the ripple effect, but may create a few challenges for ripple effect mitigation and control. BDA, Industry 4.0, and additive manufacturing, have mixed influences on the ripple effect, while advanced T&T systems have a positive impact.

Structuring analysis in terms of the supply chain operations reference (SCOR) model, *sourcing and production* activities involving additive manufacturing and Industry 4.0 imply higher exposure to external risks and ripple effect. This could be due to an increase in complexity and probable reduction in time and demand risks due to higher flexibility and shorter lead times. Higher supply risks can be encountered if a disruption happens in the upstream SC since there is no intermediate inventory in between the stages. *Delivery* process risks in the SC are alleviated by big data analytics due to better SC visibility and forecast accuracy, reduction in information disruption risks, and better quality of contingency plan activation. For integrated SC *planning*, reductions in supply and time risks can be achieved by using advanced T&T systems that enable real-time coordination and timely activation of contingency policies.

At the proactive stage, SCs are typically protected from disruptions by employing risk mitigation inventory, capacity reservations, and backup sources. This is expensive, especially if no disruption happens. Blockchain could help reduce these inefficiencies if we are able to create a record of activities and data needed for recovery in terms of synchronized contingency plans. Additive manufacturing can reduce the need for risk mitigation inventory and capacity reservations as well as for the backup contingent suppliers. The decentralized control principles in Industry 4.0 systems make it possible to diversify the risks and reduce the need for structural SC redundancy, using manufacturing flexibility.

At the reactive stage, if a disruption happens, the contingency plans from proactive stage can be deployed faster and implemented effectively if SC visibility were increased. BDA and advanced T&T systems in general, and Blockchain technology in particular, can help us to trace the roots of disruptions, to observe disruption propagation (i.e., the ripple effect), to select short-term stabilization actions based on a clear understanding of what capacities and inventories are available (emergency planning), to develop a mid-term recovery policy and to analyze the long-term performance impact of the ripple effect. Additive manufacturing has the potential to reduce disruption propagation in the SC, since the number of SC layers and the resulting complexity would be reduced.

Table 2 Contribution of digital technologies to ripple effect control in the SC

Reasons for ripple effect in the SC	Countermeasures	Digital technologies impact on ripple effects
Single sourcing	Multiple/Dual sourcing/Backup suppliers	Additive manufacturing tends to reduce the number of SC layers and suppliers—mitigates ripple effect Advanced T&T systems allow better SC coordination in real time—mitigates ripple effect Industry 4.0 increases sourcing coordination complexity—may delay detection and response to ripple effects BDA increase the quality of procurement processes—mitigates ripple effects
Low inventory	Risk mitigation inventory	Additive manufacturing tends to reduce the inventory in the SC—enhances ripple effects Advanced T&T systems allow inventory control in real time—mitigates ripple effects
Inflexible capacity	Postponement	Industry 4.0 and additive manufacturing increase demand and production flexibility—mitigates ripple effects
SC complexity	Global SC contingency plans	Advanced T&T systems allow better SC coordination in real time and faster contingency plan activation—mitigates ripple effects Industry 4.0 increases the SC coordination complexity—enhances ripple effects BDA contributes to an increase in supply chain visibility—mitigates ripple effects
Multistage SCs	Supplier segmentation according to disruption risks	Additive manufacturing tends to reduce the number of SC layers and suppliers—mitigates ripple effects Industry 4.0 increases the SC complexity—connectivity enhances ripple effect Advanced T&T systems allow better SC coordination in real time and faster contingency plan activation—mitigates ripple effects

Fig. 3 Low-certainty-need supply chain framework (Ivanov and Dolgui 2018)

4 Supply Chain Resileanness: Low-Certainty-Need (LCN) Framework

4.1 Conceptual Framework

The LCN SC framework (Ivanov and Dolgui 2018) suggests approaching SC disruption risk and the ripple effect field from another perspective. Rather than opposing the efficiency and resilience, we suggest considering their mutual intersections to enhance each other based on synergetic effects in terms of SC *resileanness*.

Major costs of disruption management are seen in disruption prediction, protective redundancy, and reactive capabilities as a result of a higher need for certainty and the resulting higher redundancy and recovery efforts. As such, we suggest studying these areas from the perspective of efficiency and resilience complementarity (Fig. 3).

According to Fig. 3, structural complexity, process inflexibility and non-flexible usage of resources, and insufficient parametric redundancy increase uncertainty and disruption risk propagation in the SC. The ultimate objective of the LCN SC design is to develop the ability to operate according to planned performance regardless of environmental changes. As such, the LCN SC design possess two critical capabilities, i.e.,

- low need for uncertainty consideration in planning decisions and
- low need for recovery coordination efforts.

Structural variety, process flexibility, and parametrical redundancy ensure disruption resistance and recovery resource allocation and allow for SC operation in a broad range of environmental states. This means that planning activities in the LCN SCs do not heavily rely on uncertainty prediction and proactive protection investments. Similarly, recovery coordination efforts are reduced to a minimum. Note that the LCN SC design does not necessarily imply higher costs, but rather seeks for an efficient combination of lean and resilient elements.

Let us discuss the principles of implementing the LCN SC framework in practice using digital technology.

4.2 Process and Resource Utilization Flexibility

Process and resource utilization *flexibility* means in a wider sense an establishment of universal, very flexible workstations such as those postulated in Industry 4.0 systems. Similar, the usage of universal materials can be considered with regards to recovery flexibility in the SC. Additive manufacturing technology can also positively influence product and process flexibility resulting in a combination of efficiency and resilience. Additive manufacturing can reduce the need for backup contingency suppliers. The decentralized control principles in Industry 4.0 systems make it possible to diversify the risks with the help of manufacturing flexibility increases. New research directions can be seen with regards to the impact of the digitalization on the SC design resilience (Ivanov et al. 2019a). For example, Big Data analytics and advanced Trace &Tracking systems in general, and Blockchain technology in particular, can help to trace the roots of disruptions, to observe disruption propagation (i.e., the ripple effect), to select short-term stabilization actions based on a clear understanding of what capacities and inventories are available (emergency planning), to develop a mid-term recovery policy, and to analyze the long-term performance impact of the ripple effect. Additive manufacturing has the potential to reduce disruption propagation in the SC since the number of SC layers and the resulting complexity would be reduced.

4.3 Non-expensive Parametric Redundancy

Non-expensive parametric redundancy targets the efficient reservations of capacity, inventory, and lead time. More specifically, those reservations need to be considered not as a non-used redundancy, but rather for use in normal operation modes as well. Network redundancy optimization can be viewed as a new research topic in this area. Another aspect of parametric redundancy is its efficient allocation. A new research direction extending the existing value-stream mapping techniques toward the SC resilience can be considered. Efficient redundancy can be implemented by using additive manufacturing that helps to reduce the need for risk mitigation inventory and capacity reservations. Finally, new material classification schemes need to be developed subject to material criticality and risk exposure in terms of the efficient and resilience SC design.

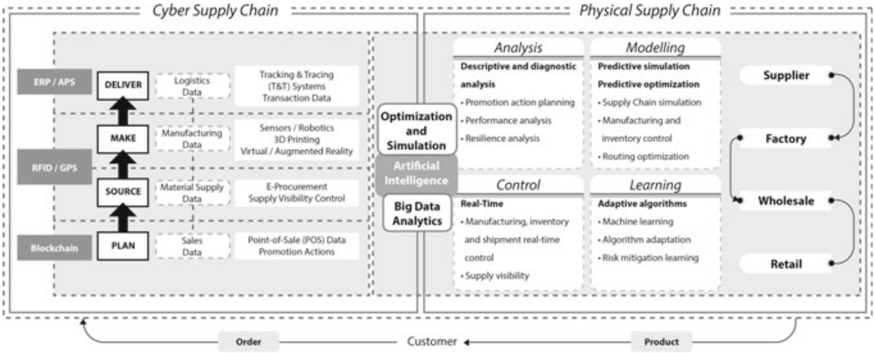

Fig. 4 Service and material flow coordination in the cyber-physical supply chain

5 Digital Supply Chain Twin: Data-Driven Optimization and Simulation to Manage the Disruption Risks

5.1 Supply Chains as Cyber-Physical Systems

Today and looking at the near future, the SC will be as good as the digital technology behind it. *The recent examples of digital technology applications to SCs allow for the new proposition that the competition is not between SCs, but rather between SC services and the analytics algorithms behind the SCs.* The services may be ordered in packages or as individual modules (Fig. 4).

Examples of SC and operations analytics applications include logistics and SC control with real-time data, inventory control, and management using sensing data, dynamic resource allocation in Industry 4.0 customized assembly systems, improving forecasting models using Big data, machine learning techniques for process control, SC visibility, and risk control, optimizing systems based on predictive information (e.g., predictive maintenance), combining optimization and machine learning algorithms, and simulation-based modeling and optimization for stochastic systems.

Success in SC competition will become more and more dependent on analytics algorithms in combination with optimization and simulation modeling. Initially intended for process automation, business analytics techniques now disrupt markets and business models and have a significant impact on SCM development. *As such, new disruptive SC business models will arise where SCs will be understood not as rigid physical systems with a fixed and static allocation of some processes to some firms. Instead, different physical firms will offer services of supply, manufacturing, logistics, and sales which will result in a dynamic allocation of processes and dynamic SC structures.* Recent literature documented the possibility of modeling such integrated service-material flow SCs (Ivanov et al. 2014c).

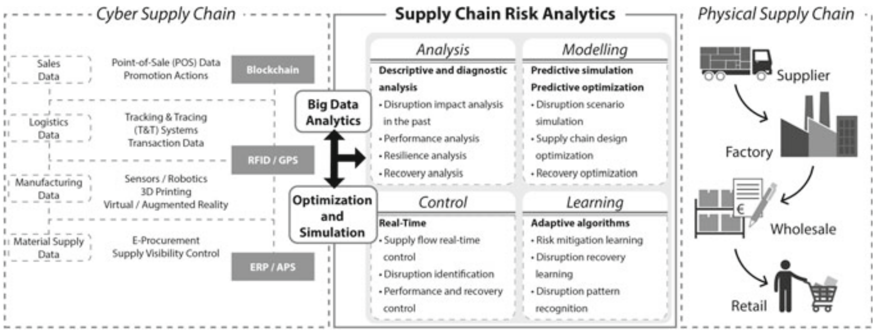

Fig. 5 Digital supply chain risk analytics framework

5.2 Supply Chain Digital Twins

Dunke et al. (2018) underline that digitalization and Industry 4.0 may significantly influence the optimization techniques in the SC domain as well as disruption propagation impacts on SC performance. With the help of optimization and simulation approaches, current research generates new knowledge about the influence of disruption propagation on SC output performance considering disruption location, duration and propagation, and recovery policies. New digital technologies create new challenges for the application of quantitative analysis techniques to SC ripple effect analysis and open new ways and problem statements for these applications.

In the past decades, simulation and optimization have played significant roles in solving complex problems. Successful examples include production planning and scheduling, SC design, and routing optimization, to name a few. However, many problems remain challenging because of their complexity and large scale, and/or uncertainty and stochastic nature. In addition, the major application of optimization and simulation methods in the last decades was seen in decision support, meaning that decision makers were to manually provide the model input and interpret the model output. On the other hand, the rapid rise of business analytics provides exciting opportunities for Operations Research and the reexamination of these hard optimization problems, as well as newly emerging problems (Fig. 5).

Sourcing, manufacturing, logistics, and sales data are distributed among very different systems, such as ERP, RFID, sensors, and Blockchain. Big data analytics integrates this data to information used by AI algorithms in the cyber SC and managers in the physical SC. As such, a new generation of simulation and optimization models is arising. The pervasive adoption of analytics and its integration with Operations Research shows that simulation and optimization are key, not only in the modeling of physical SC systems, but also in the modeling of cyber SC systems and learning from them.

An example of a decision-support system that combines a simulation, optimization, and data analytics is shown in Fig. 6.

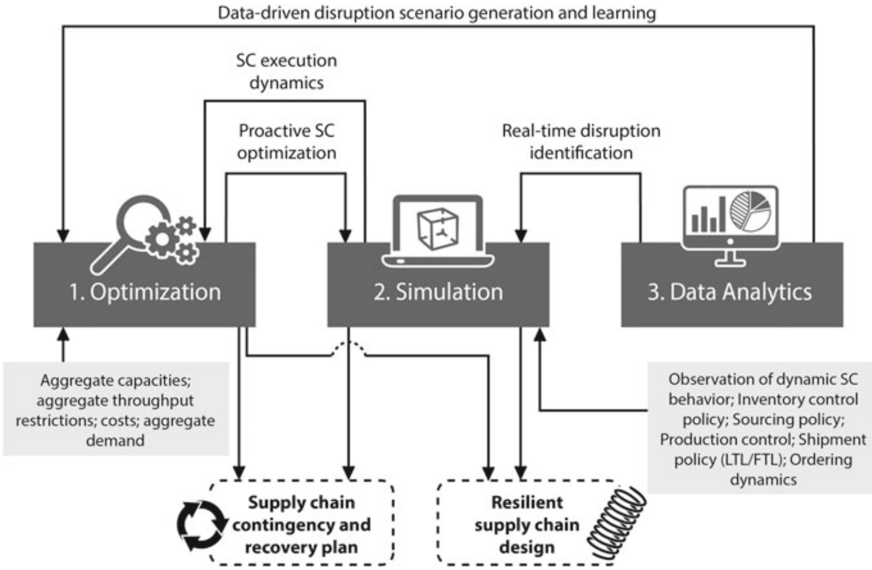

Fig. 6 Concept of a decision-support system for supply chain risk analytics (Ivanov et al. 2019a)

The decision-support system for SC risk analytics aims at proactive, resilient SC design in anticipation of disruptions and structural–parametrical adaptation in the case of disruptions. *The decision-support system is based on a concept that combines simulation, optimization, and data analytics.* The simulation–optimization part of the system is intended to provide proactive, resilient SC optimization and simulation of SC dynamic behavior in the event of possible disruptions or disruption scenarios. In addition, this supports reactive, predictive simulation of disruption impacts on SC performance and of recovery policies which are subsequently optimized in a prescriptive manner using an analytical model. The data analytics part of the system is applied to disruption identification in real time using process feedback data, e.g., from sensors and RFID. In addition, this aims at automated data input of disruption data into the reactive simulation model for recovery policy simulation and optimization. Finally, data analytics is used as data-driven learning system at the proactive stage, helping to generate adequate disruption scenarios for resilient SC design and planning.

At the proactive level, mathematical programming models produce notable insights for managers and can be applied where the probability of disruption can be roughly estimated. On the one hand, big data analytics and advanced trace and tracking systems may help in predicting disruptions and providing more accurate data to build sophisticated disruption scenarios for resilient SC design analysis. Digital technologies open new problems for resilient SC design. For example, additive manufacturing changes SC designs whereby new resilient sourcing problems may arise. This area can further be enhanced using collaborative purchasing platforms.

At the reactive level and with regards to mitigation strategies and identifying disruption impact on finance and operational performance, digital technologies can be extensively used to obtain real-time information on the scope and scale of disruptions, their propagation in the SC and to simulate possible recovery strategies. In addition, at the reactive level, adaptation is necessary for achieving desired output performance by ensuring the possibility of changing SC plans and inventory policies. Adaptation processes in ripple effect control can be supported by feedback and adaptive control methods using decentralized agent techniques with the help of digital technologies (Levalle and Nof 2017). Visualizing these processes through virtual reality-supported simulation has not yet been done extensively to model the ripple effect in the supply chain. For this, simulation models, along with new digital technologies, can improve tools which are already used in developing SC agility and visibility in terms of disruption velocity.

A combination of simulation and optimization can extend the scope of both. Combining the methods enables:

- Network optimization to minimize total SC cost.
- Dynamic analysis of ordering, production, inventory, and sourcing control policies using simulation.

Simulation is a newer tool and especially powerful when combined with optimization. More SC managers are now adopting the practice of using these techniques together.

What can a typical SC simulation-optimization model include, and what factors can it account for when working on risk analysis?

Network design and geographical information
Network design, with regard to the geographical location of sites, is the core of most SC simulation models. GIS maps are used in simulation models to locate the sites, and calculate distances, routes, and travel times along real roads. In addition to geospatial calculations, they provide visualization and transparency in a model.

Operational parameters
Inventory control policies, back-order rules, production batching, and scheduling algorithms, as well as shipment rules and policies, need to be defined in the model and balanced against each other for both normal and disrupted operation modes. Modern SC simulation tools enable visual modeling of these policies and do not require programming skills.

Disruptions and recovery
The duration of random or scheduled disruption events can be modeled with the probability distribution. As to recovery, analysts can set individual recovery policies for different sites and define the rules of policy activation depending on when the event occurs, the expected duration, and the severity of the disruption.

Performance impact
The direct impact of the ripple effect is reflected in changes to KPIs. Revenue, sales, service level, fill rate, and costs are typically calculated. Unlike analytical models

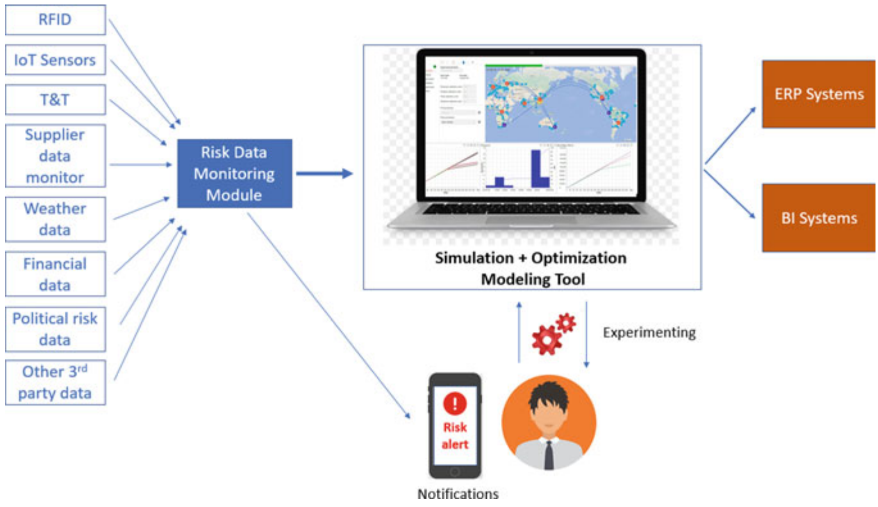

Fig. 7 Supply chain digital twin (Ivanov 2018c)

that usually focus on a particular metric (e.g., costs/profit), simulation enables the simultaneous measurement of all metrics in the same model. Their values can be checked at any chosen moment of the time period modeled. This way, disruption duration can be modeled, performance impact measured, and mitigation policies evaluated for efficiency.

A simulation model that considers all of these factors can be the basis for building a successful *digital twin* of a physical SC that can be used for complex analysis of SC risks, the development of contingency plans, and more efficient operational management.

A *digital SC twin* can support decision-making about the physical SC on the basis of data. At each point of time, the digital twin mirrors the physical SC: the actual transportation, inventory, demand, and capacity data and can be used for planning and real-time control decisions. The combination of simulation, optimization, and data analytics constitutes a full stack of technologies which can be used to create an SC digital twin—a model that always represents the state of the network in real time (Fig. 7).

As stated, a digital twin reflects the current state of an SC, with the actual transportation, inventory, demand, and capacity data. For example, if there is a strike at an international logistics hub, this disruption can be spotted by a risk data monitoring tool and transmitted to the simulation model as a disruptive event. Then, simulation in the digital twin can help forecast possible disruption propagation and quantify its impact. In addition, simulation enables efficient testing of recovery policies and the adaptation of contingency plans—for example, alternative network topologies and backup routes can be reconsidered on the fly. These screenshots are taken from any Logistix™ software and show the map-based model animation and the model-building editor.

The output data from a digital twin simulation can be transferred to an ERP system or a business intelligence (BI) tool to analyze the performance impact of the disruptions. Additionally, a simulation model can activate BI algorithms. For example, if the service level in a simulation model decreases to a certain level, the digital twin might activate a BI algorithm to search for the cause of the problem. Interacting with other SCM tools, a digital twin provides a control tower for end-to-end SC visibility.

6 Conclusions

The impact of digitalization and Industry 4.0 on the ripple effect in the SC has been studied in this chapter. Despite some partial efforts to uncover new insights in the impact of digital technologies on SC risks, the understanding of the individual contribution and the interplay of different digital technologies on specific SC disruption risk management and ripple effect is still vague. This study contributes to the body of knowledge in the field by combining the results gained from two isolated areas, i.e., the impact of digitalization on SCM, and managing the ripple effect in the SC.

Digitalization is expected to increasingly penetrate industry in the coming years, greatly changing operating and business systems, and the economy. Such potential offers new approaches to SC risk management that bring both opportunities and challenges. The fusion of the digital world with industrial processes is the so-called digital transformation. In addition to internal and cross-company processes in production and logistics, this also applies to the products and services offered to customers that need to be refined through the use of digital technologies. This chapter explained digital technologies can be used in managing SC disruption risks and the ripple effect.

The trend toward the application of digital technologies goes beyond the manufacturing company. The supplier network, the customer network, and the logistics service providers must also install and develop digital technologies to make the entire SC in nonstop delivery flexible. For this reason, the focus must be on risk management for every SC actor in the event of more frequent incidents such as natural catastrophes or supplier disruptions. The sources and handling process of risks need to be understood to facilitate the successful application of digital technologies. Digital technologies can potentially offer SCs enormous benefits in terms of transparency, visibility, cost reduction, efficiency, and resilience. However, there is still great uncertainty about the application and acceptance of the technologies, as many technologies are still in development, and industry standards are not yet established.

More specifically, this study found that at the *proactive* stage, digital technologies increase demand responsiveness and capacity flexibility. This may have a positive impact on reductions in risk mitigation inventory in ripple effect control. In addition, shorter lead times due to additive manufacturing enhance the impact of digitalization on inventory control. Industry 4.0 and additive manufacturing with the support of

BDA and T&T technologies facilitate a new quality of proactive planning of risk management infrastructure and increase the ability to reconfigure resources at the recovery stage. At the *reactive* stage, Blockchain, T&T technologies, and BDA allow a principally new quality of data coordination and SC visibility when simulating and activating recovery policies.

In terms of the SCOR model, *sourcing and production* activities can be adversely affected by additive manufacturing and Industry 4.0, which carry higher exposure to external risks and ripple effect. A plausible explanation is the increase in complexity and the reduction in time and demand risks that occur, driven in turn by greater flexibility and shorter lead times. Higher supply risks can be encountered if a disruption happens in the upstream SC, since there is no intermediate inventory in between the stages. The risks in the *delivery* processes are influenced by big data analytics with regards to a reduction in demand risks due to better SC visibility and forecast accuracy, reduction in information disruption risks and better quality of contingency plan activation. Reductions in supply and time risks in integrated SC *planning* can be achieved by using Blockchain and advanced T&T systems that provide real-time coordination while activating contingency policies. Designing a resilient SC can be influenced by higher information risks, higher exposure to external risks and a reduction in time and demand risks on the basis of Industry 4.0 technology and additive manufacturing.

A number of directions for simulation and optimization applications to SCM have been identified for digital technology application. BDA and advanced T&T systems may help in predicting disruptions and providing more accurate data to build sophisticated disruption scenarios for resilient SC design analysis. Digital technologies can be used extensively to obtain real-time information on the scope and scale of disruptions, their propagation in the SC, and to simulate possible recovery strategies. In addition, at the reactive level, adaptation is necessary for achieving the desired output performance by ensuring the possibility of changing SC plans and inventory policies. Adaptation processes in ripple effect control can be supported by feedback and adaptive control methods using decentralized agent techniques with the help of digital technologies. Visualizing these processes through virtual reality-supported simulation has not yet been done extensively to model the ripple effect in the SC.

Future decision-support systems will extensively utilize digital technologies and the digital SC twin, i.e., a computerized model of an SC updated with actual data in real time.

Notwithstanding the rapid developments in SCs and their digital twins, a number of questions arise:

- Is the SC as resilient as the digital technology behind it?
- If yes, what will provide the most competitive advantage in the future: physical SCs or their digital twins?
- Will SC resilience be managed by human, artificial intelligence, or a hybrid of both?
- What will be the role of future SC risk managers?

There is much research and practical potential with regards to the questions stated above. These can hopefully motivate new insightful developments in research on the ripple effect and disruption risk.

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