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Use of data for informed decision-making : Contributions in operations and supply chain management

par
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Résumé

Les données sont utilisées depuis longtemps dans la gestion des opérations et de la chaîne d'approvisionnement (GOCA) à l'aide de multiples méthodes quantitatives. Néanmoins, de nombreuses entreprises ne sont pas encore arrivées à utiliser judicieusement les données disponibles sur la chaîne d'approvisionnement. Cette thèse applique des méthodologies fondées sur des données mais aussi sur une base théorique pour contribuer à résoudre ce problème sous plusieurs aspects via differents projets de recherche. Le premier projet vérifie la structure des connaissances de la GOCA basée sur des données afin que les autres chercheurs s'appuient sur les fondements théoriques existants et entreprennent des études pertinentes de façon pratique et académique pour combler les lacunes de la littérature et soutenir les entreprises dans l'utilisation des données. Les deux projets suivants fournissent des exemples où les compagnies peuvent exploiter des données afin d'améliorer leur GOCA. En particulier, le deuxième projet développe un cadre dans lequel une plateforme d'avis peut tirer parti du contenu créé par ses utilisateurs et par leurs activités (données générées par les utilisateurs) pour faire des recommandations d'avis pertinentes et personnalisées et accroître l'affinité des utilisateurs envers la plateforme. Les résultats des analyses prédictives et contrefactuelles basées sur l'apprentissage automatique démontrent que le modèle proposé augmente l'efficacité des opérations de recommandation d'avis de la plateforme. En réponse au besoin d'une gestion des risques basée sur des données dans la gestion de la chaîne d'approvisionnement (GCA) mondiale, le troisième projet utilise des banques de données accessibles au public afin d'opérationnaliser les mesures du nationalisme économique, dont l'impact sur la GCA mondiale est ensuite testé

par une modélisation multiniveaux. Ce projet propose des indicateurs faciles à mesurer pour informer les gestionnaires de la chaîne d'approvisionnement mondiale des changements possibles dans les sentiments ou politiques nationalistes économiques sur un marché donné afin que les décisions de gestion des risques puissent être prises en temps opportun.

Mots-clés

Gestion des opérations et de la chaîne d'approvisionnement basée sur des données, recommandation d'avis personnalisée, plateforme en ligne, opérations de services, affinité de l'utilisateur, mesures du nationalisme économique basées sur des données secondaires, analyse des co-citations, partitionnement en *k*-moyennes, modélisation par équations structurelles, analyse factorielle, modélisation par équations structurelles par moindres carrés partiels, apprentissage automatique, modélisation multiniveaux, risque politique, gestion des risques, nationalisme économique, approvisionnement international, politique publique, relations fournisseurs, incertitude politique

Méthodes de recherche

Analyse des co-citations, partitionnement en *k*-moyennes, modélisation par équations structurelles, analyse factorielle, modélisation par équations structurelles par moindres carrés partiels, apprentissage automatique, modélisation multiniveaux

Abstract

Data have long been used in operations and supply chain management (OSCM) through multiple quantitative methods. Nevertheless, many firms have not managed to make judicious use of the supply chain data available. This dissertation applies data-driven yet theoretically-grounded methodologies to help to address this issue in several aspects via different research projects. The first project ascertains the knowledge structure of data-driven OSCM so that fellow scholars draw on the existing theoretical foundations and undertake practically and academically relevant studies to bridge the literature gaps and support enterprises in data utilization. The next two projects provide examples where companies can exploit data to improve their OSCM. In particular, the second project develops a framework whereby a review platform can leverage the contents created by its users and their activities (user-generated data) to make relevant and personalized review recommendations and increase user affinity toward the platform. The machine-learning-based predictive and counterfactual analysis results demonstrate that the proposed model increases the effectiveness of the platform's review recommendation operations. In response to the need for data-driven risk management in global supply chain management (SCM), the third project utilizes publicly available databases to operationalize measures of economic nationalism, whose impact on global SCM is then tested by multilevel modeling. This project offers easy-to-measure indicators to inform global supply chain managers of possible changes in economic nationalist sentiment or policies in a given market so that risk-handling decisions can be made in a timely manner.

Keywords

Data-driven operations and supply chain management, personalized review recommendation, online platform, service operations, user affinity, secondary-data-based measures of economic nationalism, co-citation analysis, *k*-means clustering, structural equation modeling, factor analysis, partial least squares structural equation modeling, machine learning, multilevel modeling, political risk, risk management, economic nationalism, global sourcing, public policy, supplier relationships, policy uncertainty

Research methods

Co-citation analysis, *k*-means clustering, structural equation modeling, factor analysis, partial least squares structural equation modeling, machine learning, multilevel modeling

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List of Acronyms

ABBR Abréviation (Abbreviation)

AIC Akaike information criterion

aka also known as

ANN Artificial neural network

ARIMA Auto-regressive integrated moving average

AVE Average variance extracted

B2C Business-to-consumer

B-P LM Breusch-Pagan Lagrange multiplier

BC Bagging classifier

BD Big data

BDA Big data analytics

BIC Bayesian information criterion

cf. confer/conferatur (compare)

CGS D Canada Graduate Scholarship-Doctoral

CI Confidence interval

Corr. Correlation

CR Composite reliability

EFA Exploratory factor analysis

e.g. exempli gratia (for example)

ERP Enterprise resource planning

etc. et cetera (and so on/forth)

et al. et alia (and others)

FA Factor analysis

GBC Gradient boosting classifier

GTA Global Trade Alert

HEC Hautes Études Commerciales

i.e. id est (that is)

IoT Internet of Things

IPC Information processing capability

IT Information technology

ITS Intelligent transportation system(s)

IS Information systems

KS Kolmogorov–Smirnov

MDS Multidimensional scaling

ML Machine learning

MPD Manifesto Project Dataset

NSERC Natural Sciences and Engineering Research Council

OIPT Organizational information processing theory

OM Operations management

OSCM Operations and supply chain management

PhD Doctorat (Doctor of Philosophy)

PLC Product life cycle

PLS Partial least squares

Prof. Professor

RFC Random forest classifier

RFID Radio-frequency identification

SAA Sample average approximation

SC Supply chain

SCA Supply chain analytics

SCM Supply chain management

SEM Structural equation modeling

SLR Systematic literature review

SVM Support vector machine

WB World Bank

WOS Web of Science

Y2K Year 2000

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Chapter 1, which has been published, is included in this doctoral thesis by permission of its publisher: © Nguyen, D. T., Adulyasak, Y., Cordeau, J.-F., and Ponce, S. I. (2022). Data-driven operations and supply chain management: established research clusters from 2000 to early 2020. *International Journal of Production Research*, 60(17):5407–5431. https://doi.org/10.1080/00207543.2021.1956695 reprinted by permission of Informa UK Limited, trading as Taylor & Francis Group, http://www.tandfonline.com.

Preface

HEC Montréal's Research Ethics Board confirmed that all projects and associated methods in this dissertation (Project #2023-5242) do not require ethics review.

The published version of Chapter 1 can be found online at [Nguyen, D. T., Adulyasak, Y., Cordeau, J.-F., and Ponce, S. I. (2022). Data-driven operations and supply chain management: established research clusters from 2000 to early 2020. *International Journal of Production Research*, 60(17):5407–5431]. As the lead investigator, I was responsible for all major steps, from conceptualization through data collection and analysis to manuscript composition. Prof. Ponce was involved from the early stages of conceptualization and data analysis, and contributed to manuscript edits. Prof. Adulyasak and Prof. Cordeau were the supervisory authors on this project and contributed to data analysis and manuscript edits.

I was the lead investigator for the projects reported in Chapters 2 and 3, responsible for all major steps, from conceptualization through data collection and analysis to manuscript composition. Prof. Khern-am-nuai was involved from the early stages of conceptualization and data collection, and contributed to data analysis and manuscript edits for the project located in Chapter 2. Regarding the project reported in Chapter 3, Prof. Charpin was involved from the early stages of conceptualization, and contributed significantly to literature review, and data collection, data analysis, and manuscript composition. Prof. Adulyasak and Prof. Cordeau were the supervisory authors on both projects and contributed to concept formation, data analysis, and manuscript edits.

General Introduction

Data have long been used in operations and supply chain management (OSCM) through statistics, optimization (Tiwari et al., 2018), and analytical tools and techniques, which are conceptualized as supply chain analytics (SCA) (Chae et al., 2014a; Souza, 2014). The existing literature has reported positive correlations between the use of data-based techniques/tools and OSCM performance (Chavez et al., 2017). A survey of 309 merchants on an online B2C platform in China run by Alibaba Group shows the impact of data analytics on the merchants' performance under the interaction with product variety and competitive intensity (Song et al., 2018). From a different perspective, Chae et al. (2014b), by deploying partial least squares-structural equation modeling to analyze a global survey sample of 533 manufacturing plants in 15 countries and 14 industries, prove an indirect yet significant influence of advanced analytics on operational performance via the mediation of such supply chain management (SCM) initiatives as Total Quality Management and Just-in-Time. The results also illuminate an indirect effect of data accuracy on operational performance through the moderation of SCM initiatives and mediation of manufacturing and planning quality (Chae et al., 2014b). Parlaying the same data and research method, Chae et al. (2014a) corroborate the significant associations, both direct and indirect, between operational performance and three SCA components, namely data management resources, IT-based supply chain (SC) planning resources, and performance management resources. Some other examples can be found in the papers of Dubey et al. (2019), Fosso Wamba et al. (2015), and Trkman et al. (2010).

In addition to empirical findings, the current literature on OSCM also discusses frameworks and models to build up data-driven SCs. One example is the decision-making model developed by Long (2018) to contend with the turbulence and intricacy of internal and external factors in SCs. In fact, the proposed high-dimensional model takes account of data granularity, inputs domain knowledge, and deploys agent-based simulation for parameter adjustment and verification before the solution is finalized (Long, 2018). There have been indeed several machine-learning (e.g., Cheng et al., 2020; Medina-González et al., 2020) and data-analytics (e.g., Fu and Chien, 2019; Wang and Yao, 2021) models proposed for OSCM. Even with agri-food, such technological advances are transforming its SC into a digital data-driven environment (Kamble et al., 2020). Detailed discussions about empirical and modeling-based scholarship in data-driven OSCM areas where there has been an extensive body of literature will be provided in Chapter 1.

Nevertheless, there are several subfields in OSCM where data utilization for decision-making has remained understudied or inefficient. Before delving into some typical under-explored subdomains of data-driven OSCM, this dissertation provides their overviews in the next subsections.

Data-driven systematic literature review in OSCM scholarship

Systematic literature reviews are of recognized necessity in ascertaining and evaluating the existing knowledge base so that relevant research agendas can be set on the basis of what is known and what is not (Rousseau et al., 2008; Tranfield et al., 2003). In addition to avoiding the loss of knowledge from prior studies, such systematic literature syntheses also help inform practice and policymaking with the collective insights available (Rousseau et al., 2008; Tranfield et al., 2003). There are several proposed paradigms, e.g., those by Tranfield et al. (2003), Rousseau et al. (2008), and Durach et al. (2017), for scholars to undertake a rigorous systematic literature review that takes into consideration research themes, theoretical lenses, methodologies, units of analysis, data sources, contexts, results, and implications of the works reviewed. The ultimate goal of a systematic literature review is to synthesize the theoretical foundations that have already been built and to determine the literature gaps or debates that have yet to be addressed. Overall, a systematic literature review procedure is composed of topic specification, literature retrieval and selection, literature synthesis, and reporting (see Chapter 1).

In addition to content analysis, co-citation analysis as a common bibliometric method is a recommended data-based technique to identify the knowledge structure and evolution of a given field of study (Bhatt et al., 2020; Swanson and Santamaria, 2021; Tandon et al., 2021) while minimizing the subjectivity or bias of investigators' judgments in literature synthesis (Feng et al., 2017; Tandon et al., 2021; Wang et al., 2017). Under the assumption that authors cite articles that are deemed relevant to their research (Rao et al., 2013; van Raan, 2012), clusters of highly co-cited references in the bibliographies of the papers in the domain under analysis indicate its subfields or topical areas (Caviggioli and Ughetto, 2019; Feng et al., 2017; Maditati et al., 2018; Thomé et al., 2016) and can be considered to represent its knowledge structure (Samiee and Chabowski, 2012; Uddin et al., 2015). Indeed, González-Benito et al. (2013) and Samiee and Chabowski (2012) argue that only research highly cited by subsequent publications in the field can be regarded as part of its foundations. The growth and (citation-based) impact of the discipline can be illustrated by analyzing the publications and citations of each research cluster over time (Tandon et al., 2021; Thomé et al., 2016; Xu et al., 2020), which also helps to detect understudied topics. Therefore, co-citation analysis has become a prominent tool in systematic literature reviews (Tandon et al., 2021; Thomé et al., 2016; Wang et al., 2017).

There are many data-driven review papers in the literature (e.g., Feng et al., 2017; Maditati et al., 2018; Thomé et al., 2016; Xu et al., 2020), but research on data-driven OSCM has seen few literature reviews in this discipline that leverage such data-driven techniques as co-citation analysis to produce robust and replicable results. In actual fact, factor analysis and *k*-means clustering, which have been widely employed in OSCM research (e.g., Hsieh and Huang, 2011; Ijadi Maghsoodi et al., 2018; Ma and Qian, 2018; Nguyen et al., 2021; Tseng et al., 2019; Yang and Lirn, 2017), can be leveraged for co-citation analysis (e.g., Wang et al., 2016; Zhao et al., 2018). More to the point, text mining, which has been used in data-driven OSCM practice and research (e.g., Arunachalam et al., 2018; Bodendorf et al., 2022; Chae, 2015; Chu et al., 2020; Hsiao et al., 2017), is also a technique for data-based literature reviews (e.g., Choudhary et al., 2008; Kaur, 2023; Romero-Silva and de Leeuw, 2021; Stead et al., 2022; Terwiesch et al., 2020; van Eck and Waltman, 2011). This suggests that scholars who undertake data-driven OSCM studies are capable of conducting high-quality data-driven literature reviews of their research areas, but there have been only a few examples so far. Hence, Chapter 1's research project is carried out to provide a concrete example of data-driven systematic literature reviews of data-driven OSCM.

More specifically, Chapter 1 demonstrates a detailed procedure so that fellow scholars can replicate the data-driven systematic literature review reported. In addition to the prior literature reviews, a theoretical lens is also discussed in order that inclusion and exclusion criteria can be justified. Unlike the previous systematic literature reviews, three clustering techniques are employed for data analysis triangulation in this research project. Keyword extraction and co-occurrence analysis are then leveraged as text-mining tools to support thematic reporting. Built on the knowledge structure ascertained, research questions and hypotheses are put forward as proposed avenues for future research. All in all, the research design established in Chapter 1 is the most original contribution of the study reported.

Data-driven service operations management

The service operations management literature is broad, spanning numerous subfields, for example, healthcare, hospitality, retailing, and transportation (Baron, 2021; Cohen, 2018; Li and Kauffman, 2012; Roy et al., 2022), to name but a few. Recent technological advances have indeed opened up opportunities for data-driven service operations management (Baron, 2021). Service providers such as banks, taxi companies, hotel chains, and online platforms have invested in recording and utilizing data on customers' (digital) trails of activities, for instance, purchases, likes, comments, browsing history, and geographical locations, to customize their service offerings and delivery such that customer satisfaction and profitability are ameliorated (Caro et al., 2020; Cohen, 2018). Aloysius et al. (2016)

argue that brick-and-mortar stores can leverage mobile checkout to collect customer data and provide personalized recommendations and promotions in real time, but their empirical findings reveal that the adoption rate depends crucially on customers' computer self-efficacy, personal innovativeness, and technology anxiety.

In the operations management research community, there have been ongoing research endeavors to develop data-driven service operations management models supporting practitioners' needs, for example, data-driven incentivization for riders and drivers using on-demand ride-hailing platforms, e.g., Uber and Lyft (cf. Cohen, 2018). As regards data-driven healthcare operations, the literature is growing, especially after 2017 (Baron, 2021; Karatas et al., 2022). Utilizing the data of healthcare centers in the U.S. to evaluate their models, Wang et al. (2020a) develop data analytics and formulate mathematical programs to optimize appointment scheduling for healthcare facilities where both appointments and walk-ins are accepted. In a similar stream of research, i.e., labor scheduling, Smirnov and Huchzermeier (2020), on the basis of historical transaction data, propose predictive analytics for customer arrivals and devise an estimation method for the load-dependent service time distribution to solve a stochastic program that supports staff planning at a fast food restaurant. In this understudied domain of data-driven restaurant operations management, including but not limited to booking management, wait time management (or queue management), table management, menu engineering, and capacity planning and control, Roy et al. (2022) put forth multiple research questions, data sources, and methodologies for fellow scholars to conduct future studies.

In Li and Kauffman's (2012) proposed approach to adaptive learning, data-driven service operations management includes: consumer data collection, consumer data analysis, integrated consumer behavior modeling and service operations, and iterative assessment of service delivery. In their example, Li and Kauffman (2012) utilize the analyzed consumer behavior insights as inputs to data-driven service design and pricing for public rail transit in a simulated urban area in the European context. In the article of Kamandanipour et al. (2020), data-driven demand modeling provides crucial inputs into dynamic pricing, capacity management, and revenue optimization built on stochastic nonlinear integer programming at a service provider of passenger rail transport in Iran. Likewise, Barfar et al. (2021) simulate data on account of a real-life logistics enterprise to test their data-driven approach for learning the complete set of multi-dimensional peaks (peak cubes) of service failure aspects for each customer, which is then deployed for predictive modeling to detect service defects early and inform managers' decision-making. Since service evaluation is a vital element in service operations management, Mejia et al. (2021) demonstrate a text mining technique to assess service quality through customer reviews (user-generated data) in social media, and their empirical analysis of restaurants in the U.S. shows that the overall quality and waiting time are significant quality-related predictors of restaurants' survival. Also in the U.S. retail context, Musalem et al. (2021) present how video analytics can be carried out to measure the rate of customer assistance at a given staffing level, which is a crucial factor in quality management and sales conversion. In addition to the data on the customers concerned, data-driven service operations might need to take into account their peers' information to control for peer effects, which are particularly found significant in library operations management, a classic example of the sharing economy (see the research of Albergaria and Chiappetta Jabbour, 2020, in Brazilian libraries). This insight remains valid for online platforms, where social influence and peer effects are notably taken into consideration for personalized recommendation (cf. Liu et al., 2019; Qian et al., 2014).

In their Australia-based research on emergency service operations, Akter et al. (2021) reveal that to promote data-driven service operations management necessitates analytics empowerment, i.e., heightening staff's feelings of self-efficacy in applying data analytics via available and upgraded information technology infrastructure and tools (technological enablement), access to information/data, analytical skills and knowledge, training and development, supportive climate (policies, procedures, and practices), and decision-making autonomy and authority. In keeping with the recognized role of data quality in data-driven OSCM (Hazen et al., 2014), the case study of Matthias et al. (2017) on service operations highlights the importance of putting in place standardized data capture and data cleaning to avoid inconsistency and facilitate data analysis. More to the point, companies must also take action to protect their customer databases from cyberattacks and data breaches, which would incur tremendous losses for the firms affected (Cohen, 2018). In addition to preventive measures, enterprises must prepare response plans, including compensation, for the event of data leakage (Kude et al., 2017). Analyzing Target's 2013 data breach case, Kude et al. (2017) find that customers' agreeableness and openness and their friends' influence (peer effects) positively impact their perceived adequacy of Target's compensation, which in turn improves its service recovery.

In accord with the data-driven OSCM literature, data-driven service operations management has a positive impact on operational performance and business value (Akter et al., 2021; Fosso Wamba et al., 2015; Matthias et al., 2017). For example, analytics empowerment capability is positively associated with the agility and adaptability of emergency service operations (Akter et al., 2021). The data-driven operations of the New South Wales State Emergency Service also result in higher performance (Fosso Wamba et al., 2015). In hospitality, the positive association between social media analytics and customer satisfaction is conditional on external stakeholders' characteristics, i.e., supply chain partner diversity and localized rivalry, which are in turn moderated by customer engagement (see the Greece-based study of Wang et al., 2020b). These results accord with the data-driven OSCM literature in general, where external and internal factors moderate or mediate the relationship between data analytics and firm performance (cf. Chen et al., 2015; Dubey et al., 2019, 2021; Srinivasan and Swink, 2018; Zhu et al., 2018).

Of particular note, online platforms have transformed a significant part of service operations given that they can collect data on customers' tastes, habits, and social networks to produce properly customized recommendations (Cohen, 2018). In response to the need for more analytical models in service operations, that are both data-driven and theoretically-grounded (Huang and Rust, 2013), Chapter 2 refers to various theoretical lenses to justify its operationalization of latent variables which are measured through partial least squares-structural equation modeling (PLS-SEM) and used as inputs into subsequent analytical models to assist an online review platform to recommend relevant reviews to its users in a personalized manner. Feature engineering and theoretical justification to analyze users' affinity toward their platform (part of customer behavior) are important contributions of Chapter 2's research project to theory and practice in the data-driven service operations management literature.

Data-driven risk management in OSCM

Risk management, which consists of risk identification, risk assessment, and risk mitigation (Shojaei and Haeri, 2019), has played a critical part in logistics and SCM (Wu et al., 2017). In actual fact, today's long-linked supply chains, where plenty of businesses are partnered and interconnected notwithstanding geographical or cultural distance, are faced with innumerable risks in operations, logistics, and supply chain processes and activities (Engelseth and Wang, 2018), several of which lie beyond any firm's direct control (Heckmann et al., 2015). Examples of risk considerations encompass cargo loss resulting from cargo damage or cargo theft (Wu et al., 2017), supply disruptions in consequence of suppliers' late deliveries (Brintrup et al., 2020), product recalls caused by poor quality control (Ting et al., 2014), stockout and excess inventory owing to sharp demand fluctuation and low forecast accuracy (Breiter and Huchzermeier, 2015), and policy uncertainty triggered by politician turnover (Dong et al., 2022). An overview of various types of risk in OSCM can be found in the papers of Rajagopal et al. (2017), Jüttner (2005), and Christopher and Peck (2004). Overall, sources of supply chain risk can be divided into five main categories: demand risk, supply risk, process risk, control risk, and environmental risk (Christopher and Peck, 2004).

With the interconnection between supply chain members, disruptions at a certain supply chain node are likely to cascade upstream and/or downstream its network (Engelseth and Wang, 2018; Simchi-Levi et al., 2015). For instance, the floods in Thailand in 2011 disrupted Ford's global production (Simchi-Levi et al., 2015). In another example, a ten-minute fire at a subsupplier's small yet only production cell for radio-frequency chips in 2000 led to Ericsson's inability to make its key handset product for many months, prompting this firm to exit the market for this item the year after (Norrman and Jansson, 2004).

Wang et al. (2021) find that a company's supply risk increases when there is an overlap of tier-2 suppliers. In effect, Toyota has been well-known for its quick responses to natural disasters (Iwao and Kato, 2019) but still suffered delayed recovery from the 2011 Tohoku Earthquake in that all of its first-tier vendors of microcontroller units sourced solely from the same semiconductor manufacturer – Renesas Electronics (Matsuo, 2015). These examples highlight the importance of collaborating with supply chain stakeholders, notably suppliers of critical components or materials (Matsuo, 2015), for concerted risk management efforts across the supply chain (Bechtsis et al., 2022; Iwao and Kato, 2019; Norrman and Jansson, 2004).

In addition to risk-handling processes, data-driven risk management in OSCM encompasses data collection, management, and analysis for risk management purposes (Er Kara et al., 2020). In fact, to augment the efficacy of risk management entails effective management of knowledge, data, and information generated in an enterprise's system, shared among supply chain partners, and/or obtained from external sources (Er Kara et al., 2020; Neef, 2005). In particular, risk identification requires collecting (or receiving), processing, and analyzing data from suppliers or customers to obtain illuminating insights (Engelseth and Wang, 2018). Matsuo's (2015) case study suggests that information shared by first-tier vendors helps identify hidden upstream entities that likely create bottlenecks when a disruptive event takes place so that appropriate measures can be taken to assess and mitigate the related risks. In the research of Simchi-Levi et al. (2015), such information on the risk exposure level of each node in the supply chain is of cardinal importance in resource allocation for risk management and contingency planning (or response planning) among various suppliers and subsuppliers of the firm under analysis. Empirical research articles have illustrated that effective risk management is positively associated with data analytics (Bag et al., 2023; Gupta et al., 2022; Li et al., 2023). Furthermore, there have been several studies on data-driven risk management models and frameworks for OSCM in the recent literature.

As an application example of data-driven risk management in OSCM, Wu et al. (2017) utilize data analytics to assist an electronics manufacturer in contending with cargo loss in its global logistics network, which involves complex intermodal transportation. Using a decision tree algorithm and logistic regression, Wu et al. (2017) determine important features in classifying cargo loss severity for each item, thereby proposing viable mitigation strategies. Engelseth and Wang's (2018) case study on a Norwegian importer of mechanical parts from China demonstrates that the amelioration of high-quality information flow thanks to efficient data capture, processing, and sharing plays a fundamental role in data-driven risk management in OSCM. Seeing prior OSCM research focused largely on one or two aspects of data-driven risk management, such as data management (Engelseth and Wang, 2018), data analysis (Wu et al., 2017), risk measurement (Lee et al., 2016), and especially risk identification (Lee et al., 2016; Aboutorab et al., 2022), Er Kara et al. (2020) propose a comprehensive data-mining framework for risk management in OSCM and test it in a Turkey-based case study on a global enterprise in heavy machinery. In addition to the processes mentioned in the preceding paragraph, i.e., risk identification, assessment, and mitigation, and data warehousing and mining, the framework of Er Kara et al. (2020) also prescribes the formation of a team comprised of risk management, data-mining, IT, and domain experts to undertake data-driven risk management. Other examples of data-driven risk management in OSCM scholarship can be found in the papers of Bechtsis et al. (2022), Chu et al. (2020), Jia and Zhang (2021), and Yildiz et al. (2022), to name but a handful.

Given the practical relevance and academic interest in data-driven risk management in OSCM, research in this area is in high demand (Bechtsis et al., 2022; Er Kara et al., 2020), which has been particularly underscored since the COVID-19 pandemic outbreak (Mavi et al., 2022). Even before the pandemic, articles reviewing supply chain risk management had been found to have the highest impact in operations research and management science (Romero-Silva and de Leeuw, 2021). According to the review of Rajagopal et al. (2017), supply and demand sources of risk have been most extensively studied in the literature. Of particular note, multiple aspects of supply chain risk factors have been investigated, but political risk has remained overall underexplored in OSCM research (Charpin et al., 2021; Fan et al., 2023). Perceived as probable yet unwanted conditions, policies, or government action in the political environments that might impinge on a focal company's operations (Delios et al., 2010), political risk factors have implications for firms involved in foreign trade and global supply chains (Charpin et al., 2021; Fan et al., 2023) that are exposed to differing political environments across countries. Several events during the past ten years, e.g., Brexit (the U.K.'s withdrawal from the European Union), U.S.-China trade war, and COVID-19, have raised turbulence in the political environments worldwide, underlining the pressing necessity of political risk management in global SCM (Charpin et al., 2021; Charpin, 2022; Dong et al., 2022; Fan et al., 2023; Zhang, 2021). This practical need and the literature gap aforementioned generate the motivation for the research project reported in Chapter 3.

In particular, Chapter 3 focuses on economic nationalism, which is a political risk factor for firms dealing with foreign sourcing and has experienced an upward trend over the past decade in many developed and developing countries striving to protect their national economies and domestic enterprises from foreign rivalry (Charpin, 2022; Colantone and Stanig, 2019). The most important contribution of this research project to data-driven risk management in OSCM is that it offers an operationalization of economic nationalism using public data so that fellow scholars can replicate the measurement for future research attempts and that global supply chain managers can easily monitor the variable to inform their decision-making.

As demonstrated in the previous three subsections, there are multiple gaps in the literature on data-driven OSCM. So far, innumerable enterprises have not been able to leverage the available SC data fully (Viet et al., 2021), especially when it comes to big data analytics in several OSCM-related fields (Baig et al., 2019; Kamble and Gunasekaran, 2020; Lamba and Singh, 2017; Mishra et al., 2018). As a result, there is a dire need for more works on how to use data for OSCM effectively. Seeing this practically relevant and academically interesting research agenda, I focus my dissertation on investigating how to utilize data for decision-making in operations and supply chain management. The overview of each research project reported in this dissertation is provided in the following section.

Dissertation outline

After the General Introduction and discussion about the theoretical framework, this dissertation proceeds with its projects as reported respectively in the following chapters:

- Chapter 1 presents how data-driven methodologies can be applied to conduct a rigorous literature review in OSCM scholarship. In particular, by utilizing three clustering techniques, the research project reported in Chapter 1 analyzes the literature on data-driven OSCM from 2000 to early 2020 to ascertain clusters of highly cocited studies in the field and its literature lacunae. The knowledge base synthesized therein helps point out important factors in data-driven OSCM while the literature gaps identified suggest relevant pathways for future studies. These results offer research directions for the next two projects.

- Chapter 2 develops a data-driven yet theoretically-grounded framework for review recommendation whereby a review platform can leverage the contents created by its users and their activities (user-generated data) to recommend relevant information in a personalized manner and increase user affinity for the platform. This conceptualized model is tested using predictive and counterfactual analyses. This research project provides an example where enterprises can use the data recorded in their systems and the contextual information embedded in their operational environments to improve operations in general and service operations in particular.

- Chapter 3 utilizes publicly accessible databases to operationalize the measurement of economic nationalism, whose influence on global supply chains is then tested by multilevel modeling. In keeping with the call for data-driven risk management in global SCM (Bechtsis et al., 2022), this study offers easy-to-measure indicators to detect probable changes in economic nationalist sentiment and policies in a given market and inform global supply chain managers' decision-making with reference to risk handling. Indeed, in addition to heeding related policies, practitioners should closely monitor the sentiments in political manifestos that precede changes in economic nationalism.

- Chapter 4 presents application examples and guidelines to leverage the findings of the previous three chapters. This extended chapter demonstrates possible directions to expand the stream of research conducted in Chapter 3 with two prescriptive programming examples and utilises the insights from Chapters 1–3 to provide generic guidelines for practitioners and researchers with respect to data-driven supply chain risk management.

The General Conclusion is the last chapter that summarizes the findings reported in this dissertation and discusses its contributions to both scholarship and practice as well as possible directions for future research.

Contributions

This dissertation is overall expected to make the following contributions toward the literature on data-driven OSCM:

- First, by presenting the procedure to conduct a data-based yet theoretically driven literature review of OSCM (see Chapter 1), this dissertation demonstrates how fellow scholars in the field can carry out a rigorous and replicable systematic literature review to ascertain the knowledge structure and literature lacunae in their field of study and inform their future research attempts. In particular, data analysis triangulation by different clustering techniques (see Chapter 1) is a recommended method to augment the rigor of a literature review. Moreover, the research project reported in Chapter 1 also acknowledges the significant role of theory in guiding an arguably robust literature selection procedure.

- In addition, Chapter 1's findings, including the identified knowledge base of data-driven OSCM (defined as clusters of journal articles interconnected by co-citations) and its literature gaps, provide fellow researchers with potentially fruitful research avenues and research questions as well as with suggested theories, frameworks, and insights (e.g., organizational information processing theory) to conduct practically relevant and academically interesting studies that can help bridge the literature lacunae and support enterprises in data utilization. This chapter synthesizes the cited and citing scholarship of data-driven OSCM along with the vital factors discussed therein as important points of reference for fellow academics to draw on.

- Next, by empirically testing the variables in a company's recorded data that are theoretically justified to help determine relevant reviews for users, Chapter 2 points out crucial yet understudied factors (e.g., users' interaction-based similarity and social connectedness) that similar firms ought to heed in their recorded data. These factors have been examined in English-based contexts (cf. Zhang and Lin, 2018) or related areas (e.g., followee recommendation), but Chapter 2's research theoretically and empirically demonstrates that they remain pertinent to the review-recommendation operations of the non-English Asia-based review platform in question, thereby bolstering practitioners' confidence in the existing literature.

- More to the point, Chapter 2 discusses typical theoretical lenses, for example, signaling theory, network effect, and Hofstede's (2001) cultural dimensions, that practitioners and researchers can draw on to determine new, unexplored, or understudied features that are justifiably germane to their OSCM contexts of interest, especially those in sister domains (for instance, review recommendation and followee recommendation). Although the theoretical foundations presented in this chapter are not meant to be exhaustive, they provide concrete examples where the inclusion or operationalization of a new yet likely pertinent variable in a model under analysis can be expounded from a theoretical perspective.

- In Chapter 3, this dissertation shows global SC scholars and managers how to measure economic nationalism based on enforced and announced policies and economic nationalist sentiment in political manifestos. These measures facilitate the risk management of companies involved in foreign trade and global SCs in that such political risk can be quantified and monitored by publicly accessible data. This chapter's research findings suggest that global SC managers should be vigilant about not only a holistic set of policies, e.g., those on foreign trade, foreign investment, and migration, which have implications for their international operations, but also the climate of hostility, which can be indicated by the economic nationalist sentiment in political manifestos, an antecedent of economic nationalist policy interventions.

- Given that the longitudinal cross-country data utilized therein allow for better generalization of the results, Chapter 3's research project helps policymakers assess the expected effect of their implemented and announced economic nationalist policy instruments, especially on critical industries or sectors (e.g., those that provide essential goods, i.e., food and medical supplies). In particular, by discouraging domestic enterprises from doing business with foreign suppliers, governments can increase the proportion of domestic sourcing. Nevertheless, in accordance with the findings of Fan et al. (2023), Chapter 3 argues that governments should also introduce policies that strengthen domestic supply bases and facilitate domestic SC transactions and relationship development to promote reshoring in a sustainable and competitive manner.

- Finally, Chapter 4 demonstrates two examples to illustrate how the research findings of Chapter 3 can inform prescriptive programming which facilitates data-driven risk management in global supply chains. Chapter 4 also suggests possible directions for prescriptive modeling and discusses a managerial framework which can benefit both practitioners and scholars who work on data-driven supply chain risk management. The primary contribution of this chapter is to show the applicability of the insights produced by this dissertation's research projects.

The detailed contributions of each research project reported in this dissertation will be discussed in its respective chapter from both managerial and academic perspectives.

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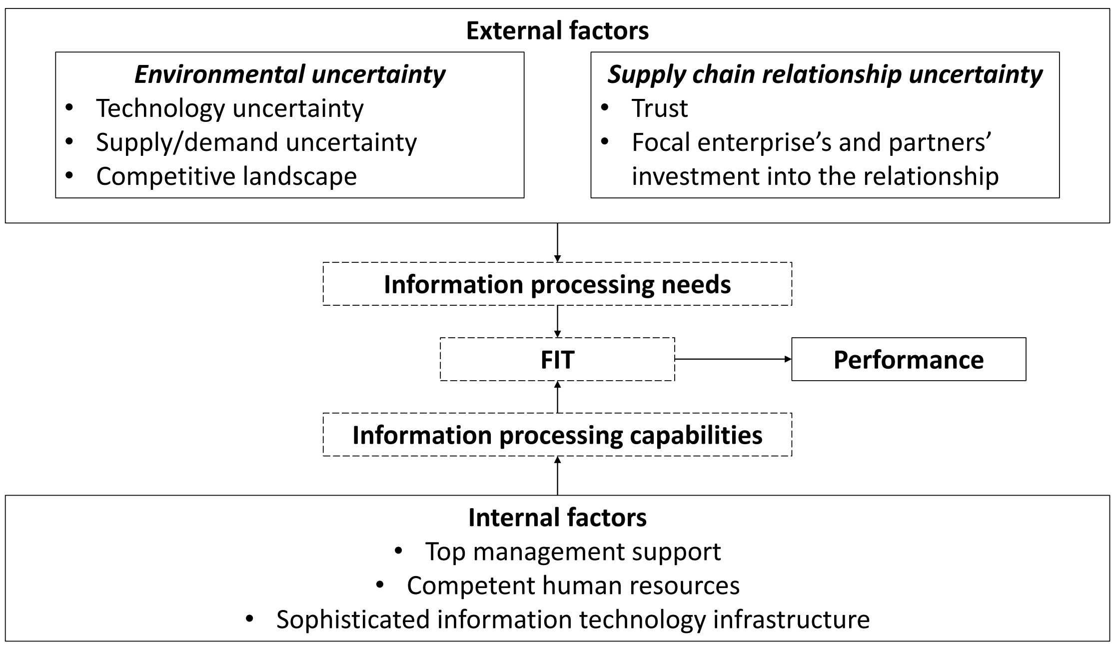
Theoretical Framework

To investigate how to leverage data for operations and supply chain management (OSCM), this dissertation draws on multiple theories for each research project. Nonetheless, the primary theoretical framework revolves around *organizational information processing theory* (Galbraith, 1974), which has been adopted in several academic works on data analytics in OSCM (e.g., Dubey et al., 2019; Chen et al., 2015; Srinivasan and Swink, 2018; Williams et al., 2013). Organizations in fact need information to cope with the turbulence in the external and internal environments where their operations and supply chains are situated (Galbraith, 1974). However, to translate available information into improved performance necessitates information processing capabilities (IPCs), which are broadly defined as the abilities to process and leverage data for a specific purpose (Srinivasan and Swink, 2018; Williams et al., 2013). In particular, the fit between information processing needs and information processing capabilities results in greater performance (Galbraith, 1974; Premkumar et al., 2005). Conducting surveys and interviews with firms in manufacturing industries in the U.S., Premkumar et al. (2005) reveal that the interaction between information processing needs and information processing capabilities has a stronger influence on performance than the main effect (i.e., the direct impact of IPCs on performance), supporting the importance of the fit between information processing needs and information processing capabilities.

There are plenty of empirical research findings (e.g., Chen et al., 2015; Dubey et al., 2019, 2021; Srinivasan and Swink, 2018; Zhu et al., 2018) that substantiate this theory. Overall, there is empirical support for the direct effect of IPCs (or data analytics) on the target performance indicator, for instance, asset productivity and business growth (Chen et al., 2015), collaborative performance (Dubey et al., 2019), operational cost and product delivery (Srinivasan and Swink, 2018), supply chain transparency (Zhu et al., 2018), and supply chain resilience and competitivity (Dubey et al., 2021). Furthermore, the impact of IPCs can also be mediated or moderated by other variables, e.g., environmental dynamism or turbulence (Chen et al., 2015), supply uncertainty (Zhu et al., 2018), trust (Dubey et al., 2019), and organizational flexibility (or agility and adaptability to changes) (Dubey et al., 2021; Srinivasan and Swink, 2018).



Source: adapted from Premkumar et al. (2005) and Chen et al. (2015)

Figure 0.1: Theoretical framework for data-driven operations and supply chain management

Figure 0.1 summarizes the conceptual models of Premkumar et al. (2005) and Chen et al. (2015), who apply organizational information processing theory to OSCM, taking account of both internal and external factors. The framework depicted in Figure 0.1 is not to enumerate exhaustively all possible variables for consideration in data-driven OSCM but to provide an overview of the major groups of factors that likely influence data utilization in OSCM. Noticeably, the mediator or moderator variables analyzed by the scholars referenced in the preceding paragraph are either external or internal to the focal firm.

This theoretical framework provides the theoretical foundations for the projects in this dissertation which aims to propose models on how to use data and data analytics (or IPCs) for OSCM. In particular,

- Chapter 1 synthesizes the knowledge base of the existing scholarship on data-driven OSCM and identifies its literature lacunae so that future research can develop relevant IPCs (or data analytics) for the underexplored subdomains of OSCM to boost organizational performance in such subfields. Organizational information processing theory is used to justify the inclusion and exclusion criteria for literature selection in this chapter.

- In Chapter 2, a framework is proposed to leverage user-generated data to improve review recommendation operations. Multiple variables relating to the external environment, for example, the national culture and brand strength, which determine the information processing needs, are utilized to inform the development of the model conceptualized. It is essential to interpret user-created data appropriately to gain the insights needed for personalized review recommendation.

- Chapter 3 deals with environmental uncertainty by investigating how to use publicly available data to detect possible changes in economic nationalism, which is a source of political risk in foreign trade and global supply chains. The model developed can assist firms to process information on this external uncertainty factor to guide their global OSCM. As the databases utilized are publicly accessible, analyzing them is an efficient approach for businesses to evaluate and monitor their political risk.

- As an extension of Chapter 3, Chapter 4 illustrates how the insights obtained from Chapter 3's data analysis can inform prescriptive programming that addresses global supply chain managers' need to determine the optimal proportion of domestic (foreign) sourcing and minimize the expected total cost given possible changes detected in public policy interventions. This chapter also discusses a managerial framework built on the theoretical framework depicted herein.

When there exists asymmetric or hidden information between parties to a transaction or relationship (Fan and Stevenson, 2018; Premkumar et al., 2005; Spence, 2002; Tao et al., 2017), the literature recommends several mechanisms in accord with organizational information processing theory, e.g., information sharing and cooperation, to tackle this issue (Ellram et al., 2020; Galbraith, 1974). *Signaling theory*, which was first proposed by Spence (1973) and has attracted attention in OSCM (Fan and Stevenson, 2018; Srinivasan et al., 2023), postulates that information asymmetry can also be reduced through informational cues (or signals) for the party with less information. When faced with asymmetric information, customers can in effect make use of observable cues to assess the quality of the product or service they consider purchasing, especially those whose quality can only be evaluated after purchase and on consumption (Filieri et al., 2021). For instance, certificates of excellence and high scores of average rating are signals that the expected service quality of the hotel in question is high (Filieri et al., 2021). In online retail, shoppers interpret return policy leniency as a signal of high quality (Oghazi et al., 2018; Rao et al., 2018). In another example, Yang et al. (2019) find that, when reviewers disclose their real names in reviews, readers regard that as a signal of authenticity or reliability and generally perceive the reviews to be more helpful. This theoretical lens particularly applies to the research project reported in Chapter 2, where the review platform under analysis cannot directly measure several indicators, e.g., reviewer expertise and reviewer-user similarity, but needs such information to recommend relevant reviews to the user in question.

In the risk management literature, a firm might be arguably unwilling to disclose its financial issues to its customer, but the fact that it requests payment earlier than usual might signal that it is having problems with its cash flow (Bode et al., 2014; Fan and Stevenson, 2018). Additionally, frequent staff turnover may imply quality risk in consequence of lost expertise (Fan and Stevenson, 2018). In the stock market, announcements of cross-border acquisitions & mergers and institutional information on the countries involved act as signals to investors about future profitability of investment in the firm in question (Tao et al., 2017). When a disruptive event takes place, company-generated tweets with positive sentiments signal to stakeholders that the company is taking appropriate measures to respond to that disruption, which in turn helps to preserve its shareholder value (Srinivasan et al., 2023). In connection with Chapter 3, which also copes with risk management, economic nationalist sentiment in political manifestos can send early signals to global supply chain managers about possible changes in economic nationalist policy interventions in the focal country.

Nonetheless, not all signals are equally important (Connelly et al., 2011). There can be noise, i.e., irrelevant signals, introduced by the external environment, competitors, or other signal senders (signalers) (Connelly et al., 2011). Such cases necessitate information processing capabilities that can differentiate significant signals from noise and interpret them properly. Previous research (e.g., Matthias et al., 2017; Opresnik and Taisch, 2015) has substantiated the vitality of implementing the correct strategy and skill set for data exploitation. Therefore, while other theoretical perspectives, e.g., signaling theory, may be adopted to fit the particularities of each research project undertaken, the conceptual framework built on organizational information processing theory illustrated in Figure 0.1 plays a significant part in the development of this dissertation. Overall, this dissertation focuses on how to process the available information or data to satisfy organizational information processing needs. All the research projects reported herein utilize theoretical justification to collect data and select pertinent variables. Chapter 1 implements multiple cluster analysis techniques to check the robustness of the results and retain the most significant journal articles to represent the knowledge structure of data-driven OSCM scholarship. In Chapter 2, dimensionality reduction is carried out for noise reduction and feature engineering. In Chapter 3, different measures of the variables of interest are taken for robustness checks. These are recommended practices for both researchers and practitioners with reference to data-driven OSCM.

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Chapter 1

Data-driven operations and supply chain management: established research clusters from 2000 to early 2020

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Abstract

Despite the long-recognized importance of data-driven operations and supply chain management (OSCM) scholarship and practice, and the impressive development of big data analytics (BDA), research finds that firms struggle with BDA adoption, which suggests

the existence of gaps in the literature. Therefore, we conduct this systematic literature review of journal articles on data-driven OSCM from 2000 to early 2020 to ascertain established research clusters and literature lacunae. Using co-citation analysis software and double-checking the results with factor analysis and multidimensional-scaling-based k-means clustering, we find six clusters of studies on data-driven OSCM, whose primary topics are identified by keyword co-occurrence analysis. Five of these clusters relate directly to manufacturing, which, in line with the existing literature, indicates the crucial role of production in OSCM. We highlight the evolution of these research clusters and propose how the literature on data-driven OSCM can support BDA in OSCM. We synthesize what has been studied in the literature as points of reference for practitioners and researchers and identify what necessitates further exploration. In addition to the insights contributed to the literature, our study is among the first efforts to deploy multiple clustering techniques to undertake a rigorous data-driven systematic literature review (SLR) of data-driven OSCM.

1.1 Introduction

Through statistics, optimization (Tiwari et al., 2018), and other supply chain analytics tools and techniques (Chae et al., 2014), data have long been exploited in operations and supply chain management (OSCM), where production and logistics play key roles. Indeed, since 2000, the cusp of the new millennium, a period of vast enterprise resource planning (ERP) adoption where companies sought solutions to the Y2K (Year 2000) problem (Irani et al., 2001), data-driven decision-making has received increasing attention from production researchers (Kuo and Kusiak, 2019) as such technological advances increase the possibility for collecting and, later on, leveraging data. Empirical research has shown positive correlation between the use of data-based tools and OSCM efficacy in multiple countries and industries (see Chae et al., 2014; Chavez et al., 2017; Song et al., 2018).

In addition to empirical findings, the literature on OSCM has discussed frameworks and models to further develop data-driven supply chains (SCs). For instance, in an attempt to allay overreliance on expert yet possibly subjective judgment, Cheng et al. (2020) propose a data-driven technique based on support vector machine (SVM) for supplier evaluation and use simulation based on a big firm's dataset for model assessment. Aimed at dealing with external uncertainty, the multi-objective data-driven model of Medina-González et al. (2020) exploits machine learning (ML), robust optimization, and meta-multiparametric programming to handle the stochasticity related to raw materials, demand, and environmental and social impact parameters to optimally manage a bio-energy production SC. In response to intermittent demand, shortening product life cycle, long lead time, etc., in the semiconductor industry (Uzsoy et al., 2018), Fu and Chien (2019) propose a UNISON-based analytics model, which integrates ML and adopts temporal aggregation-disaggregation mechanisms for demand forecasting, and validate their framework with a global electronics distributor.

Data from end-to-end supply chain management (SCM) processes are now exponentially increasing, heightening the need to analyze big data (BD) (Meriton et al., 2021). Thus, scholars and companies are striving to develop big data analytics (BDA) capabilities (Tiwari et al., 2018). Nevertheless, despite the growth in academic publications on BDA in OSCM (e.g., Dubey et al., 2019; Maheshwari et al., 2021; Meriton et al., 2021), many firms are struggling with BDA adoption (Viet et al., 2021; Kamble and Gunasekaran, 2020). Only a few companies have succeeded in BDA in SCM (Wang et al., 2016a; Meriton et al., 2021) while others have not been able to make judicious use of the BD available (Lamba and Singh, 2017; Mishra et al., 2018). This calls for more research on BDA adoption.

Irfan and Wang (2019) use two constructs, namely IT resources and data assimilation, to operationalize data-driven capabilities. In particular, the former include IT infrastructure and databases, whereas the latter denotes if data are utilized for order management, forecasting, or planning. This accords with empirical SCM research predicated on organizational information processing theory (OIPT) (Srinivasan and Swink, 2018; Williams et al., 2013; Chen et al., 2015) where information processing capabilities (IPCs) moderate/mediate the correlation between organizational performance/competitiveness and SC visibility enabled by the data gained from IT utilization. Williams et al. (2013) and Srinivasan and Swink (2018) broadly define IPC as the ability to process and leverage data for a specific purpose while Chen et al. (2015) particularly model BDA as the unique IPC mediating the relationship conceptualized. In effect, several studies define or refer to data-driven SCs as those that leverage BDA to improve SC competitiveness (Yu et al., 2018), sustainability (Kamble et al., 2020), or performance (Gawankar et al., 2020; Yu et al., 2019). This might indicate a shift of focus to BDA in research on data-driven OSCM. In fact, BDA has recently grown fast in SCM (Chehbi-Gamoura et al., 2020).

Recognizing those issues and paradigm shifts, we conduct a systematic literature review (hereinafter referred to as SLR) to identify the knowledge structure of research on data-driven OSCM since 2000. The aims include determining clusters of studies on data-driven OSCM and ascertaining subfields and lacunae in emergent research topics, e.g., ML and BDA, so that directions and avenues for further research could be elicited. In other words, the objectives of this SLR are to answer the following research questions:

i. What is the knowledge structure of research on data-driven OSCM from 2000 to early 2020 (published after 1999 and accepted for publication before 2020)?

ii. Are there any topics on data-driven OSCM which have recently been heeded by both scholars and practitioners or integrated into an established subfield?

Our SLR is in line with the need for systematic, transparent, and rigorous synthesis of a comprehensive body of literature to provide a high-quality evidence base to inform practice, policymaking, and research, and avoid loss of knowledge from earlier studies (Tranfield et al., 2003; Rousseau et al., 2008; Meriton et al., 2021). By reviewing the germane studies accumulated in the first two decades of this millennium, which saw the rise of data-driven decision-making and BDA, our work can offer interesting insight into how research on data-driven OSCM developed longitudinally, whereby an overview of the current theoretical foundations can be provided and research avenues identified.

This SLR will contribute directly to the advancement of production research because SCM has been among the major areas in production research literature (Kuo and Kusiak, 2019; Silva et al., 2019). Indeed, according to Vrijhoef and Koskela (2000), SCM derives from and thrives in the manufacturing sector. Meanwhile, before incorporating other organizational functions, e.g., procurement and logistics, into its scope, OM (operations management) "*referred primarily to manufacturing production*" (Bayraktar et al., 2007).

According to Uddin et al. (2015), the knowledge structure of a study domain, which can be ascertained by statistical and visualization techniques, illustrates the evolution of its subfields. It is generally understood that the knowledge structure of a research area, based on which studies are developed, can be represented by the bibliographies of its publications over a given period of time as a means to identify its "building blocks" (Samiee and Chabowski, 2012). Therefore, in our paper, the knowledge structure of data-driven OSCM scholarship is regarded as a network of pertinent journal articles, whose clustering is based on co-citation.

We define *data-driven* or *data-based OSCM* broadly as the use of data for OSCM practices, e.g., forecasting, tracking, and scheduling, in accordance with Williams et al. (2013), Srinivasan and Swink (2018), and Irfan and Wang (2019). The selected papers from the Web of Science (WOS) and other databases, which were published after 1999 and accepted for publication before 2020, are then analyzed, using co-citation analysis to identify research clusters. Factor analysis (FA) and multidimensional scaling (MDS) are carried out to validate the clustering results. Next, we read the papers retained from the analyses and use keyword co-occurrence analysis to determine each cluster's theme.

There have been SLRs on OSCM using data-driven approaches (Xu et al., 2018) or on a subfield of data-driven OSCM (Kamble et al., 2020), but so far we have seen few SLRs on data-driven OSCM, which employ such data-driven approaches as co-citation analysis. Therefore, our study will be among the first attempts to apply this data-driven methodology for a literature review on data-driven OSCM. We emphasize that our SLR focuses on research into data-driven OSCM practices and applications, not on fundamental research which advances data-driven methodology without evident connection to OSCM practices. For instance, if a paper uses BDA to illuminate the characteristics of multinationals' SCs rather than address an OSCM issue, e.g., supply management and inventory planning (these OSCM issues will be enumerated in Section 1.2.2), we do not include that article in our sample. Likewise, an optimization study might be excluded unless data play a role in its model formulation and a practical issue, e.g., demand uncertainty, is explicitly targeted. Conversely, our sample incorporates qualitative papers which, for example, discuss the benefits or performance of data-driven OSCM or the management and utilization of data for OSCM.

This chapter is divided into five sections. Following this Introduction, the next section presents our paper's methodology, whereas the third one illustrates the clustering results. Implications for research and practice based on our findings are provided in Section 1.4, and Conclusion is the last section, which also discusses this study's contributions and limitations.

1.2 Methodology

This paper is framed in line with the six-step SLR protocol of Durach et al. (2017), which specifically addresses the characteristics of the SCM context and is built on the integration of the most cited and applied SLR guidelines, including those of Tranfield et al. (2003).

i. First, we define the research questions and justify the timeliness, relevance, and expected contribution of our SLR (see Introduction).

ii. Then, we determine the inclusion and exclusion criteria.

iii. Next, we retrieve a sample of potentially pertinent literature and specify the search procedure, databases, and keywords.

iv. By applying the predefined inclusion and exclusion criteria, we choose the relevant papers.

v. Given the selected articles, we synthesize the literature, using co-citation analysis, FA, MDS, and keyword co-occurrence analysis.

vi. Finally, we present a descriptive summary of the selected publications and report the thematic findings.

In comparison to Tranfield et al. (2003) and Rousseau et al. (2008), Durach et al. (2017) suggest one additional step which requires specifying the search procedure, databases, and keywords, including possible synonyms. We believe that the recency of their SLR paradigm, its focus on SCM scholarship, and its heightened specificity will enhance our SLR transparency and replicability. Similar procedures can be found in other literature reviews, e.g., Seyedghorban et al. (2020), Badi and Murtagh (2019), Martins and Pato (2019), and Rebs et al. (2019). Nonetheless, each step can be modified to support the research. For instance, in the sampling step, some authors utilize cross-referencing or backward snowball search to find additional pertinent papers in the bibliographies of the selected papers (Rebs et al., 2019; Kamble et al., 2020; Hosseini et al., 2019). In forward snowball search, authors seek relevant studies that cite the selected articles (Martins and Pato, 2019; Karttunen, 2018). Another example is the use of bibliometric software to support co-citation-based cluster analysis (Feng et al., 2017; Rebs et al., 2019; Seyedghorban et al., 2020). Since the procedure Durach et al. (2017) discuss is commonly adopted, we frame our research in line with their guidelines to reinforce our SLR rigor. However, the validity and originality of our review are further enhanced by the deployment of multiple co-citation analysis methods in step (v.) for data analysis triangulation, which Durach et al. (2017) do not explicitly point out. We elaborate on the applied procedure in the next subsections, beginning with step (ii.).

1.2.1 Inclusion and exclusion criteria

We adopt the inclusion criteria utilized in the SLR of Glock et al. (2019), which are in conformity with prior studies as follows:

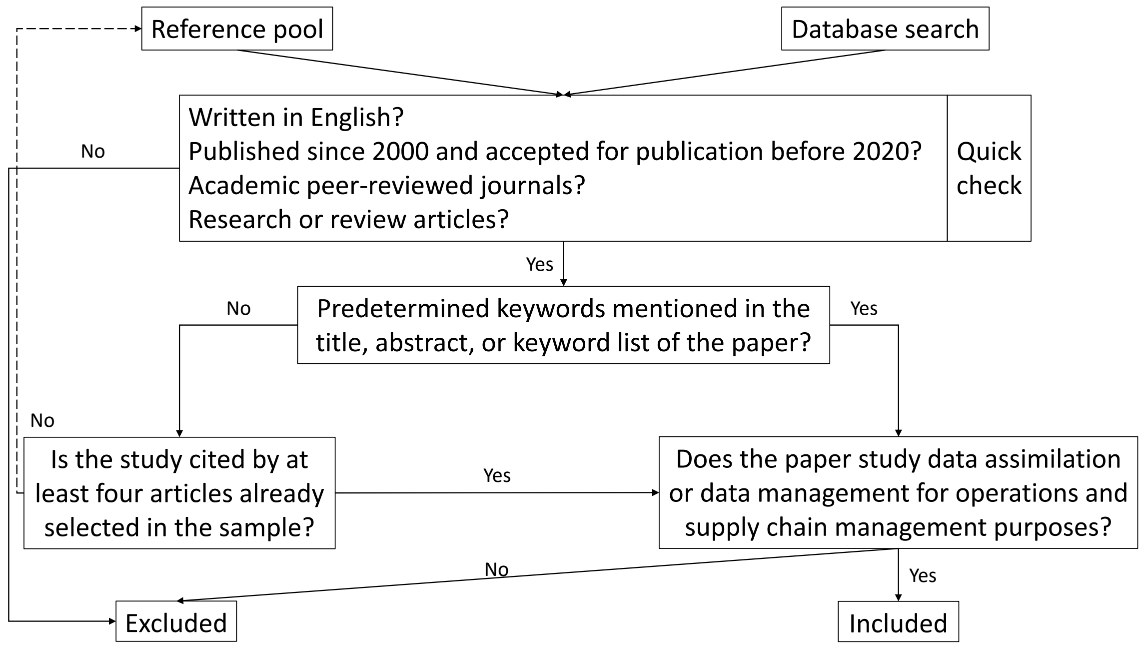


Figure 1.1: Graphical summary for the literature retrieval procedure

- Language: English.
- Time span: from 2000 to 2019. Papers with publication time after 2019 which were accepted for publication and became available online before 2020 are also included in the sample.
- Article type: Academic (peer-reviewed) journal article. In accordance with prior literature reviews (e.g., He et al., 2018; Xu et al., 2018), we only include research or review papers published in peer-reviewed journals in our study because such publications are considered verified knowledge (Ramos-Rodríguez and Ruíz-Navarro, 2004).
- At least one search keyword is mentioned in the title, abstract, or keywords of the paper (cf. Badi and Murtagh, 2019). Words with similar or related meaning are accepted, e.g., manufacturing and production, and purchasing and procurement.

Regarding the exclusion criteria, we eliminate the papers which include the keyword(s) but do not pertain directly to OSCM, e.g., research on trading and price prediction of financial assets. Since we follow the broad conceptualization of data-driven OSCM (cf. Irfan and Wang, 2019), the research papers selected can focus on data assimilation or data management resources (e.g., IT) but must explicitly mention the purpose(s) for which the data (recorded internally, obtained from external sources, or shared with partners) are used in practice. In other words, the data in the selected articles must be employed to address a practical issue, e.g., supplier selection and inventory management, rather than test a conceptual model unless it is about the relationship between data-driven OSCM and organizational performance. We peruse the abstract and research question(s) of each paper to assess its relevance to our SLR focus.

The graphical summary for the inclusion and exclusion criteria is provided in Figure 1.1, which will be further elaborated in the next subsections.

1.2.2 Databases and keywords

To retrieve relevant literature, we primarily use the WOS, which provides access to over "*100 million references from 33,000 journals*" (Martins and Pato, 2019). This platform has been used by many scholars for literature reviews, e.g., Kamble et al. (2020), Seyedghorban et al. (2020), and Rebs et al. (2019). Nonetheless, other researchers, e.g., Badi and Murtagh (2019) and Martins and Pato (2019), also access other databases to ensure holistic literature retrieval. Indeed, in the literature review of Liu et al. (2017), other databases contain a nontrivial number of unique publications that are not included on the WOS. Therefore, we add Emerald, INFORMS, ProQuest, Sage, Science Direct, Springer, Taylor & Francis, and Wiley to our search databases, and use the WOS template to reformat the data.

Table 1.1: Some keywords used in recent literature reviews on OSCM

Keywords	Studies
"*operations management*"	He et al. (2018); Seyedghorban et al. (2020)

(continued next page)

Table 1.1 (continued)

Keywords	Studies
"*capacity management*" or "*capacity planning*"	Fahimnia et al. (2019)
"*demand forecasting*," "*demand planning*," or "*demand management*"	Fahimnia et al. (2019); Huang et al. (2020); Nguyen et al. (2018); Tiwari et al. (2018)
"*inventory management*," "*inventory planning*," or "*inventory control*"	Fahimnia et al. (2019); Glock et al. (2019); Huang et al. (2020); He et al. (2018); Nguyen et al. (2018); Swanson et al. (2018); Tiwari et al. (2018)
"*supply management*"	Karttunen (2018); Swanson et al. (2018)
"*procurement*"	Fahimnia et al. (2019); Karttunen (2018); Nguyen et al. (2018); Tiwari et al. (2018)
"*distribution planning*" or "*distribution management*"	He et al. (2018)
"*logistics*"	Glock et al. (2019); Nguyen et al. (2018); Swanson et al. (2018); Seyedghorban et al. (2020); Tiwari et al. (2018)
"*production management*"	Fahimnia et al. (2019); Glock et al. (2019)
"*production planning*"	He et al. (2018); Nguyen et al. (2018); Tiwari et al. (2018)
"*transportation management*," "*transportation planning*," or "*transportation system*"	Nguyen et al. (2018); Swanson et al. (2018)
"*retail management*" or "*retail operations*"	Wen et al. (2019)
"*service operations*"	Fahimnia et al. (2019)

(continued next page)

Table 1.1 (continued)

Keywords	Studies
"*supply chain*"	Nguyen et al. (2018); Swanson et al. (2018); Chehbi-Gamoura et al. (2020)

With regard to the keywords, we use "*data-driven*" or "*data-based*" with those that have been utilized in previous literature reviews or deemed to be important OSCM themes (Table 1.1). Although these keywords cannot cover all OSCM topics, we believe that such generic keywords as SC and operations help find publications on uncommon subfields. To avoid overlooking important papers, we adopt cross-referencing to identify commonly cited articles in our sample. Specifically, if a peer-reviewed journal paper is cited at least four times by our selected studies and satisfies the inclusion criteria aforesaid, we add that publication to our sample. The four-citation threshold is proposed by Feng et al. (2017).

1.2.3 Literature synthesis

To determine clusters of research in the selected publications, we deploy co-citation analysis, which was put forth by Small (1973). When two papers are cited together in another study, we regard that as one co-citation, whose frequency indicates the similarity of the papers' research topics (Small, 1973). Therefore, co-citation analysis is primarily to identify the main research topics in the literature (Feng et al., 2017).

We follow the four-citation threshold recommended by Feng et al. (2017) to ensure adequacy and tractability of the citation data for analysis (Zupic and Čater, 2015). To analyze the co-citation data, we use VOSviewer open-source software (version 1.6.10), which is developed by van Eck and Waltman (2010) and has been employed in co-citation-based literature reviews, e.g., Wang et al. (2016b) and Zhao et al. (2018).

As van Eck et al. (2010) explain, VOSviewer determines the locations of n items on a map based on their co-citation similarity and then clusters them on the basis of their distances. Papers assigned to the same cluster by VOSviewer are those that are often co-cited. In their comparison study, van Eck et al. (2010) find that VOSviewer visualization is more effective than that of MDS, which, by minimizing a stress function, projects items into a low-dimensional space such that the distance between any two items can best reflect their dissimilarity. To check the robustness of VOSviewer results, we utilize MDS (followed by *k*-means clustering) in scikit-learn (Pedregosa et al., 2011) and FA in STATA 15.1 for data analysis triangulation. With FA, we can find the high-order level factors that capture most of the correlation space in the co-citation matrix. Items captured by the same factor are highly correlated with each other and associated with the same latent variable, or in other words, an overarching topic. These analyses were performed by Zhao et al. (2018) and Wang et al. (2016b), but our paper is among the first to use all three tools for a data-driven SLR of data-driven OSCM.

We use Bibexcel (Persson et al., 2009) to adapt the input data for analysis in different software (cf. Xu et al., 2018; Zhao et al., 2018; Feng et al., 2017; Hosseini et al., 2019). We then apply the three clustering techniques to the preprocessed data and retain the papers that are consistently clustered by all the methods. Next, we read the papers in each cluster to determine its theme with the support of VOSviewer keyword co-occurrence analysis (cf. Zupic and Čater, 2015; Ikeziri et al., 2019). In addition to the author-assigned and WOS-provided keywords in the metadata, we employ the PageRank-based algorithm of Wang et al. (2007) to extract important tokens in each paper's abstract and title. If these tokens are not included in the keyword sections of that article, we add them to the database before carrying out VOSviewer keyword co-occurrence analysis. With this, we can take advantage of the abstract content in the metadata and make additional contributions to our rigorous analysis. Details on our keyword extraction are given in Appendix A.

1.2.4 Result report

The clustering results are reported for the papers published after 1999 and accepted for publication before 2020. Given that the WOS metadata give credit to first authors only, we focus our analysis on the papers rather than their researchers. As citation is commonly used to measure a study's impact (Feng et al., 2017), we use four indices, namely, global citation index, WOS citation index, in-sample citation index, and PageRank, to identify influential papers in our sample. We utilize Google Scholar citation index as a proxy for our global citation index since Google Scholar covers several academic platforms including the WOS (Feng et al., 2017). The in-sample citation index shows how many papers in our sample cite a given article. To obtain a comprehensive picture of research impact, we use PageRank, which indicates the degree to which a paper is cited by highly cited studies (Xu et al., 2018). Descriptive details of the selected papers can be found in Appendix A.

1.3 Results and discussion

The preceding sections describe the first three steps in the procedure of Durach et al. (2017). We discuss the remaining steps, namely literature retrieval and selection, literature summary, and thematic report, in the next subsections.

1.3.1 Literature retrieval and selection

By setting the English language and academic/scholarly journal as search parameters, and using the aforementioned keywords, we retrieve a total of 2341 search results from all the databases. Then, we apply the inclusion and exclusion criteria and remove duplications to obtain a sample of 398 pertinent papers, 365 of which were published from 2011 onward. This accords with prior findings that there has been mounting growth of interest in BD from both scholars and practitioners since 2011 (Nguyen et al., 2018; Tiwari et al., 2018).

As we focus on the WOS, papers which were found in both WOS and another database are credited to the WOS only (26 September 2020). In other words, the figures reported for each non-WOS database after duplication check in Figure 1.2 (those remarked with *) refer to the number of unique publications retrieved from that platform only. As can be inferred from Figure 1.2, 94.22% of the shortlisted articles are included on the WOS.

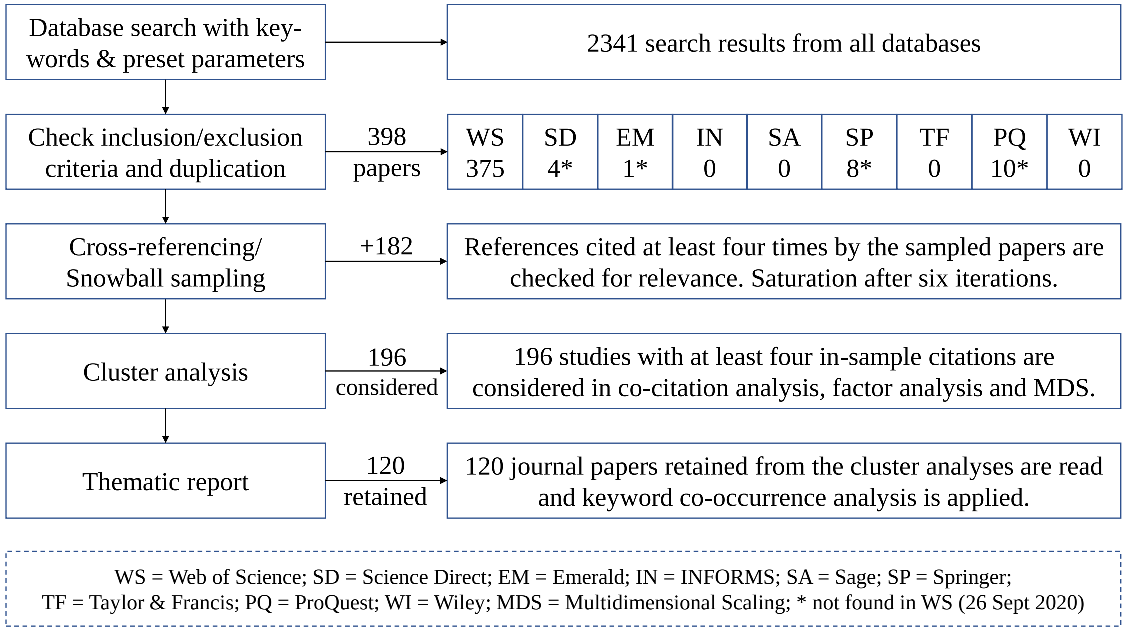


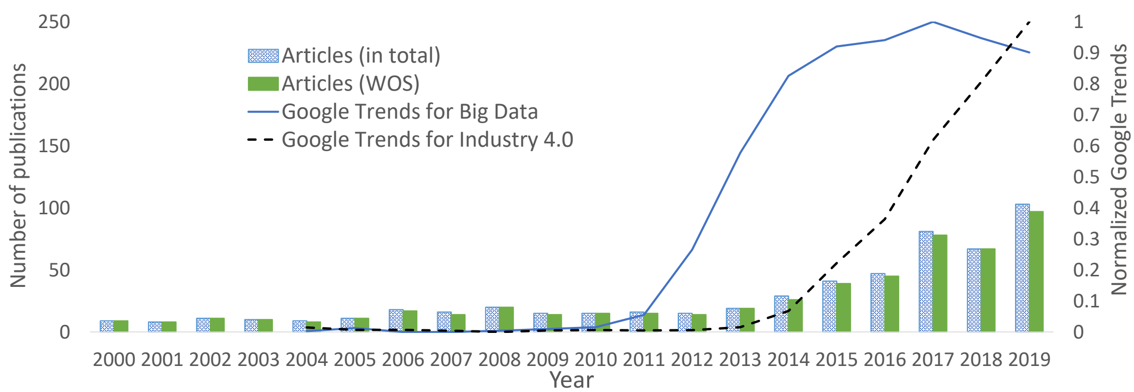
Figure 1.2: Literature retrieval and selection results

This ratio is 95.07% for publications after 2010 and 84.85% of those published before. The difference between these proportions is marginally significant at the 5% significance level, implying that the WOS publication coverage for data-driven OSCM can be deemed consistent between the two periods.

With an initially shortlisted sample of 398 papers, we conduct cross-referencing to identify highly cited and relevant references in these publications. Journal papers with at least four in-sample citations that relate to data-driven OSCM are added to the sample and we repeat the process until no new highly cited reference can be found. In line with the conceptualization of data-driven OSCM discussed, the papers considered relevant can focus on data assimilation or IT/data infrastructure but must explicitly mention how data are utilized for OSCM. After six iterations, we find another 182 relevant studies. In total, 580 papers are deemed relevant to data-driven OSCM and their bibliographies constitute the metadata for our cluster analysis. We note that this sample update has no statistically significant impact on the aforementioned distribution of publications before and since 2011 nor between the WOS and the other platforms.

The decrease in the WOS coverage proportion of papers from 2018 to 2019 in Figure

1.3 is because some studies were accepted for publication and made available on the publisher's database but have not yet been updated on the WOS. Another reason is that with the growth in attention to data-driven OSCM from both scholars and practitioners, relevant studies are published in various journals, some of which are not included on the WOS. One interesting insight from Figure 1.3 is the high correlation between the research volume of data-driven OSCM and Google Trends for "*Big Data*" and "*Industry 4.0*." Indeed, the observed upsurge in Google user search for "*Big Data*" after 2010 was followed by the increase in popularity of "*Industry 4.0*" search queries and the growth in studies on data-driven OSCM some years later. This partially reflects the attention of OSCM scholarship to practitioners' needs.



Correlation	(1)	(2)	(3)	(4)
(1) Articles (WOS)	1.0000			
(2) Articles (in total)	0.9991	1.0000		
(3) Google Trends for Big Data	0.8008	0.7994	1.0000	
(4) Google Trends for Industry 4.0	0.9751	0.9710	0.7521	1.0000

Note: Data for Google Trends for "*Big Data*" and "*Industry 4.0*" are normalized for trend comparison. (trends.google.com, accessed on 5 Feb 2020).

Figure 1.3: Number of publications in data-driven OSCM from 2000 to 2019 and Google Trends for "*Big Data*" and "*Industry 4.0*"

From the 580 journal papers selected for literature synthesis, those which are cited four times or more by other selected studies are considered in co-citation analysis as Feng et al. (2017) recommend. The sample in clustering then includes 196 journal articles, but the metadata for PageRank computation and co-citation database are from the 580-paper pool. Summarized details of these papers are provided in Appendix A.

The next subsection synthesizes those publications to attain an overall picture of the data-driven OSCM literature before cluster analysis is performed.

1.3.2 Literature summary

Overall, the 580 papers selected were published in 229 peer-reviewed journals, among which the journals with the largest numbers of selected publications are presented in Table 1.2. Of particular note is that there is no huge difference between the numbers of papers selected from these publication outlets. In fact, no journal accounts for a majority of research articles on data-driven OSCM in our sample. This is consistent with the broadening interdisciplinary and integrative scope of OM (Manikas et al., 2020) and SCM (Swanson et al., 2018). In addition to journals specializing in transportation and production, two subfields of OSCM, we can see, in Table 1.2, journals in operations research and engineering, which also relate to OSCM. The diverse yet mostly high impact factors of these journals signify that there are many high-quality studies on data-driven OSCM.

Table 1.2: Journals with the most papers included in the sample

Journal	Number	Impact factor*	
	of papers	2019	5-year
International Journal of Production Economics	26	5.134	6.205
Transportation Research Part C: Emerging Technologies	24	6.077	7.080
International Journal of Production Research	23	4.577	4.145
IEEE Transactions on Intelligent Transportation Systems	20	6.319	6.709
Computers & Industrial Engineering	18	4.135	4.296
Journal of Transportation Engineering	12	1.520	1.486
Production and Operations Management	12	2.590	3.740

(continued next page)

Table 1.2 (continued)

Journal	Number of papers	Impact factor*	
		2019	5-year
Applied Energy	12	8.848	9.086
Computer-Aided Civil and Infrastructure Engineering	12	8.552	6.212
Journal of Cleaner Production	11	7.246	7.491
Operations Research	11	2.430	3.621
IEEE Transactions on Industrial Informatics	10	9.112	9.008
European Journal of Operational Research	10	4.213	4.729
International Journal of Advanced Manufacturing Technology	9	2.633	2.925
Expert Systems with Applications	9	5.452	5.448
Annals of Operations Research	7	2.583	2.574
Manufacturing & Service Operations Management	6	4.281	4.097
Computers & Operations Research	6	3.424	3.804
IIE Transactions	6	2.884	2.504
International Journal of Computer Integrated Manufacturing	6	2.861	2.571
Journal of the Operational Research Society	6	2.175	2.108

Note: * taken from the Web of Science on 27 September 2020.

Looking at some of the most highly cited papers in our sample (see Table 1.3), we can observe a similar pattern between Google Scholar (proxy for global citation) and WOS citation indices, which is not surprising since Google Scholar citation index includes that of the WOS. Indeed, the correlation between global (Google Scholar) and WOS citation indices is 0.9320 for the 580 papers selected. However, the correlation between in-sample citation and Google Scholar citation (WOS citation) is only 0.5689 (0.6021). As shown in Table 1.3, only one paper belongs to both groups of top-ten globally and in-sample cited research. According to Feng et al. (2017), this disparity can be explicated by the varying degree of attention from scholars in different fields. This means that some globally highly cited research is less heeded or deemed less pertinent by academics in data-driven OSCM and vice versa.

Table 1.3: Highly cited papers in the sample with respect to global and in-sample citation

Paper \ Citation	Global*		WOS*		In-sample		PageRank	
10 most highly cited papers in the sample with respect to Google Scholar citation index								
Hippert et al. (2001)	2341	(01)	1104	(01)	8	(35)	0.006	(17)
Ho et al. (2010)	2267	(02)	962	(02)	4	(134)	0.002	(97)
Raghupathi and Raghupathi (2014)	2103	(03)	–	(–)	5	(93)	0.003	(95)
Lv et al. (2015)	1656	(04)	891	(03)	10	(21)	0.004	(46)
Xu (2012)	1650	(05)	850	(04)	7	(50)	0.003	(53)
Elmaghraby and Keskinocak (2003)	1509	(06)	638	(07)	6	(71)	0.003	(89)
Ben-Tal et al. (2004)	1335	(07)	655	(06)	6	(71)	0.005	(28)
Zhao and Magoulès (2012)	1193	(08)	699	(05)	6	(71)	0.005	(24)
Wu et al. (2004)	1072	(09)	459	(12)	7	(50)	0.002	(130)
Fosso Wamba et al. (2015)	1039	(10)	447	(13)	22	(2)	0.006	(18)
Top 10 in-sample cited papers in the sample								
Smith et al. (2002)	972	(11)	494	(10)	23	(01)	0.008	(09)
Fosso Wamba et al. (2015)	1039	(10)	447	(13)	22	(02)	0.006	(18)
Hazen et al. (2014)	597	(26)	263	(32)	22	(03)	0.008	(11)
Stathopoulos and Karlaftis (2003)	549	(32)	284	(30)	18	(03)	0.005	(27)
Wang et al. (2016a)	662	(19)	310	(24)	17	(03)	0.004	(36)

(continued next page)

Table 1.3 (continued)

Paper \ Citation	Global*		WOS*		In-sample		PageRank	
Vlahogianni et al. (2005)	613	(24)	336	(20)	17	(03)	0.003	(57)
Yin et al. (2002)	472	(41)	253	(33)	17	(07)	0.008	(10)
Vlahogianni et al. (2004)	530	(36)	294	(29)	15	(08)	0.002	(99)
Trkman et al. (2010)	496	(38)	164	(65)	15	(08)	0.005	(25)
Zhong et al. (2015)	319	(67)	177	(58)	15	(08)	0.003	(64)

Note:
In parentheses is the rank of the paper with respect to the relevant indicator in our sample. * updated on 26 September 2020. – not indexed on the Web of Science.

With respect to Google Scholar citation, the top-ten papers study a variety of OSCM subfields, e.g., OSCM overall (Fosso Wamba et al., 2015), supply management (Ho et al., 2010), inventory and sales (Elmaghraby and Keskinocak, 2003; Ben-Tal et al., 2004), healthcare operations (Raghupathi and Raghupathi, 2014), production (Xu, 2012), and demand/transportation forecasting (Lv et al., 2015; Zhao and Magoulès, 2012; Hippert et al., 2001; Wu et al., 2004). Nonetheless, most of them are literature reviews (Elmaghraby and Keskinocak, 2003; Ho et al., 2010; Zhao and Magoulès, 2012; Hippert et al., 2001; Raghupathi and Raghupathi, 2014). Modeling-based studies include those of Lv et al. (2015), Ben-Tal et al. (2004), and Wu et al. (2004), whereas Fosso Wamba et al.'s (2015) and Xu's (2012) articles are empirical and conceptual, respectively. It is interesting that although modeling (normative, descriptive, and predictive) dominates research on data-driven OSCM in general, literature reviews account for the largest proportion of the ten globally most cited papers in our sample. Explicably, literature reviews give an overview of a certain research topic and thus can be commonly cited.

On the other hand, except for one paper on BD-driven logistics in manufacturing (Zhong et al., 2015), the top-ten papers most cited by our sample focus on BD (Analytics) in SCM in general (Hazen et al., 2014; Trkman et al., 2010; Wang et al., 2016a;

Fosso Wamba et al., 2015) and forecasting in transportation (Smith et al., 2002; Vlahogianni et al., 2004, 2005; Lv et al., 2015; Yin et al., 2002). They adopt diverse research methods, namely, descriptive/normative modeling (Smith et al., 2002; Stathopoulos and Karlaftis, 2003; Vlahogianni et al., 2005; Yin et al., 2002; Zhong et al., 2015), conceptual modeling (Hazen et al., 2014; Wang et al., 2016a), survey (Trkman et al., 2010), case study (Fosso Wamba et al., 2015; Hazen et al., 2014), and literature review (Wang et al., 2016a; Vlahogianni et al., 2004).

As indicated in Table 1.3, none of the top-ten papers in terms of Google Scholar citation is among the ten most influential papers according to PageRank score computed on our selected research on data-driven OSCM. Out of the top in-sample cited research, only two belong to the group of ten most influential articles as per this index. The correlation between in-sample citation and PageRank index in our sample is 0.5886 while the figure is 0.5689 for global citation and PageRank index. This result is expected as highly cited research is not necessarily influential because PageRank-based research impact is determined by the extent to which a study is cited by high-impact papers (Xu et al., 2018; Brin and Page, 1998). Hence, the nominal value of citations may not fully reflect a paper's influence as indicated by PageRank index.

The next subsection will discuss the knowledge structure or, in other words, research clusters on data-driven OSCM studied since 2000.

1.3.3 Thematic report

We load the 580-publication metadata used for PageRank computation into VOSviewer, but only relevant references with at least four in-sample citations are considered. We then identify seven clusters of research on data-driven OSCM as depicted in Figure 1.4.

We check the robustness of VOSviewer results by performing FA in STATA and MDS in scikit-learn for data analysis triangulation.

For FA, we utilize the eigenvalues and factor rotation (Yong and Pearce, 2013) to select the high-order level factors that capture most correlation in the co-citation space.

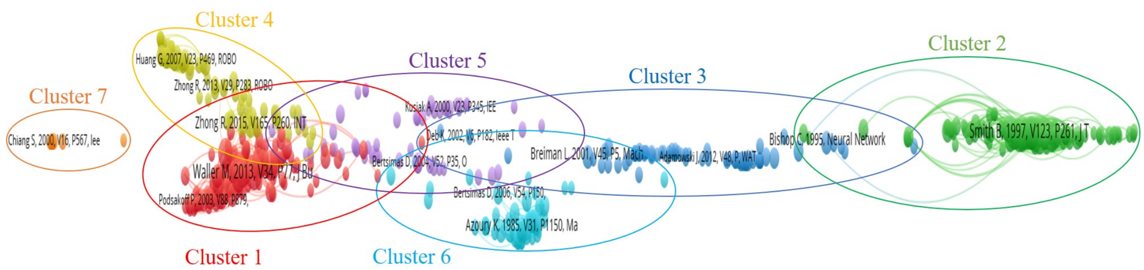


Figure 1.4: Research clusters identified by VOSviewer software

From the bibliographies of the 580 selected studies, we compile co-citation matrix $\mathbf{C}_{|N|\times|M|}$, where N and M are respectively the references and the 196 relevant journal publications cited by at least four articles in our 580-paper sample. $\mathbf{C}_{ij}$ indicates the number of studies in our sample that cite both i and j. $\mathbf{C}_{ii} = 1, \forall i \in \{1,2,\ldots,|M|\}$. Then, we run iterated principal factor analysis of $\mathbf{C}$ and factor rotation. Each factor here can be interpreted as a cluster of closely related studies and each item in a factor is a paper in our retained sample. There are 26 factors with eigenvalues greater than 1, which altogether explain 100% of the variation, but only nine of them have more than three items with loadings greater than or equal to 0.7 each. To test the significance of the results, we run structural equation modeling to perform convergent validity analysis (Sethi and King, 1994) and discriminant validity analysis (Fornell and Larcker, 1981).

Table 1.4: Factor analysis of co-citation matrix

Factor	Number of items	α	CR	AVE	Correlations							
1	41	.99	.99	.74	1.0							
2	26	.98	.97	.71	-.19	1.0						
3	11	.98	.98	.81	-.12	-.12	1.0					
4	11	.98	.98	.80	-.09	-.11	-.06	1.0				
5	08	.97	.97	.81	-.09	-.06	-.06	-.05	1.0			
6	07	.96	.96	.77	-.12	-.01	-.08	-.07	.06	1.0		
7	07	.95	.95	.74	-.08	-.08	-.06	-.05	-.04	-.05	1.0	
8	05	.94	.94	.76	.49	-.14	-.09	-.07	-.07	-.09	-.06	1.0
9	05	.90	.90	.64	-.08	-.08	-.06	-.04	-.05	-.06	-.05	-.06

Note:
α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted.

As illustrated in Table 1.4, the Cronbach's alpha of each factor exceeds the 0.7 threshold, indicating consistency among the items included therein (Dunn et al., 2014). While the correlations between factors is below the recommended 0.85 threshold (Yu et al., 2018), which indicates good discriminant validity, the Average Variance Extracted (AVE) of each factor being higher than its squared correlations with other factors is another discriminant validity indicator (Song et al., 2018). All factor loadings are of acceptable magnitude (greater than 0.7) and statistically significant, implying good convergent validity (Sethi and King, 1994). The Composite Reliability and AVE are respectively above the thresholds of 0.7 and 0.5 (Fornell and Larcker, 1981; Yu et al., 2018), further confirming the convergent validity. Thus, these nine factors can be considered robust.

Table 1.5: VOSviewer and Factor Analysis results

		VOSviewer results							Retained
		C1	C2	C3	C4	C5	C6	C7	120 papers
Factor Analysis results	F1		41						41
	F2	25			01				25
	F3						11		11
	F4			11					11
	F5				08				08
	F6				07				07
	F7					07			07
	F8		05						05
	F9			05					05

Table 1.5 demonstrates that most factors identified in FA fit entirely in the clusters appearing in VOSviewer result. Although the number of clusters/factors differs, the membership stays consistent. With these results, six clusters and 120 papers are retained.

According to van Eck et al. (2010), the similarity index used in MDS stress function can be the correlation between two items or their cosine. We run MDS with these similarity indices in scikit-learn (Pedregosa et al., 2011) and select the results of lowest dimensionality whose stress level is below the recommended 0.1 threshold (Kruskal, 1964; Zhao et al., 2018). Afterward, we perform the modified (Bagirov, 2008) and fuzzy

(Khan et al., 2020) *k*-means algorithms to cluster the cited papers. Despite changes in the number of clusters identified, the 120 papers retained in Table 1.5 fit neatly in the *k*-means clusters appearing in MDS outputs. Our implementation and detailed results of MDS and *k*-means clustering are provided in Appendix A.

Overall, out of the seven VOSviewer-assigned clusters, only six survive all the three clustering methods and we have a final sample of 120 papers for thematic interpretation.

On a separate note, we notice that among the 196 papers, which are cited by at least four papers in this pool and thus selected for cluster analysis, around one third (63) have four in-sample citations. The figure is similar for the papers published since 2015 (12/40). However, among the 120 articles commonly retained by the three analysis techniques and hence included in thematic reporting, one fifth (24) are cited by four other in-sample studies. For the publications since 2015, the ratio is 5/24. We can see that papers with four in-sample citations are less likely to survive all the three clustering techniques deployed and that recent research, i.e., published since 2015, can also receive more than four citations. From these statistics, we believe that the threshold of four in-sample citations recommended by Feng et al. (2017) is suitable because decreasing that threshold may not necessarily increase the number of studies retained for thematic reporting while raising it will reduce the contents covered.

In the next step, we read the 120 peer-reviewed journal articles retained from the analyses and use keyword co-occurrences to identify the themes. The lower right corner of each figure in the next subsections shows the average publication year of the papers mentioning the colored keyword. It is to note that there are many papers in Clusters 1 and 2, so we will mainly mention the highly cited articles on Google Scholar or those written by authors with multiple publications in that cluster as they are considered influential. Also, we will mention the papers whose topics we believe should be further explored though less common in their clusters.

1.3.3.1 Big data (data analytics) in OSCM

This cluster corresponds to Factor 2 with 25 papers retained. At Figure 1.5's center are "*big data*," "*analytics*," and "*supply chain*," the keywords co-occurring most often with other keywords in this cluster. Indeed, most papers therein discuss the application or benefits of BD/analytics in OSCM via literature reviews (Hazen et al., 2018; Wang et al., 2016a), surveys and interviews (Chen et al., 2015; Schoenherr and Speier-Pero, 2015; Yu et al., 2018; Gunasekaran et al., 2017), case studies (Hazen et al., 2014; Tan et al., 2015; Zhao et al., 2017), conceptual framework proposition (Chae, 2015; Hazen et al., 2014; Giannakis and Louis, 2016), or simulation (Hofmann, 2017). For instance, Hazen et al. (2014) use a brief case study on jet engine remanufacturing to illuminate how the data quality problem could be addressed to enhance data-driven SCM. In another example, utilizing data from Twitter related to companies in manufacturing, logistics, news, and IT, Chae (2015) demonstrates his proposed analytical framework and the value of social media data in SCM. Schoenherr and Speier-Pero (2015) interview experts from several firms, including professional service providers (e.g., consultancies), and find that data analytics skills are desired for SCM professionals.

Some papers discuss the application or benefits of BDA in a specific OSCM subfield, e.g., Fosso Wamba et al. (2015) present a case study on data-driven operations of the New South Wales State Emergency Service. Chong et al. (2016) and Cui et al. (2018) develop predictive models for retailing. Opresnik and Taisch (2015) propose a conceptual framework for BD strategy in servitization, a hybrid model of service provision and manufacturing. Nonetheless, the sector discussed most often by this cluster's papers is manufacturing. To leverage BD for fault detection in manufacturing, Kumar et al. (2016) propose a MapReduce framework, which can handle imbalanced data. Carrying out empirical research on the manufacturing industry in India, Dutta and Bose (2015) and Dubey et al. (2016) investigate the influence of BD via a case study and survey, respectively. In another Asian country's context (China), Tan et al. (2015) and Zhao et al. (2017) develop a BD-based model and illustrate it in a case study, whereas Yu et al. (2018) use survey

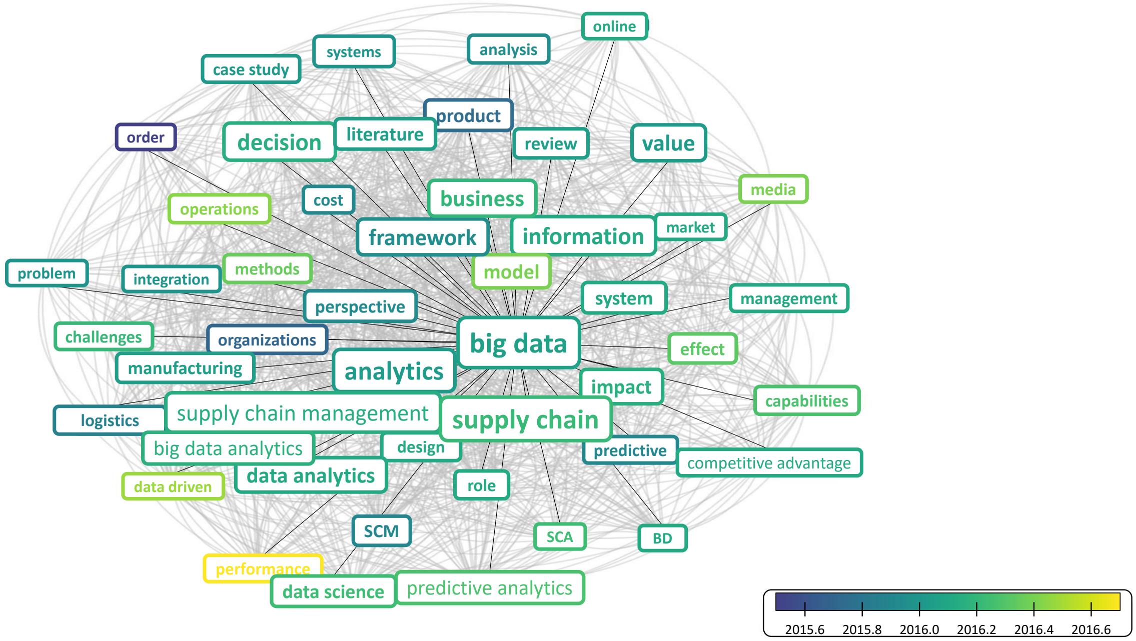


Figure 1.5: Keyword co-occurrences in Cluster 1

data from manufacturing firms to validate the relationship between data-driven SCs and firm performance. In addition to the empirical research mentioned in the preceding paragraph, other examples related to the manufacturing sector are the modeling-based papers of Huang and Van Mieghem (2014) and Wu et al. (2017). This reflects a finding in the extant literature that the manufacturing sector accounts for a large proportion of OSCM research.

Given the publication time (Figure 1.5's lower right corner), we can see that this is a recent cluster of research given the recent rise of BD research (Fosso Wamba et al., 2015; Nguyen et al., 2018; Tiwari et al., 2018; Chehbi-Gamoura et al., 2020), but three of the top-ten in-sample cited papers in our sample belong to this cluster and one of them also appears in the top-ten globally cited papers (Table 1.3). This implies the importance of this research cluster on data-driven OSCM. Hazen et al. (2014) are among the highly cited authors with multiple publications in this cluster. Although modeling is a widely used methodology in data-driven OSCM, empirical research dominates Cluster 1. Since empirical studies constitute a critical part of OM research (Gattiker and Parente, 2007), the formation of a cluster of highly co-cited research dominated by this method can be expected. An interesting insight is that we do not use "*big data*," "*data analytics*," or "*data science*" as search keywords, but their appearance in our keyword co-occurrence analysis heralds the upward trend of (B)DA in data-driven OSCM.

1.3.3.2 Transportation and traffic flow prediction

Figure 1.6 shows that the central keywords in this cluster are "*traffic*" and "*model*" or, more specifically, traffic flow forecasting models, which are deemed, by all research in this cluster, vital in (operating) advanced/intelligent transportation systems (ITS). This cluster's primary methodology is modeling, which includes both traditional (statistical) methods, e.g., auto-regressive integrated moving average (ARIMA) and econometric regression (Stathopoulos and Karlaftis, 2003; Min and Wynter, 2011), and ML schemes, e.g., *k*-nearest neighbors (Smith and Oswald, 2003), SVM (Wu et al., 2004), and artificial neural networks (ANN) (Dia, 2001; Vlahogianni et al., 2005). Some authors, e.g., Chen et al. (2001) and Chan et al. (2012), combine both approaches in their models, but there are overall twice as many papers adopting ML algorithms as conventional method-based articles in this cluster. Nonetheless, the publication time shows the parallel development of these two research streams. Overviews and comparisons of both statistical and ML techniques can be found in the reviews of Vlahogianni et al. (2004) and Karlaftis and Vlahogianni (2011), whereas the literature survey of Zhang et al. (2011a) focuses exclusively on ML. Overall, there is an increase in complexity of the models studied, but Karlaftis and Vlahogianni (2011) claim that simple and complex models can produce equally good results.

Revisiting Table 1.3, we find four articles in Cluster 2 among the top-ten in-sample cited papers, which partially reflects this cluster's popularity. Stathopoulos and Karlaftis (2003) and Vlahogianni et al. (2005) are examples of authors with multiple publications in this cluster. Overall, this is an established cluster that contributes to the methodological landscape of data-driven OSCM, where modeling dominates.

Nearly 85% of the 46 papers in this cluster mention their data sources and around three quarters of them collect data from western economies, including Australia. Even in

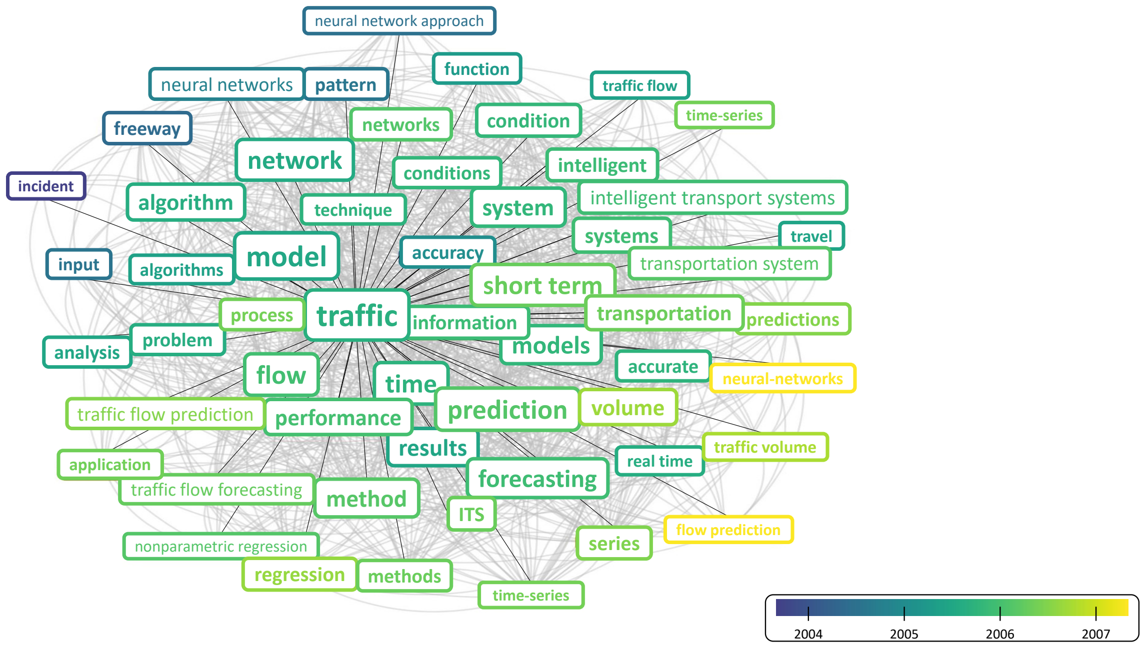


Figure 1.6: Keyword co-occurrences in Cluster 2

Asia, the research data are obtained from the countries with developed infrastructure, e.g., Taiwan, Singapore, and South Korea. This is not surprising given the infrastructure necessitated for ITS, where data can be recorded in large volumes by detector stations (Chan et al., 2012; Dia, 2001) or loop detectors (Stathopoulos and Karlaftis, 2003; Min and Wynter, 2011). With noisy or corrupt data recorded in such systems, Chen et al. (2001) and Quek et al. (2006) investigate the impact of missing data and noise tolerance, respectively, of ANN-based traffic flow prediction, whereas others develop models to address this issue, which include data imputation (Chen et al., 2012; Qu et al., 2009) or denoising (Jiang and Adeli, 2004). With more data-recording devices in ITS, voluminous traffic data have been collected (Zhang et al., 2011a), but we note that the retained papers do not explicitly discuss BD.

1.3.3.3 Demand forecasting

This VOSviewer-assigned cluster comprises two FA factors, one relates to water demand forecasting (Factor 4) and the other to energy consumption prediction (Factor 9). We can infer from the three keywords at Figure 1.7's center that this cluster's topic is "*de-*

mand forecasting." Like Cluster 2, over 90% of this cluster's research deploys predictive modeling. The publication time (Figure 1.7) of this cluster's papers illustrates that this is an established research cluster, which is consistent with the vital role of forecasting in OSCM (Huang et al., 2020), power system planning (Taylor, 2003), and water distribution (Adamowski, 2008).

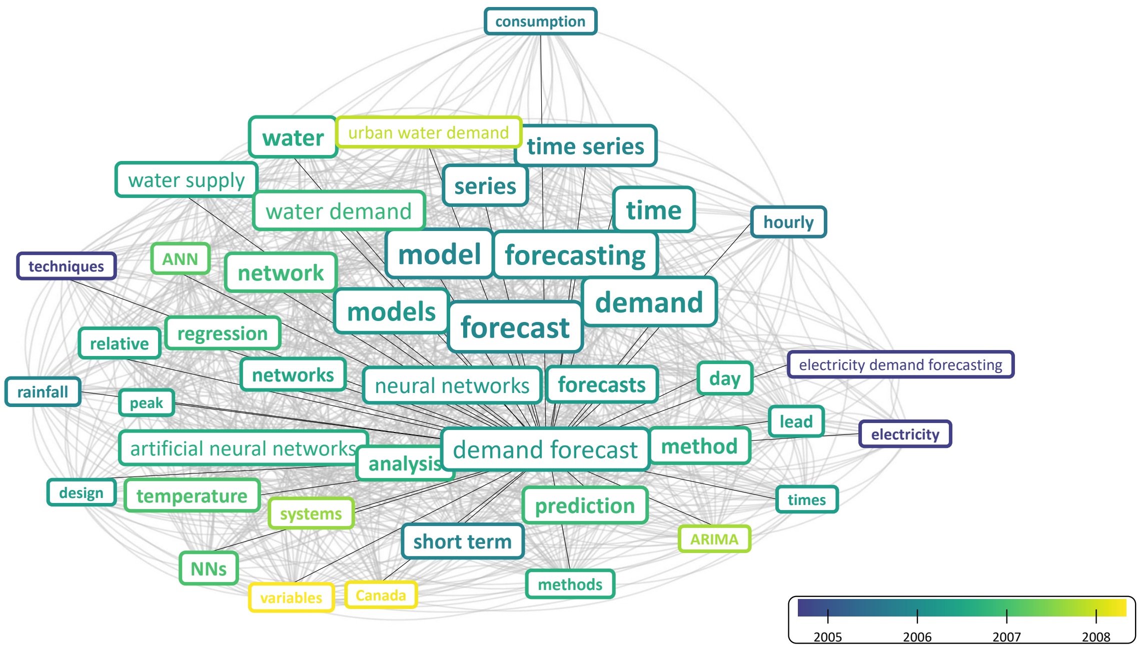


Figure 1.7: Keyword co-occurrences in Cluster 3

Both traditional statistical methods, e.g., ARIMA, regression, and exponential smoothing, and ML schemes, i.e., ANNs, are deployed almost equally in this cluster, but those published in the early 2000s focus more on the former (e.g., Taylor and Majithia, 2000; Zhou et al., 2000, 2002; Taylor, 2003; Taylor and Buizza, 2003). The predictive power of both modeling approaches are compared in more recent papers, of which typical examples include the research of Adamowski et al. (e.g., Adamowski et al., 2012; Adamowski and Karapataki, 2010; Adamowski, 2008). According to Donkor et al. (2014), ML algorithms are often used for short-term prediction, whereas traditional models, especially regression, are for long-term decision-making. This partly explains the parallel development of both approaches, but we predict that this cluster will see growth in publications combining both schemes like Cluster 2.

Of particular note is that over 85% of this cluster's 16 studies use data from western countries, including Australia. Since those are industrialized and urbanized nations whose electricity and water infrastructures were built long ago and are now subject to ageing and deterioration, there is a compelling need for research into those distribution systems given that electricity and water are deemed vital in the economy and urban life (Adamowski et al., 2012; Hong and Fan, 2016). This partly explains why we obtain an established research cluster on those topics. Another reason is the use of smart meters in the system to track demand more accurately (Adamowski et al., 2012; Hong and Fan, 2016).

1.3.3.4 System integration in manufacturing

This is a recent cluster of research with an average publication year of 2011 (Figure 1.8) and a standard deviation of 2.50. This cluster is in fact composed of Factors 5 and 6 in FA. While Factor 5's articles study manufacturing in the context of radio frequency identification (RFID) (e.g., Huang et al., 2007, 2008a,b; Zhang et al., 2008, 2010, 2011b,c), their counterparts in Factor 6 deal with the Internet of Things (IoT) context (e.g., Tao et al., 2014a,b,c; Xu, 2011; Xu et al., 2014). Except literature reviews (i.e., Bi et al., 2014; Xu, 2011; Xu et al., 2014), most studies in Cluster 4 are based on conceptual modeling, where conceptual frameworks/architectures are proposed to apply the IoT or RFID to modern/wireless/cloud manufacturing.

We can notice that the concept behind these 15 papers is system integration, which is required to provide timely information for decision-making in manufacturing (Huang et al., 2008b). As can be inferred from the discussion of Jun et al. (2009) about RFID applications in product life cycle (PLC) management, data need to be shared and analyzed at each PLC phase to facilitate decision-making and augment efficiency, e.g., manufacturing, maintenance, and reverse logistics. With regard to cloud manufacturing, a recent model where production resources can be shared and operated in the cloud among multiple enterprises (Tao et al., 2014a,c), real-time data sharing and analysis are clearly entailed for system monitoring. Obviously, such wireless technologies as the IoT and RFID now play an integral role in collecting and synchronizing information in manufacturing sys-

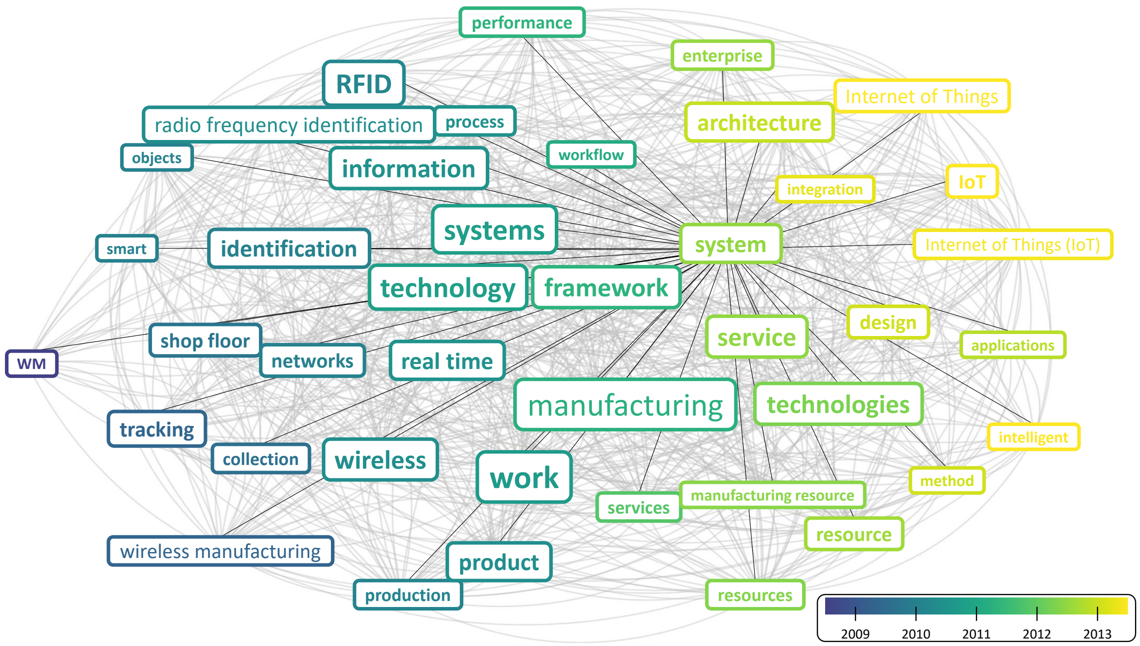


Figure 1.8: Keyword co-occurrences in Cluster 4

tems with multiple processes, levels, and resources (Bi et al., 2014; Huang et al., 2007). Given the content commonality among this cluster's publications, the keyword "*system*" is explicably located at Figure 1.8's center, connecting all other vertices. Therefore, we name this cluster "*System integration in manufacturing*." Like Cluster 1, this cluster is not dominated by normative, predictive, or descriptive modeling as the primary methodology, but is anticipated to see more highly cited case studies, action research, and prototyping-based papers examining the empirical performance of those frameworks and architectures (e.g., Fernández-Caramés et al., 2019). The publication time (Figure 1.8) illustrates a research shift over time to the IoT, which leverages RFID at an advanced level (Xu et al., 2014).

1.3.3.5 Data mining in manufacturing

As can be seen at Figure 1.9's center, this cluster's seven articles study data mining in manufacturing. Indeed, manufacturing systems record and accumulate a large volume of data, which can in turn provide meaningful insight for decision-making if properly analyzed (Chien et al., 2007). Therefore, research on knowledge extraction from manufacturing data has long been carried out by scholars, among whom the highly cited authors with multiple publications in this cluster include Kusiak et al. (e.g., Agard and Kusiak, 2004; Kusiak, 2000, 2001; Kusiak and Kurasek, 2001).

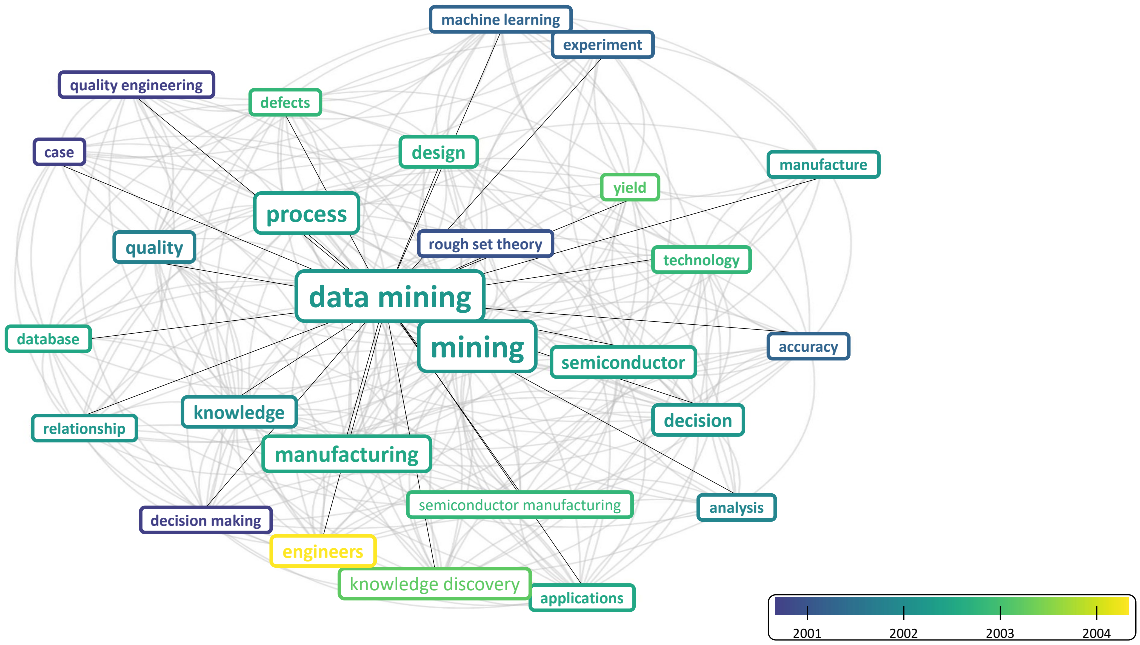


Figure 1.9: Keyword co-occurrences in Cluster 5

An overview of data mining applications in manufacturing, including design, production operations, quality control, and maintenance, can be found in the review of Harding et al. (2005). For example, Kusiak (2001) proposes a rule-structuring algorithm based on rough set theory for data-driven knowledge discovery in semiconductor manufacturing. For yield enhancement in that industry, Chien et al. (2007) propose a fault diagnosis framework while Braha and Shmilovici (2002) experiment with data mining methods to improve processes. Via case studies, Kusiak (2000) and Kusiak and Kurasek (2001) illustrate data mining applications to fault detection in wafer manufacturing and electronics assembly, respectively. An example of data mining applications to product design is the framework Agard and Kusiak (2004) propose to handle product families. Overall, this is an established cluster with diverse research methods adopted, but the retained studies do not specifically target BDA. Yet, they indubitably lay foundations for recent research on BDA in OSCM (e.g., Dutta and Bose, 2015).

1.3.3.6 Data-driven inventory management

The keyphrases linking all other vertices in Figure 1.10 include "*inventory*," "*lost sales*," "*newsvendor*," "*censored*," "*demand*," and "*distribution*." In effect, this cluster's 11 articles develop models to address inventory management problems where demand distribution or its parameters are unknown.

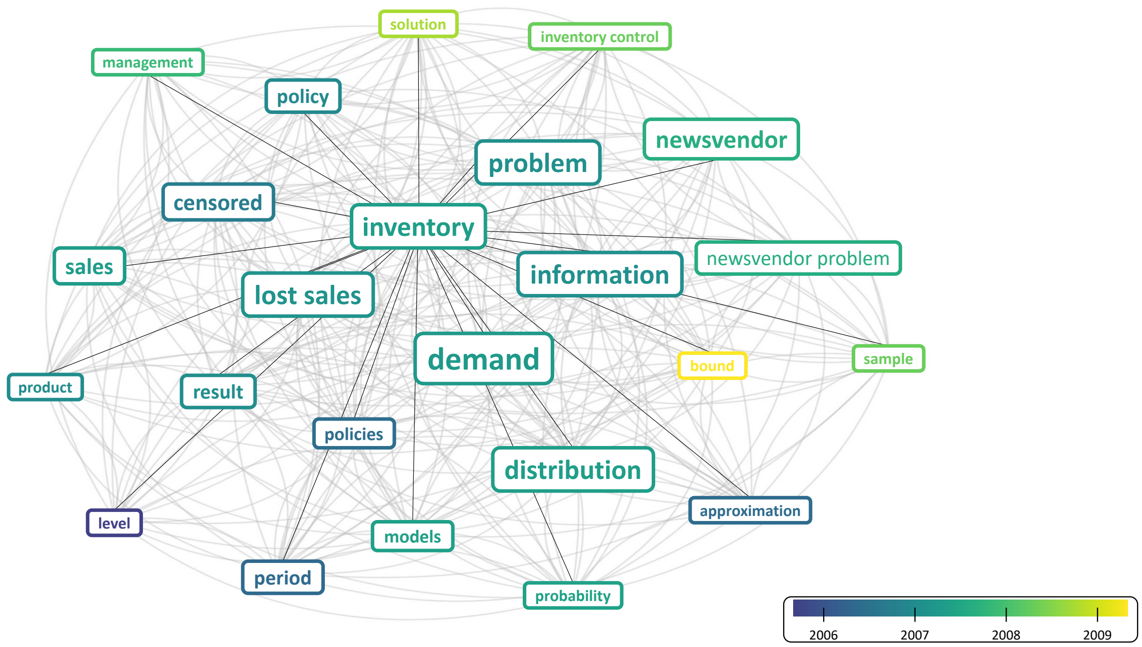


Figure 1.10: Keyword co-occurrences in Cluster 6

In particular, Burnetas and Smith (2000) employ a multiarmed bandit framework and a stochastic approximation procedure respectively to propose an adaptive pricing and ordering mechanism for perishable items, where the policy is updated as new information arrives. Meanwhile, Godfrey and Powell (2001) leverage the concave adaptive value estimation algorithm to directly arrive at an optimal decision in response to a given level of remaining inventory and emphasize that they need not estimate demand distribution. Likewise, under the assumption of no information on demand distribution or its family, ordering decisions can be optimized by using only sales data with adaptive inventory policies developed on the basis of stochastic gradient descent and online convex programming (Huh and Rusmevichientong, 2009) or the Kaplan-Meier Estimator (Huh et al., 2011). In a different research vein, Liyanage and Shanthikumar (2005) propose operational statistics, where demand estimation and inventory optimization can be carried out together in one single step, directly estimating the optimal order quantity from the data under the assumption that demand distribution, although unknown, belongs to a given family. It is important to make full use of market data for high-quality inventory management decisions (Wen et al., 2019). Yet, the data utilized for inventory management in practice are just samples of the true demand distribution, so Levi et al. (2007) theoretically analyze the number of samples and sample size required to guarantee that the decision taken would result in a total cost within a predefined confidence level given that the SAA (sample average approximation) is deployed for the single-period problem and (shadow/approximate) dynamic programming for the multi-period problem. Later, Levi et al. (2015) derive a tighter bound for the SAA applied to data-driven inventory management under censored demand. Overall, the impact of censored demand on inventory management can be found in the theoretical analysis of Besbes and Muharremoglu (2013) and Ding et al. (2002).

This is an established research cluster on data-driven OSCM (publication time in Figure 1.10) with the primary methodology being modeling. We can see, in recent publications citing this cluster's research (e.g., Ban and Rudin, 2019; Bertsimas and Kallus, 2020), a rising trend of adopting ML and BDA to optimize inventory management decisions with one-step algorithms instead of the traditional two-step approach where demand (distribution) must be estimated and then inputted into prescriptive analytics.

1.3.4 Result analysis

Since SCM, which derives from and thrives in the manufacturing sector (Vrijhoef and Koskela, 2000), has been among the main research areas in production scholarship (Kuo and Kusiak, 2019; Silva et al., 2019) and OM originally "*referred primarily to manufacturing production*" before incorporating other organizational functions, e.g., logistics and procurement (Bayraktar et al., 2007), our SLR of data-driven OSCM unsurprisingly ascertains findings closely related to production research. Figure 1.11 depicts the publication and citation of the identified research clusters on data-driven OSCM.

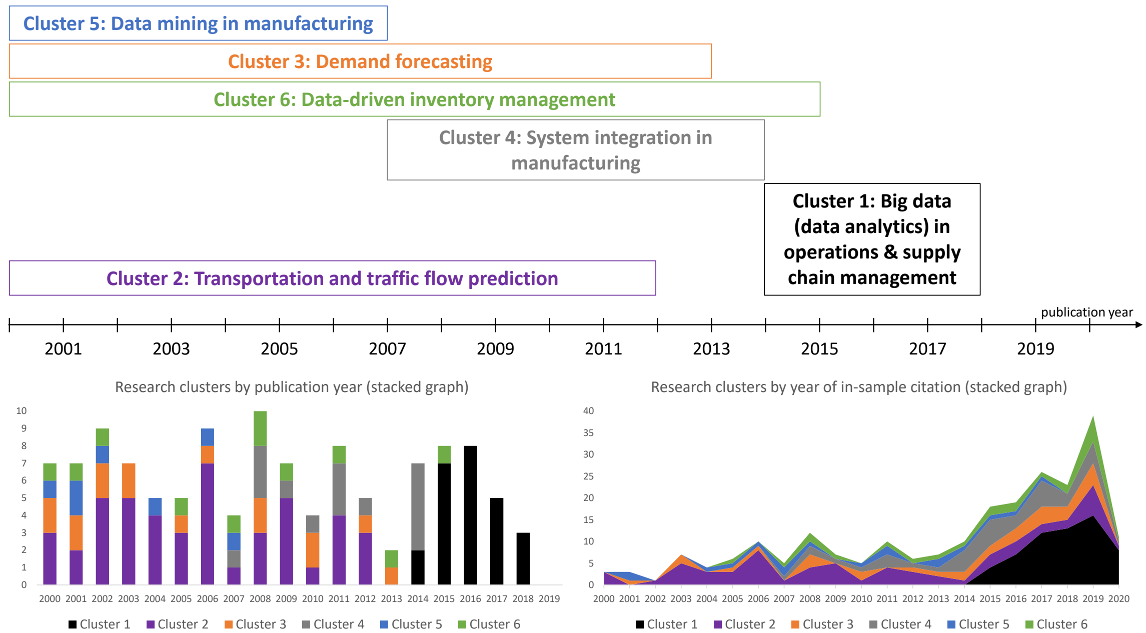


Figure 1.11: Publication and in-sample citation of research clusters on data-driven OSCM

Since 2000, data-driven decision-making has received increasing attention from production scholars in response to technological advances, which facilitate data management and storage (Kuo and Kusiak, 2019). Thus, we can see clusters of studies where data are used to support production and its related fields, i.e., demand forecasting, inventory control, and transportation.

Next, when data-driven decision-making became more popular in manufacturing, there was a dire need to collect and synchronize information in manufacturing systems with several levels and processes (Bi et al., 2014; Huang et al., 2007). Therefore, a research cluster on system integration, which is required to provide timely information for decision-making in manufacturing (Huang et al., 2008b), was formed.

Recently in SCM, BDA has grown fast (Chehbi-Gamoura et al., 2020). Therefore, the most recent research cluster in our SLR is Big data (data analytics) in OSCM, where the manufacturing sector accounts for a large proportion.

We can see that the early clusters in our SLR study IPCs, which, according to OIPT, can be reinforced by organizational integration and information systems (IS) (Srinivasan and Swink, 2018; Irfan et al., 2019; Williams et al., 2013; Trkman et al., 2010), a research theme established a few years later in data-driven OSCM. Thence, with IPCs supported by IS assimilation across the SC, firms can leverage voluminous data for OSCM (Irfan et al., 2019). This evolution of the highly co-cited literature on data-driven OSCM in our SLR leads us to hypothesize that companies planning to implement BDA should develop data analytics capabilities for their staff and SC partners on the basis of shared data in a coordinated manner so that they can be accustomed to sharing and working on the same dataset before rolling out the new yet integrated IS. In other words, our hypothesis is that organizational data analysis capabilities can develop into BDA when moderated by adequate human and technology resources. This hypothesis accords with the content analysis of Sun et al. (2018), where having human resources with appropriate competencies for BDA adoption ranks higher than technology resources among the most vital factors in BDA adoption. Indeed, consultants recommend that feasibility analysis and staff education precede software/system rollout in organizational change processes (cf. Nguyen et al., 2021).

We synthesize conceptual models/frameworks from the retained papers and determine other relevant elements in data-driven OSCM in addition to data assimilation and data management resources as operationalized in line with OIPT in our paper. The result is overall in accord with Sun et al. (2018), but we subsume technological and environmental factors under the external group, which also includes competitive pressures (Chen et al., 2015; Opresnik and Taisch, 2015) and interorganizational cooperation (Giannakis and Louis, 2016; Opresnik and Taisch, 2015). Meanwhile, the internal variables comprise managerial support (Chen et al., 2015; Gunasekaran et al., 2017) and intrafirm collaboration (Dutta and Bose, 2015; Giannakis and Louis, 2016). We hypothesize that these elements support BDA implementation and thus should be taken in account when managers consider BDA adoption.

To help practitioners find relevant technical/managerial details in the literature, we point out the retained papers discussing these factors in Appendix A.

1.4 Implications for research and practice

1.4.1 Research avenues and implications

Our thematic discussion highlights that manufacturing, demand prediction, inventory planning, and transportation/traffic forecasting are commonly studied in data-driven OSCM. Given the broad scope of OSCM (Manikas et al., 2020; Swanson et al., 2018), the small number of established research clusters on data-driven OSCM might partly account for the reasons why firms face difficulty adopting BDA. Indeed, ML, BDA, and related technologies, e.g., IoT and RFID, are not explicitly discussed in several clusters. This opens many research directions.

First, despite the recognized importance of service operations in OSCM scholarship and practices (Heineke and Davis, 2007), there has not been an established cluster for that subfield in research on data-driven OSCM. Even in the recently published cluster (Cluster 1), most papers remain largely focused on manufacturing, which Clusters 4 and 5 directly support. With servitization being facilitated by today's BD (Opresnik and Taisch, 2015), OSCM scholars might attend to data-driven service operations and servitization to ensure practical relevance of their research endeavors. For instance, production researchers could examine which insight or model in data-driven production is transferable to data-driven service operations and vice versa, and what hinders knowledge transfer between the two sectors.

As regards studies on data-driven transportation, the main focus was on flow prediction and description in transportation systems. This does not mean that there are no journal-published papers on prescriptive models for data-driven transportation. Examples include the ML-based vehicle-routing research (Mao and Shen, 2018; Tang et al., 2019; Lee et al., 2020). Nonetheless, with so few articles in the literature, there are obviously plentiful opportunities for further research, e.g., empirical evaluation of such data-driven vehicle-routing models. Future research could investigate how the improved traffic flow forecast can benefit delivery planners and logistics managers, and which forecast horizon optimally facilitates their operations planning.

Turning next to demand forecasting studies, we can see articles in the utilities sector (electricity and water). This implies that research on demand forecasting for other products and services has plenty of scope for further exploration, e.g., how to leverage data analytics for demand forecasting in e-commerce (see Ferreira et al., 2016) and how to integrate traditional and ML approaches into a firm's system if their combination improves demand planning. Case studies and action research can boost practitioners' confidence in the model's efficacy and provide them with implementation guidelines, which should illuminate what and how to change, and how much to invest.

About data-driven inventory management papers, their cluster is dominated by modeling. Thus, empirical studies on those models' real-life performance are essential additions to this research topic. Moreover, the data-driven inventory management literature can be enriched by applying ML schemes and comparing or combining traditional optimization approaches and ML algorithms (e.g., Ferreira et al., 2016; Bertsimas and Kallus, 2020). There are similar papers in our 580-paper pool (e.g., Sachs and Minner, 2014; Ban and Rudin, 2019), but their in-sample citations are currently below the inclusion threshold in our co-citation analysis. Fellow scholars might investigate how to select a suitable model (or a combination of models) to manage inventory, how to put it in place, and which benefit to reap in reality.

Finally, there are several articles on other subfields of OSCM such as supply management (Cheng et al., 2020), warehousing (Fernández-Caramés et al., 2019), distribution planning (Chen et al., 2017), retail operations (Ozgormus and Smith, 2020), and maintenance (Kumar et al., 2018), some of which are highly cited and included in our sample, e.g., supply management (Ho et al., 2010; Cheng et al., 2020), but have not established a distinct cluster in data-driven OSCM. Thus, the need for further research is undeniable.

Considering the academic vantage point, our paper demonstrates a concrete example of data-driven SLR where a well-established protocol is followed and data analysis triangulation is performed to enhance robustness and reduce subjectivity. Moreover, vis-à-vis other recent OSCM literature reviews, our paper searches more databases, uses more search keywords, and covers a longer time span (cf. Brinch, 2018; Mishra et al., 2018; Chehbi-Gamoura et al., 2020; Winkelhaus and Grosse, 2020). Also, by using cross-referencing, we can retrieve highly cited and relevant papers that are not indexed in the predetermined databases. Hence, our paper can uncover a broader overview of data-driven OSCM where BDA now features prominently.

From a theoretical perspective, we ascertain the literature evolution and knowledge structure of studies on data-driven OSCM which future research can rely on.

OIPT (Galbraith, 1974), on the basis of which we define data-driven OSCM in this work, is one theoretical lens adopted by several papers in our selected sample, e.g., Trkman et al. (2010), Hazen et al. (2014), Chen et al. (2015), Srinivasan and Swink (2018), and Dubey et al. (2019). The reviews of Gupta et al. (2020) and Kamble and Gunasekaran (2020) also propose other theoretical frameworks, but overall, organizational theories are less commonly considered in our selected literature on data-driven OSCM from 2000 to early 2020. Thus, we recommend drawing on diverse theoretical perspectives to enrich the theoretical bases of (big) data-driven OSCM scholarship. The following open research questions may suggest fruitful research agendas:

- As a manufacturing system involves multiple processes (Bi et al., 2014; Huang et al., 2007), e.g., demand forecasting, distribution management, capacity planning, inventory control, and supply management, how should manufacturers implement BDA in these processes (simultaneously)? Which department will play a leading role? What is a guiding theory for that rollout? OIPT provides an important theoretical framework, but the other theories discussed by Gupta et al. (2020) and Kamble and Gunasekaran (2020) are also worth considering.

- Interorganizational collaboration is an influencing factor in BDA adoption (Opresnik and Taisch, 2015; Giannakis and Louis, 2016). However, Nguyen et al. (2021) show that the benefits of reduced stockout, inventory, and bullwhip effect via information sharing are least salient at retail outlets in a fully integrated distribution resource planning system. How should manufacturing firms engage their retailers in

BDA implementation then? (Supply) uncertainty reduction in line with OIPT might be a good candidate to justify cooperation, but we do not exclude the potential of other theoretical lenses for this question.

- In addition to retail partners, other SC players in a manufacturing system, e.g., suppliers and third-party logistics providers, also need to be involved. It is hence open to question what SC configuration is optimal to put BDA in place. What intermediaries may become redundant then? Upon BDA adoption, what benefits should be measured? Will those benefits be enjoyed fairly among SC members or should some redistribution mechanisms be in place to encourage ongoing BDA in that interconnected system? The answers likely lie in the information needs or core processes of the focal company (OIPT), but other theoretical perspectives, e.g., those on competitive pressures (Chen et al., 2015; Opresnik and Taisch, 2015), might equally come into play.

- BDA can be deemed a disruptive technology (Brinch, 2018; Fu and Chien, 2019), so adopting it may entail a new perspective. What theory can provide such a revelatory perspective on BDA in OSCM? We refer interested readers to the theories listed by Gupta et al. (2020) and Kamble and Gunasekaran (2020) for potential starting points.

1.4.2 Practical implications

For practitioners, our paper synthesizes highly cited papers that can inform their decision-making, especially in manufacturing, demand forecasting, inventory management, and transportation. Several highly cited models and frameworks have been developed to utilize data, which can be voluminous, noisy, or incomplete (as in censored demand). Practitioners in production can refer to these established clusters to guide their decision-making but need to consider if the research context and assumptions are relevant to their enterprises. It should be noted that simple and complex models can perform equally (Karlaftis and

Vlahogianni, 2011), so managers should assess the fit between a model/framework and their system/practice and carefully plan the change process before deciding on adoption.

1.5 Conclusion

In this paper, we utilize the keywords and databases commonly used in the OSCM literature to seek pertinent publications and apply co-citation analysis to determine the knowledge structure of data-driven OSCM since 2000, which is also when data-driven decision-making started receiving attention from production researchers (Kuo and Kusiak, 2019). There are prior reviews on data-driven OSCM and co-citation-based SLRs, but our paper retrieves a larger literature sample thanks to cross-referencing and it is among the first endeavors to conduct a data-driven SLR of data-driven OSCM with multiple clustering tools, i.e., VOSviewer, FA in STATA, and scikit-learn MDS-based enhanced *k*-means clustering, as data analysis triangulation. This is the originality of our study.

There are six clusters of research appearing in our analysis results, namely *Big data (data analytics) in OSCM*, *Transportation and traffic flow prediction*, *Demand forecasting*, *System integration in manufacturing*, *Data mining in manufacturing*, and *Data-driven inventory management*, five of which closely relate to production. This is unsurprising because OSCM is closely associated with production research as previously discussed. Traditional statistical and econometric approaches remain widely deployed in forecasting, but ML programs and BDA are becoming popular. Indeed, ML and BDA have been frequently undertaken in the literature on SCM, production, traffic prediction, and demand forecasting. We synthesize these clusters of studies as crucial points of reference for production research and practice based on ML and BDA. The evolution of the identified clusters also suggests a procedure for BDA adoption in production, where staff's data analysis capabilities must be prioritized and developed with the support of proper technology resources so that BDA can be rolled out successfully, which is in line with OIPT. Also, competitive rivalry, inter/intra-organizational collaboration, and managerial support are important factors to consider in BDA adoption.

Given the interdisciplinary nature of OSCM (Manikas et al., 2020; Swanson et al., 2018) and manufacturing systems involving multiple processes, levels, and resources (Bi et al., 2014; Huang et al., 2007), we expect to see more clusters of highly cited research on ML and BDA for inventory control, supply management, distribution planning, etc., to improve the knowledge base that production scholars and practitioners can directly leverage.

Albeit we carry out a systematic literature review, which allows finding answers to our research questions, our study has limitations. First, the clusters identified may have been confined to the keywords utilized for database search. However, since generic keywords such as SCM, OM, and logistics were used and research on other OSCM subfields was also retrieved, the clusters identified here may well reflect the current knowledge state of the data-driven OSCM literature published since 2000. Second, one inherent drawback of co-citation analysis is its inability to identify emerging research areas (Fahimnia et al., 2019) as lately published articles are less likely to be included given their insufficient time to accumulate citations. Nonetheless, this indirectly confirms the proposed research opportunities.

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Chapter 2

A framework for affinity-based personalized review recommendation

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Abstract

Online review platforms have proliferated thanks to technological advances and consumers' increased dependence on each other's opinions in purchase decisions. However, users typically face an enormous number of online reviews and suffer from information overload. Unlike existing studies that rely mainly on popularity, crowd-based evaluation, or filtering methods, we propose a framework for personalized review recommendation based on user-review affinity. Indeed, this study seeks to identify and recommend reviews to each user on the basis of the probability that he/she will like (hit the helpfulness vote/like button), comment on, or re-read those reviews, whereby user login time increases, which in turn correlates positively with user affinity toward the platform. We

hypothesize a conceptual model, conduct predictive analytics, and perform counterfactual simulations on the log data of a large restaurant review platform in Southeast Asia and find that reviewer-user similarity is among the most significant explanatory factors, which is in line with the Asian culture. Built on the results of the explanatory analysis, machine learning-based predictive models are then applied to predict the likelihood that each user will interact with each review for each business. Our counterfactual analysis demonstrates the potential of the resultant affinity-based ranking to increase user engagement with the platform.

2.1 Introduction

Online review platforms have become one of the primary data sources for customers (Siering and Janze, 2019). Prior studies have shown that many consumers rely on online reviews in their decision-making process (Choi et al., 2022), resulting in strong empirical connections between online reviews and product sales (Anderson and Lawrence, 2014; Sun, 2012). Hence, many platforms that aggregate online reviews have proliferated (Luca and Zervas, 2016), especially for products that consumers cannot directly evaluate before consumption such as restaurants and hotels (Khern-am nuai et al., 2018). These platforms have competed to attract and retain content contributors over the years (Qiao et al., 2020). Nonetheless, content increases also trigger unforeseen issues for online review platforms. That is, users who access an enormous number of online reviews on the platform suffer from information overload (Gonzalez Camacho and Alves-Souza, 2018), which likely causes difficulty in filtering pertinent information (Zhou and Guo, 2017). This problem has become increasingly important since recent studies have reported that it may dampen platforms' success (Chen et al., 2020). Several approaches have been adopted by online review platforms to mitigate this issue, including the utilization of crowd-based content assessment such as review (un)helpfulness scores (Orlikowski and Scott, 2014) and structured content filtering such as tags and badges (Rao et al., 2017). This research studies an approach for helping users overcome information overload with online reviews. Specifically, we build a personalized review recommendation framework on a theory-driven yet readily implementable model.

In the era of big data, the concept of personalized recommendation has been widely adopted by various services. Service providers, including online platforms, have invested in capturing and analyzing data on customers' digital trails of activities, such as browsing history, geographical locations, purchases, likes, and comments, to customize their service offerings/delivery such that customer satisfaction and profitability are improved (Cohen, 2018; Caro et al., 2020). Indeed, online platforms have transformed a significant part of service operations given that they can collect data on customers' tastes, habits, and social networks to make appropriate recommendations (Cohen, 2018). The literature has covered the design and use of personalized recommendation in multiple contexts, e.g., product advertising (Fleder and Hosanagar, 2009; Hosanagar et al., 2014), news media (Prawesh and Padmanabhan, 2014), and crowdsourcing contests (Mo et al., 2018). Nevertheless, interestingly, the use of personalized recommendation in online reviews is fairly rare in research and practice. Meanwhile, existing works that study personalized review recommendation are mostly limited to a certain aspect of online reviews such as review sentiment (Zhang et al., 2018; Huang et al., 2020), review quality (Paul et al., 2017), and consumer segment (Salehan et al., 2017). Inspired by this gap in research and practice, this paper leverages a unique dataset obtained via collaboration with a large restaurant review platform in Southeast Asia to propose a personalized review recommendation framework built on user-review affinity, which can be broadly characterized as users' positive attitude to media content (Ji and Fu, 2013). In effect, emotional attachment can boost customer loyalty (Khan and Rahman, 2017). We discuss the proxies for user-review affinity adopted herein in Section 2.3.2.

Our research design includes exploratory, predictive, and counterfactual analyses (see Figure 2.1). First, we survey prior online review studies to identify factors that potentially impact user-review affinity. Particularly, this article runs exploratory analysis by partial least squares structural equation modeling or PLS-SEM (Henseler et al., 2016), which is commonly performed for hierarchical models in big data analytics (Akter et al.,

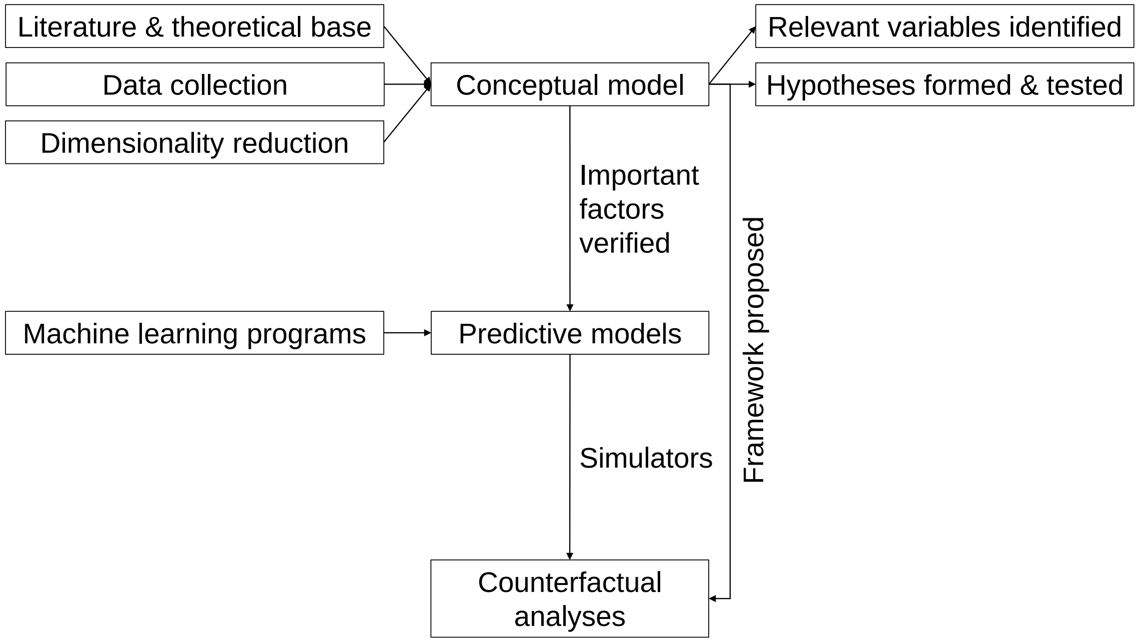

Figure 2.1: Research design

2017), to test a conceptual model that connects explanatory variables to user-review affinity. Afterward, we develop a predictive model using machine learning (ML) algorithms and factors identified in the previous step as predictors of the likelihood that a user will interact with each review for each business. To test the efficacy of the proposed review recommendation framework in our exploratory analysis, we rely on the results from our predictive modeling to run counterfactual simulations, which have gained traction as a research methodology to validate proposed strategies (Xu et al., 2019).

This paper's contributions are threefold. First, we identify and verify crucial variables that are theoretically and empirically supported in determining relevant and useful reviews which in turn help to increase user affinity for the platform. Second, we show that several ML models built on the verified factors can achieve comparable predictive performance at shorter runtime vis-à-vis their high-dimensional counterparts. Lastly, we illustrate that arranging reviews in descending order of their predicted effect on user affinity rather than in time order is more effective in improving user affinity for the platform and its service operations.

The rest of the paper is organized as follows. In Section 2.2, we review background literature related to this study. Our data and research context are described in Section 2.3. Section 2.4 discusses our exploratory model, followed by predictive modeling in Section 2.5 and counterfactual analysis in Section 2.6. Finally, we discuss limitations and future research avenues and conclude our study in Section 2.7.

2.2 Related literature

In this section, we survey the background literature that is related to our study. Particularly, we first review research on recommender systems and then discuss previous works on personalized review recommendations.

2.2.1 Recommender systems

There is an extensive body of literature on recommender systems (Mo et al., 2018), which have been strategically deployed by businesses to provide relevant recommendations to customers on the basis of their purchase history and preferences (Xu et al., 2017; Gorgoglione et al., 2019). According to Eirinaki et al. (2018), the most commonly used techniques include content-based, which analyzes a user's historical activities, and collaborative, which is based on other users with similar interests. In addition to platform users' demographics, other details to build the model can derive from their own comments, search history (Bai et al., 2017), or social networks (Li et al., 2017). Gonzalez Camacho and Alves-Souza (2018) find that social networks parlayed in collaborative algorithms are helpful in giving recommendations to new users or those with incomplete profiles, where preferences are not specified, or to suggest new items to existing users, who may be interested in trying those products. In fact, to make recommendations for a new user, Son (2015) proposes a procedure which leverages similar users and similar items to his/her previously purchased products to predict ratings of a set of items for the user in question.

Nevertheless, such recommender systems must consider the accuracy-diversity dilemma since popular items in peers' profiles may not perfectly fit the user in question, which requires diversifying the algorithm into identifying or exploring items that are probably better suited for the targeted customer's idiosyncrasies (Zhang et al., 2017). Moreover, Zhang et al. (2017) raise the caveat that recommender systems must attend to data recency as user tastes and preferences evolve over time. Indeed, recent research has taken account of the evolution of both sellers and buyers, which may have emerged from their past interactions, to make recommendations (Malgonde et al., 2020), but there is overall a lack of studies from business perspectives where user-centric and business-centric goals, e.g., satisfaction and profit, are considered (Gorgoglione et al., 2019). As recommender systems aim to help customers improve experiences and interactions with businesses, which consist of browsing, purchasing, and giving feedback (Gorgoglione et al., 2019), our article focuses on predicting the probability that a user in question will interact more with a given review for a certain business via liking (hitting the helpfulness vote/like button), commenting on, or re-reading (by clicking again on) that review. This will be further justified and elaborated in Section 2.3.

2.2.2 Personalized review recommendations

User-generated reviews which are often provided along with product recommendations have become an important source of information for customers' decision-making and there has been ongoing research on personalized review recommendation (Mudambi and Schuff, 2010; O'Mahony and Smyth, 2010).

Wu (2017) finds that, in determining review efficacy for sales conversion, review popularity is as vital as review helpfulness, which emphasizes the relevance to the customer under analysis. Also, as the country, where the online review platform in our research is based, scores high on collectivism (Hofstede, 2001), implying a strong inclination toward conformity (Tsao et al., 2015), review popularity in collaborative-based recommender systems can be relevant.

With user tastes and preferences evolving over time (Zhang et al., 2017), recently posted reviews are regarded by review readers as more helpful (Hu et al., 2008; Filieri et al., 2015; Zhou and Guo, 2017). Several other features of the review itself and its reviewer are also found significant in the helpfulness of the review and its impact on sales (Fang et al., 2016; Hu and Chen, 2016; Hu et al., 2017), many of which are confirmed in the meta-analysis of Hong et al. (2017). Further, Hong et al. (2017) validate the moderating role of the platform host and product category in determining the helpfulness of the review. In effect, consumers deem reviews obtained from third-party platforms to be more reliable than those from seller-hosted platforms, and experience products/services, whose quality evaluation is subjective and user-specific and thus hard to obtain via objective information search, necessitate consulting more online reviews (Anderson and Lawrence, 2014; Mankad et al., 2016), especially those whose reviewers have common interests and personalities with the customer in question (Hong et al., 2017).

Inasmuch as our dataset was collected from a third-party platform for online reviews of hospitality businesses, which primarily provide experience products, we can focus our model on attributes associated with reviews, review writers (reviewers), and (platform) users (who are seeking reviews).

2.2.3 Related theories

In addition to the cultural dimensions of Hofstede (2001), which have been widely utilized across disciplines, including service operations (Yayla-Küllü et al., 2015), our work also adopts the network effect (Chen et al., 2020; Farrell and Klemperer, 2007) and signaling theory (Spence, 1973). In effect, the platform with most users is valued most (Chen et al., 2020) since customers of a product/service/system value compatibility with peers (Farrell and Klemperer, 2007) and Albergaria and Chiappetta Jabbour (2020) particularly provide evidence of peer effects that service operations managers should consider. Likewise, reviews with most likes are most probably considered helpful and reviewers who have received many helpfulness votes from platform users or have a large network of followers and followees are likely to write helpful reviews. This may well be supported in collectivist culture as in Southeast Asia, where conformity to the norm is appreciated

(Hofstede, 2001). As regards signaling theory, consumers, given asymmetric information, have to use observable cues, aka signals, to evaluate product or service quality (Filieri et al., 2021; Spence, 2002). In our context, attributes of a review and its reviewer can be employed as signals to platform users. These underpinnings will be elaborated in the next section, where potential variables for our model are operationalized and hypothesized. By building our conceptual framework on theoretical foundations, we respond to the need for more data-driven service operations models that are also theoretically grounded (Huang and Rust, 2013), and ensure that the findings are not confined to our specific dataset but likely generalizable (see Bansal et al., 2020).

It should be noted that a majority of existing publications focus on English reviews or English-based contexts as highlighted by Zhang and Lin (2018). The literature reviews of Gao et al. (2017) and Wu (2017) illustrate that the review platforms frequently studied are headquartered in the U.S., e.g., Yelp, Amazon, TripAdvisor, Apple's App Store, Yahoo!, and CNET. Zhang and Lin (2018) therefore argue that models developed in English-based contexts may not be perfectly transferable to non-English settings. By leveraging the features substantiated in the literature, we can test if research results for review recommendation in developed, western, or English-speaking nations are applicable to Asian markets, where Hofstede's (2001) cultural dimensions can differ.

2.3 Data and research context

2.3.1 Data descriptions

We obtained our dataset through collaboration with a large restaurant review platform in Southeast Asia, which then had over three million users and more than ten million reviews and photos for restaurants and other businesses (e.g., beauty salons and shopping malls) in around three hundred thousand locations in its home market.

Our dataset contains 4,151,904 user-review interactions on the platform in 2017, including those where users read, liked, or commented on reviews. For 216,556 unique

Table 2.1: Descriptive statistics of the dataset

	Unique number	Number of interactions recorded: Mean	Standard deviation	5th percentile	Median	95th percentile
Users†	216,556	8.47	10.24	2	4	59
Reviews*	435,512	5.45	6.39	1	3	34
Reviewers*	57,218	9.36	18.84	1	3	140
Businesses*	76,703	23.78	38.94	2	8	234

†: data indicate users' interactions with reviews;
*: data indicate interactions between reviews and users.

(platform) users, 435,512 reviews, 57,218 reviewers (review writers), and 76,703 businesses in our data, descriptive statistics of interactions on the platform are given in Table 2.1. Users within the 5th–95th percentile had, on average, 8.47 interactions with reviews on the platform. Nevertheless, most of them had no more than four interactions, suggesting that the data are heavily left-skewed. Meanwhile, on the review side, each review received 5.45 interactions from platform users on average, but the majority of them attained no more than three interactions. Reviewers on the platform had their reviews read, liked, or commented on 9.36 times on average. Businesses on the platform, on the other hand, had their reviews read/liked/commented on 23.78 times on average. The left skewness nature of the interactions is observed at these levels too.

2.3.2 User-review affinity

The dependent variable of this study is user-review affinity, a variable of interest to most online review platforms as it correlates strongly with media-viewing time and frequency (Perse, 1986; Ji and Fu, 2013), which are directly associated with the platform's revenue and sustainability. To operationalize the concept of user-review affinity we consider three activities: like (hit the helpfulness vote/like button), comment, and re-read (by clicking on the review again) as indicators of increased user-review affinity (hereinafter referred to as *user-review affinity*). Specifically, user affinity for a review equals 1 if, within seven days after the initial read, the user liked (hit the helpfulness vote or like button), re-read (by clicking again on), or commented on the review, and 0 otherwise. We select the seven-day threshold as the Ebbinghaus forgetting curve is relatively flat afterward (Wixted and Ebbesen, 1997; Li, 2018).

From platform users' perspective, these activities indicate their affinity for reviews. In effect, helpfulness votes indicate that users find the review helpful for their decision-making (Tsai et al., 2020; Filieri et al., 2021), which in turn increases their affinity toward the review and the platform. In addition, prior literature has shown that helpful reviews tend to receive reader comments (Malik and Hussain, 2018). As such, prompting review readers to make comments can theoretically herald as review relevance and increased user affinity since they log in more often or longer. Lastly, prior works also consider readership for review evaluation (Chua and Banerjee, 2017). As users re-read by clicking again on the review within seven days, they would visit the platform more often and spend more time on the content, which can also be seen as increased affinity. Additionally, from the platform's perspective, these activities are also regarded by our collaborating platform as a key performance measure because users tend to stay longer and access the platform more often when they like, comment on, or re-read reviews. These activities are also in line with the construct of user affinity in the literature (Sivasubramaniam and Chandrasekar, 2019).

With the defined dependent variable of interest, the core idea of our model is to recommend reviews that are likely to attain high affinity from users (i.e., reviews that users are likely to like, comment on, or re-read). We next develop a framework to produce personalized review recommendations based on user-review affinity. In the next section, we begin by exploring prior literature on factors that may affect user-review affinity.

2.4 Exploratory model

In this section, we describe our exploratory model that is built to identify factors that could influence user-review affinity. In this regard, we draw on prior works that study the effect of numerous variables on user affinity. Results from this exploratory model will be used to inform our predictive modeling and counterfactual analysis.

Here, we frame the problem at hand as a classification problem (i.e., the target variable captures whether a user would like/comment on/re-read a review or not). We follow the three fine-grained steps of Mathias et al. (2013) for a classification model, i.e., feature extraction, dimensionality reduction, and classification. User (she) and Reviewer (he) denote the focal (platform) user (review reader) and reviewer (review writer), respectively, in each datapoint.

2.4.1 Explanatory variables and dimensionality reduction

In accord with the literature (Hong et al., 2017; Malik and Hussain, 2018; Liang et al., 2019; Hu and Yang, 2021), the independent variables in our model belong to three groups, namely reviewer characteristics, review features, and product attributes. From an extensive survey of previous research, we compile in Table 2.2 the list of explanatory variables used in this study. Next, we develop an integrated model that verifies the influence of Table 2.2's variables on user affinity.

Table 2.2: List of variables

Group	Definition/Operationalization/Feature	Prior studies
	Review valence: the star ratings of the review (range between 1 and 5).	Purnawirawan et al. (2015); Quaschning et al. (2015)
	Review positivity: 1 if the rating is greater than 3, –1 if less than 3, 0 otherwise.	Sparks and Browning (2011); Filieri et al. (2021)

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Table 2.2 (continued)

Group	Definition/Operationalization/Feature	Prior studies
Review features	Difference between review valence and business average rating.	Hu et al. (2008); Zhang et al. (2013); Fang et al. (2016)
	Difference between review valence and reviewer average rating.	
	Difference between review positivity and business average rating positivity.	
	Difference between review positivity and reviewer average rating positivity.	
	Review variance: The absolute difference between review rating and business average rating.	Quaschning et al. (2015); Xiang et al. (2017)
	Review helpfulness score: The (average) number of (helpfulness) votes that the review received.	Hu and Chen (2016); Zhou and Guo (2017); Wu (2017)
	Review age: The time difference between review posting and review reading.	Hu and Chen (2016); Gao et al. (2017); Hong et al. (2017)
	Review length: The number of words or characters in the review (measured by the platform in question)	Gao et al. (2017); Karimi and Wang (2017); Aghakhani et al. (2021)
	Review picture: The number of pictures in the review.	Yang et al. (2017); Ma et al. (2018); Filieri et al. (2018)
	Reviewer's total number of prior reviews.	Filieri et al. (2018); Zhou and Guo (2017)
	Reviewer's total number of reviews with quality flag.	Filieri et al. (2019)

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Table 2.2 (continued)

Group	Definition/Operationalization/Feature	Prior studies
Reviewer characteristics	Reviewer's total number of photos.	Filieri et al. (2018); Fang et al. (2016)
	Reviewer's number of followers.	Hong et al. (2017); Yu et al. (2018); Aghakhani et al. (2021)
	Reviewer's number of followees.	
	Reviewer's number of followings (unique followers and followees) or Reviewer followings.	
	Reviewer social connectedness (or reviewer social network).	Hong et al. (2017); Zhou and Guo (2017)
	User started following Reviewer recently (becoming friends within one day, one week, two weeks, one month, or three months before).	Qian et al. (2014); Lee et al. (2015); Wang et al. (2018a); Liu et al. (2019)
	Reviewer started following User recently (becoming friends within one day, one week, two weeks, one month, or three months before).	
	User's votes (likes and dislikes) for Reviewer's posts (within one day, one week, two weeks, one month, or three months before).	Yu et al. (2023)
	Reviewer's votes (likes and dislikes) for User's posts (within one day, one week, two weeks, one month, or three months before).	
	User's comments on Reviewer's posts before.	

(continued next page)

Table 2.2 (continued)

Group	Definition/Operationalization/Feature	Prior studies
	Reviewer's comments on User's posts before.	
	Reviewer-User common followers.	Xu et al. (2015)
	Reviewer-User common followees.	
	Reviewer-User indirect followships: Reviewer's followers are User's followees and vice versa.	
	Reviewer locality: If the reviewer is a local in the region of the reviewed business, reviewer locality is 1, 0 otherwise.	Yang et al. (2017)
Product attributes	Brand strength: The business average rating.	Ho-Dac et al. (2013); Blal and Sturman (2014); Tsao et al. (2019)

Given 58 variables, we face two issues. First, as demonstrated by Lin et al. (2013), having many exploratory variables with millions of observations would likely result in an overfitted model. Second, incorporating too many input variables can cause computational issues. For example, in a Random Forest Classifier model with M trees, n instances per decision tree, and $mtry$ features per tree, the algorithm complexity is $O(M \cdot mtry \cdot n \cdot \log n)$ (Wang et al., 2018c). While M and n are hyperparameters to fine-tune in the classification step, the existing literature demonstrates that $mtry$ should equal $\sqrt{TotalFeatures}$ (Wang et al., 2018b). Taking both issues together, we proceed by performing dimensionality reduction to improve model identification and computational efficiency.

To ensure that relevant variables are incorporated while multicollinearity is avoided, we first conduct exploratory factor analysis (EFA). Eigenvalues and factor rotation (Yong and Pearce, 2013) are used to select high-order level factors that capture most of the original variables not only for dimensionality reduction as in principal component analysis

(Mason and Perreault, 1991) but also for identification of latent features underlying certain sets of variables (Yong and Pearce, 2013). We only retain factors whose Cronbach's alpha exceeds 0.7 (Dunn et al., 2014; Hair et al., 2019) and which comprise at least two items with absolute loadings greater than 0.7. Table 2.3 illuminates the latent variables derived from our factor analysis whose interpretations are based on the literature. After EFA and PLS-SEM, we find ten composite scores that satisfy the convergent and discriminant validity criteria.

Table 2.3: Composite scores from EFA and PLS-SEM

Composite scores	Attributes	Loadings
Review valence frame* AVE = 0.83; CR = 0.97 α = 0.9606 Scale Corr. = 0.9988	Review valence (rValence)	0.935
	Review positivity $(\mathbb{I}(\text{rValence} > 3) - \mathbb{I}(\text{rValence} < 3))$	0.954
	Difference between review valence and business average rating	0.882
	Difference between review valence and reviewer average rating	0.883
	Difference between review positivity and business average rating positivity	0.915
	Difference between review positivity and reviewer average rating positivity	0.911
Reviewer expertise* AVE = 0.87; CR = 0.96 α = 0.9668 Scale Corr. = 0.9818	Log of Reviewer's total number of prior reviews	0.990
	Log of Reviewer's total number of reviews with quality flag	0.993
	Log of Reviewer's total number of photos	0.963
	Log of Reviewer's total number of followers	0.769
	Log of User's likes for Reviewer's posts before	0.951

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Table 2.3 (continued)

Composite scores	Attributes	Loadings
Reviewer-user similarity* AVE = 0.77; CR = 0.98 α = 0.9727 Scale Corr. = 0.9511	Log of User's votes for Reviewer's posts before	0.951
	Log of User's comments on Reviewer's posts before	0.834
	Log of Reviewer's likes for User's posts before	0.950
	Log of Reviewer's votes for User's posts before	0.950
	Log of Reviewer's comments on User's posts before	0.816
	User's recent votes (likes) for Reviewer's posts	0.875
	Reviewer's recent votes (likes) for User's posts	0.863
	Log of Reviewer-User common followers	0.843
	Log of Reviewer-User common followees	0.782
	Log of Reviewer-User indirect followship 1	0.840
	Log of Reviewer-User indirect followship 2	0.864
Review quality** AVE = CR = α = Scale Corr. = 1	Log of review's average number of votes received	1.000
	Log of review's average number of likes received	1.000
Review votes (likes)** AVE = CR = α = Scale Corr. = 1	Log of review's number of votes received	1.000
	Log of review's number of likes received	1.000
User following Reviewer recently** AVE = 0.83; CR = 0.95 α = 0.93 Scale Corr. = 0.98	User started following Reviewer within 1 day before	0.827
	User started following Reviewer within 7 days before	0.941
	User started following Reviewer within 14 days before	0.959

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Table 2.3 (continued)

Composite scores	Attributes	Loadings
	User started following Reviewer within 30 days before	0.913
Reviewer following User recently** AVE = 0.85; CR = 0.94 α = 0.91 Scale Corr. = 0.95	Reviewer started following User within 7 days before	0.888
	Reviewer started following User within 14 days before	0.953
	Reviewer started following User within 30 days before	0.916
Social connectedness** AVE = 0.92; CR = 0.96 α = 0.93; Scale Corr. = 1.00	Log of Reviewer number of followees	0.930
	Log of Reviewer followings	0.990
User's recent votes (likes) for Reviewer's posts*** α = 0.9926 Scale Corr. = 0.9983	Log of User's likes for Reviewer's posts within 7 days	0.953
	Log of User's likes for Reviewer's posts within 14 days	0.987
	Log of User's likes for Reviewer's posts within 30 days	0.988
	Log of User's likes for Reviewer's posts within 90 days	0.960
	Log of User's votes for Reviewer's posts within 7 days	0.953
	Log of User's votes for Reviewer's posts within 14 days	0.987
	Log of User's votes for Reviewer's posts within 30 days	0.988

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Table 2.3 (continued)

Composite scores	Attributes	Loadings
	Log of User's votes for Reviewer's posts within 90 days	0.960
Reviewer's recent votes (likes) for User's posts*** α = 0.9910 Scale Corr. = 0.9982	Log of Reviewer's likes for User's posts within 7 days	0.939
	Log of Reviewer's likes for User's posts within 14 days	0.983
	Log of Reviewer's likes for User's posts within 30 days	0.985
	Log of Reviewer's likes for User's posts within 90 days	0.954
	Log of Reviewer's votes for User's posts within 7 days	0.939
	Log of Reviewer's votes for User's posts within 14 days	0.983
	Log of Reviewer's votes for User's posts within 30 days	0.985
	Log of Reviewer's votes for User's posts within 90 days	0.954

Note:
AVE = Average Variance Extracted; CR = Composite Reliability; α = Cronbach's alpha; * *Latent variable*: aggregate variable created in PLS-SEM that are also supported in SEM; ** *Composite score*: aggregate variable created in PLS-SEM (Hair et al., 2020); *** *Item parceling*: aggregating items into a parcel which is used as an indicator in SEM (Hall et al., 1999); Scale Corr. = correlation between the weighted and unweighted scales.

Review valence, review positivity, and its difference from business/reviewer average rating (positivity) correlate highly and reflect altogether whether a review is in favor of the reviewed business vis-à-vis other reviews, which we name *review valence frame*. The higher rating a reviewer gives, the more likely that rating outstrips business or reviewer average rating, implying his higher favor toward the business compared to an average reviewer and vice versa. Indeed, review rating and sentiment scores are positively correlated (Mankad et al., 2016).

We can observe that the total number of prior reviews and the total number of prior reviews with quality flag (i.e., reviews that receive multiple helpfulness votes), which are visible in the system, can serve as cues for User about Reviewer's expertise and the likely helpfulness of the focal review. More precisely, Reviewer's expertise relates to his number of previous reviews and helpfulness votes (Zhou and Guo, 2017; Filieri et al., 2019). Given that reviews posted with photos are likely deemed helpful (Fang et al., 2016; Filieri et al., 2018), Reviewer with many reviews with quality flag might have posted many pictures. So, the number of his posted photos can indicate his expertise. In line with Yu et al. (2018), Reviewer's number of followers correlates with these reviewer expertise elements in our data. Hence, the latent attribute underlying these variables can be interpreted as *reviewer expertise*.

Neirotti et al. (2016) find that, when User and Reviewer share similar interests or know each other, she tends to trust his review and may like, comment on, or re-read it. On our study's platform, these attributes can be captured by prior reviewer-user interactions such as comments or likes for previous reviews between User and Reviewer. However, our results show that common followship features, measured by the common followers and followees of Reviewer and User, are also captured by the same latent variable as other attributes of reviewer-user interactions. Since these common followship measures can be used to reflect the similarity between a focal user and a potential followee in the followee-recommendation literature (Xu et al., 2015), the latent variable capturing both reviewer-user interactions and common followship can be interpreted as *reviewer-user similarity*.

Next, we perform PLS-SEM and confirmatory composite analysis (Hair et al., 2020) to assess the EFA results. We choose PLS-SEM whose add-in package for STATA was developed by Venturini and Mehmetoglu (2019) as it allows relaxing normality assumptions, testing theoretical models for predictive purposes, and leveraging latent scores for subsequent analyses (Hair et al., 2019). We carry out convergent validity analysis (Sethi and King, 1994) and discriminant validity analysis (Fornell and Larcker, 1981), which are commonly adopted (Henseler et al., 2016; Hair et al., 2019) to substantiate scale validity. As can be seen in Table 2.3, all standardized path coefficients are of acceptable magnitude and statistical significance, implying good convergent validity (Sethi and King, 1994; Hair et al., 2019). As regards the discriminant validity, Table 2.3 illustrates that all factors have good composite reliability, which is above the 0.7 threshold (Fornell and Larcker, 1981; Hair et al., 2020). Also, each factor's average variance extracted (AVE) exceeds the 0.5 threshold and its squared correlations with other factors (see Table 2.4), which is another indicator of good discriminant validity (Henseler et al., 2016; Hair et al., 2020). By considering only factors in EFA with Cronbach's alpha greater than 0.7, which is considered a lower bound to internal consistency (Sijtsma, 2009; Henseler et al., 2016), we believe that the factors reported herein are properly measured by their items, whose contents are relevant to the target latent variables. We also ran covariance-based SEM, and the results were robust for the three latent variables in Table 2.3.

Overall, the tests above corroborate the validity of the factors arising from our factor analysis. From the original set of variables, we develop eight composite scores and remove those with contents related to the composite scores created. The eight composite scores include *review valence frame*, *review quality*, *review votes/likes*, *reviewer expertise*, *reviewer social connectedness*, *reviewer-user similarity*, *reviewer following user recently*, and *user following reviewer recently*. Also, there are nine variables, i.e., *review variance*, *review age*, *review length*, *review picture*, *reviewer dislikes for user*, *user dislikes for reviewer*, *reviewer locality*, *reviewer-user common locality*, and *brand strength*, which are directly measured by one single feature and are not captured by the eight composite scores in our factor analysis. Finally, we obtain a new model with 17 variables. We report the correlation of these variables in Table 2.4.

Table 2.4: Correlations between explanatory variables in the structural part of PLS-SEM

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
0.83																
–.43	1.00															
–.01	–.05	1.00														
0.02	–.02	0.32	1.00													
0.01	0.02	0.17	0.47	1.00												
0.08	–.06	0.24	0.44	0.48	1.00											
0.05	0.09	–.29	0.31	0.16	0.03	1.00										
–.07	–.04	0.22	0.52	0.46	0.44	0.09	0.87									
–.02	–.03	0.48	0.13	0.09	0.11	–.13	0.15	0.77								
0.00	–.01	0.07	0.01	0.01	0.02	–.03	0.01	0.07	0.83							
–.01	–.01	0.09	0.02	0.01	0.02	–.03	0.03	0.22	0.01	1.00						
0.00	–.01	0.09	0.00	0.00	0.01	–.04	0.00	0.11	0.21	0.02	0.85					
–.01	0.00	0.09	0.03	0.02	0.02	–.02	0.03	0.21	0.01	0.06	0.01	1.00				
–.03	–.06	0.27	0.66	0.36	0.36	0.14	0.61	0.17	0.02	0.03	0.02	0.03	0.92			
0.00	–.01	–.01	–.02	–.02	–.02	–.02	–.03	0.01	0.00	0.00	0.00	0.01	–.02	1.00		
0.02	0.03	–.07	–.08	–.04	–.04	0.02	–.09	–.07	0.00	–.02	–.01	–.02	–.06	–.07	1.00	
0.28	–.11	0.02	–.01	–.02	0.04	0.02	–.12	–.01	0.01	0.00	0.00	0.00	–.05	0.01	0.02	1.00

Note: Values less than 1.00 on the diagonal are the Average Variance Extracted of the corresponding composite score or latent variable. (1) Review valence frame; (2) Review variance; (3) Review quality; (4) Review votes (likes); (5) Review length; (6) Review picture; (7) Review age; (8) Reviewer expertise; (9) Reviewer-user similarity; (10) User following Reviewer recently; (11) User dislikes for Reviewer; (12) Reviewer following User recently; (13) Reviewer dislikes for User; (14) Reviewer social connectedness; (15) Reviewer locality; (16) Reviewer-user common locality; (17) Brand strength.

When combining the items captured by a common factor, we test the correlation between their unweighted and weighted average and find a strong correlation of at least 0.95 in all cases (Scale Corr. in Table 2.3). Therefore, we proceed with the unweighted average to build our predictive model, which is called *model with unweighted scales* as it is convenient to create and repeat (Bobko et al., 2007). We also perform robustness checks by comparing this model to the one *with weighted scores* where the weight vector for a composite score's items is computed by PLS-SEM (Venturini and Mehmetoglu, 2019). The latter's performance is qualitatively similar to the former's.

2.4.2 Hypothesis development and testing

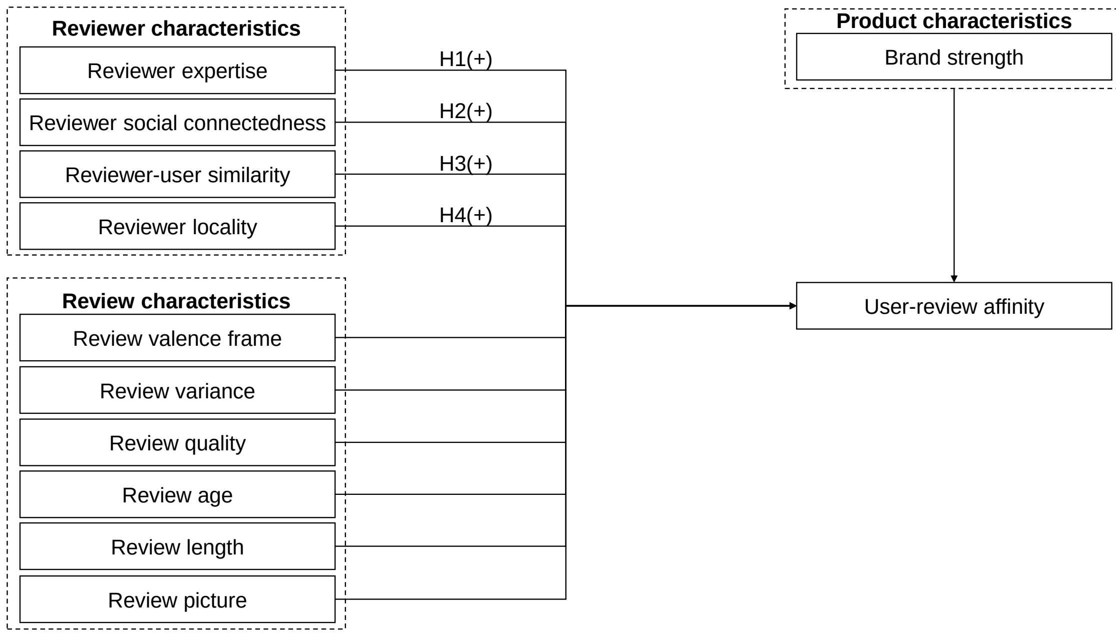

Figure 2.2: Conceptual framework

As we obtain the set of independent variables of interest, we next formally develop hypotheses to test if they affect user affinity statistically. The model conceptualized for the three groups of variables identified in Section 2.4.1, i.e., reviewer characteristics, review attributes, and product features, is illustrated in Figure 2.2. As many of the reviewer characteristics obtained from the previous step involve unique interactions with users, they help personalize review recommendation. Thus, we formulate hypotheses for them in the first part of Section 2.4.2. The second and third parts of Section 2.4.2 elaborate on review features and product attributes as control variables. The last subsection presents the hypothesis test results.

2.4.2.1 Reviewer characteristics

According to Filieri et al. (2019) and Quaschning et al. (2015), reviews whose valence is inconsistent with most other reviews are still perceived as helpful if the reviewers are considered expert. This signals that reviewer expertise is an important variable in predicting review helpfulness. Indeed, Hu and Yang's (2021) meta-analysis shows that the impact of reviewer expertise on review helpfulness is significant and positive yet declining over time. Zhou and Guo (2017) also find that reviewer expertise impacts review helpfulness positively. In addition, reviewer expertise attenuates the influence of the number of prior reviews on the perceived helpfulness of the focal review (Zhou and Guo, 2017). Hong et al. (2017), Lee et al. (2017), and Yang et al. (2019) find similar results.

Reviewer expertise is a multi-faceted concept, which has been operationalized differently in the literature, and the effect of each reviewer expertise feature on review helpfulness is mixed. While Siering et al. (2018) and Yang et al. (2019) operationalize reviewer expertise by the reviewer rank computed on Amazon.com, Filieri et al. (2019) measure that variable by the number of helpfulness votes the reviewer gained. In the meta-analysis of Hong et al. (2017), while reviewer expertise as operationalized by *expert title/label* has a consistently positive impact on review helpfulness, the result for the total number of posted reviews as a reviewer expertise attribute is inconsistent. As measured by the number of helpfulness votes gained, reviewer expertise positively affects review helpfulness, whereas reviewer reputation (rank) has a negative impact in the paper of Lee et al. (2017) because their variable of interest is *emotional intensity* in negatively valenced reviews, which may lower information diagnosticity perceived by readers. Filieri et al. (2018) also study extreme reviews and demonstrate that the number of posted reviews as a reviewer expertise element is not statistically significant. Aghakhani et al. (2021) and Liang et al. (2019) even find a negative effect of that variable on review helpfulness. Zhou and Guo (2017) combine both the number of posted reviews and elite membership to measure reviewer expertise and report an aggregate positive impact on review helpfulness.

The review platform under analysis has a reviewer rank index, but we cannot backtrack its value to the time each review was read, so we do not include it in the model. In our work, reviewer expertise is measured by Reviewer's total prior votes, likes, photos, and followers (dimensionality reduction results). With reference to signaling theory, we can see that the total prior votes, likes, photos, and followers, which are visible in the system, can serve as cues for User about Reviewer's expertise and the likely helpfulness of the focal review. Since reviewer expertise increases review helpfulness, User is more likely to cast a helpfulness vote, which then indicates her increased affinity for the platform. Thus, we hypothesize:

H1. Reviewer expertise increases user-review affinity.

As studied by Filieri et al. (2019) and Quaschning et al. (2015), the possible interaction between reviewer expertise and review variance should be considered. To compute this interaction term, we multiply review variance (single item) by each standardized item of reviewer expertise (Chin et al., 2003). The interaction term between review variance and reviewer expertise is the 18th variable in our model.

In addition to expertise, reviewer social connectedness (or social network) has direct and moderating effects on review helpfulness (Zhou and Guo, 2017). Social connectedness is defined as the relationships with other platform users and measured by the number of friends on Yelp in Zhou and Guo's (2017) paper. Zhang and Lin (2018) use the number of friends and followers (fans) on Yelp to operationalize reviewer social networks. On our review platform, this concept can be computed by the *number of followers* and the *number of followees*. Hong et al. (2017) ascertain that the *number of followers* and the *number of followees* have a consistently positive influence on review helpfulness. Aghakhani et al. (2021) log-transform these figures in their model, but the results are insignificant. Yu et al. (2018) consider these two indices in computing a user's expertise in a field. Let $fe(u_i)$ denote the set of followees of user i on the platform and $fr(u_i)$ denote the set of followers of user i on the platform. In our paper, *reviewer followings* $= fe(u_i) \cup fr(u_i)$, and reviewer social connectedness is measured by reviewer's number of followees and followings (see Section 2.4.1). As the network effect postulates, reviewers with many followings are likely to write quality and relevant reviews, which can make readers cast helpfulness votes, pass comments, or re-read. Hence, our hypothesis is:

H2. Reviewer social connectedness increases user-review affinity.

Other research has reported that users tend to follow their friends when rating an item or business (Lee et al., 2015; Wang et al., 2018a) or trying a new product/service, which is leverageable for personalized recommendation (Qian et al., 2014; Liu et al., 2019). As

Neirotti et al. (2016) discuss, users assign greater weight to reviews written by friends in their network. Thus, a follower-followee relationship or frequent interactions, i.e., votes and comments, between User and Reviewer can signal that his review is more likely to be perceived by her as helpful.

Even if User and Reviewer have not established a follower-followee relationship, we can identify prospective followees as posited by followee-recommendation scholarship. Since the followees recommended may well share common interests with User (Armentano et al., 2013; Li et al., 2016), their reviews can be relevant and helpful to her. As the candidate followees are not yet in User's network, suggesting their reviews to her could boost review recommendation diversity. To identify relevant followees, we can compute the similarity between the focal user (user i) and another user (user $j, j \neq i$) by: $sameFe = |fe(u_i) \cap fe(u_j)|$; $sameFr = |fr(u_i) \cap fr(u_j)|$; $indirectFollowship1 = |fe(u_i) \cap fr(u_j)|$; and $indirectFollowship2 = |fr(u_i) \cap fe(u_j)|$ (Xu et al., 2015).

By computing these indicators from followee-recommendation studies, we can ascertain the common followship level between User and Reviewer, thereby predicting review relevance. The network effect and collectivism can justify this choice as User is apt to find shared values with her followers or followees, who then have commonality with Reviewer. Given high collectivism in Southeast Asia, where members hold common values within their group (Hofstede, 2001), a review written by a friend can be deemed helpful or relevant.

As indicated in our dimensionality reduction results, we conceptualize this variable as *reviewer-user similarity*. Given a high level of *reviewer-user similarity*, User may well find shared values directly via prior interactions or indirectly through common followships with Reviewer; hence, she is more likely to like, comment on, or re-read his review. Incorporating this variable along with the lagged term of user-review affinity within seven days before (the 19th variable) in our model can help account for possible autocorrelation, where User would continue to like and comment on Reviewer's reviews as she has been doing. Further, frequent interactions between users of similar interest clearly boost their positive attitude to the platform. Therefore, we hypothesize:

H3. Reviewer-user similarity increases user-review affinity.

Yang et al. (2017) find that reviews contributed by local reviewers, who reside in the vicinity of the reviewed business, are perceived as more helpful. Explanations comprise Reviewer's hands-on experience in the region and in using the product of the business reviewed, which implies that his review is more credible. Thus, we hypothesize that reviews posted by reviewers from the same neighborhood are likely considered helpful. Additionally, as reviewer region ID is observable on the platform, User can check if Reviewer is from her locality. Given high collectivism in Southeast Asia, where members hold shared values within their group (Hofstede, 2001), we can hypothesize that if User and Reviewer have the same region ID, his review is more probably relevant to her, prompting her to cast helpfulness votes, pass comments, or re-read.

H4. Reviewer locality increases user-review affinity.

2.4.2.2 Review characteristics

The first control variable of interest is the review valence frame (i.e., the polarity of the review), which has been widely studied. In particular, Quaschning et al. (2015) find in their experimental and field data that the valence of a review significantly affects its helpfulness when it accords with other reviews. In the same vein, Lee et al. (2017) expand on the influence of review valence on review helpfulness and show that reviews with negative valence are usually perceived as more helpful than those with positive valence, but their helpfulness declines when the negative emotions therein are intense. Purnawirawan et al. (2015) ascertain in their meta-analysis that review valence has a significant effect on review helpfulness votes for experience goods and unfamiliar brands.

Next, we control the impact of the consistency of review valence (i.e., the variance of the review) on user-review affinity. Yelp's strong review helpfulness is indeed ascribable to the high variance of its review sentiments (Xiang et al., 2017). Meanwhile, signaling theory postulates that if the valence of a review is widely dispersed from the average rating, that inconsistency might signal the reviewer's idiosyncrasy/heterogeneity (Quaschning et al., 2015). In this regard, Gao et al. (2017) show that users are more likely to cast helpfulness votes when there is consistency between the focal review's valence and other reviews'. The aforementioned empirical evidence suggests that high review variance negatively affects review helpfulness perceived by users.

Many scholars (Hu et al., 2017; Lu et al., 2018; Liang et al., 2019) find a direct and significant influence of review quality on review helpfulness, whereas Lee et al. (2018) show that review quality has poor predictive performance for review helpfulness. We measure review quality by the number of votes a review had already received prior to being read by User, which is supported in the literature (Yang et al., 2017). On our work's platform, review votes include likes and dislikes, so we incorporate all those figures into the model. Our dimensionality reduction shows that the total number of review votes and likes are captured by one composite scale, so are the average number of review votes and likes that respectively equal the total number of review votes and likes divided by the time lapse in days since review post. As old reviews have more time to accumulate votes, we use the average number of votes and likes to proxy review quality and penalize less recent reviews (Hu et al., 2017; Lee et al., 2018; Tsai et al., 2020).

In line with signaling theory, prior votes, likes, and dislikes are visible clues for readers about review quality. As the network effect and collectivism dictate, User likely conforms with the majority and interacts with such reviews by liking, commenting, or re-reading within seven days.

Another commonly discussed review feature is review age, which is measured in days elapsed since review post (Hu and Chen, 2016; Hong et al., 2017; Hu and Yang, 2021) and can be rescaled logarithmically (Gao et al., 2017; Aghakhani et al., 2021). While Hu and Chen (2016), Gao et al. (2017), and Hong et al. (2017) find that review age raises the perceived review helpfulness, Wu's (2017) results are mixed, differing by product type, but the aggregate impact is negative. Meanwhile, Yang et al. (2019) illustrate a negative influence, which means older reviews are deemed less helpful. As the businesses reviewed on the platform in question provide hedonic/experience products, our study is in favor of the findings of Wu (2017) and Yang et al. (2019), where review age lowers the helpfulness or relevance of the review for such items and users are less likely to cast helpfulness votes or spend time re-reading or commenting on a less relevant/helpful review.

Our review platform arranges reviews in ascending order of review post time lapse (review position rank). We adopt that measure as a proxy for review age. Utilizing this feature in our model also helps us with counterfactual analysis given that review arrangement in the system can be manipulated.

In a separate research vein, Quaschning et al. (2015), Fang et al. (2016), Gao et al. (2017), Wu (2017), and Hu and Yang (2021) illustrate that review length positively affects review helpfulness. Zhou and Guo (2017) show a marginally significant moderating impact of review length, whereas Karimi and Wang (2017) and Zhang and Lin (2018) find a negative effect as lengthy reviews are less likely to be perused and thus less likely to be assessed. The review length which is readily measured on our work's platform is log-rescaled in our model as in the articles of Gao et al. (2017), Karimi and Wang (2017), and Aghakhani et al. (2021). By including this as a control variable, we can exclude the possibility that some reviews were re-read because they were lengthy.

Another control variable whose mean, median, and standard deviation are similar between the two review groups in our database is *review picture*. According to Zhou and Guo (2017), Yang et al. (2017), and Ma et al. (2018), when a review is accompanied by at least one photo related to the reviewed item, users are more likely to perceive that review as helpful. Filieri et al. (2018) find that the perceived helpfulness of extreme reviews increases when they are long and posted with pictures, which are deemed more convincing than words (Fang et al., 2016).

2.4.2.3 Product characteristics

As can be seen from our discussion in Section 2.4.2.2, *product type* plays the moderating role (Mudambi and Schuff, 2010; Wu, 2017). Nonetheless, as all the businesses reviewed on the platform deliver hedonic/experience products in hospitality, product type cannot differentiate review helpfulness in our model, thus not considered. Nevertheless, we can see in the cited literature some other less commonly controlled yet relevant features such as brand similarity (Purnawirawan et al., 2015), hotel features (Anderson and Lawrence, 2014; Liang et al., 2019; Filieri et al., 2021), total reviews received (Lee and Choeh, 2016; Filieri et al., 2021), product awareness, quality, and popularity (Zhang and Lin, 2018), and average rating (Filieri et al., 2021). We find these variables appertain to *brand strength*.

Prior research (Choi and Mattila, 2018; Sridhar and Srinivasan, 2012) has shown that customers' ratings are affected by peer pressure. Particularly, reviewers may give a higher rating than their actual product experience if prior ratings are positive (Sridhar and Srinivasan, 2012). As a strong brand usually has good cumulative ratings, new customers may well follow that norm when rating. Another explanation relates to Tsao et al.'s (2019) that, for strong brands, negative reviews exert a stronger impact on sales than positive ones and that management is advised to address such negative reviews. Therefore, the overall ratings are higher for stronger brands. We thus operationalize brand strength by business average rating.

There are mixed results for this variable in prior works. Purnawirawan et al. (2015) find that reviews for unfamiliar brands are deemed more helpful while brand strength indices studied by Lee and Choeh (2016), Zhang and Lin (2018), and Filieri et al. (2021) positively influence or moderate review helpfulness, notably for experience goods, which are pertinent to the review platform under analysis in this article. The network effect and collectivism may predict that patronizing strong brands implies compatibility with peers or the majority, which is valued by User, so reading reviews or even accessing a review platform for information is less helpful.

We use the first six months of the data to test the conceptual model (Figure 2.2). The last six months' data will be utilized for out-of-sample tests of the model's generalization to unseen instances. In this paper, except for binary and ordinal variables (e.g., rating), continuous variables are log-transformed and normalized.

2.4.2.4 Hypothesis testing

Table 2.5 presents the test results for the conceptual model, from which crucial features are input into predictive and counterfactual analyses. We compute the variance inflation factor (VIF) to check if multicollinearity persists after dimensionality reduction. As the VIF is less than 10, the structure of our model is supported (Marquaridt, 1970). Also, the R-squared is in the acceptable range for human behavior research when most explanatory variables are significant (Ozili, 2023).

Table 2.5: PLS-SEM Path analysis

Number of observations = 1813431 Absolute GOF = 0.33842
Average R-squared = 0.13486 Relative GOF = 0.98227
Average communality = 0.88241 Average redundancy = 0.13486
Dependent variable = User-review affinity

	Variable	Coefficient	P>|z|	VIF
(1)	Review valence frame	0.0147	0.000	1.360
(2)	Review variance	–0.0009	0.259	1.290
(3)	Review quality	0.0462	0.000	1.722
(4)	Review votes (likes)	–0.0121	0.000	2.473
(5)	Review length	–0.0207	0.000	1.542
(6)	Review picture	0.0006	0.495	1.508
(7)	Review age	–0.0050	0.000	1.401
(8)	Reviewer expertise	–0.0517	0.000	1.929
(9)	Reviewer-user similarity	0.1099	0.000	1.463
(10)	User following Reviewer recently	0.0078	0.000	1.053
(11)	User dislikes for Reviewer	–0.0058	0.000	1.049
(12)	Reviewer following User recently	0.0113	0.000	1.060
(13)	Reviewer dislikes for User	–0.0039	0.000	1.047
(14)	Reviewer social connectedness	0.0266	0.000	2.193
(15)	Reviewer locality	0.0015	0.033	1.007
(16)	Reviewer-user common locality	0.0132	0.000	1.021
(17)	Brand strength (busAvgRating)	–0.0018	0.013	1.110
(18)	Review variance $\times$ Reviewer expertise	0.0088	0.000	1.030
(19)	Lagged user-review affinity (7 days)	0.3069	0.000	1.054

Turning first to the group of review features, Table 2.5 illustrates that review valence frame creates a significant and positive influence on user-review affinity. In other words, positive reviews are more likely to boost user affinity for the platform. Meanwhile, review variance has a negative but insignificant coefficient. With regard to the significant control variables at the 1% level, review length correlates negatively with user-review affinity, signifying that long reviews are less likely to be liked, commented on, or re-read.

Prior studies use either total review votes/likes or average review votes/likes per day to measure review quality. Our paper results support the latter, which is in line with Hu et al. (2017), Lee et al. (2018), and Tsai et al. (2020). Meanwhile, the impact of total review votes/likes is negative, which can be explained by the fact that old reviews have more time to accumulate votes but are considered less helpful. The negative effect of total review votes/likes on user-review affinity is consistent with the negative impact of review age in our data.

As regards our hypotheses, reviewer expertise negatively influences user-review affinity, leading to H1 rejection. The negative sign remained unchanged even when we used Reviewer's average number of (good) reviews and photos per day since his joining time (detailed results are provided in Table 1 in Appendix B). However, the interaction term between reviewer expertise and review variance makes a positive impact on user-review affinity. This means that reviewer expertise moderates the relationship between review variance and user-review affinity, in line with the findings of Quaschning et al. (2015) and Filieri et al. (2019), where reviews written by expert reviewers are deemed more helpful when deviating more from business average ratings (see Appendix B).

The positive and statistically significant coefficient of reviewer social connectedness provides support for H2. This signifies that reviewers with many followings are likely to write high-quality and valuable reviews, which can prompt readers to cast helpfulness votes, make comments, or re-read.

The positive influence of reviewer-user similarity on user-review affinity in Table 2.5 substantiates H3. This accords with Neirotti et al.'s (2016) findings that when User and Reviewer know each other or find common interests via prior interactions or common followships, she tends to trust his review and like/comment on/re-read it.

In line with Yang et al. (2017), the positive coefficient of reviewer locality denotes that reviews written by local reviewers are deemed to boost user-review affinity, corroborating H4. Our data also reveal that user-review affinity increases when User and Reviewer are from the same region, which was understudied in the literature but can be explained by

Southeast Asia's high collectivism, where in-group members hold shared values (Hofstede, 2001).

Given the tested conceptual model, we replicate Venturini and Mehmetoglu's (2019) PLS-SEM algorithm in Python to calculate the composite scores in Figure 2.2 as inputs for our predictive and counterfactual analyses.

2.5 Predictive model

Given the insights from the previous section, we leverage them for predictive modeling and demonstrate that our results also apply to out-of-sample instances. We begin by considering ML algorithms for our predictive model.

In 18.20% of the instances in our sample, users either liked, commented on, or re-read the review within seven days, so our dataset might epitomize the imbalanced class problem. Based on Napierala and Stefanowski's (2016) categorization, 72.92% of these minority class data points are either "*safe*" or "*borderline*," which can be classified by their nearest neighbors, suggesting that class imbalance may not pose problems for our predictive modeling.

According to Paul et al. (2018), Random Forest Classifier (RFC) is a widely-used ensemble learning algorithm to handle data imbalance. The upper bound to its generalization error is theoretically proven in Breiman's (2001) seminal paper and its consistency is substantiated in several recent papers with theoretical analyses (Scornet et al., 2015; Wager and Athey, 2018) and empirical findings (Calderoni et al., 2015; Mercadier and Lardy, 2019). Scholars report Random Forest's superior performance compared with other methods, such as support vector machine and regression tree (Wang et al., 2018d), logistic regression and artificial neural networks (ANN) (Wang et al., 2018b). Albeit outperformed by other techniques in some instances, Random Forest is still favored since it requires less parameter tuning (Ahmad et al., 2017; Mercadier and Lardy, 2019). Yet, to select a robust model, we compare RFC with some other common algorithms (Abellán et al., 2017; Huber et al., 2019), namely ANN (Hornik, 1991), bagging classifier (BC)

(Breiman, 1996), and gradient boosting classifier (GBC) (Friedman, 2001).

ANNs are also deemed effective for this classification problem (Aziz et al., 2018). Several techniques have been proposed to improve ANN's performance (Lolli et al., 2017; Wang et al., 2018b; Huber et al., 2019). For example, in Arcos-García et al.'s (2017) research, their ANN model performance was not compromised by data imbalance while Huber et al.'s (2019) ANN algorithm can perform well in the presence of relaxed normality assumption provided that the dataset is big enough. Nonetheless, ANNs are often considered a black box (Chen and Hao, 2017) with many hyperparameters, e.g., number of neurons and layers, to fine-tune (Ahmad et al., 2017). In Wang et al.'s (2018b) review, ANNs are suited to such specialized data domains as image and natural language processing, but outperformed by Random Forest in arbitrary domains.

In BC, the trees are built on randomly bootstrapped copies of the original instances, where features for node splitting can be drawn with or without replacement (Louppe and Geurts, 2012). Given this added randomness, the correlation between decision trees in the forest decreases and the model performance improves, along with overfitting avoided and variance reduced (Seyedhosseini and Tasdizen, 2015; Mercadier and Lardy, 2019). According to Scornet et al. (2015), BC is among the most computationally effective schemes for high-dimensional data.

GBC is a robust technique to handle outliers and heterogeneous attributes in multidimensional data (de Santis et al., 2017). The algorithm utilizes gradient-based approximations to split the tree node on the negative gradient for loss minimization (Athey et al., 2019), thereby allowing optimizing an arbitrary loss function (Friedman, 2001). Both BC and GBC are deemed effective for accuracy improvement of the classification problem (Dietterich, 2000). Malik and Hussain's (2018) is among the earliest papers applying GBC for review helpfulness prediction built on reviewer characteristics and review content variables. Their results show that GBC has lower (root) mean squared error than RFC and ANN.

As regards some hyperparameters selected for our models, which are run on scikit-learn ML package (Pedregosa et al., 2011), the three hyperparameters of interest in RFC are the number of decision trees (M), the tree depth, and the number of features per tree ($mtry$). While the optimal number of features per tree receives a broad consensus in empirical findings (Wang et al., 2018b,d), the number of decision trees and the tree depth vary across studies. For instance, the optimal number of nodes per tree is 5 (Tsagkrasoulis and Montana, 2018), 8 (Zhou and Qiu, 2018), 15 (Genuer et al., 2017; Mercadier and Lardy, 2019), and 20 (Chen et al., 2018). Ahmad et al. (2017) find that RFC performance deteriorates after the max depth exceeds 10, so we test the tree depth at 5, 8, and 10. We also run the scenarios where the tree depth is not limited ($treeDepth =$ None). With respect to the number of trees (M), we try four thresholds (30, 50, 100, and 200) to select the best alternative. To ensure fair comparisons, these hyperparameters are also applied to the BC, GBC, and ANN models where suitable. In particular, the ANN model has three hidden layers $(M, 50, 15)$ for M equal to the number of decision trees.

We iteratively select one month from July to December as a test dataset and bootstrap data from one up to six months before the test set to train the model. The bootstrap data have the same size as the original training data. This bootstrap-train-test procedure is repeated 30 times for each model. Given the features selected in the prior section, our predictive models are to predict if User will like, comment on, or re-read the review within seven days of the first read. Of particular note is that there is no single model that outperformed others in all three criteria (precision, recall, and F1). The ANN method was the least stable with very large standard deviations compared to other models. BC, GBC, and RFC had similar performance, but GBC's runtime was far longer. Thus, we focus on discussing the BC and RFC results. The complete results are available from Figures 4a–7f in Appendix B.

Overall, the models with weighted scores and unweighted scales yielded similar results, whereas the models with all variables were slightly better but their computation took more than double the runtime of their counterparts with reduced dimensionality. The only exception with respect to computational time is RFC, where the processing time difference was only a few minutes. These results imply that our low-dimensional models save substantial runtime with marginal predictive power loss.

We also find that enlarging the training dataset by including less recent instances produced insignificant changes in the performance of RFC, BC, and GBC. Indeed, the models trained on the data one month before had comparable results to their counterparts trained on more data. This suggests that we focus on a smaller yet more recent dataset to save the training time without compromising the predictive model performance. This lends empirical support to Zhang et al.'s (2017) statement that most recent data should be attended to.

Table 2.6: Confusion matrix for RFC averaged on monthly testing data (July–December)

Predicted \ Actual	Positives			Negatives		
Positives	390332 (0.08%)	387410 (0.09%)	387546 (0.09%)	31316 (1.04%)	32767 (0.79%)	32967 (0.95%)
Negatives	162100 (0.20%)	165022 (0.21%)	164886 (0.20%)	1754679 (0.02%)	1753228 (0.02%)	1753028 (0.01%)
	(1)	(2)	(3)	(1)	(2)	(3)

Note: in parentheses are the coefficients of variation. (1) model with all variables. (2) model with weighted scores. (3) model with unweighted scales. Number of estimators = 100. Max depth = None.

Table 2.7: Confusion matrix for BC averaged on monthly testing data (July–December)

Predicted \ Actual	Positives			Negatives		
Positives	388830 (0.17%)	384825 (0.19%)	385929 (0.15%)	46386 (0.92%)	43991 (1.01%)	44205 (0.93%)
Negatives	163602 (0.40%)	167608 (0.43%)	166503 (0.36%)	1739609 (0.02%)	1742004 (0.03%)	1741790 (0.02%)
	(1)	(2)	(3)	(1)	(2)	(3)

Note: in parentheses are the coefficients of variation. (1) model with all variables. (2) model with weighted scores. (3) model with unweighted scales. Number of estimators = 100.

The confusion matrices in Tables 2.6, 2.7, and 2.8 present the prediction results averaged over the latter half of year 2017 in our data. The BC models made more positive

Table 2.8: Predictive performance for RFC and BC averaged on monthly testing data (July–December)

	RFC			BC		
Precision	92.57% (0.05%)	92.20% (0.06%)	92.16% (0.06%)	89.34% (0.10%)	89.74% (0.11%)	89.72% (0.10%)
Recall	70.66% (0.73%)	70.13% (0.78%)	70.15% (0.78%)	70.39% (0.71%)	69.66% (0.76%)	69.86% (0.77%)
F1	80.14% (0.37%)	79.66% (0.40%)	79.66% (0.40%)	78.74% (0.40%)	78.44% (0.43%)	78.56% (0.43%)
	(1)	(2)	(3)	(1)	(2)	(3)

Note: in parentheses are the coefficients of variation. (1) model with all variables. (2) model with weighted scores. (3) model with unweighted scales. Number of estimators = 100. Max depth = None.

predictions, whereas their RFC counterparts made overall more true-positive (TP) predictions and less false-positive predictions, leading to a higher precision. The F1 rates and forecast accuracy (TP + true negatives) of the RFC models were also higher. This suggests that the recommender system based on RFC can work well for users who prefer to receive fewer yet more helpful reviews. Meanwhile, with BC, the system might boost its recommendation diversity. We will use RFC and BC for counterfactual analysis of our personalized review recommendation.

2.6 Counterfactual analysis

Based on our exploratory analysis, we propose that reviews be recommended on the basis of their likelihood of increasing user affinity. In the preceding section, we demonstrate that our predictive models (BC and RFC) can predict user affinity for each review consistently and can be used to run counterfactual what-if analysis (Dickerman and Hernán, 2020). In particular, for each unique platform user, reviews triggering higher estimated user-review affinity based on the conceptual model parameters are put before those with lower user-review affinity. This *affinity-based* ranking will replace the *original* review-age-based ranking, and the trained predictive models will simulate if more users would like, comment on, or re-read the review within seven days. This counterfactual what-if simulation is to demonstrate the performance of our personalized review commendation system.

Reviews with ranking from 1st to 10th (first-page reviews) are considered promoted in our analysis. Since the platform can change this arrangement, we want to test if user-review affinity will grow if reviews are arranged in a personalized manner such that first-page reviews (reviews ranking 1st to 10th) are the most relevant or useful to each user concerned. Based on the confirmed conceptual model parameters (Table 2.5) and a data subset, we re-rank each review based on its estimated user-review affinity vis-à-vis other reviews (both read and unread) for the same business in descending order. Since reviewer-user similarity, shared locality, and prior interactions (following and dislikes) vary by reviewer-user pair, each platform user would see a different set of promoted reviews. Given our model's particular relevance for businesses with so many reviews that users may face information overload, our data subset for counterfactual analysis focuses on those with at least 50 reviews (five review pages).

Table 2.9: p-value of statistics tests for subsets of the original and affinity-based ranking data

	Tests			
Indicators	t-test	KS test	z-test	Businesses with
Business average rating	0.320	0.789	0.321	$\geq$ 40 reviews
Price range	0.093	0.774	0.092	
Business age	0.535	0.908	0.534	
Business average rating	0.480	0.974	0.480	$\geq$ 50 reviews
Price range	0.209	0.208	0.118	
Business age	0.789	0.985	0.789	
Business average rating	0.615	0.999	0.615	$\geq$ 60 reviews
Price range	0.513	0.999	0.513	
Business age	0.879	0.973	0.879	

Table 2.9 shows there is no statistical difference in terms of business average rating, price range, and business age at the 1% level between the subsets of data where reviewed

Table 2.10: Proportion of simulated positives in subset of reviews ranked 1st–10th for businesses with at least 50 reviews

	Original ranking			Reranking		
RFC	12.70% (0.0009)	12.23% (0.0010)	12.07% (0.0012)	**31.60**% (0.0116)	**21.87**% (0.0165)	**21.09**% (0.0152)
BC	12.81% (0.0012)	12.99% (0.0014)	12.95% (0.0015)	**30.29**% (0.0158)	**29.42**% (0.0178)	**28.81**% (0.0190)
	(1)	(2)	(3)	(1)	(2)	(3)

Note: in parentheses are the standard deviations. (1) model with all variables. (2) model with weighted scores. (3) model with unweighted scales. In bold are the proportions which are statistically greater than their counterparts at the 1% significance level.

Table 2.11: Average positive user interaction rate for businesses with at least 50 reviews, reviews ranked 1st–10th under affinity-based re-ranking

	Original ranking			Reranking		
RFC	20.60% (0.2016)	20.00% (0.2000)	19.88% (0.2023)	**30.39**% (0.3229)	20.69% (0.2630)	20.06% (0.2567)
BC	20.30% (0.1931)	20.69% (0.2006)	20.66% (0.1994)	**29.15**% (0.3017)	**28.50**% (0.2930)	**27.71**% (0.2885)
	(1)	(2)	(3)	(1)	(2)	(3)

Note: in parentheses are the standard deviations. (1) model with all variables. (2) model with weighted scores. (3) model with unweighted scales. In bold are the proportions which are statistically greater than their counterparts at the 1% significance level.

businesses had different thresholds for the minimum number of reviews by the end of 30 November 2017 (2017-11-30 23:59:59). All the statistics tests (t-test, KS test, and z-test) indicated consistent results: raising or lowering this threshold by 10 reviews did not alter the statistical comparability of those subsets (see Table 2.9). The counterfactual analysis results reported in Tables 2.10 and 2.11 are for businesses which had at least 50 reviews. In our counterfactual analysis, a business is considered to have non-decreased user-review affinity when its positive user interactions (likes, comments on, or re-reading of its reviews) simulated with affinity-based ranking are greater than or equal to those with original ranking.

As can be seen in Tables 2.10 and 2.11, the reviews promoted by the novel affinity-based ranking, which builds on the conceptual model, increased user affinity to the platform (by liking, commenting on, or re-reading the reviews within seven days), and this improvement is statistically significant in most of the simulators considered at the 1% significance level. In particular, for businesses with at least 50 reviews, the re-ranking increased user interactions in all simulators. Users reading the promoted reviews for those businesses also interacted more with those reviews and that jump in interactions was statistically significant at the 1% level in most simulators. Thus, review platforms can leverage this insight to rearrange product reviews in a personalized fashion for each user to boost user-review affinity. Moreover, in line with Tables 2.6 and 2.7, the BC-based system produced more recommendations and thus likely boosted the diversity of recommended reviews.

2.7 Discussion and Conclusion

Online reviews have become an integral part of many online platforms. While spending considerable resources attracting users to contribute online reviews, these platforms encounter critical issues where their customers have too many reviews to read, leading them to suffer from information fatigue. We propose to alleviate those issues by developing a personalized review recommendation framework that can help online platforms with their service operations by selectively displaying reviews to their user based on the probability that the user will engage with each review.

We begin by conducting an exploratory analysis where we survey previous research to identify key independent variables that can affect user affinity (i.e., the tendency that a user would like, comment on, or re-read the reviews). To reduce high dimensionality and avoid multicollinearity, we use factor analysis and confirmatory composite analysis. Our results corroborate several important features, especially reviewer-user similarity, (shared) locality, and followship, which are crucial yet underexplored in the review-recommendation literature. The importance of these variables suggests that service operations managers of online review platforms pay attention to peer effects on users, in line with Albergaria and

Chiappetta Jabbour's (2020) recommendations. Robustness checks for our hypotheses are provided in Appendix B.

Following that, we leverage the insights uncovered from our exploratory analysis for predictive modeling. Here, our goal is to ensure that our insights apply to out-of-sample instances to verify the external validity of our findings. In addition, this exercise allows us to predict the likelihood that each user would interact with each review, which is the key ingredient used for our personalized review recommendation system in the next step. With a consistently accurate predictive model, we proceed to counterfactual analysis where we re-rank reviews based on their potential user affinity. Our counterfactual simulation results illustrate that re-ranking reviews can attain significantly more user engagement, which generally leads to improved service operations and higher user satisfaction and retention with the platform.

Despite our effort to carry out a theory- and data-driven study of service operations, our paper still has limitations. In particular, our dataset was collected from only one platform and our counterfactual analysis was run on a random subset of the data. Nonetheless, given that our research is built on the theoretical underpinnings relevant to service operations management (Albergaria and Chiappetta Jabbour, 2020; Chen et al., 2020; Farrell and Klemperer, 2007; Spence, 1973; Yayla-Küllü et al., 2015), our findings are likely generalizable in this field of study (Bansal et al., 2020). The second limitation can be addressed by scaling up the sample size for counterfactual analysis or field experimentation in future research.

Overall, this work contributes toward the literature by studying an online platform as a typical case for data-driven service operations (Cohen, 2018). In addition to theoretically and empirically investigating vital variables in online review recommendation as part of online platforms' service operations, we provide evidence that models with theoretically grounded dimensionality reduction can perform equally well vis-à-vis their sophisticated counterparts. Further, our counterfactual analysis results show that theory- and data-driven review ranking based on user-review affinity can improve user engagement with the platform, thereby giving support to the need for service operations models that are both theory- and data-driven (Huang and Rust, 2013). This call is particularly relevant in today's context with opportunities opened up by recent technological advances for service operations (Baron, 2021).

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Chapter 3

Analyzing economic nationalism's impact on domestic sourcing and anticipating its change with political manifestos

Chapter information: The result of this chapter has been submitted as a research paper and the coauthors are Rémi Charpin, Yossiri Adulyasak, and Jean-François Cordeau.

Abstract

State interventions which discriminate against foreign commercial interests are ubiquitous and represent a source of supply risk for firms that trade with foreign suppliers. This research investigates economic nationalism's effect on firms' supplier selection and how firms can anticipate changes in economic nationalism. We analyze archival data covering 35,153 firms in 114 countries over the 2012–2020 period and find that economic nationalism leads firms to increase their share of domestic supplier relationships. This impact is stronger for firms operating in the food and medical supplies industries. Furthermore,

we utilize political manifestos from 47 countries to demonstrate that economic nationalist sentiment during election years is associated with economic nationalist policy interventions. This study contributes to the theory on policy uncertainty and political risk by using economic nationalist sentiment to anticipate whether future policy changes are likely to increase supply risk for firms with foreign suppliers and by introducing a new operationalization of political risk for foreign trade. Additionally, it provides insights into the signals that managers can use to better evaluate political risk and design proper risk mitigation strategies. Lastly, it informs policymakers how economic nationalism affects their domestic production goals.

3.1 Introduction

"You know that to build a truly strong economy, we need a future that's made in America. That means using products, parts, materials, built right here in the United States of America. It means bringing manufacturing back, jobs back, building [supply chains] SCs here at home, not outsourcing abroad, so we have better jobs and lower prices here."[1] While this quote seems to embrace Donald Trump's economic nationalist rhetoric, it is an excerpt from a speech Joe Biden gave in Pittsburgh in January 2022. This kind of appeal to encourage domestic sourcing – *the selection of suppliers producing within the buyer's home country* – is not restricted to one political inclination, new or limited to the U.S.A. Back in 2016, the Council on Foreign Relations had already noted: "Trade itself is becoming less of a driver of global growth and is confronted by a resurgence of protectionism across nearly all major markets… The rise of protectionism, both in terms of formal trade-restrictive measures and public sentiment, present[s] a challenge for both global trade and global SC resilience." This desire to breed local SCs and develop national champions is a trend that has been observed not only in many developed nations, but also in emerging ones (Charpin, 2022). The objective is to develop domestic supply capabilities by producing more at home and relying less on foreign partners. To support these nationalist endeavors, governments implement policies that aim to give domestic firms relative preferential treatment over their foreign counterparts. Seventy-seven percent of all state interventions put in place during the past decade on foreign trade have involved policies discriminating against foreign commercial interests (Global Trade Alert, 2022).

The purpose of this article is to analyze economic nationalism's effect on firms' supplier selection and to examine how firms can better anticipate changes in economic nationalism, which affect foreign trade, and in turn, supply conditions. Economic nationalism reflects a government's desire to protect its national interests "in the context of world markets" (Pryke, 2012, p. 285). Even though economic nationalism can represent various principles, from autarky to trade liberalization (McGrath, 2020), it is most commonly used "to refer to the preference for natives over foreigners in economic activities" (Dinc and Erel, 2013, p. 2472). Thus, we define "economic nationalism" as *a set of principles and policies discriminating against foreign commercial interests in favor of domestic commercial interests* (Evenett, 2019). This definition reflects contemporary nationalist trends characterized by politicians and grassroots alike needing to reclaim control of their country and fight a globalization process that is deemed to have gone too far (Colantone and Stanig, 2019; Rodrik, 2018).

Economic nationalism is related to uncertainty and risk. While uncertainty is unpredictable, risk can be anticipated to some extent as it can be associated with an outcome distribution (Müllner, 2016). Economic nationalism is enforced through policies that are themselves inherently uncertain since we do not know whether they will harm or benefit a firm. Policy uncertainty influences SC practices by reducing a firm's environmental predictability (e.g., Darby et al., 2020). In this study, we focus on the uncertainty associated with policy changes which alter foreign trade and thereby increase supply risk for firms that source from foreign suppliers. Policies which discriminate against foreign entities distort market competition and are hence of great importance to managers (Evenett, 2019). For example, economic nationalism affects foreign mergers and acquisitions (Dinc and Erel, 2013), foreign direct investment (Jakobsen and Jakobsen, 2011), and foreign labor flows (Showkat et al., 2023). Despite its potential to greatly affect foreign trade and SC practices, economic nationalism has remained largely unexplored in the SC literature.

Therefore, this study aims to answer the following two questions: *Does economic nationalism affect firms' supplier selection?* and *How can firms anticipate economic nationalism changes?* The answer to the first question is crucial because a firm's competitiveness is highly dependent on its suppliers' performance and regulations that alter supply conditions increase a firm's supply risk exposure. The answer to the second question is also essential, as it should help firms design mitigation strategies to reduce their supply risk.

To address these questions, we use data from multiple datasets dating from 2012 to 2020 to investigate 1) the effect that policies that discriminate against foreign commercial interests have on a firm's proportion of domestic suppliers, 2) the moderating role essential goods (i.e., food and medical supplies) play in that relationship, and 3) the effect that economic nationalist sentiment has on economic nationalist policies. We achieve this by using multilevel modeling to test the first two hypotheses in 114 countries, and the third hypothesis in 47 countries. We utilize a different sample set to test the third hypothesis due to the availability of data for the economic nationalist sentiment variable. Our results indicate that economic nationalist policies lead firms to increase their share of domestic sourcing and that this effect is stronger among firms operating in essential industries. We also find that the economic nationalist sentiment expressed in political manifestos can help predict economic nationalist policy interventions.

This article contributes to SC risk management research, SC practices, and foreign trade policymaking. First, from a theoretical perspective, this study helps to link the concepts of policy uncertainty and political risk. SC researchers have shown that policy uncertainty leads firms to adapt their SC decisions (e.g., Darby et al., 2020; Dong et al., 2022; Leung and Sun, 2021). However, firms do not know whether this uncertainty will eventually harm their operations since uncertainty is not predictable and does not necessarily result in unfavorable outcomes (Dong et al., 2022). From this postulate, it is difficult to determine if firms' reactions to uncertainty are appropriate given that policy uncertainty does not inevitably lead to negative consequences for the firm. Our study helps to bridge this lacuna by showing that foreign trade policy uncertainty is associated with nationalist sentiment, which indicates whether future policy changes are likely to increase supply risk. We introduce in our empirical analysis a key distinction between nationalist sentiment and policies, and therefore contribute to the literature on SC risk and uncertainty by revealing how nationalist sentiment can be leveraged to derive a measurable risk of policy uncertainty.

Second, our study presents important practical insights for managers who must navigate increasingly uncertain political environments as governments occupy a critical role in shaping foreign trade. To our knowledge, our paper is the first to use political manifestos to anticipate economic nationalist policies, which affect a firm's supply conditions. Understanding a nation's sentiment toward economic nationalism can help firms to proactively design (and potentially implement) strategies ahead of the enactment of these policies. These findings enrich the SC risk management literature by offering insights into the signals that managers can use to assess political risk and design appropriate mitigation strategies.

Third, our results offer policymakers insights into the impact that economic nationalist policies have on firms' use of domestic sourcing. Our findings support the posit that firms located in countries with a high level of economic nationalism tend to increase their share of domestic supplier relationships. The SC literature shows that government regulations and laws influence firms' SC practices (Helper et al., 2021). This study contributes to this stream of literature as it is the first to empirically assess economic nationalist policies' effect on domestic sourcing. Therefore, it informs policymakers whether their nationalistic policies produce the desired results or fail to achieve their domestic production goals.

3.2 Background and hypothesis development

3.2.1 Economic nationalism

Economic nationalism refers to state interventions in the economy to support national interests. The objective is to maximize the nation's wealth and power (Baughn and Yaprak, 1996) by not leaving its fortunes "determined by the world market alone" (Pryke, 2012,

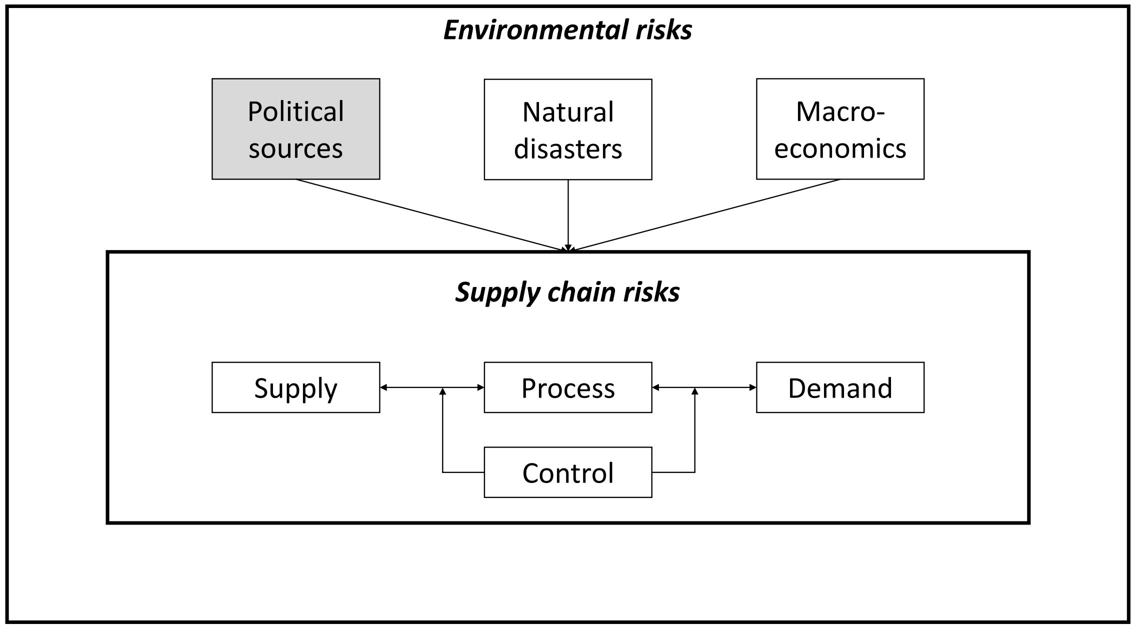
p. 285). Although economic nationalism in the 1990s leaned toward liberalism for nations which wanted to keep asymmetrical trade partnerships in their favor (Diesen, 2017), it is more commonly associated with protectionism such as in the 1930s and the early 1980s, and more recently, since the 2008 financial crisis. According to Friedrich List, protectionism is necessary to develop nascent industries and to provide a level playing field for them before trade liberalization (McGrath, 2020). While protectionism intends to protect domestic entities from foreign competition, economic nationalism also includes the notion of serving national goals, such as maintaining sovereignty and maximizing relative gains in an interstate system, which is perceived by states as a zero-sum game (Baughn and Yaprak, 1996; Helleiner, 2021). In the event of interstate conflicts, nations might see their foreign supply cut off, hence the necessity for nations to have their own production capabilities and to not rely blindly on other nations. For instance, many European nations currently face an unprecedented energy crisis as their supply of Russian gas is cut off in retaliation for the economic sanctions imposed on Russia for invading Ukraine.[2]

In this paper, we adopt this protectionist view of economic nationalism as it echoes recent economic and political shifts. First, this view fits contemporary deglobalization trends – there has been an increase in protectionist policies since the 2008 financial crisis, which has led to a decrease in international trade and foreign direct investment worldwide (Witt, 2019). Second, this view has been reflected in anti-globalization and national sovereignty sentiments in recent elections (Colantone and Stanig, 2019). These sentiments have been leveraged by both radical left and right populist political parties, which vouch to reduce free trade as they deem it to benefit only the elite (Halikiopoulou et al., 2012). These observed economic and political changes point to a growing desire for nations to embrace economic nationalism so as to defend their sovereignty and prevent globalization from deciding the fate of their economies. Consequently, there has been a sharp increase in state interventions that discriminate against foreign commercial interests since the 2008 financial crisis (Meyer, 2017). While these interventions are generally considered in the literature in the form of trade restrictions on imported goods, they can also consist of restrictions on imported and exported goods and services, investment, and labor migration, all of which affect foreign trade (Evenett, 2019). We take a holistic approach in our work.

By discriminating against foreign entities in favor of native ones, economic nationalism impacts business practices. In finance, it influences the outcome of mergers and acquisitions by discriminating against foreign acquirers. Nationalist governments are more likely to intervene in hostile takeovers (Rowoldt and Starke, 2016) and oppose an acquisition (Dinc and Erel, 2013) when the bidder is a foreign firm. Nationalist reactions to mergers and acquisitions also discourage future acquisitions from foreign companies (Dinc and Erel, 2013). More generally, economic nationalism deters foreign direct investment in emerging countries (Jakobsen and Jakobsen, 2011). It also affects human resources by challenging the flow of global talent through more restrictive immigration policies and favoring natives (Showkat et al., 2023). In SC management, economic nationalism influences global SC relationships since engaging with foreign business partners becomes riskier when government interventions alter the relative treatment of foreign firms (Evenett, 2019; Fan et al., 2023). All else equal, these state interventions targeting trade, investment, and immigration affect foreign suppliers' competitiveness and accessibility. Therefore, in this study, we investigate how economic nationalism may affect supplier relationships as a source of supply risk.

3.2.2 Supply risk and supplier relationships

While there is no consensus on the definition of *risk* in SC management (Sodhi et al., 2012), it is usually characterized as unexpected events that trigger adverse consequences for a supply chain (Ho et al., 2015). Therefore, *risk* integrates a source (i.e., the triggering event) and an outcome (i.e., the impact on the firm in question). Political sources of risk in SC management occur beyond the company's SC boundaries and thus have been categorized as either environmental (e.g., Jüttner, 2005), external (e.g., Wu et al., 2006), or exogenous (e.g., Wicaksana et al., 2022) risk since enterprises exert little to no control over them (Heckmann et al., 2015). Figure 3.1 illustrates that political sources of risks can cause other types of SC risk because environmental risk overlaps with firms' demand, supply, and operational risk (Jüttner, 2005).



Source: Adapted from Christopher and Peck (2004), Jüttner (2005), and Mason-Jones and Towill (1998)

Figure 3.1: Sources of SC risks

In this paper we focus on *supply risk*, which we define as *unexpected events that have a negative impact on a firm's supply conditions*. While governments are recognized conceptually as a source of supply disruptions (Ellis et al., 2011; Kleindorfer and Saad, 2005), the empirical SC literature has devoted more attention to supplier failures (e.g., quality problems and relationship issues) and market characteristics (e.g., sole source and market shortages) as sources of supply risk (Ellis et al., 2011; Zsidisin, 2003). Economic nationalism via government interventions can also trigger supply risk, which in turn generates disruptions for companies trading with foreign firms. For instance, the tariffs the U.S. government imposed on steel and aluminum in 2018 increased the price and the volatility of foreign supplies for U.S. manufacturers.[3] These nuisances have been exacerbated by the COVID-19 crisis and have reinforced supply uncertainty (Sodhi and Tang, 2021).

Economic nationalism exposes domestic firms to supply risk by distorting trade with foreign suppliers. A home government (i.e., the government of the country where the buyer is located) can implement policies to protect the national economy from foreign competition and reduce the country's dependence on global markets. One goal is to deter domestic firms from using foreign suppliers in order to support local firms, jobs, and technologies (Gehlen et al., 2020). Another goal is to defend the nation's sovereignty by ensuring that the country has access to local sources of supply, thereby preventing over-reliance on foreign countries. These economic nationalist practices may generate supply disruptions for buyers that use foreign suppliers (Charpin, 2022). For instance, tariffs lead to cost increases, while quotas reduce companies' ability to meet their quantity requirements. Both can hinder firms' operational performance. Fan et al. (2023) find that the U.S.-China trade war 1) leads U.S. firms that have suppliers in China to increase their inventory to mitigate their risk exposure and 2) has a negative effect on their performance. In addition to trade restrictions, investment and immigration constraints can influence foreign suppliers' competitivity, further hindering trade between domestic and foreign firms (Evenett, 2019).

Overall, state interventions that discriminate against foreign commercial interests increase the supply risk exposure of firms that trade with foreign suppliers and encourage them to use domestic sources when local alternatives exist. Beyond these risk considerations, enterprises that operate in nationalistic environments may also feel pressured to rely more on domestic firms and limit their use of foreign suppliers. Accordingly, we posit that economic nationalism leads to an increase in domestic sourcing.

Hypothesis 1: Economic nationalist policies increase firms' proportion of domestic sourcing.

3.2.3 Moderating role of essential goods

Economic nationalism does not target all products and services alike. Governments have more incentive to support sovereignty when it comes to the goods that are deemed essential for the national economy (Charpin, 2022). Achieving self-sufficiency in certain key sectors is a vital objective for many countries that rely on foreign partners to fulfill critical needs. Two such sectors for which governments have been very vocal about pushing reshoring initiatives and developing local sources of supply are food and medical supplies (Evenett, 2020). First, food product shortages caused by overreliance on imported products are met with public outcry and a desire to develop local SCs. For instance, France, the largest consumer of mustard in the world, was hit by a shortage of mustard in 2022 due in part to poor mustard seed harvests in Canada, its main source of imports. Although many other domestic factors such as pests, pesticide regulations, climate change, and consumer behavior contributed to the shortage, the repatriation of mustard seed production was deemed to be the solution to the crisis.[4] Second, ensuring the sovereignty of medical supplies is also perceived by governments as key to meet national healthcare needs when demand surges (Gereffi et al., 2022). Vaccine nationalism and the fights that ensued among nations over medical supplies during the COVID-19 pandemic pointed toward a desire to decouple medical supplies from global SCs (Evenett, 2020; Gereffi et al., 2022). Therefore, we expect economic nationalism's influence on domestic sourcing to be stronger in industries that are perceived as fulfilling essential needs.

Hypothesis 2: The positive effect of economic nationalist policies on firms' proportion of domestic sourcing is stronger for firms that operate in industries that are deemed essential.

Economic nationalism is a driver of political risk, which firms respond to by taking measures to modify their SC practices (Charpin, 2022). Since these actions take time and carry their own risks, being able to predict political risk becomes a clear advantage (Kurosawa et al., 2019). From a firm perspective, it would be helpful to be able to anticipate these harmful policy changes. We thus turn our attention to data that could be used to predict economic nationalism.

3.2.4 Political manifestos and economic nationalism

In this era of populism and economic nationalism, the role of the state and selective policies that give primacy to national interests is expected to be more prominent (Gereffi et al., 2022). Thus, being able to predict surges in economic nationalism would help firms adopt strategies that reduce their exposure to political risk (Kurosawa et al., 2019). To support this endeavor, we review two sources of secondary data – newspaper articles and political manifestos – that could be helpful in anticipating policy changes that affect global SCs.

Newspapers are used to create policy uncertainty indices that are based on the number of occurrences in news articles of terms related to policy uncertainty. Baker et al. (2016) use this method to develop the economic policy uncertainty (EPU) index.[5] In SC management, high levels of EPU are perceived as increasing risk and lead firms to increase their inventory (Darby et al., 2020), diversify their customer base (Leung and Sun, 2021), and decrease their SC involvement (Dong et al., 2022). However, EPU captures any type of uncertainty in the economy at large[6] and seems ill-suited for predicting state interventions that discriminate against foreign economic interests. Baker et al. (2016) also create eleven policy category- and subcategory-specific EPU indices by adding category-relevant terms to their initial EPU index. The category of interest to us focuses on trade.

The trade policy uncertainty (TPU) index[7] is also built on newspaper coverage frequency of keywords connected to trade uncertainty (see Caldara et al., 2020). While the news-based TPU index follows a similar pattern to U.S. trade policy history and captures episodes of trade uncertainty (Caldara et al., 2020), it focuses on imports and tariffs and hence ignores other important facets of economic nationalism (de Bolle and Zettelmeyer, 2019; Evenett, 2019). Furthermore, this TPU index is currently available for four countries only and is not based on a consistent methodology. We notice that there also exist firm-level TPU indices derived from firms' quarterly earning calls (Caldara et al., 2020) and annual reports (Benguria et al., 2022). In the context of our study, these indices have two limitations. First, they reflect the firms' perception of uncertainty rather than information that could be leveraged to predict surges in economic nationalism and hence do not fit our purpose. Second, they target public firms from a single country, so they limit the ability to conduct cross-country comparisons or include private firms in the analysis.

In sum, the EPU index seems too broad, and the TPU indices too narrow, to capture economic nationalism in various countries using a consistent method. Newspaper-derived indices also suffer from two important shortcomings. First, they do not fully capture the meaning of economic nationalism. While they capture a fraction of its economic component (e.g., specific trade policies), they ignore its political aspect (i.e., the defense of sovereignty and national preference). Second, these indices increase when policy changes become more prominent and hence provide a retrospective view of the phenomenon. It is actually the imposition of tariffs that gives rise to TPU (Benguria et al., 2022), as newspapers and companies increase their focus on it by the time such policies are released. Therefore, we review another source of information – political manifestos – that takes a more forward-looking approach to economic nationalism and policy changes.

Political manifestos are written statements declaring the platform and aims of a political party or candidate. They are issued before elections, which are themselves correlated with periods of uncertainty (Cazals and Léon, 2023) as firms do not know whether the replacement of a country's top political leader will affect trade with foreign partners positively or negatively (Dong et al., 2022). In our context, we are not interested in the political turnover per se, but the risk related to the potential discrimination of foreign commercial interests. Manifestos suit our purpose since they indicate political parties' inclination toward economic nationalism, which is closely associated with policy formulation (Baughn and Yaprak, 1996; Colantone and Stanig, 2018; Lee et al., 2014). When combined with election results, they provide timely and relevant information about expected policy changes that could cause supply disruptions.

Political manifestos feature many points pertaining to topics such as trade and immigration (de Bolle and Zettelmeyer, 2019) and have been used as proxies for anti-globalization sentiment (Burgoon and Schakel, 2022) and group appeals to nationalism (Howe et al., 2022). Therefore, they not only capture politicians' intentions with respect to economic nationalism, but they also reflect voters' preferences with regard to sovereignty and national interests. Politicians, despite aiming to pursue their own interests ultimately, attempt to satisfy voters' preferences in order to be elected or reelected (Downs, 1957) and thus embed public preferences in their manifestos. Consequently, we expect political manifestos to predict policy interventions that discriminate against foreign commercial interests.

Hypothesis 3: Economic nationalist sentiment in political manifestos has a positive effect on economic nationalist policies.

In sum, our study contributes to the literature on the influence of public policy on SC decisions. More specifically, it focuses on economic nationalism, which is a crucial and timely topic because TPU in 2018 reached such levels that had not been seen since the 1970s (Caldara et al., 2020). Moreover, Rammal et al. (2022) notice in their review of the literature on economic nationalism and the internationalization of services that there was a lack of understanding of how policymaking changes, which limits researchers' ability to predict economic nationalism. By using political manifestos to predict policy changes, our study addresses this issue and answers the call to integrate in management an international relations perspective on governments to better predict their actions (Meyer and Li, 2022).

3.3 Methods

3.3.1 Sample

To construct our dataset, we use data from various sources: information about supplier relations from the FactSet Supply Chain Relationships database (hereinafter referred to as the FactSet database),[8] data on policy interventions affecting foreign commercial interests from the Global Trade Alert (GTA) database,[9] details about economic nationalist sentiment from the Manifesto Project Dataset (MPD),[10] firm-level characteristics from the Orbis[11] and FactSet databases, and country-level characteristics from the World Bank (WB)[12] website. After merging the data sources, our final samples cover the 2012–2020 period and include 113,739 firm-country-year observations from 35,153 firms in 114 countries for Hypotheses 1 and 2, and 18,535 country-year observations from 47 countries for Hypothesis 3. The sample sizes differ due to the availability of data on political manifestos. Table 5 in Appendix C indicates the number of countries, firms, and observations that were retained in each step of the data collection process. Our unit of analysis is a firm in a focal country making the decision to source from domestic or foreign suppliers. Table 6 in Appendix C features the list of countries used in this study, with the number of firms and observations considered for each country.

3.3.2 Measures

3.3.2.1 Domestic sourcing

We operationalize *domestic sourcing* as the proportion of domestic to total supplier relationships a given firm had in year t. Supplier relationships are extracted from the FactSet database, which is the most complete database of international customer and supplier relationships and has been used in previous research on SC relationships and configurations (Piraveenan et al., 2019; Son et al., 2021; Wang et al., 2021). In that database, company A is reported to have a supplier relationship with company B if it has purchased a product (or group of products) from company B. Each supplier relationship is recorded in a separate entry with its start date (*sd*) and end date (*ed*). If the relationship is still active, the end date field is empty. In our work, company A is considered to have a supplier relationship with company B in year t if its supplier relationship with company B: started before the end of year t ($year(sd) \leq t$); and ended after the beginning of year t ($year(ed) \geq t$) or remained active (undefined *ed*). We determine domestic suppliers according to their headquarters location in FactSet. While it is possible that a supplier's headquarters and operational locations differ, Charoenwong et al. (2023) show that for U.S. customers, supplier relationships retrieved from FactSet corroborate firms' shipment data. The latter is deemed to capture more accurately the supplier's operational location. Still, their results were robust to both relationships and shipment data, hence validating the use of supplier's headquarters location as a proxy to determine the operational location of the firm.

3.3.2.2 Economic nationalist policies

We use the GTA database to collect data on policies related to foreign commercial interests. It is managed by a team of researchers who compile and analyze policies influencing cross-border commerce and indicates whether the policies discriminate against or improve foreign commercial interests (Evenett, 2019). In this work, "foreign commercial interests" refers to the trade-related interests of all foreign countries that traded with the focal nation in year t. The database also indicates the date a policy was announced, came into effect, and ended if it is no longer in effect. We can thus count the cumulative number of announced policies in year t. To operationalize economic nationalist policies, we generate the *ENpolicies* variable, which measures the proportion of the cumulative number of announced policies that discriminate against foreign commercial interests[13] to the cumulative number of total policies for a given country in year t.

3.3.2.3 Economic nationalist sentiment

We obtain our measure of economic nationalist sentiment from the MPD, which represents the proportion of sentences from political manifestos that reveal a certain sentiment. We build on the article of Colantone and Stanig (2018), who use the MPD to measure the three elements undergirding economic nationalism: autarky, a pro-market position on domestic economic issues, and a strong nationalist stance. Even though protectionism is recognized as a vector of economic nationalism (Colantone and Stanig, 2018; Dinc and Erel, 2013; Jakobsen and Jakobsen, 2011; Wegren, 2011), Colantone and Stanig (2018) show that a *laissez-faire* attitude concerning domestic economic policies and appeals to national sovereignty are key elements of economic nationalism as well. Accordingly, we leverage the items[14] selected by Colantone and Stanig (2018) to operationalize economic nationalist sentiment as the ratio of manifestos that support economic nationalism to those that are against it. This measure is computed as follows:

$$ENsentiment = \ln \frac{Z^{+}}{Z^{-}}, \tag{3.1}$$

where Z^{+} is the sum of the variables for sentiments against internationalism but in favor of protectionism, a free market economy, economic orthodoxy (economically healthy policymaking), supply-side-oriented economic policies, and welfare state limitation, and

Z^{-} is the sum of the variables for sentiments against protectionism but in favor of internationalism, market regulation, nationalization, economic planning, a controlled economy, a mixed economy, demand-side-oriented economic policies, and welfare state expansion. This logit scale has previously been used to analyze the sentiments expressed in legislative (Proksch et al., 2019) and political (Gavras and Höhne, 2022) speeches.

Each entry in the MPD indicates the attitude (as included in the *ENsentiment* variable) of party p, which received v percent of the votes in country c at time t. In our study, the attitude of country c at time t ($\bar{a}_{tc}$) is averaged over the attitudes of all the parties running in country c at time t (a_{tp_c}) as follows:

$$\bar{a}_{tc} = \frac{\sum\limits_{p_c} a_{tp_c} v_{tp_c}}{\sum\limits_{p_c} v_{tp_c}}, \forall c, \forall t \tag{3.2}$$

If $v_{tp_c} \in \emptyset$, we set v_{tp_c} to zero. If $v_{tp_c} \in \emptyset, \forall p_c$, we set $v_{tp_c} = \frac{1}{|P_{ct}|}, \forall p_c$ with $|P_{ct}|$ being the number of parties in country c at time t.

3.3.2.4 Essential goods

We create an *essential goods* dummy variable for critical industries. Based on Evenett's (2020) definition of essential goods – food and medical supplies – companies operating in the fish/meat/dairy, specialty/candy, food manufacturing, food distribution, food retail, medical distribution, and medical specialties industries are assigned a value of one for this variable. Other firms are assigned a value of zero for the variable. This variable enables us to test whether discrimination against foreign trade is stronger in the sectors deemed by governments to be of national interest.

3.3.2.5 Control variables

As is depicted in Figure 3.1, macroeconomic factors play a vital role in shaping SC networks (cf. Chopra and Meindl, 2016, p. 110). We collect from the WB website two indicators that impact firms' ability to source from domestic suppliers: (logarithmic) *gross domestic product (GDP) per capita* and *GDP growth rate* to control for the country's wealth and economic growth. We collect firm-level data from the Orbis and FactSet datasets. We use *operating revenue* to control for firm size (Muir et al., 2019) since it is associated with foreign trade activities (Gashi et al., 2014) and global operations (Chedid et al., 2021). Similarly, we include *net asset turnover* to control for the firm's efficiency as the ability to generate revenue from assets is associated with its foreign trade (Ganotakis and Love, 2011; Zhang et al., 2022). Finally, we control *industry* and *entity type* (e.g., publicly traded company and private firm), which may influence the firm's adherence to the nationalist rhetoric.

Table 3.1 below presents the summary statistics for the independent, dependent, and control variables.

Table 3.1: Summary statistics

	N	SD	Mean	1st quartile	Median	3rd quartile
Dependent and independent variables for Hypotheses 1 and 2						
Domestic sourcing	113,739	.41	.53	.00	.50	1.00
$ENpolicies$	113,739	.12	.61	.51	.58	.71
Essential goods	113,739	.25	.06	.00	.00	.00
Dependent and independent variables for Hypothesis 3						
$ENpolicies$	18,535	.11	.61	.51	.58	.71
$ENsentiment$	18,535	.47	$-.86$	-1.14	$-.78$	$-.47$
Control variables						
Focal country GDP growth rate (%)	113,739	2.24	2.86	1.56	2.29	3.50
Focal country GDP per capita (log-transformed)	113,739	1.03	10.15	9.34	10.61	10.86
Operating revenue (Turnover) (US$ billion)	113,739	13.3	3.12	.08	.40	1.69
Net assets turnover (%)	113,739	12.25	2.38	.49	1.07	2.06

Note: N = number of observations; SD = standard deviation.

3.3.3 Model estimation

As our panel data vary over time across firms based in different countries, multilevel (or hierarchical) modeling is considered appropriate (Antonakis et al., 2021). This method is employed to analyze longitudinal and cross-sectional data in operations and SC management research (Ertekin et al., 2020; Hardcopf et al., 2019; Ketokivi et al., 2021). Ignoring between-group variation to make a completely pooled estimate ($\bar{y}_{\text{all}}$) may well yield biased results when such variation exists. Multilevel modeling accounts for the between-group variation in coefficients and thereby makes it possible to predict the effects of new groups (Gelman et al., 2007). More importantly, when an indicator variable is used for the fixed effect at the highest level, the coefficients of other variables measured at that level cannot be estimated (Bell et al., 2019). In comparison to using indicator variables to produce unpooled estimate $\bar{y}_j$ for each group j in the data, multilevel modeling helps avoid overstating the impact of the explanatory variable when the sample size of a given group is small (Gelman et al., 2007). The multilevel estimate $\left(\hat{\alpha}_j^{\text{multilevel}}\right)$ can be approximated as follows:

$$\hat{\alpha}_j^{\text{multilevel}} \approx \frac{\frac{n_j}{\sigma_y^2}\bar{y}_j + \frac{1}{\sigma_\alpha^2}\bar{y}_{\text{all}}}{\frac{n_j}{\sigma_y^2} + \frac{1}{\sigma_\alpha^2}},$$

where n_j denotes group j's sample size; σ_y^2 is the within-group variance (assumption: $\sigma_y^2 = \sigma_{y_i}^2 = \sigma_{y_j}^2, \forall i \neq j$, for simplicity); and σ_α^2 is the between-group variance (Gelman et al., 2007). This approximation shows that overstatement owing to small sample size n_j is less likely to bias the estimate because $\frac{n_j}{\sigma_y^2} \to 0$.

We estimate the effect that *ENpolicies* has on *domestic sourcing* of firm f in country c in year t using the following model:

$$\begin{aligned} \textit{Domestic sourcing}_{t,f,c} = {} & \beta_0 + \beta_1(ENpolicies_{t-1,c}) + \beta_2(essentialgoods_{f,c}) \\ & + \beta_3[(ENpolicies_{t-1,c}) \times (essentialgoods_{f,c})] + \alpha X_{t-1,f,c} \\ & + \theta Z_{t-1,c} + \gamma(year_t) + \varepsilon_{t,f,c} + \varepsilon_{f,c} + \varepsilon_c, \end{aligned} \tag{3.3}$$

where $domestic\ sourcing_{t,f,c}$ is the proportion of domestic supplier relationships of firm f in country c in year t; $ENpolicies_{t-1,c}$ denotes the economic nationalist policies of country c in year $t-1$; $essentialgoods_{f,c}$ is equal to 1 if firm f in country c is considered to provide essential goods and 0 otherwise; $X_{t-1,f,c}$ is the set of firm-level control variables in year $t-1$; $Z_{t-1,c}$ is the set of country-level control variables in year $t-1$; γ is the coefficient associated with $year_t$ and indicates the trend over time; $\varepsilon_{t,f,c} \sim \mathscr{N}(0,\sigma^2)$ is the random error for time-level variance; $\varepsilon_{f,c} \sim \mathscr{N}(0,\sigma^2_{\mathscr{F}})$ is the random error for variance across firms in country c; and $\varepsilon_c \sim \mathscr{N}(0,\sigma^2_{\mathscr{C}})$ is the random error for variance across countries. All independent and control variables are lagged by one year to mitigate reverse causality concerns. We include year, firm type, and industry dummies to account for time-variant and time-invariant unobserved factors.

Once the model is fitted, we can decompose the variation in the dependent variable (Peugh and Heck, 2017) as follows: $\frac{\sigma^2}{\sigma^2+\sigma^2_{\mathscr{F}}+\sigma^2_{\mathscr{C}}}$ of the variation occurs across time within i firms based in j countries (within-firm effect); $\frac{\sigma^2_{\mathscr{F}}}{\sigma^2+\sigma^2_{\mathscr{F}}+\sigma^2_{\mathscr{C}}}$ of the variation occurs across the mean value of *domestic sourcing* of i firms based in j countries (between-firm effect); and $\frac{\sigma^2_{\mathscr{C}}}{\sigma^2+\sigma^2_{\mathscr{F}}+\sigma^2_{\mathscr{C}}}$ of the variation occurs across the mean value of *domestic sourcing* for j countries (between-country effect).

Per the random effects assumption, the covariance of a given independent variable x and $\varepsilon_{f,c}$ (or ε_c) is assumed to be zero $(cov(x,\varepsilon_{f,c}) = cov(x,\varepsilon_c) = 0)$. In accordance with Antonakis et al. (2021), we compute the model likelihood with and without the group means to test this assumption. The following group means represent the contextual effects whose statistical significance indicates that unobserved cluster effects should not be ignored: $\bar{X}_{f,c} = mean\{X_{t,f,c}\}_t$ for the set of control variables for each firm f; $\bar{X}_{\bar{f},c} = mean\{\bar{X}_{f,c}\}_f$ for the set of control variables for all firms in country c; $\bar{Z}_{t,c} = mean\{Z_{t,c}\}_t$ for the set of control variables for country c; and $\overline{ENpolicies}_c = mean\{ENpolicies_{t,c}\}_t$ for the $ENpolicies$ measure in country c. According to Pesaran (2006), this use of cross-sectional averages helps treat possible cross-sectional dependence in panel data (Rodríguez-Caballero, 2022). The outcome of the likelihood-ratio test is significant (see Table 3.2), so the random effects assumption is rejected; hence we include the group means in our models for Hypotheses 1 and 2.

We test the effect of the economic nationalist sentiment in country c in election year t ($ENsentiment_{t,c}$) on economic nationalist policies one year later ($ENpolicies_{t+\Delta t,c}$) using the following model:

$$\begin{aligned} ENpolicies_{t+1,c} = \lambda_0 + \lambda_1(ENsentiment_{t,c}) + \lambda_2(year_t) \\ + \lambda_3\overline{ENsentiment}_c + \varepsilon_{t,c} + \varepsilon_c, \end{aligned} \tag{3.4}$$

where $\overline{ENsentiment}_c = mean\{ENsentiment_{t,c}\}_t$; $\varepsilon_{t,c} \sim \mathcal{N}(0, \sigma_\tau^2)$ is the random error for time-level variance; and $\varepsilon_c \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ is the random error for variance across countries. This formula takes into consideration the effect of the economic nationalist sentiment expressed in the election year on economic nationalist policies one year after.

To calculate economic significance, we scale the coefficient of the independent variable by the standard deviation of the dependent variable as follows: $E_{xy} = \left|\frac{b_x s_x}{s_y}\right|$, where b_x is the coefficient of the independent variable (x), and s_x and s_y are the sample standard deviation of the independent and dependent variables, respectively. Economic significance measures scaled by the sample standard deviation rather than by the sample mean of the dependent variable are theoretically and empirically more robust (Mitton, 2022).

3.4 Results

First, we examine the results for our baseline regressions, which assess the effect of economic nationalist policies on domestic sourcing and the effect of economic nationalist sentiment on economic nationalist policies. Second, we present various robustness tests.

3.4.1 Baseline results

We review the regression results for the three hypotheses in Table 3.2. Models 1–4 study the effect of *ENpolicies* on *domestic sourcing* while Model 5 shows the results for the

Table 3.2: Test results for Hypotheses 1–3

Dependent variable	Domestic sourcing				*ENpolicies*
	(1)	(2)	(3)	(4)	(5)
ENpolicies			.0209⁑	.0198⁑	
			(.0023)	(.0023)	
ENpolicies $\times$*essentialgoods*				.0171*	
				(.0071)	
Essential goods				$-$.2220⁑	
				(.0637)	
GDP growth rate		$-$.00115	$-$.00023	$-$.00021	
		(.0022)	(.0022)	(.0022)	
GDP per capita		$-$.0294⁑	$-$.01422	$-$.01415	
		(.0086)	(.0087)	(.0087)	
Operating revenue		$-$.00431	$-$.00438	$-$.00433	
(Turnover)		(.0025)	(.0025)	(.0025)	
Net assets turnover		$-$.00177	$-$.00178	$-$.00178	
		(.0016)	(.0016)	(.0016)	
ENsentiment					.1619⁑
					(.0041)
Constant	.3234⁑	.4863⁑	.5146⁑	.5142⁑	$-$.7063⁑
	(.0200)	(.0531)	(.0543)	(.0543)	(.1197)
Country $var(cons), \sigma^2_{\mathscr{C}}$	.03455	.03405	.03215	.03224	.64541
	(.0057)	(.0057)	(.0054)	(.0054)	(.1369)
Firm $var(cons), \sigma^2_{\mathscr{F}}$	.12773	.11590	.11591	.11591	
	(.0011)	(.0010)	(.0010)	(.0010)	
Time $var(residual), \sigma^2$	.03510	.03516	.03512	.03512	.05206
	(.0002)	(.0002)	(.0002)	(.0002)	(.0005)
Observations	113,739	113,739	113,739	113,739	18,535
Log likelihood (with group means)		$-10,569$	$-10,526$	$-10,523$	927
Log likelihood (without group means)	$-11,998$	$-10,585$	$-10,541$	$-10,539$	926
Likelihood ratio test $\left(Prob > \chi^2\right)$		.000	.000	.000	.323
Akaike information criterion (AIC)	24,004	21,485	21,402	21,400	$-1,841$
Bayesian information criterion (BIC)	24,043	23,153	23,090	23,095	$-1,794$

$*p<0.05$; ⁑$p<0.01$.
Standard errors are shown in parentheses. Continuous independent variables are standardized. The models reported here are those with group means.

effect of *ENsentiment* on *ENpolicies*. Model 1 – the intercept-only model – enables us to decompose the variation in *domestic sourcing*, which is explained at the time, firm, and country levels. Table 3.2 shows that 17.79% [.0351 / (.0351+.1277+.0345)] of the variation in *domestic sourcing* occurs over time (i.e., within-firm effect), 64.72% [.1277/ (.0351+.1277+.0345)] occurs across firms (i.e., between-firm effect), and 17.49% [.0345/ (.0351+.1277+.0345)] occurs across countries (i.e., between-country effect). The high overall variance percentages that are attributable to between-firm and between-country effects justify the use of multilevel modeling. Model 2 includes the control variables. The likelihood ratio test indicates that Model 2 has better goodness of fit than Model 1 (p<.01), which supports the inclusion of control variables. The goodness of fit is further improved in Model 3 (p<.01), which includes the main independent variable – *ENpolicies*.

The results for Model 3 show that the effect of *ENpolicies* on *domestic sourcing* is positive and statistically significant (β=.0209, p<.01); hence Hypothesis 1 is supported. In terms of economic significance, a one standard deviation increase in *ENpolicies* is associated with a 4.05% standard deviation increase in *domestic sourcing*. Regarding the moderating effect of *essentialgoods*, Model 4 shows that the interaction term between *essentialgoods* and *ENpolicies* is positive and significant (β=.0171, p<0.05). This result supports Hypothesis 2: the positive influence of economic nationalist policies on domestic sourcing is strengthened when companies operate in an essential industry. Finally, Model 5 estimates the effect of *ENsentiment* on *ENpolicies*. Model 5 demonstrates that *ENsentiment* expressed in the election year has a significant effect on *ENpolicies* that are announced within a year (β=.1619, p<.01). Thus, Hypothesis 3 is supported. This finding implies that economic nationalist sentiment extracted from political manifestos can be used to predict policy interventions that discriminate against foreign commercial interests, our source of supply risk.

3.4.2 Robustness tests

We run additional robustness tests to mitigate concerns with the measurement of our dependent and independent variables and the presence of small countries in our sample. First, our dependent variable measure is based on the number of supplier relationships that the focal firm had in a given year. However, this measure does not make it possible to differentiate between relationships that last one day and relationships that last 365 days (or more), which could create a bias in our results. Based on the work of Charoenwong et al. (2023), we use an alternative measurement of domestic sourcing that takes into consideration the duration of each relationship. Our alternative dependent variable *domestic sourcing days* is operationalized as the fraction of domestic supplier relationship days to total supplier relationship days where supplier relationship days indicate the number of days that the relationship lasted in year t. For instance, if company A had a supplier relationship with company B in year 2010 (t = 2010), then we measure the duration of that supplier relationship as follows:

$$\Delta = \min\{ed, \text{2011-01-01}\} - \max\{sd, \text{2010-01-01}\}$$

Table 3.3 shows that when we replace the number of supplier relationships with the number of supplier relationship days in the calculation of our dependent variable, the results are in line with the results in Table 3.2. Therefore, Hypotheses 1 and 2 are still supported.

Second, our independent variable is based on the time the economic nationalist policies were announced. In our dataset, close to 10% of the policies were implemented the year after they were announced. Therefore, in Table 3.4, we replace announced economic nationalist policies with implemented economic nationalist policies to see whether firms react differently to announced versus enforced policies. Model 4 shows that the results remain qualitatively unchanged, which lends additional support to Hypotheses 1 and 2. Similarly, Model 5 shows that the effect of economic nationalist sentiment on policies remains positive and significant.

Table 3.3: Test results with domestic sourcing days for Hypotheses 1–2

Dependent variable	Domestic sourcing days			
	(1)	(2)	(3)	(4)
ENpolicies			.0244‡	.0233‡
			(.0024)	(.0024)
ENpolicies × *essentialgoods*				.0180*
				(.0072)
Essential goods				−.2260‡
				(.0642)
GDP growth rate		−.00311	−.00204	−.00202
		(.0023)	(.0023)	(.0023)
GDP per capita		−.0365‡	−.0187*	−.0187*
		(.0088)	(.0090)	(.0090)
Operating revenue (Turnover)		−.00381	−.00389	−.00384
		(.0026)	(.0026)	(.0026)
Net assets turnover		−.00170	−.00171	−.00172
		(.0016)	(.0016)	(.0016)
Constant	.3236‡	.4819‡	.5102‡	.5098‡
	(.0200)	(.0535)	(.0547)	(.0547)
Country $var(cons), \sigma^2_{\mathscr{C}}$	.03458	.03405	.03213	.03223
	(.0057)	(.0057)	(.0054)	(.0054)
Firm $var(cons), \sigma^2_{\mathscr{F}}$	.12943	.11740	.11742	.11741
	(.0011)	(.0010)	(.0010)	(.0010)
Time $var(residual), \sigma^2$	.03697	.03702	.03697	.03697
	(.0002)	(.0002)	(.0002)	(.0002)
Number of observations	113,739	113,739	113,739	113,739
Log likelihood (with group means)		−12,909	−12,854	−12,851
Log likelihood (without group means)	−14,341	−12,927	−12,870	−12,867
Likelihood ratio test $(Prob > \chi^2)$		.000	.000	.000
Akaike information criterion (AIC)	28,691	26,165	26,057	26,053
Bayesian information criterion (BIC)	28,730	27,833	27,745	27,750

$*p<0.05$; ‡$p<0.01$.
Standard errors are shown in parentheses. Continuous independent variables are standardized. The models reported here are those with group means.

Table 3.4: Test results with implemented economic nationalist policies for Hypotheses 1–3

Dependent variable	Domestic sourcing				*ENpolicies*
	(1)	(2)	(3)	(4)	(5)
ENpolicies			.0244‡	.0234‡	
			(.0024)	(.0025)	
ENpolicies $\times$ *essentialgoods*				.0171*	
				(.0075)	
Essential goods				−.2222‡	
				(.0637)	
GDP growth rate		−.00115	−.00021	−.00021	
		(.0022)	(.0022)	(.0022)	
GDP per capita		−.0294‡	−.01186	−.01175	
		(.0086)	(.0088)	(.0088)	
Operating revenue		−.00431	−.00438	−.00433	
(Turnover)		(.0025)	(.0025)	(.0025)	
Net assets turnover		−.00177	−.00178	−.00178	
		(.0016)	(.0016)	(.0016)	
ENsentiment					.1419‡
					(.0038)
Constant	.3234‡	.4863‡	.5148‡	.5145‡	−.6701‡
	(.0200)	(.0531)	(.0543)	(.0543)	(.1147)
Country $var(cons), \sigma^2_{\mathscr{C}}$	.03455	.03405	.03212	.03221	.59351
	(.0057)	(.0057)	(.0054)	(.0054)	(.1256)
Firm $var(cons), \sigma^2_{\mathscr{F}}$	.12773	.11590	.11592	.11592	
	(.0011)	(.0010)	(.0010)	(.0010)	
Time $var(residual), \sigma^2$	.03510	.03516	.03511	.03511	.04412
	(.0002)	(.0002)	(.0002)	(.0002)	(.0005)
Observations	113,739	113,739	113,739	113,739	18,535
Log likelihood (with group means)		−10,569	−10,516	−10,514	2,458
Log likelihood (without group means)	−11,998	−10,585	−10,531	−10,529	2,457
Likelihood ratio test $(Prob > \chi^2)$		.000	.000	.000	.389
Akaike information criterion (AIC)	24,004	21,485	21,383	21,379	−4,904
Bayesian information criterion (BIC)	24,043	23,153	23,070	23,076	−4,857

$*p<0.05$; ‡$p<0.01$.
Standard errors are shown in parentheses. Continuous independent variables are standardized. The models reported here are those with group means.

Table 3.5: Test results in a subset of countries for Hypotheses 1–3

Dependent variable	Domestic sourcing				*ENpolicies*
	(1)	(2)	(3)	(4)	(5)
ENpolicies			.0209⁑	.0199⁑	
			(.0023)	(.0023)	
ENpolicies $\times$*essentialgoods*				.0175*	
				(.0071)	
Essential goods				−.2434⁑	
				(.0653)	
GDP growth rate		−.00108	−.00016	−.00015	
		(.0022)	(.0022)	(.0022)	
GDP per capita		−.0292⁑	−.01393	−.01386	
		(.0086)	(.0088)	(.0088)	
Operating revenue (Turnover)		−.00431	−.00440	−.00434	
		(.0025)	(.0025)	(.0025)	
Net assets turnover		−.00178	−.00179	−.00179	
		(.0016)	(.0016)	(.0016)	
ENsentiment					.1619⁑
					(.0041)
Constant	.3574⁑	.5295⁑	.5504⁑	.5501⁑	−.5626⁑
	(.0207)	(.0538)	(.0544)	(.0544)	(.1052)
Country $var(cons), \sigma^2_{\mathscr{C}}$	.03311	.02809	.02642	.02646	.44824
	(.0056)	(.0048)	(.0046)	(.0046)	(.0975)
Firm $var(cons), \sigma^2_{\mathscr{F}}$	.12784	.11599	.11601	.11600	
	(.0011)	(.0010)	(.0010)	(.0010)	
Time $var(residual), \sigma^2$	.03515	.03520	.03516	.03516	.05206
	(.0002)	(.0002)	(.0002)	(.0002)	(.0005)
Observations	113,576	113,576	113,576	113,576	18,531
Log likelihood (with group means)		−10,590	−10,547	−10,544	940
Log likelihood (without group means)	−12,023	−10,607	−10,565	−10,562	940
Likelihood ratio test $(Prob > \chi^2)$		.000	.000	.000	.888
Akaike information criterion (AIC)	24,055	21,526	21,444	21,440	−1,867
Bayesian information criterion (BIC)	24,093	23,194	23,131	23,137	−1,821

$*p<0.05$; ⁑$p<0.01$.
Standard errors are shown in parentheses. Continuous independent variables are standardized. The models reported here are those with group means.

Third, some countries in our data only have a few firms. To address this potential issue, we rerun our analyses for the subset of countries where the number of firms available is above the 25th percentile. These countries are highlighted in Table 6 in Appendix C. Table 3.5 shows that the results remain unchanged, lending further support to Hypotheses 1–3.

Additional robustness checks are provided in Appendix C.

3.5 Discussion

In this research, we ascertain that economic nationalist policies that discriminate against foreign commercial interests lead firms to increase their proportion of domestic sourcing. Companies increase the proportion of domestic supplier relationships to reduce their foreign sourcing risk exposure as foreign suppliers become less competitive and might cause supply disruptions when economic nationalism increases. This effect is stronger for firms operating in the food and medical supplies industries, which governments consider to be priority industries for national sovereignty. Further, we find that economic nationalist sentiment can predict economic nationalist policy interventions. We review the implications of these findings in terms of theoretical, practical, and policymaking contributions.

3.5.1 Theoretical contributions

Our first contribution is to link policy and risk by leveraging economic nationalist sentiment to predict whether upcoming policy changes are likely to increase focal enterprises' exposure to supply risk. Table 3.6 provides an overview of quantitative empirical studies that use archival data to examine the influence of policy uncertainty and political risk on firms' SC practices.

While policy uncertainty is considered to have unknown (i.e., either positive or negative) consequences, the findings of the studies in Table 3.6 show that firms respond to uncertainty in ways that mitigate their risk exposure. Firms decrease their SC involvement (Dong et al., 2022) and the number of relationships they have with suppliers (Charoen-

Table 3.6: Studies that use archival data to examine the influence of policy uncertainty and political risk on SC decisions

Authors	Source of political uncertainty/risk	Sample	Key findings related to political risk
Charoenwong et al. (2023)	Trade policy uncertainty and economic policy uncertainty	U.S. public firms	Trade policy uncertainty leads firms with mostly domestic sales to increase their domestic supplier ratios and those with mostly foreign sales to decrease them. Firms reduce their relations with suppliers based in countries with high economic policy uncertainty.
Chen (2021)[15]	Firm-level perceived trade policy uncertainty	U.S. public firms	Firms increase their inventory and reduce their foreign customer ratios in response to a perceived increase in trade policy uncertainty.
Chen et al. (2022)	Firm-level perceived trade war effect uncertainty	Chinese public firms	Firms reduce their innovation investments in response to a perceived increase in trade war effect uncertainty.
Darby et al. (2020)	Firm-level perceived policy risk and economic policy uncertainty	U.S. public firms	Firms increase their inventory in response to a perceived increase in policy risk. This response is stronger when economic policy uncertainty increases.
Dong et al. (2022)	Politician turnover and economic policy uncertainty	U.S. public firms	Firms decrease their SC involvement in countries where there is politician turnover, which is a source of economic policy uncertainty.
Fan et al. (2023)	U.S.-China trade war	U.S. public firms	U.S. firms that have direct suppliers in China see a decrease in their return on assets and increase their inventory due to the trade war.
Leung and Sun (2021)	Economic policy uncertainty	U.S. public firms	Economic policy uncertainty prompts companies to diversify their customer base.
Our study	Economic nationalist sentiment and policies	Public & private firms (worldwide)	Economic nationalist sentiment is a predictor of economic nationalist policies. Economic nationalism leads firms to increase their proportion of domestic sourcing.

wong et al., 2023) in countries with high policy uncertainty while they increase their inventory (Chen, 2021[15]; Darby et al., 2020) and diversify their customer base (Leung and Sun, 2021) when facing greater uncertainty in their home country. These strategies all intend to mitigate risk and demonstrate that firms are concerned mostly with the negative outcomes of uncertainty, not with its potential benefits. The limitation of using uncertainty as a proxy for risk is that we do not know whether the policy changes ultimately alter the business environment in ways that are detrimental to the firms in question.

Therefore, it is difficult to assess whether the mitigation strategies used are justified given that we cannot measure the "riskiness" of policy uncertainty. The implications are critical, since firms modify their SC practices and incur significant costs and tie up resources to do so, whereas these changes might not be warranted. Overall, analyses based on policy uncertainty lack the ability to determine whether future policy changes will pose a risk. Our findings contribute to filling this gap in the realm of policy changes that affect foreign trade. We reveal that economic nationalist sentiment foretells policy interventions that discriminate against foreign commercial interests, thus helping determine the likelihood that future policy changes will increase supply risk. By considering both the nationalist sentiment expressed in the manifestos of political parties and the share of the votes each party received during the most recent elections, we can better define the nature of the uncertainty to make it a measurable risk.

Second, we contribute to the literature on political risk in SC management by introducing an operationalization of political risk for foreign trade, which is not limited to trade barriers or to specific events. On the one hand, in analytical models, the influence of foreign trade policies on global SC decisions is considered on the sole basis of a limited number of trade policies such as tariffs on imported goods (e.g., Chen et al., 2022; Dong and Kouvelis, 2020). In our study, we consider all state interventions that distort foreign trade by using the most complete database of such policies that exists to date (Evenett, 2019). Our economic nationalist policies measure offers a more holistic view of political risk associated with foreign trade, which features not only trade barriers that dampen imports, but also investment and immigration restrictions that make it more difficult for foreign firms to operate in the market. This tenet is in line with Dinc and Erel (2013), who find that economic nationalism generates a climate of hostility that leads foreign firms to avoid the country. On the other hand, empirical studies capture political risk through trade-disruptive events such as the U.S.-China trade war (Fan et al., 2023) and the U.S. government's 2018 ban on the Chinese company ZTE (Jacobs et al., 2022). Our study offers a dynamic measure of political risk that can be used to assess economic nationalist policies on a continuous basis. In sum, our operationalization of political risk can help analytical researchers to include in their models additional policies that distort foreign trade and help empirical researchers to shift from event-focused to longitudinal study designs.

Finally, as shown in Table 3.6, our study includes firms from a wide array of countries and thus expands upon the empirical literature investigating the influence of policy uncertainty and risk on firms from a single country. Cross-country studies allow for better generalization of the results. Our findings present global trends regarding the prediction and impact of economic nationalism and enable us to depart from the prism of U.S. public firms as our sample includes public and private firms from many countries.

3.5.2 Practical contributions

By showing that economic nationalist sentiment can be assessed and, in turn, used to predict the intervention of economic nationalist policies, our findings inform SC managers' global sourcing decisions in anticipation of supply disruptions. It is essential to take into account potential policy changes to design SCs that are resilient to turbulent political environments (Cohen and Lee, 2020). Studies that examine how firms respond to country- or firm-level indices of perceived policy uncertainty have limited utility for managers since they reflect the companies' own decisions. This information provides managers with "a normative understanding of common practices" (Dong et al., 2022, p. 23), which can help firms "to predict how competitors are likely to respond to increases in policy uncertainty" (Darby et al., 2020, p. 17). However, to manage risk, practitioners need external information that signals whether an increase in policy uncertainty is forthcoming so that they can make more informed decisions.

With respect to foreign trade, one such signal could be politician turnover, which indicates that the policy environment will likely become uncertain as the incumbent or successor takes over (Dong et al., 2022). However, it remains unclear whether an upcoming change will bring in policies that are beneficial or harmful to firms; hence we concur with Dong et al. (2022) that politician turnover is more suitable to predict policy uncertainty than political risk. Said differently, elections signal policy uncertainty, whereas the nature of policy changes indicates political risk. By drawing on political manifestos to measure economic nationalist sentiment, our study shows that managers can use such data to predict policy changes that discriminate against foreign commercial interests. These changes alter supply conditions and increase supply risk. Managers can better anticipate supply risk when they can predict policy changes.

Moreover, our findings suggest that SC practitioners pay more attention to politicians' intentions concerning foreign trade than to their political affiliations. Dong et al. (2022) find that companies tend to reduce their SC involvement more in countries where politician turnover involves a switch from the right wing to the left wing in that the latter traditionally expresses less support for free trade than the former. However, a government's political agenda regarding economic nationalism is not necessarily tied to its political affiliation. In effect, in 18 of the 20 countries in the G20, there are no significant differences in terms of trade protectionism between left and right parties (de Bolle and Zettelmeyer, 2019). Therefore, taking a binary approach for forecasting policy changes that are likely to distort foreign trade might not be sufficient. It is indeed important to take into consideration political parties' intentions with respect to foreign trade alongside election results to more accurately predict policy changes that are likely to increase supply risk.

3.5.3 Policymaking contributions

This study contributes toward the research on the influence of public policy on firms' SC practices. While there are numerous empirical studies investigating healthcare and environmental regulations (see Helper et al., 2021; Joglekar et al., 2016, for recent reviews), there is a shortage of empirical research on state interventions that regulate foreign trade. We focus on policies that have been made rather than perceived policy uncertainty and can thus assess their effect on SC relationships. Our findings show that policy interventions that discriminate against foreign commercial interests lead companies to increase their proportion of domestic supplier relationships. This implies that politicians' attempts to increase domestic sourcing through economic nationalism are, on average, successful. However, we make no claims about the consequences of these changes on the home country. For instance, Fan et al. (2023) find that the U.S.-China trade war decreased the competitiveness of U.S. firms that have first-tier suppliers in China. We observe a higher proportion of domestic sourcing when economic nationalism increases but do not claim that it is beneficial for the home country. In fact, findings about TPU's effect on domestic sourcing in the U.S. are ambiguous as Chen (2021)[15] finds no evidence of increased domestic supplier relationships while Charoenwong et al. (2023) show that these relationships increase only for firms with mostly domestic sales. However, these two studies examine policy uncertainty rather than *realized* policies; hence, further research is needed to assess the (long-term) effect of economic nationalist policies on reshoring initiatives.

Moreover, we contribute to the understanding of public sentiment's influence on policymaking. Public policy formulation in developed democracies is strongly affected by public policy preferences (Brooks and Manza, 2006). Our findings corroborate this tenet and support Charpin's (2022) proposition that economic nationalist sentiment is an antecedent of economic nationalist policies. This sentiment can stem from voters who want to protect their economic interests from foreign competition or politicians who attempt to exploit public sentiment to promote their political interests (Jakobsen and Jakobsen, 2011). The policies resulting from electoral promises appear to be driven more by political interests than reasonable economic principles, which is a common issue with public policy (Dixit, 1998). While policymakers' goals are to support the national economy by incentivizing home country firms to use domestic suppliers, their nationalist policies (e.g., tariffs) also generate uncertainty, which increases firms' transaction costs and harms their competitiveness (Fan et al., 2023). Thus, policymakers who implement policies that discriminate against foreign commercial interests should also support domestic supply capabilities with investments (e.g., in education, training, equipment, and technology) aimed at reducing supply risk for domestic firms.

3.5.4 Limitations and future research

This study features limitations, which offer opportunities for future research. First, our research is exploratory since our objective is to investigate trends across many countries. Even though we intend to mitigate endogeneity concerns by lagging the independent and control variables by one year and control for time variant and certain time invariant unobserved factors, our findings do not imply causality. Future research could rely on alternative identification strategies to examine further the causal effects of economic nationalism on SC practices. Second, our prediction of economic nationalist policies is limited to 47 countries due to the availability of data for the economic nationalist sentiment variable. Future research could explore other sources of data and ways to include more countries in the analysis, especially those that do not hold elections or those in which political parties are banned. Third, our moderator, *essential goods*, highlights an interest shared by most countries – the desire to achieve national sovereignty over food and medical supplies. Future research could examine whether economic nationalism targets certain industries more than others on the basis of country-specific priorities. While we expect the role of essential goods to become even more critical given the increased frequency of natural disasters and the prospect of new pandemics, understanding the idiosyncratic needs of nations in terms of the industries they want to reshore would help to improve the design of supply risk mitigation strategies. More generally, the variables we introduce in this study could be used to investigate economic nationalism's effect on various SC practices in specific contexts.

In sum, our study provides important insights into economic nationalist policies and sentiment, which will be needed to further investigate how firms can better navigate the playing field of international cooperation, which has been crumbling and worsening since the COVID-19 pandemic began. Ultimately, this effort will help firms make global sourcing decisions that reduce their exposure to the risk associated with foreign trade policy changes.

Notes

1. Gangitano, A. (2022). *Biden calls for return of US manufacturing, touts infrastructure law during Pittsburgh visit*. Retrieved October 15, 2022 from https://thehill.com/homenews/administration/591874-biden-focuses-on-manufacturing-in-america-infrastructure-investments/

2. Meredith, S. (2022). *Russia has cut off gas supplies to Europe indefinitely. Here's what you need to know*. Retrieved October 15, 2022 from https://www.cnbc.com/2022/09/06/energy-crisiswhy-has-russia-cut-off-gas-supplies-to-europe.html

3. Russ, K. and Cox, L. (2020). *Steel Tariffs and U.S. Jobs Revisited*. Retrieved October 10, 2022 from https://econofact.org/steel-tariffs-and-u-s-jobs-revisited

4. Timsit, A. (2022). France's mustard shortage fuels drama and panic in grocery stores. *The Washington Post*. https://www.washingtonpost.com/world/2022/07/27/france-mustard-shortage-canada-seeds/

5. https://www.policyuncertainty.com/all_country_data.html

6. For instance search terms for the U.S. are "uncertainty" or "uncertain"; "economic" or "economy"; and one of the following policy terms: "Congress," "deficit," "Federal Reserve," "legislation," "regulation," or "White House" (see Baker et al., 2016).

7. https://www.policyuncertainty.com/trade_uncertainty.html

8. https://www.factset.com/ (data downloaded 2021-09-30)

9. https://www.globaltradealert.org/data_extraction (data downloaded 2021-08-27)

10. https://manifesto-project.wzb.eu/datasets (data downloaded 2021-11-27)

11. https://www.bvdinfo.com/ (data downloaded in October and November 2021)

12. https://data.worldbank.org/ (data downloaded 2021-12-07)

13. Policies that discriminate against foreign commercial interests are labeled "red policies" on the GTA dataset.

14. Except for items related to the European Union since our samples contain non-European countries.

15. Chen, K. (2021). Trade Policy Uncertainty: Measurement and Impacts on US Firms in Global Value Chains. *Working Paper*. https://www.kairongchen.com/assets/pdf/Chen_Kairong_JMP.pdf

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Chapter 4

Application examples and guidelines

Chapter information: This chapter presents example models and directions to leverage and expand the findings from the preceding three chapters. It was written under the supervision of Prof. Yossiri Adulyasak and Prof. Jean-François Cordeau.

Abstract

The findings from Chapter 3's research project can help inform data-driven risk management, which is in high demand (Bechtsis et al., 2022; Er Kara et al., 2020), particularly with regard to political risk, an area underexplored yet increasingly heeded in the supply chain management literature (Charpin et al., 2021; Charpin, 2022; Dong et al., 2022; Fan et al., 2023; Zhang, 2021). The estimated influence of economic nationalist sentiment in political manifestos on economic nationalist policies, which in turn affect the proportion of domestic sourcing, can be utilized as inputs for stochastic programming with recourse to design a robust supply chain network under risk (Martel and Klibi, 2016a). A shortage of proper operationalization of economic nationalism as a source of political risk creates one difficulty in incorporating this risk consideration into supply chain network configuration. This issue has been addressed in Chapter 3. This extended chapter discusses possible directions to expand the line of research conducted in Chapter 3 and provide generic guidelines for practitioners in terms of how to take advantage of this external yet highly

relevant information for their global supply chain management. Section 4.1 demonstrates two example prescriptive programs where Chapter 3's findings can be leveraged as inputs, whereas Section 4.2 presents a conceptual framework for managers regarding data-driven supply chain risk management based on the inputs from the previous three chapters.

4.1 Example programming models

Let us assume that global supply chain managers must decide their supply network configurations at the beginning of each year. Global supply chain managers must then adjust their domestic sourcing proportion in compliance with the proportion of economic nationalist policies in their home country. With information on economic nationalist sentiment in political manifestos, global supply chain managers are able to detect early signals concerning possible changes in the proportion of economic nationalist policies, thereby optimizing their domestic sourcing proportion. This proactive approach can be implemented by prescriptive analytics. The two examples in this section formulate the problem at hand as a single-period model (subsection 4.1.1) and a stochastic program with recourse (subsection 4.1.2).

4.1.1 Single-period modeling to determine the proportion of domestic sourcing

The notation for this single-period model to determine the optimal proportion of domestic sourcing is presented in Table 4.1. Let us assume that foreign sourcing provides materials of the same quality as domestic sourcing but at a lower unit cost ($a < l$). Otherwise, the problem becomes uninteresting as foreign sourcing is uneconomical and the firm should always use domestic sourcing. Also, it is assumed that unwanted purchases are disposed (single-period decision-making).

Before delving into the single-period problem in question, let us look at a clairvoyant situation where the focal enterprise knows for certain the total demand (D), the constraint

Table 4.1: Notation for domestic and foreign sourcing as a single-period problem

Notation	Description	Type
$Q_l \in [0,1]$	proportion of domestic sourcing when the contract is signed	decision variable
$Q_a \in [0,1]$	proportion of foreign sourcing when the contract is signed	decision variable
$y \in \{0,1\}$	decision to invest in foreign sourcing	decision variable
I	fixed investment cost in foreign sourcing	parameter
D	total demand (assumed to be deterministic)	parameter
l	unit cost of domestic sourcing	parameter
$a < l$	unit cost of foreign sourcing	parameter
q_0	minimum proportion of domestic sourcing imposed by the home government	parameter
q	new q_0 derived from changes in government regulations (economic nationalist policies)	parameter
p_q	probability of q	parameter
$l' > l$	unit cost for recourse of increasing domestic sourcing	parameter
r	unit cost for recourse of unneeded (foreign) purchases	parameter

imposed by the government (i.e., the required minimum proportion of domestic sourcing q_0), and other parameters. At the beginning of each year, the company can determine the proportion of domestic sourcing for the year after by solving the following linear program:

$$\min g(y, Q_l) = \min\{yI + lQ_lD + a(1 - Q_l)D\} \tag{4.1}$$

subject to

$$Q_l \leq 1 \tag{4.2}$$

$$Q_l \geq q_0 \tag{4.3}$$

$$1 - Q_l \leq y \tag{4.4}$$

$$y \in \{0,1\} \tag{4.5}$$

Constraints (4.2) and (4.3) ensure that the proportion of domestic sourcing (Q_l) chosen is neither greater than one nor less than the minimum set by the government. Meanwhile, constraint (4.4) imposes that no foreign sourcing is possible if the company decides not to invest in foreign sourcing (i.e., $y = 0 \Rightarrow Q_l = 1$ because $1 - Q_l \leq 0$ and $Q_l \leq 1$).

If the company decides not to invest in foreign sourcing (i.e., $y = 0$), (4.1) is minimized at $Q_l^* = 1$ and $g(0,1) = lD$.

Let us assume that the company decides to invest in foreign sourcing (i.e., $y = 1$) and that (4.1) is minimized at Q_l^*, then we have:

$$f(Q_l^*) = I + lQ_l^*D + a(1 - Q_l^*)D = I + (l - a)Q_l^*D + aD \tag{4.6}$$

This decision to invest is optimal

$$\begin{aligned}
&\iff \begin{cases} I + (l-a)Q_l^*D + aD \leq lD \\ \text{(4.2)–(4.3) satisfied} \end{cases} \\
&\iff \begin{cases} (l-a)Q_l^*D \leq (l-a)D - I \\ \text{(4.2)–(4.3) satisfied} \end{cases} \\
&\iff \begin{cases} Q_l^* \leq 1 - \frac{I}{(l-a)D} \\ \text{(4.2)–(4.3) satisfied} \end{cases} \\
&\iff q_0 \leq Q_l^* \leq 1 - \frac{I}{(l-a)D}
\end{aligned} \tag{4.7}$$

As can be inferred from condition (4.7), if $q_0 \nleq 1 - \frac{I}{(l-a)D}$, the optimal decision is not to invest in foreign sourcing (i.e., $y = 0$) but to procure everything from domestic sourcing to satisfy the total demand (i.e., $Q_l^* = 1$).

If the given parameters, which can be estimated from the firm's available data, meet condition (4.7), then the optimal decision includes investing in foreign sourcing and we obtain (4.6). As $(l - a)D > 0$ (because $a < l$ and $D > 0$), (4.6) is an increasing function on $Q_l^* \in \left[q_0, 1 - \frac{I}{(l-a)D}\right]$. This means that (4.6) is minimized at $Q_l^* = q_0$.

Hereinafter, let us assume that condition (4.7) is satisfied.

Once Q_l^* has been finalized and sourcing contracts signed, the firm in question cannot decrease this proportion over the course of the next year.

However, if the government changes its regulations, which affect condition (4.7) and thereby the imposed $q_0 \to q$, the firm will incur opportunity (shortage) or overage (excess) costs, especially when it has concluded the sourcing contracts. In particular, setting a high proportion of domestic sourcing Q_l may unnecessarily increase the total cost given that the government allows buying more from foreign sourcing at a lower cost (opportunity cost). On the other hand, if proportion of domestic sourcing Q_l is low, the company risks violating the government regulation and must take corrective action (overage cost).

The problem at hand can be regarded as a single-period model (Stevenson, 2015, pp. 576–580) because it requires minimizing the long-run opportunity and overage costs under the assumption that unwanted purchases are disposed. Like any other rational policies, which consist in optimization in the presence of random and nonrandom non-controlled conditions (Arrow et al., 1951), the formulated program herein considers the government-imposed constraint q stochastic (random non-controlled condition) and demand deterministic (nonrandom non-controlled parameter). Despite such differences from traditional inventory management models where demand is assumed to be uncertain, the logic and goal to minimize the long-run opportunity and overage costs remain unchanged.

If $q \geq 1 - \frac{I}{(l-a)D}$, the optimal solution is to solely use domestic sourcing as explained in (4.7). If $q < 1 - \frac{I}{(l-a)D}$, but the firm only deploys domestic sourcing, then the opportunity cost is:

$$
\begin{aligned}
& \int_{0}^{1-\frac{I}{(l-a)D}} [lD - f(q)] p_q dq \\
= & \int_{0}^{1-\frac{I}{(l-a)D}} [(l-a)(1-q)D - I] p_q dq \qquad (4.8) \\
= & \left\{ \int_{0}^{q_0} [(l-a)(1-q)D - I] p_q dq \right\} + \left\{ \int_{q_0}^{1-\frac{I}{(l-a)D}} [(l-a)(1-q)D - I] p_q dq \right\}
\end{aligned}
$$

If the company decides to invest in foreign sourcing and uses an arbitrary proportion of domestic sourcing $\tilde{Q}_l$, we can see that:

- Setting $\tilde{Q}_l \in \left[1 - \frac{I}{(l-a)D}, 1\right]$ is not optimal because the expectation of the opportunity and overage costs will be:

$$\left[\int_{0}^{1-\frac{I}{(l-a)D}} [f(\tilde{Q}_l)-f(q)]p_q dq\right] + \left\{\int_{1-\frac{I}{(l-a)D}}^{\tilde{Q}_l} [f(\tilde{Q}_l)-lD]p_q dq\right\} + \left[\int_{\tilde{Q}_l}^{1} (l'+r)(q-\tilde{Q}_l)Dp_q dq\right] \tag{4.9}$$

When $q < 1-\frac{I}{(l-a)D}$, the optimal cost is $f(q)$, so the opportunity cost is then equal to $f(\tilde{Q}_l)-f(q)$ [the first term of (4.9)]. When $q \in \left[1-\frac{I}{(l-a)D}, \tilde{Q}_l\right]$, the optimal cost is lD, so the opportunity cost is then $f(\tilde{Q}_l)-lD$ [the second term of (4.9)]. Finally, when $q > \tilde{Q}_l$, the firm must increase its proportion of domestic sourcing in accordance with the new government regulations at a unit cost of l' and dispose of unneeded foreign purchases at a unit of r.

Given condition (4.7), we have $f(\tilde{Q}_l) \geq lD$ for $\tilde{Q}_l \in \left[1-\frac{I}{(l-a)D}, 1\right]$, which means that the first term of (4.9) is greater than or equal to (4.8) and that the last two terms are positive. Consequently, (4.9) is always greater than (4.8), hence not the optimal solution to our minimization problem.

- If $\tilde{Q}_l \in \left[0, 1-\frac{I}{(l-a)D}\right]$ and $q \leq \tilde{Q}_l$, then the opportunity cost is:

$$\int_{0}^{\tilde{Q}_l} [f(\tilde{Q}_l)-f(q)]p_q dq = \int_{0}^{\tilde{Q}_l} (l-a)(\tilde{Q}_l-q)Dp_q dq \tag{4.10}$$

- If $\tilde{Q}_l \in \left[0, 1-\frac{I}{(l-a)D}\right]$ and $q \geq \tilde{Q}_l$, the overage costs include the cost of increasing the proportion of domestic sourcing to meet the new regulations $\left[l'(q-\tilde{Q}_l)D\right]$ and the cost of getting rid of the surplus quantity from the signed contract for foreign sourcing $\left[r(q-\tilde{Q}_l)D\right]$.

Therefore, we obtain the expected sum of opportunity and overage costs for $\tilde{Q}_l \in \left[0, 1-\frac{I}{(l-a)D}\right]$ as follows:

$$\left[\int_0^{\tilde{Q}_l}(l-a)(\tilde{Q}_l-q)Dp_q dq\right] \quad + \quad \left[\int_{\tilde{Q}_l}^{1}(l'+r)(q-\tilde{Q}_l)Dp_q dq\right]$$

$$= \left[(l-a)D\tilde{Q}_l\int_0^{\tilde{Q}_l} p_q dq\right] - \left[(l-a)D\int_0^{\tilde{Q}_l} qp_q dq\right] \quad + \quad \left[(l'+r)D\int_{\tilde{Q}_l}^{1} qp_q dq\right]$$

$$- \quad \left[(l'+r)D\tilde{Q}_l\int_{\tilde{Q}_l}^{1} p_q dq\right] \tag{4.11}$$

The findings of Chapter 3 provide the inputs (mean and standard deviation) to estimate the probability distribution of q under the influence of policy risk. Since q is the proportion of domestic sourcing, which cannot be less than zero or greater than one, we have:

$$\int_{-\infty}^{\tilde{Q}_l} p_q dq = \int_0^{\tilde{Q}_l} p_q dq, \quad \text{and} \quad \int_{\tilde{Q}_l}^{\infty} p_q dq = \int_{\tilde{Q}_l}^{1} p_q dq.$$

$$\text{Let } P_{\tilde{Q}_l} = \int_{-\infty}^{\tilde{Q}_l} p_q dq = \int_0^{\tilde{Q}_l} p_q dq. \quad \text{Then,} \quad 1-P_{\tilde{Q}_l} = \int_{\tilde{Q}_l}^{\infty} p_q dq = \int_{\tilde{Q}_l}^{1} p_q dq.$$

As a result, (4.11) becomes:

$$F(\tilde{Q}_l) = (l-a)D\tilde{Q}_l P_{\tilde{Q}_l} - (l-a)D\int_0^{\tilde{Q}_l} qp_q dq \quad + \quad (l'+r)D\int_{\tilde{Q}_l}^{1} qp_q dq - (l'+r)D\tilde{Q}_l(1-P_{\tilde{Q}_l})$$

$$= (l-a)D\tilde{Q}_l P_{\tilde{Q}_l} - (l'+r+l-a)D\int_0^{\tilde{Q}_l} qp_q dq \quad + \quad (l'+r)D\int_0^{\tilde{Q}_l} qp_q dq + (l'+r)D\int_{\tilde{Q}_l}^{1} qp_q dq$$

$$- \quad (l'+r)D\tilde{Q}_l(1-P_{\tilde{Q}_l})$$

$$= (l-a)D\tilde{Q}_l P_{\tilde{Q}_l} - (l'+r+l-a)D\int_0^{\tilde{Q}_l} qp_q dq \quad + \quad (l'+r)D\mathbb{E}[q] - (l'+r)D\tilde{Q}_l(1-P_{\tilde{Q}_l}) \tag{4.12}$$

The first derivative of (4.12) with respect to $\tilde{Q}_l$ is:

$$
\begin{aligned}
\frac{\partial\left(F(\tilde{Q}_l)\right)}{\partial \tilde{Q}_l} &= (l-a)DP_{\tilde{Q}_l} + (l-a)D\tilde{Q}_l P'_{\tilde{Q}_l} - (l'+r+l-a)D\tilde{Q}_l p_{\tilde{Q}_l} \\
&\quad -(l'+r)D(1-P_{\tilde{Q}_l}) + (l'+r)D\tilde{Q}_l P'_{\tilde{Q}_l} \\
&= (l-a)DP_{\tilde{Q}_l} - (l'+r)D + (l'+r)DP_{\tilde{Q}_l} \\
&\quad +(l'+r+l-a)D\tilde{Q}_l P'_{\tilde{Q}_l} - (l'+r+l-a)D\tilde{Q}_l p_{\tilde{Q}_l} \\
&= (l'+r+l-a)DP_{\tilde{Q}_l} - (l'+r)D \\
&\quad \cancel{+(l'+r+l-a)D\tilde{Q}_l P'_{\tilde{Q}_l}} - \cancel{(l'+r+l-a)D\tilde{Q}_l p_{\tilde{Q}_l}} \\
&\overset{want}{=} 0 \\
\iff P^*_{\tilde{Q}_l} &= \frac{l'+r}{l'+r+l-a}
\end{aligned}
\tag{4.13}
$$

Also, the second derivative of (4.12) with respect to $\tilde{Q}_l$ is $(l'+r+l-a)Dp_{\tilde{Q}_l} \geq 0$.

If $\tilde{Q}^*_l = P^{-1}_{\tilde{Q}_l}\left(\frac{l'+r}{l'+r+l-a}\right) \leq 1 - \frac{I}{(l-a)D}$, then the result from (4.13) shows that (4.12) admits a minimum at $\tilde{Q}^*_l = P^{-1}_{\tilde{Q}_l}\left(\frac{l'+r}{l'+r+l-a}\right)$, which is equal to:

$$
(l'+r)D\mathbb{E}[q] - (l'+r+l-a)D\int_0^{\tilde{Q}^*_l} qp_q dq \tag{4.14}
$$

If $\tilde{Q}^*_l = P^{-1}_{\tilde{Q}_l}\left(\frac{l'+r}{l'+r+l-a}\right) > 1 - \frac{I}{(l-a)D}$, then the optimal cost equals (4.8) as proven in (4.9).

Expressions (4.8) and (4.14), which are estimable from the available data, provide the expected sum of the opportunity and overage costs for each of the two candidate solutions that the company may take when signing sourcing contracts as a single-period problem.

However, if the company can reserve room for recourse action when a scenario transpires, then the problem at hand can be reformulated as a stochastic program with recourse (Martel and Klibi, 2016a), which will be discussed in the next subsection.

4.1.2 Stochastic programming to determine the proportion of domestic sourcing

In addition to the notation described in Table 4.1, the remaining notation for the stochastic program with recourse in (4.15) is provided in Table 4.2.

Table 4.2: Additional notation for domestic and foreign sourcing as a stochastic program with recourse

Notation	Description	Type
$a' \in (a, l)$	unit cost for recourse of increasing foreign sourcing	parameter
Q_{lq}	increased proportion of domestic sourcing (recourse action) when q is realized	decision variable
Q_{aq}	increased proportion of foreign sourcing (recourse action) when q is realized	decision variable
Q_{rq}	decreased proportion of foreign sourcing (recourse action) when q is realized	decision variable

Note: Increasing the proportion of foreign sourcing (Q_{aq}) means making additional purchases from foreign sourcing at a unit cost of a' after the sourcing contract has been concluded. On the other hand, decreasing the proportion of foreign sourcing (Q_{rq}) refers to disposing of the unwanted quantity from foreign sourcing at a unit cost of r if the realized proportion of foreign sourcing $(1-q)$ allowed by the government is less than the one initially set in the sourcing contract. Given that a' and r are not necessarily the same, two decision variables Q_{aq} and Q_{rq} are needed for these two parameters, respectively.

Unlike the model in subsection 4.1.1, in this stochastic program with recourse, the firm does not need to set the total proportions of domestic and foreign sourcing when signing the sourcing contracts. In particular, the company first decides whether to invest in foreign sourcing and might specify the initial proportions of domestic and foreign sourcing when the sourcing contracts are concluded (i.e., Q_l and Q_a), which offer more favorable costs (i.e., l and a). Afterward, the remaining proportions of domestic and foreign sourcing are determined according to the realized q, but the unit costs will be less favorable then. It is to note that setting $Q_l + Q_a = 1$ would result in the same problem as in (4.1). Setting $Q_l + Q_a > 1$ is not optimal because this solution always incurs the expected cost of (4.1) plus the cost for disposal of unneeded purchases $[D(Q_l + Q_a - 1)r]$ regardless of the realization of q. Thus, $Q_l + Q_a$ should not exceed one. Also, Q_l should not exceed $1 - \frac{I}{(l-a)D}$ as proven in (4.9).

$$\min f(Q_l,Q_a,Q_{lq},Q_{aq},Q_{rq}) = \min\left\{yI + lQ_lD + aQ_aD + \int_0^1 D\left(l'Q_{lq} + a'Q_{aq} + rQ_{rq}\right)p_q dq\right\} \tag{4.15}$$

subject to

$$Q_l + Q_a + Q_{lq} + Q_{aq} - Q_{rq} = 1,\ \text{for } q \in [0,1] \tag{4.16}$$

$$Q_l + Q_{lq} \geq q,\ \text{for } q \in [0,1] \tag{4.17}$$

$$Q_a - Q_{rq} \geq 0,\ \text{for } q \in [0,1] \tag{4.18}$$

$$Q_a + Q_{aq} \leq y,\ \text{for } q \in [0,1] \tag{4.19}$$

$$y \in \{0,1\} \tag{4.20}$$

$$Q_l, Q_a, Q_{lq}, Q_{aq}, Q_{rq} \in [0,1] \tag{4.21}$$

Next, the firm waits until the realization of q to take recourse action (i.e., Q_{lq}, Q_{aq}, and Q_{rq}) such that the total demand is satisfied as in constraint (4.16) and that the minimum proportion of domestic sourcing imposed by the government is met as in constraint (4.17). Constraint (4.18) ensures that the proportion of foreign sourcing decreased (Q_{rq}) cannot exceed the proportion of foreign sourcing initially set (Q_a). Along with constraint (4.19), foreign sourcing is not possible if the firm decides not to invest in foreign sourcing (i.e., $y = 0 \Rightarrow Q_{aq} = Q_a = 0 \Rightarrow Q_{rq} = 0$ because $0 \leq Q_{rq} \leq Q_a \leq 1$).

If the company decides not to invest in foreign sourcing, then $y = 0 \Rightarrow Q_a = Q_{aq} = Q_{rq} = 0 \Rightarrow Q_l + Q_{lq} = 1 \Rightarrow Q_l = 1$ and $Q_{lq} = 0$. It should be noted that $Q_{lq} > 0$ is not part of an optimal solution in this case because the decision not to invest in foreign sourcing only allows purchasing from domestic sourcing and the firm ought not to wait until the realization of q just to procure from the same source at a higher cost $l' > l$. Therefore, the opportunity cost will be the same as (4.8).

If the company decides to invest in foreign sourcing (i.e., $y = 1$), it first sets the proportion of domestic and foreign sourcing when signing the sourcing contracts (i.e., Q_l and

Q_a) that offer more favorable costs, and waits until the realization of q to take corrective action (recourse by determining Q_{lq}, Q_{aq}, and Q_{rq}) at less favorable costs.

- If $q \in [1-Q_a, 1]$, then the initially set proportion of foreign sourcing (Q_a) is higher than allowed ($q \leq 1$ is required and $q + Q_a \geq 1$). This means that the firm incurs the recourse cost for unneeded foreign purchases ($rQ_{rq}D = r\,[q-(1-Q_a)]\,D$). Furthermore, given that $Q_l + Q_a \leq 1$ as previously discussed, $Q_l \leq 1 - Q_a \Rightarrow Q_l \leq q$. Consequently, the company in question also incurs the recourse cost for increasing the proportion of domestic sourcing, which equals $l'Q_{lq}D = l'(q - Q_l)D$. Therefore, the expected overage cost for this scenario is:

$$
\begin{aligned}
& rD \int_{1-Q_a}^{1} Q_{rq} p_q dq && + \quad l'D \int_{1-Q_a}^{1} Q_{lq} p_q dq \\
= \quad & rD \int_{1-Q_a}^{1} [q-(1-Q_a)]\, p_q dq && + \quad l'D \int_{1-Q_a}^{1} (q-Q_l)\, p_q dq \\
= \quad & \left(rD \int_{1-Q_a}^{1} q p_q dq \right) - \left[rD\,(1-Q_a) \int_{1-Q_a}^{1} p_q dq \right] && + \quad l'D \int_{1-Q_a}^{1} q p_q dq \\
& && - \quad l'DQ_l \int_{1-Q_a}^{1} p_q dq
\end{aligned}
\tag{4.22}
$$

- If $q \in [Q_l, 1-Q_a]$, the company is supposed to increase the proportion of domestic sourcing from the initially set Q_l to the realized q at a unit cost of $l' > l$ and have the remaining demand satisfied from foreign sourcing at a unit cost of $a' \in (a, l), l < l' \Rightarrow a' < l'$. Then, the expectation of the overage cost for this scenario is:

$$
a'D \int_{Q_l}^{1-Q_a} Q_{aq} p_q dq \quad + \quad l'D \int_{Q_l}^{1-Q_a} Q_{lq} p_q dq
$$

(*continued next page*)

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$$
\begin{aligned}
= \quad & a'D \int_{Q_l}^{1-Q_a} [(1-Q_a)-q]\, p_q dq && + \quad l'D \int_{Q_l}^{1-Q_a} (q-Q_l)\, p_q dq \\
= \quad & \left[a'D(1-Q_a) \int_{Q_l}^{1-Q_a} p_q dq \right] - \left(a'D \int_{Q_l}^{1-Q_a} q p_q dq \right) && + \quad l'D \int_{Q_l}^{1-Q_a} q p_q dq \\
& && - \quad l'DQ_l \int_{Q_l}^{1-Q_a} p_q dq
\end{aligned}
\tag{4.23}
$$

- If $q \in [0, Q_l]$, the company has already met the minimum required by the government and ought to have the remaining demand $(1-Q_a-Q_l)$ satisfied from foreign sourcing to save costs (since $a' < l'$). Its overage cost will be $a'(1-Q_a-Q_l)D$. At the same time, its opportunity cost will be $(l-a)(Q_l-q)D$ given that it should not have purchased $(Q_l-q)D$ at a unit cost of l from domestic sourcing but could have used foreign sourcing at a unit cost of a. Then, the expected sum of its overage and opportunity costs for $q \in [0, Q_l]$ will be:

$$
\begin{aligned}
& a'(1-Q_a-Q_l)D \int_0^{Q_l} p_q dq && + \quad \int_0^{Q_l} (l-a)(Q_l-q) D p_q dq \\
= \quad & \left[a'(1-Q_a)D \int_0^{Q_l} p_q dq \right] - \left(a'Q_l D \int_0^{Q_l} p_q dq \right) && + \quad (l-a)Q_l D \int_0^{Q_l} p_q dq \\
& && - \quad (l-a)D \int_0^{Q_l} q p_q dq
\end{aligned}
\tag{4.24}
$$

From (4.22), (4.23), and (4.24), the expected sum of the opportunity and overage costs will be:

$$
\begin{aligned}
& \left(rD\int\limits_{1-Q_a}^{1} qp_q dq\right) - \left[rD\,(1-Q_a)\int\limits_{1-Q_a}^{1} p_q dq\right] && + \; l'D\int\limits_{1-Q_a}^{1} qp_q dq \\
& && -l'DQ_l\int\limits_{1-Q_a}^{1} p_q dq \\
+ \; & \left[a'D\,(1-Q_a)\int\limits_{Q_l}^{1-Q_a} p_q dq\right] - \left(a'D\int\limits_{Q_l}^{1-Q_a} qp_q dq\right) && + \; l'D\int\limits_{Q_l}^{1-Q_a} qp_q dq \\
& && -l'DQ_l\int\limits_{Q_l}^{1-Q_a} p_q dq \\
+ \; & \left[a'D\,(1-Q_a)\int\limits_{0}^{Q_l} p_q dq\right] - \left(a'Q_lD\int\limits_{0}^{Q_l} p_q dq\right) && + \; (l-a)Q_lD\int\limits_{0}^{Q_l} p_q dq \\
& && -(l-a)D\int\limits_{0}^{Q_l} qp_q dq \\
= \; & \left(rD\int\limits_{1-Q_a}^{1} qp_q dq\right) - \left[rD\,(1-Q_a)\int\limits_{1-Q_a}^{1} p_q dq\right] && + \; \left(l'D\int\limits_{Q_l}^{1} qp_q dq\right) - \left(l'DQ_l\int\limits_{Q_l}^{1} p_q dq\right) \\
+ \; & \left[a'D\,(1-Q_a)\int\limits_{0}^{1-Q_a} p_q dq\right] - \left(a'D\int\limits_{Q_l}^{1-Q_a} qp_q dq\right) && \\
- \; & \left(a'Q_lD\int\limits_{0}^{Q_l} p_q dq\right) + \left[(l-a)Q_lD\int\limits_{0}^{Q_l} p_q dq\right] && - \; \left[(l-a)D\int\limits_{0}^{Q_l} qp_q dq\right] \\
= \; & \left(rD\int\limits_{Q_l}^{1} qp_q dq\right) - \left[rD\,(1-Q_a)\int\limits_{1-Q_a}^{1} p_q dq\right] && + \; \left(l'D\int\limits_{0}^{1} qp_q dq\right) - \left(l'DQ_l\int\limits_{Q_l}^{1} p_q dq\right) \\
+ \; & \left[a'D\,(1-Q_a)\int\limits_{0}^{1-Q_a} p_q dq\right] - \left[(a'+r)D\int\limits_{Q_l}^{1-Q_a} qp_q dq\right] && \\
- \; & \left(a'Q_lD\int\limits_{0}^{Q_l} p_q dq\right) + \left[(l-a)Q_lD\int\limits_{0}^{Q_l} p_q dq\right] && - \; \left[(l'+l-a)D\int\limits_{0}^{Q_l} qp_q dq\right]
\end{aligned}
$$

(*continued next page*)

(*continued from previous page*)

$$
\begin{aligned}
= \quad & \left(rD\int_0^1 qp_q dq\right) - \left[rD(1-Q_a)\int_{1-Q_a}^{1} p_q dq\right] && + \quad (l'D\mathbb{E}[q]) - \left(l'DQ_l\int_{Q_l}^{1} p_q dq\right) \\
+ \quad & \left[a'D(1-Q_a)\int_0^{1-Q_a} p_q dq\right] - \left[(a'+r)D\int_0^{1-Q_a} qp_q dq\right] && + \quad \left[(a'+r)D\int_0^{Q_l} qp_q dq\right] \\
+ \quad & \left[(l-a-a')Q_l D\int_0^{Q_l} p_q dq\right] && - \quad \left[(l'+r+l-a)D\int_0^{Q_l} qp_q dq\right] \\
= \quad & (r+l')D\mathbb{E}[q] - \left[rD(1-Q_a)\int_{1-Q_a}^{1} p_q dq\right] && - \quad \left(l'DQ_l\int_{Q_l}^{1} p_q dq\right) \\
+ \quad & \left[a'D(1-Q_a)\int_0^{1-Q_a} p_q dq\right] && - \quad \left[(a'+r)D\int_0^{1-Q_a} qp_q dq\right] \\
+ \quad & \left[(l-a-a')DQ_l\int_0^{Q_l} p_q dq\right] && - \quad \left[(l'-a'+l-a)D\int_0^{Q_l} qp_q dq\right]
\end{aligned}
\tag{4.25}
$$

The findings of Chapter 3 provide inputs (mean and standard deviation) to estimate the probability distribution of q under the influence of policy risk. Since q is the proportion of domestic sourcing, which cannot be less than zero or greater than one, we have:

$$\int_{-\infty}^{\tilde{Q}} p_q dq = \int_0^{\tilde{Q}} p_q dq, \quad \text{and} \qquad \int_{\tilde{Q}}^{\infty} p_q dq = \int_{\tilde{Q}}^{1} p_q dq.$$

$$\text{Let } P_{\tilde{Q}} = \int_{-\infty}^{\tilde{Q}} p_q dq = \int_0^{\tilde{Q}} p_q dq. \quad \text{Then,} \quad 1 - P_{\tilde{Q}} = \int_{\tilde{Q}}^{\infty} p_q dq = \int_{\tilde{Q}}^{1} p_q dq.$$

As a result, (4.25) is equal to:

$$
\begin{aligned}
& (r+l')D\mathbb{E}[q] - rD(1-Q_a)(1-P_{1-Q_a}) && - \quad l'DQ_l(1-P_{Q_l}) \\
+ \quad & a'D(1-Q_a)P_{1-Q_a} && - \quad (a'+r)D\int_0^{1-Q_a} qp_q dq \\
+ \quad & (l-a-a')DQ_lP_{Q_l} && - \quad (l'-a'+l-a)D\int_0^{Q_l} qp_q dq \\
= \quad & (r+l')D\mathbb{E}[q] - rD(1-Q_a) - l'DQ_l && + \quad (r+a')D(1-Q_a)P_{1-Q_a} \\
+ \quad & (l'-a'+l-a)DQ_lP_{Q_l} - (a'+r)D\int_0^{1-Q_a} qp_q dq && - \quad (l'-a'+l-a)D\int_0^{Q_l} qp_q dq
\end{aligned}
\tag{4.26}
$$

The first derivative of (4.26) with respect to Q_l is equal to:

$$
\begin{aligned}
& -\frac{\partial(l'DQ_l)}{\partial Q_l} && +\frac{\partial[(l'-a'+l-a)DQ_lP_{Q_l}]}{\partial Q_l} && -\frac{\partial\left[(l'-a'+l-a)D\int_0^{Q_l} qp_q dq\right]}{\partial Q_l} \\
= \quad & -l'D && +(l'-a'+l-a)DP_{Q_l} + (l'-a'+l-a)DQ_lp_{Q_l} && -(l'-a'+l-a)DQ_lp_{Q_l} \\
= \quad & -l'D && +(l'-a'+l-a)DP_{Q_l} \overset{want}{=} 0 \\
\iff \quad & P_{Q_l} && = \frac{l'}{l'-a'+l-a}
\end{aligned}
\tag{4.27}
$$

Also, the second derivative of (4.26) with respect to Q_l equals $(l'-a'+l-a)Dp_{Q_l} \geq 0$.

The first derivative of (4.26) with respect to Q_a is equal to:

$$
\begin{aligned}
& -\frac{\partial[rD(1-Q_a)]}{\partial Q_a} && +\frac{\partial[(r+a')D(1-Q_a)P_{1-Q_a}]}{\partial Q_a} && -\frac{\partial\left[(r+a')D\int_0^{1-Q_a} qp_q dq\right]}{\partial Q_a} \\
= \quad & rD && -(r+a')DP_{1-Q_a} - (r+a')D(1-Q_a)p_{1-Q_a} && +(r+a')D(1-Q_a)p_{1-Q_a} \\
= \quad & rD && -(r+a')DP_{1-Q_a} \overset{want}{=} 0 \\
\iff \quad & P_{1-Q_a} && = \frac{r}{r+a'}
\end{aligned}
\tag{4.28}
$$

Also, the second derivative of (4.26) with respect to Q_a is equal to $(r+a')Dp_{1-Q_a} \geq 0$.

The results from (4.27) and (4.28) illustrate that (4.26) can admit a minimum at $Q_l^* = P_{Q_l}^{-1}\left(\frac{l'}{l'-a'+l-a}\right)$ and $Q_a^* = 1 - P_{1-Q_a}^{-1}\left(\frac{r}{r+a'}\right)$ with $Q_l^* \leq 1 - \frac{I}{(l-a)D}$ and $Q_l^* + Q_a^* \leq 1$.

Expressions (4.8) and (4.26), which are estimable from the available data, provide the expected sum of the opportunity and overage costs for each of the two candidate solutions that the company may take when signing sourcing contracts as a stochastic program with recourse.

4.1.3 Possible extensions

Section 4.1 demonstrates two example prescriptive programs where Chapter 3's findings can be utilized to estimate the probability distribution of the proportion of domestic sourcing required by government regulations (economic nationalist policies) and determine the optimal proportion of domestic sourcing when the focal firm signs sourcing contracts.

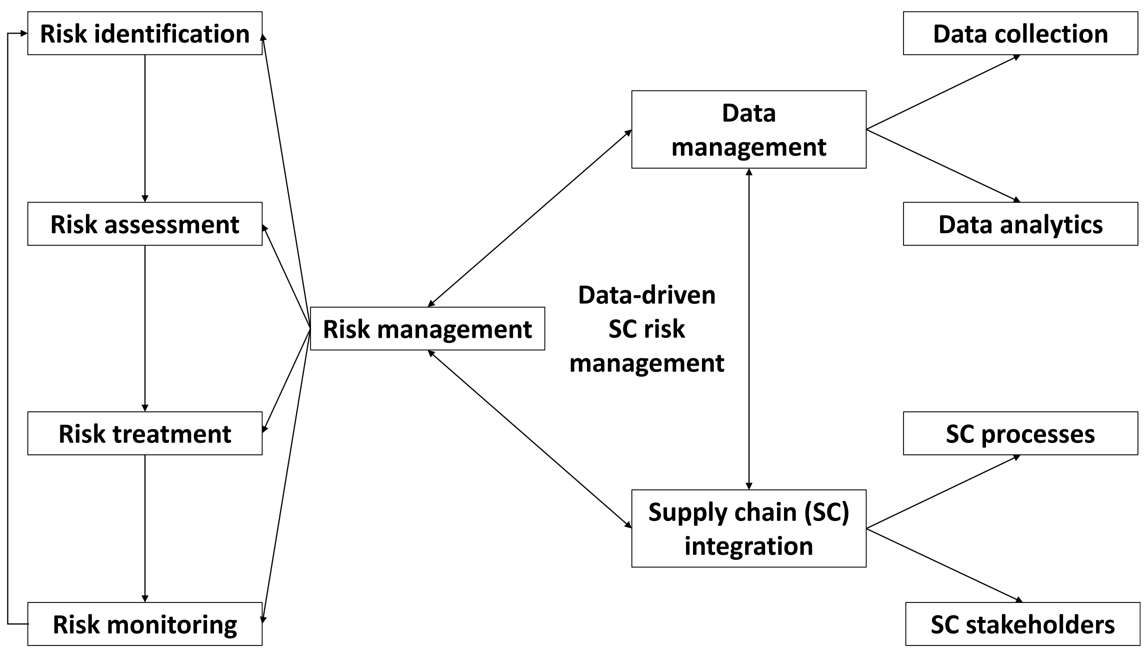
Fellow scholars can adopt other approaches, e.g., robust optimization, for solving the problem at hand. Furthermore, the proportion of sourcing from each foreign country can be regarded to be a decision variable of interest to enterprises that purchase from multiple countries. The Q_a notation would then be a vector of decision variables to be determined by the prescriptive programs formulated. Multi-period dynamic programming is another possible extension of the presented models for interested operations researchers. These are potential avenues for modeling-based studies on data-driven risk management in global supply chain management and international trade.

Comparing the efficacy of reactive and proactive approaches by simulation or real-life data (in case studies, action research, or design science research) is a helpful and fruitful empirical research pathway to bolster practitioners' confidence in incorporating such information into their global supply chain management. There are indeed multiple publicly accessible databases for practitioners to keep track of political risks or sentiments, some of which have been discussed and utilized in Chapter 3. There is high potential to explore other databases and examine their relevance to global SCM decision-making so that they can benefit more practitioners and companies. This is another pertinent research avenue.

Next, Section 4.2 presents a managerial framework for practitioners on data-driven supply chain risk management.

4.2 Managerial framework

Figure 4.1 illustrates a framework conceptualized for data-driven supply chain risk management which is synthesized from the works of Birkel and Hartmann (2020), Bode et al. (2011), and Er Kara et al. (2020). This conceptual model indeed leverages the inputs from the findings discussed throughout this dissertation for data-driven operations and supply chain management (SCM).



Source: synthesized from Birkel and Hartmann (2020), Bode et al. (2011), and Er Kara et al. (2020)

Figure 4.1: Conceptual framework for data-driven supply chain risk management

In particular, risk management, which is composed of risk identification, risk assessment, risk treatment, and risk monitoring (Birkel and Hartmann, 2020; Choudhary et al., 2020), necessitates the support of data management[1] processes such as data collection and data analytics (Er Kara et al., 2020), which has been substantiated by empirical research (Bag et al., 2023; Gupta et al., 2022; Li et al., 2023). In fact, the important information or data needed for risk management may come from the focal company's partners or other external sources (Er Kara et al., 2020; Fan et al., 2017; Neef, 2005). This implies the vital role of collaboration with supply chain stakeholders and integration of supply chain processes in data-driven risk management. Supply chain integration, which is comprised of internal integration and external integration (Chaudhuri et al., 2020), refers to the effective management and coordination of supply chain processes to facilitate information, value, and material flows across departmental and organizational boundaries (Azadegan et al., 2020; Chaudhuri et al., 2020). The empirical literature has reported that supply chain integration strengthens supply chain risk management (Hu et al., 2020; Munir et al., 2020; Phung et al., 2023). Meanwhile, supply chain partners are considered not only valuable sources of risk information sharing (Fan et al., 2017; Matsuo, 2015) but also crucial participants in concerted risk management efforts across the supply chain (Bechtsis et al., 2022; Bode et al., 2011; Iwao and Kato, 2019; Norrman and Jansson, 2004). As a result, risk management, supply chain integration, and data management ought to be interconnected to enable data-driven supply chain risk management as depicted in Figure 4.1.

In line with the theoretical framework established for this dissertation (revisit Figure 0.1), organizational information processing theory lays a theoretical foundation for Figure 4.1's data-driven supply chain risk management model (Birkel and Hartmann, 2020; Fan et al., 2017; Munir et al., 2020). Given the complexity, ambiguity, and uncertainty of supply chain risk information (e.g., information on possible abnormalities in supply chain operations) in today's turbulent environment, enterprises need information processing capabilities that can effectively capture and analyze information/data to produce revealing insights for risk management decision-making (Fan et al., 2017; Munir et al., 2020). To gain consistent and superior supply chain risk management performance, there must be a fit between firms' information processing needs and their information processing capabilities (Galbraith, 1974; Birkel and Hartmann, 2020). Information/data can be captured by modern information technologies, e.g., radio frequency identification (RFID) and the Internet of Things (IoT) (Birkel and Hartmann, 2020), and shared by supply chain partners (Fan et al., 2017; Munir et al., 2020) for joint risk-handling (Bode et al., 2011; Kauppi et al., 2016). These prior works have lent support to organizational information processing theory as a theoretical lens underlying data-driven supply chain risk management.

The next subsections will provide generic guidelines for each step of the data-driven supply chain risk management model conceptualized. All the three components, i.e., risk management, data management, and supply chain integration, will be discussed together in each stage because they are interrelated.

4.2.1 Data-driven risk identification

Supply chain risk management starts with risk identification (Birkel and Hartmann, 2020), which is to discover all probable and pertinent threats and vulnerabilities along the supply chain (Birkel and Hartmann, 2020; Fan and Stevenson, 2018b). An overview of different supply chain risk types is discussed in the papers of Christopher and Peck (2004), Ho et al. (2015), Jüttner (2005), and Rajagopal et al. (2017). Overall, sources of supply chain risk can be classified into five main groups: demand risk, supply risk, process risk, control risk, and environmental risk (Christopher and Peck, 2004). Improper identification of risk may compromise the subsequent steps of supply chain risk management (Fan and Stevenson, 2018b; Kern et al., 2012; Neiger et al., 2009).

Sharing information about supply chain risk (part of data collection) is the first stage of data management for supply chain risk management, notably risk identification (Fan et al., 2017). Matsuo's (2015) case study implies that first-tier vendors' information-sharing can help to identify hidden upstream entities that likely create bottlenecks when a disruptive event takes place. In fact, each threat or vulnerability faced by a given supply chain actor has implications for other interconnected supply chain nodes (Engelseth and Wang, 2018; Simchi-Levi et al., 2015) and Fan and Stevenson (2018a) also recognize the role of supply chain members in risk identification as those closest to the activity/process concerned have the most relevant knowledge (van Mieghem, 2011). Therefore, this step involves both data management and supply chain integration.

To facilitate data collection for supply chain risk management, supply chain mapping is a prerequisite (Sheffi, 2015). Given the global spread of today's supply chains, this may be a daunting task to undertake in-house but can be now supported by third-party services (see Sheffi, 2015). A detailed supply chain map, which should incorporate supply-demand activities/processes and information/value/material flows between supply chain members, can help identify the facilities/locations with potential threats and vulnerabilities (Martel and Klibi, 2016c; Tummala and Schoenherr, 2011). As risk materialization is associated with a source, i.e., a triggering event, and consequences, i.e., risk impact (revisit Chapter 3), past performance failures (e.g., late deliveries and stockouts) at each node ought to be recorded and attributed to specific events (Tummala and Schoenherr, 2011). Their (root) causes and interrelationships should also be explored to characterize the vulnerabilities of each site (Tummala and Schoenherr, 2011).

According to Fan and Stevenson (2018a), the focal firm can use observable cues such as supply chain partners' abnormal behaviors and complaints to identify likely risk drivers or sources in its supply chain, notably in case of asymmetric information (revisit Chapter 2). Furthermore, (third-party) inspection of facilities is also recommended for risk identification (Fan and Stevenson, 2018a). As risk identification can be viewed from three perspectives, namely competency, process, and resource, and those whose work relates most closely to the competency/process/resource in question possess the most pertinent knowledge, risk identification should be a multi-functional team effort with multi-departmental inputs (van Mieghem, 2011).

Once threats and vulnerabilities along the supply chain have been identified, risk assessment is the next step to be taken.

4.2.2 Data-driven risk assessment/evaluation

To effectively utilize the information/data collected for risk management necessitates risk assessment that can yield illuminating and useful insights for decision-making (Fan et al., 2017). This stage consists of evaluating each identified risk with respect to its probability of occurrence and its negative impact/consequence/severity (Birkel and Hartmann, 2020; Martel and Klibi, 2016b). This task requires both quantitative (i.e., objective) and qualitative (i.e., expert opinion-based) data (Birkel and Hartmann, 2020; Venkatesh et al., 2015; Zsidisin et al., 2004). In fact, despite technological advances, e.g., IoT and advanced programming, which enable data collection and analytics for objective risk assessment, most firms interviewed by Birkel and Hartmann (2020) still rely strongly on subjective expert judgment, especially for exceptional cases. Nonetheless, the overall trend is the increasing adoption of quantitative data analytics for risk evaluation (Birkel and Hartmann, 2020).

Next, the risk exposure value of each risk factor can be calculated by the multiplication of its occurrence frequency and consequence severity, on the basis of which risk ranking is determined (Tummala and Schoenherr, 2011). This index helps account for hazards or hazardous events that happen infrequently but can lead to serious disruption (Martel and Klibi, 2016b). Thus, risk exposure matrices, composed of risk likelihood and impact, have been widely used to characterize risk (Ho et al., 2015; Norrman and Jansson, 2004; Qazi et al., 2023) and inform resource allocation for risk handling between supply chain nodes (Simchi-Levi et al., 2015).

In another vein of research, risk ranking/prioritization also takes account of the likelihood of detection of each risk (Chang et al., 2014; Huang et al., 2020; Venkatesh et al., 2015). The product of risk frequency of occurrence, probability of detection, and severity of impact is then called the *classical risk priority number* (Chang et al., 2014). However, risk occurrence, detection, and impact do not always have equal importance; therefore, their relative weight should be considered in risk prioritization (Chang et al., 2014). The *exponential risk priority number* is thus proposed by Chang et al. (2014) to achieve this primary purpose.

There are complex interrelationships between risks (Fan and Stevenson, 2018a,b). A risk event may result in or from other risk factors (Venkatesh et al., 2015). The extent to which a risk source initiates others is measured by the *driving power* index, whereas the *dependence power* indicates the degree to which a risk event stems from others (Venkatesh et al., 2015). The ratio of *driving power* to *dependence power* then replaces risk occurrence likelihood in Venkatesh et al.'s (2015) calculation of risk prioritization to take risk transitivity into account. Further discussion about other variants of the risk priority number can be found in the literature review of Huang et al. (2020).

On the other hand, there are deeply uncertain events, for example, political instability and terrorism, which might exert serious-to-disastrous impact, but the information available to estimate their likelihood or influence is insufficient (Klibi et al., 2010; Martel and Klibi, 2016b). As per Walker et al.'s (2010) discussion, there are three ways to cope with large/deep uncertainties: resistance, e.g., worst-scenario analysis – robust programming (Cox, 2012; Klibi et al., 2010); resilience, e.g., anticipative steering (Coenen et al., 2018); and adaptation, e.g., adaptive steering (Coenen et al., 2018) and (model-free) reinforcement learning (Cox, 2012). As regards the adaptive approach for handling deeply uncertain events, monitoring occupies a recognized part (Kok et al., 2019; Quinn et al., 2020). In effect, risk monitoring is the final risk management step to be presented in subsection 4.2.4.

Next, risk assessment results can be classified into different thresholds using the criteria established by cross-departmental teams and senior managers in order to inform risk treat decision-making (Tummala and Schoenherr, 2011).

4.2.3 Data-driven risk treatment

Risk treatment can be categorized into five generic types: acceptance, avoidance, transfer, sharing, and mitigation, of which risk mitigation has been principally heeded in research and practice (Birkel and Hartmann, 2020; Fan and Stevenson, 2018b). The decision on risk treatment is built on not only the risk exposure (Birkel and Hartmann, 2020) but also other factors such as risk-taking preference/propensity (Fan and Stevenson, 2018b) and availability of alternatives (Hajmohammad and Vachon, 2016).

Regarding risk acceptance, firms need not invest in risk management for risk factors that have an acceptably low risk exposure value, for instance, late delivery risk of noncritical components with abundant supply (Tummala and Schoenherr, 2011). Still, it should be noted that this risk acceptance level differs across companies and contexts, depending on their idiosyncrasies such as risk aversion (Fan and Stevenson, 2018b). Take supply risk as an example. If the supply risk exposure is high, but the buying firm is dependent on a dominant supplier, then it likely accepts the risk (Hajmohammad and Vachon, 2016).

If an enterprise decides to avoid the triggering events or sources (e.g., products, suppliers, and locations) associated with a given risk factor, the strategy is called risk avoidance (Fan and Stevenson, 2018b; Hajmohammad and Vachon, 2016; Jüttner et al., 2003). If the risk exposure is high and there are other comparable alternatives with lower risk exposure, the firm can opt for risk avoidance (Hajmohammad and Vachon, 2016). This decision is advised if the company is not reliant on the product/supplier/location under consideration, nor can it exert its influence to mitigate the risk (Hajmohammad and Vachon, 2016).

For risk factors with low likelihood of occurrence but high impact, transferring them to another party (risk transfer), e.g., by obtaining insurance (Diabat et al., 2012; Zhen et al., 2016) or entering into risk transfer contracts such as options (Kim and Park, 2014; Shanker and Satir, 2021), is one suggested solution (Fan and Stevenson, 2018b). Another possible strategy is risk sharing, where both parties share the risks (Fan and Stevenson, 2018b). One example is risk sharing contracts that allow both parties to share profits and losses from variable exchange rates by agreeing to a predetermined range (Kim and Park, 2014; Shanker and Satir, 2021).

Risk mitigation, which is to reduce risk probability and/or impact, can be divided into proactive and reactive approaches, depending on whether it is implemented before or after risk materialization (Kırılmaz and Erol, 2017). Proactive risk mitigation examples consist of appropriate supplier selection and development, and portfolio diversification, whereas reactive risk mitigation comprises rerouting and expediting (Tukamuhabwa et al., 2017). Further, there are risk mitigation strategies that can be applied both before and after a disruptive event occurs, e.g., supply chain collaboration to share information and resources for pre-disruption vulnerability reduction and post-disruption response and recovery (refer to Tukamuhabwa et al., 2017, for more examples). Birkel and Hartmann's (2020) interviews reveal an intensification of both proactive and reactive risk mitigation approaches.

Once risk treatment strategies are selected, the evolution of the risk factors concerned and the efficacy and implementation of the strategies, especially the proactive ones (van Mieghem, 2011), should be monitored (Fan and Stevenson, 2018b).

4.2.4 Data-driven risk monitoring

Risk monitoring entails continuously reviewing the identified risk factors and their countermeasures so that they can be realigned if there are deviations from the desired targets (Birkel and Hartmann, 2020; Tummala and Schoenherr, 2011). Given the dynamic nature of risk, this step is vital but has often been overlooked in research and practice because it is usually merged with other risk management stages or terms, for example, risk assessment (Birkel and Hartmann, 2020; Fan and Stevenson, 2018b) and risk control (Kırılmaz and Erol, 2017; Tummala and Schoenherr, 2011).

According to Norrman and Jansson (2004), risk monitoring is notably required when the risk exposure level is high but not mitigated, which is particularly the case for deeply uncertain events discussed in subsection 4.2.2. With risk monitoring, attention should also be turned to the development and implementation of supply chain partners' risk management processes (Norrman and Jansson, 2004; Norrman and Wieland, 2020) as disruption at any supply chain member has implications for other interconnected supply chain nodes (Engelseth and Wang, 2018; Simchi-Levi et al., 2015).

Data management can support risk monitoring (Tummala and Schoenherr, 2011). Indeed, such technological advances as IoT can greatly facilitate risk monitoring since they allow faster data capture, transfer, and analysis in a more transparent and automated fashion (Birkel and Hartmann, 2020; Tsang et al., 2018). However, risk monitoring ought to be assisted by both formal processes and judgmental evaluations (Fan and Stevenson, 2018b) because sufficient information is not always available as in the case of deep uncertainties (Klibi et al., 2010; Martel and Klibi, 2016b).

Because risk monitoring can provide early warnings to inform risk prevention which is practically more cost-effective than risk mitigation, more attention ought to be directed to risk monitoring in scholarship and practice (Ho et al., 2015; Kok et al., 2019). Indeed, monitoring provides opportunities and incentives for learning and reflection on how the currently adopted risk management processes have performed over time and how to adjust them to augment their effectiveness as the context changes or new information unfolds (Norrman and Wieland, 2020; Swanson et al., 2010; Tummala and Schoenherr, 2011).

After this stage, the whole process repeats itself, restarting the risk management cycle (Norrman and Jansson, 2004) with new risk factors identified and new judgments revised (Kırılmaz and Erol, 2017).

In sum, this extended chapter has provided two prescriptive programs as application examples of Chapter 3 and presented a managerial framework for data-driven supply chain risk management that leverages the findings or inputs from Chapters 1, 2, and 3. Throughout the discussion of this chapter, several topics that have not been extensively examined in the literature are also pointed out as suggestions for further research.

Notes

1. https://www.oracle.com/ca-en/database/what-is-data-management/ (visited July 9, 2023)

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General Conclusion

This dissertation investigates the utilization of data for informed decision-making through different projects that relate to operations and supply chain management (OSCM).

By using three clustering techniques for data analysis triangulation when synthesizing the knowledge structure of data-driven OSCM, the first chapter of this dissertation ascertains six clusters of highly co-cited journal publications appearing in our analysis results, namely *Big data (data analytics) in OSCM*, *Transportation and traffic flow prediction*, *Demand forecasting*, *System integration in manufacturing*, *Data mining in manufacturing*, and *Data-driven inventory management*, five of which closely relate to production. As can be inferred from the discussed results, no cluster has been established for highly co-cited research in several OSCM subdomains, e.g., retailing, risk management, service operations, and supply planning. This dissertation then contributes to bridging these identified literature gaps by proposing models which help utilize data for OSCM in relation to service operations (Chapter 2) and risk management (Chapter 3).

In Chapter 2, where a framework is developed to leverage user-generated data to improve review recommendation operations, reviewer-user similarity is among the most significant explanatory variables, which is in keeping with the guiding theories and the national culture of the platform's country. The machine-learning-based predictive modeling and counterfactual analysis results demonstrate that the hypothesized model tested helps boost user affinity for the platform concerned. This indicates the potential of the proposed framework to improve review recommendation operations. In addition, how the inclusion of each variable is theoretically justified in Chapter 2 can help practitioners and scholars determine underexplored yet relevant variables for their service operations modeling on online platforms.

Chapter 3 reveals that economic nationalism leads firms to increase the proportion of domestic sourcing. This influence is stronger for firms operating in the food and medical supplies industries. Furthermore, the findings show that economic nationalist sentiment during an election year is associated with economic nationalist policy interventions. This study contributes to the theory on policy uncertainty and political risk by illustrating that economic nationalist sentiment can anticipate whether future policy changes are likely to increase supply risk for firms with foreign suppliers and by introducing a new operationalization of political risk for foreign trade. Additionally, it provides insights into the signals that managers can use to better assess political risk and devise risk mitigation strategies. Lastly, it informs policymakers how economic nationalism affects their reshoring goals.

On the basis of Chapter 3's research findings, Chapter 4 formulates two prescriptive programs that employ such data-driven insights to help global supply chain managers determine the optimal proportion of domestic (foreign) sourcing and minimize the expected cost given the uncertainty or risk associated with public policy interventions. This chapter also discusses a managerial framework synthesized from the insights reported in Chapters 1, 2, and 3 to provide generic guidelines for practitioners and researchers with regard to data-driven supply chain risk management.

Contributions

This dissertation's major contributions to the literature on data-driven OSCM are summarized below:

- First, this dissertation illustrates in Chapter 1 how fellow scholars can conduct a rigorous and reproducible systematic literature review to identify the knowledge structure and literature gaps in their field of study and inform their future research endeavors. In particular, cross-referencing and data analysis triangulation (see Chapter 1) are recommended techniques to enhance the rigor of a literature review. Further, the research project reported in Chapter 1 also acknowledges the significant role of theory in guiding an arguably robust literature selection procedure.

- In addition, Chapter 1's findings, including the identified knowledge base of data-driven OSCM (defined as clusters of journal articles interconnected by co-citations) and its literature gaps, provide fellow researchers with potentially fruitful research avenues and research questions as well as with suggested theories, frameworks, and insights (e.g., organizational information processing theory) to conduct practically relevant and academically interesting studies that can help bridge the literature lacunae and support enterprises in data utilization.

- The points of reference synthesized in Chapter 1 also facilitate data-driven OSCM practice built on machine learning and big data analytics. The evolution of the ascertained clusters suggests a procedure for BDA adoption, where staff's data analysis competencies must be prioritized and developed with the support of proper technology resources in order that BDA can be successfully put in place. Top management support, inter/intra-organizational cooperation, and competitive rivalry are other vital factors to be taken into consideration in BDA adoption.

- Next, Chapter 2 points out and empirically investigates important yet underexplored variables (e.g., users' interaction-based similarity) in a firm's recorded data. These factors have been examined in English-based contexts (cf. Zhang and Lin, 2018) or related domains (e.g., followee recommendation), but Chapter 2 theoretically and empirically demonstrates that they remain pertinent to the review-recommendation operations of the non-English Asia-based review platform in question, thereby bolstering practitioners' confidence in the existing literature.

- Although not meant to be exhaustive, the theoretical foundations presented in Chapter 2, for example, signaling theory, network effect, and Hofstede's (2001) cultural dimensions, provide concrete examples where the inclusion and operationalization of an understudied yet likely pertinent variable in a certain model can be explicated from a theoretical perspective. Practitioners and researchers can draw on these theoretical lenses to determine new features that are justifiably germane to their OSCM contexts of interest.

- In Chapter 3, this dissertation operationalizes economic nationalism based on public policies and economic nationalist sentiment in political manifestos. These measures support companies involved in foreign trade and global SCs since such political risk can be quantified and monitored by publicly available data. This chapter's research findings suggest that global SC managers should be vigilant about not only a holistic set of policies with implications for their businesses' international operations, but also the climate of hostility (e.g., economic nationalist sentiment), an antecedent of economic nationalist policy interventions.

- Given that longitudinal cross-country data allow for better generalization, Chapter 3 helps policymakers assess the expected effect of their economic nationalist policies, notably on critical industries (e.g., those that provide essential goods, i.e., food and medical supplies). By discouraging local firms from trading with foreign suppliers, governments can boost domestic sourcing. However, in line with Fan et al.'s (2023) findings, Chapter 3 argues that governments should also implement policies that reinforce domestic supply bases and facilitate domestic SC transactions and relations to promote reshoring in a sustainable and competitive manner.

- Finally, Chapter 4 utilizes two prescriptive modeling examples to show how Chapter 3's data analysis results can provide inputs for prescriptive programming that supports data-driven risk management in global supply chains. Along with the possible directions proposed for prescriptive modeling, Chapter 4 also discusses a conceptual model which can benefit professionals and academics whose work relates to data-driven supply chain risk management. This chapter's primary contribution is to illustrate the applicability of the insights obtained from the research projects of this dissertation.

Future research directions

Chapter 4 presents the examples where this dissertation's findings can be utilized for future studies on data-driven risk management in global OSCM. In addition to the research avenues proposed in each of the previous chapters, the overall extensions of this dissertation for future scholarly works can be synthesized as follows:

- With multiple processes/activities (e.g., purchasing, warehousing, and retailing) and stakeholders in OSCM (revisit Chapter 1), interdisciplinary research is necessitated to examine the SC configurations and mechanisms that facilitate the seamless flows of data, information, materials, and people throughout the entire SC to support data-driven OSCM in a globally optimal and sustainable way. Such studies require inputs from various sources and perspectives, e.g., stakeholders and domains. By theoretical analysis and empirical verification, future studies should clarify the role of each SC stakeholder in contributing toward data-driven OSCM that fairly benefits each SC member.

- Chapter 2 emphasizes contextual embeddedness of modeling and demonstrates that predictive models with theoretically grounded dimension reduction can deliver performance roughly comparable with their high-dimensional counterparts. According to Karlaftis and Vlahogianni's (2011) review, simple and sophisticated models can perform equally in certain contexts, so managers ought to evaluate the contextual fit of a given model before deciding on adoption. Thus, future research should engage both modelers and empiricists so that each data-driven OSCM model can be developed with theoretical foundations and relevant application contexts and guidelines for practitioners, in keeping with Dooley's (2009) recommendation.

- Chapter 3 analyzes publicly available data to produce revealing insights that in turn inform Chapter 4's model formulation for risk management in global SCM. Fellow scholars can extend this line of research by exploring other publicly accessible databases that can assist practitioners with data-driven decision-making (e.g., Charpin, 2022). In such academic works, it is first important to point out how the dataset can be germane to a certain OSCM process and how the data can be analyzed to obtain the insights that are useful and relevant to the activity concerned. Then, how those insights can be applied to decision-making, e.g., via parameterized programming, should be discussed in detail.

Since there are numerous subdomains, theoretical lenses, and research methodologies in OSCM, these projects cannot cover all the contributions of data utilization to OSCM from each perspective, particularly when OSCM continues to evolve rapidly. Nevertheless, with the ascertained knowledge structure of data-driven OSCM, proposed theoretical frameworks, presented application examples, and suggested research avenues, this dissertation enriches the knowledge base that researchers and practitioners can draw on for academic and practical tasks. This dissertation generally advocates the development of information processing capabilities and the collaboration between supply chain actors to acquire pertinent data and information that can support OSCM decision-making in a globally optimal fashion.

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Appendix A – Chapter 1's material

The supplementary document for the article presented in Chapter 1 is published online at https://doi.org/10.1080/00207543.2021.1956695.

Appendix B – Chapter 2's material

The significant interaction term between reviewer expertise and review variance means that reviewer expertise moderates the relationship between review variance and user-review affinity, where reviews written by expert reviewers are deemed more helpful when deviating more from business average ratings (see Figure 1 where [reviewer] Expertise and [review] Variance are standardized).

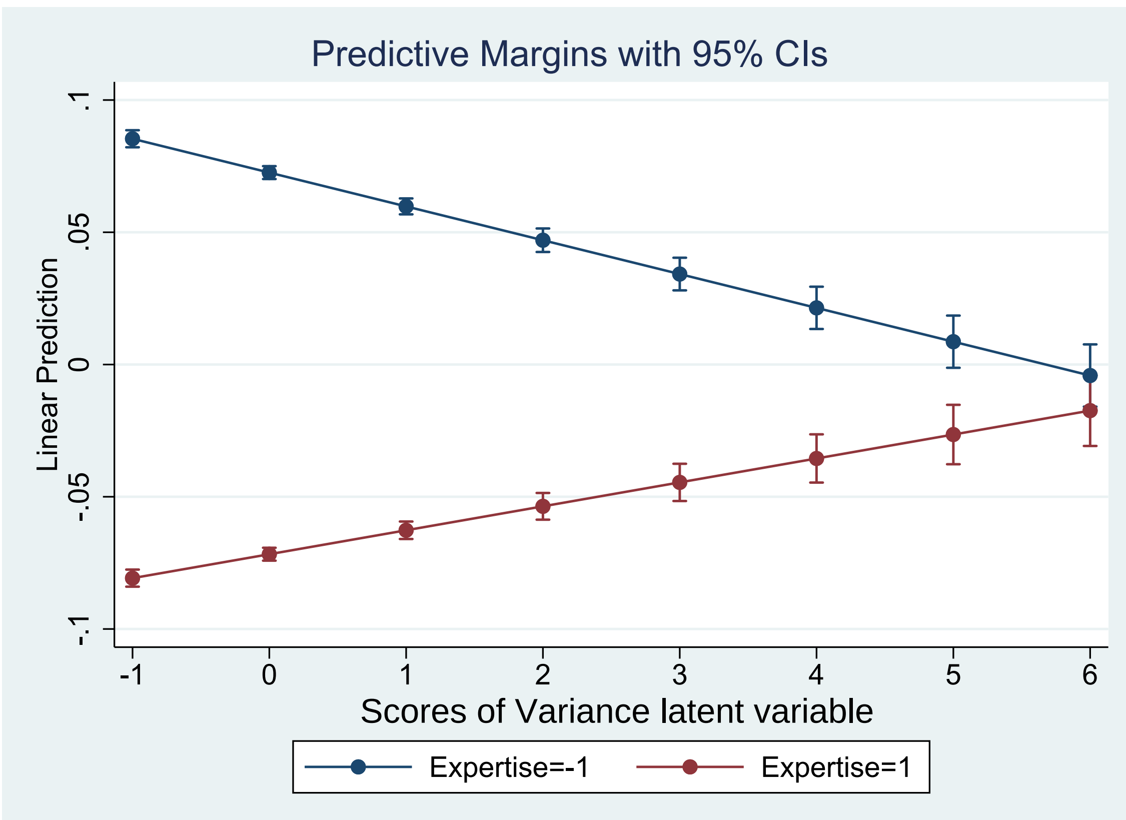

Figure 1: Interaction between review variance and reviewer expertise

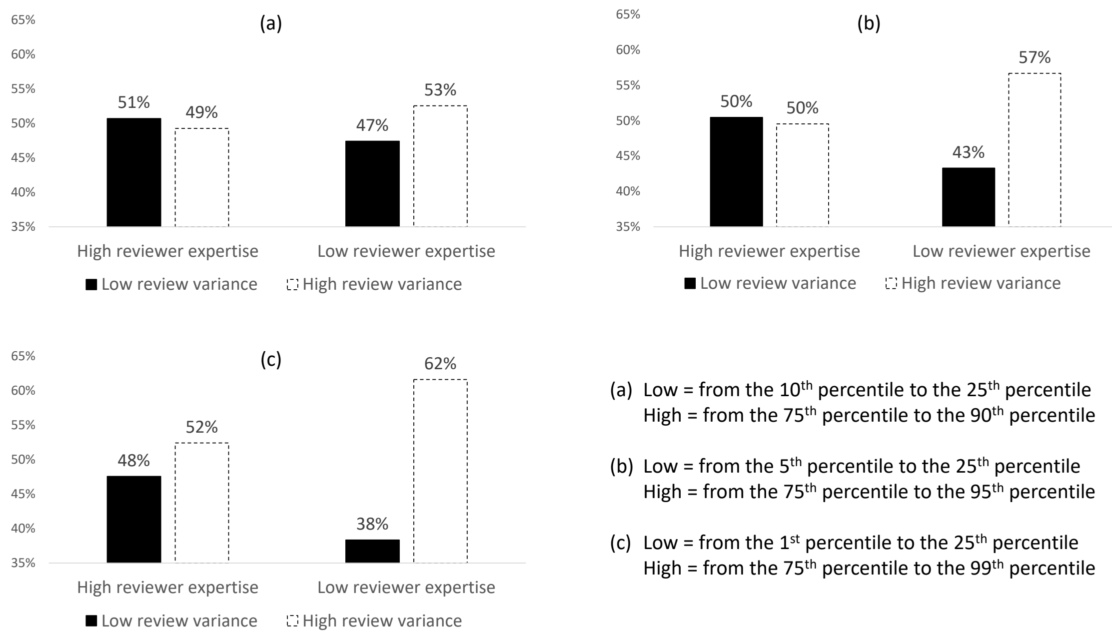

Figure 2: Review variance plotted by reviewer expertise

In our dataset, reviews written by reviewers with high expertise (reviewer expertise from the 75th percentile to the 90th, 95th, or 99th percentile) did not usually deviate largely from business average ratings compared to their counterparts written by review-

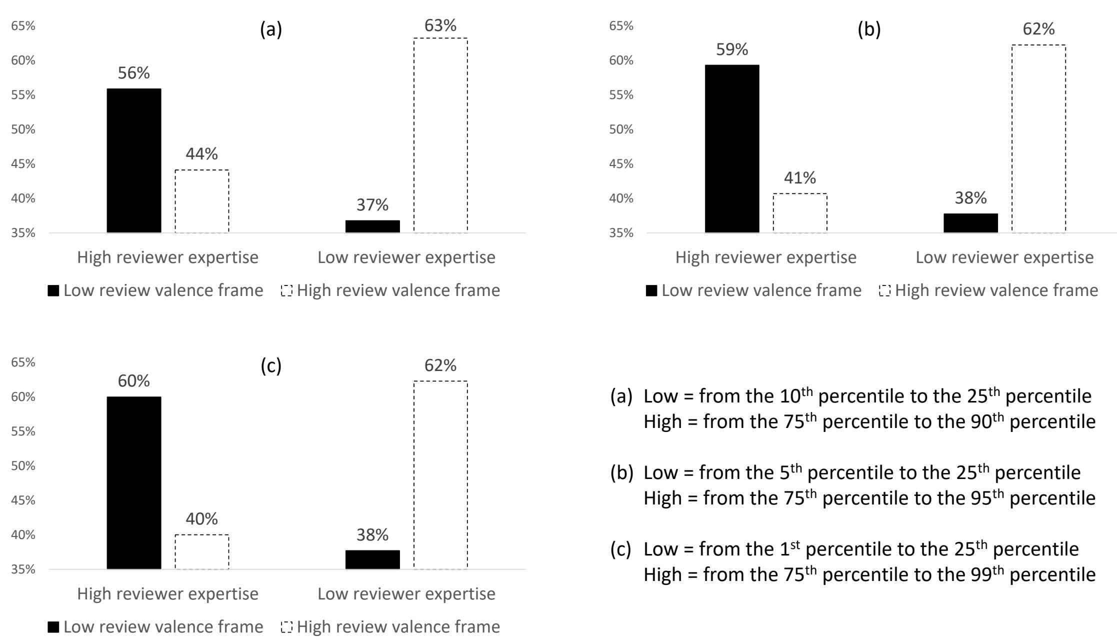

Figure 3: Review valence frame plotted by reviewer expertise

ers with low expertise (reviewer expertise from the 1st, 5th, or 10th percentile to the 25th percentile) as depicted in Figure 2. Nevertheless, when expert reviews deviated from business average ratings, they were often not in favor of the reviewed item (low review valence frame) vis-à-vis their nonexpert counterparts (see Figure 3) while high review valence frame increases user-review affinity in our results. This might explain why reviewer expertise correlated negatively with user-review affinity in our data.

The additional path analyses mentioned in Chapter 2 are provided in Tables 1–4, which are in accord with the hypothesis test results discussed therein. The evaluation of the machine learning algorithms used in Chapter 2, averaged over 30 runs for the dataset from July to December 2017 and trained on 1–6 months before, is depicted in the following figures:

- Bagging Classifier (BC): Figures 4a–4f;
- Gradient Boosting Classifier (GBC): Figures 5a–5f;
- Multi-layer Perceptron Classifier (ANN): Figures 6a–6f;
- Random Forest Classifier (RFC): Figures 7a–7f.

Table 1: Additional path analyses

	Dependent variable = User-review affinity	Model 1A		Model 1B		Model 2A		Model 2B	
	Number of observations	1813431		1813431		1813431		1813431	
	Average R-squared	0.13487		0.13486		0.13464		0.13463	
	Average communality	0.88321		0.88241		0.87612		0.87533	
	Absolute GOF	0.33864		0.33842		0.33654		0.33632	
	Relative GOF	0.98229		0.98227		0.97990		0.97987	
	Average redundancy	0.13487		0.13486		0.13464		0.13463	
	Variable	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF
(1)	Review valence frame	0.0147***	1.36	0.0147***	1.36	0.0154***	1.36	0.0154***	1.36
(2)	Review variance	–0.00090	1.29	–0.00090	1.29	–0.00050	1.29	–0.00050	1.29
(3)	Review quality	0.0462***	1.72	0.0462***	1.72	0.0473***	1.72	0.0473***	1.72
(4)	Review votes (likes)	–0.0121***	2.47	–0.0121***	2.47	–0.0136***	2.47	–0.0136***	2.47
(5)	Review length	–0.0207***	1.54	–0.0207***	1.54	–0.0239***	1.51	–0.0239***	1.51
(6)	Review picture	0.00060	1.51	0.00060	1.51	0.00070	1.52	0.00070	1.52
(7)	Review age	–0.0050***	1.40	–0.0050***	1.40	–0.0077***	1.41	–0.0077***	1.41
(8)	Reviewer expertise	–0.0517***	1.93	–0.0517***	1.93	–0.0422***	1.51	–0.0422***	1.51
(9)	Reviewer-User similarity	0.1099***	1.46	0.1099***	1.46	0.1093***	1.46	0.1092***	1.46

(continued next page)

Table 1 (continued)

	Variable	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF
(10)	User following Reviewer recently	0.0078⁑	1.05	0.0078⁑	1.05	0.0079⁑	1.05	0.0079⁑	1.05
(11)	User disliked Reviewer	–0.0058⁑	1.05	–0.0058⁑	1.05	–0.0058⁑	1.05	–0.0058⁑	1.05
(12)	Reviewer following User recently	0.0113⁑	1.06	0.0113⁑	1.06	0.0119⁑	1.06	0.0119⁑	1.06
(13)	Reviewer disliked User	–0.0039⁑	1.05	–0.0039⁑	1.05	–0.0038⁑	1.05	–0.0038⁑	1.05
(14)	Reviewer social connectedness	0.0266⁑	2.19	0.0266⁑	2.19	0.0175⁑	1.99	0.0175⁑	1.99
(15)	Reviewer locality	0.0015*	1.01	0.0015*	1.01	0.0022⁑	1.01	0.0022⁑	1.01
(16)	Reviewer-User common locality	0.0132⁑	1.02	0.0132⁑	1.02	0.0141⁑	1.02	0.0141⁑	1.02
(17)	Brand strength (busAvgRating)	–0.0018*	1.11	–0.0018*	1.11	0.00050	1.10	0.00060	1.10
(18)	Review variance $\times$ Reviewer expertise	0.0088⁑	1.03	0.0088⁑	1.03	0.0070⁑	1.03	0.0070⁑	1.03
(19)	Lagged user-review affinity (7 days)	0.3070⁑	1.05	0.3069⁑	1.05	0.3070⁑	1.06	0.3070⁑	1.06

Note:
Model 1 uses the total count of (good) reviews, photos, and followers to measure (8). Model 2 uses the average count per day for (8). Model A uses the unweighted scale for user's and reviewer's recent votes for each other in measuring (9). Model B uses the weighted score for (9). ⁑ significance at the 1% level; * significance at the 5% level. The measure of the dependent variable is the same as in Section 2.3.2 of Chapter 2.

Let x, y, and z denote whether User liked, commented on, and re-read the review within seven days of the initial read, respectively.

Then, unweighted user-review affinity is equal to:

$$\frac{x+y+z}{3}$$

Table 2: Additional path analyses by linear regression with unweighted user-review affinity

	Dependent variable = User-review affinity	Model 1A		Model 1B		Model 2A		Model 2B	
	Number of observations	1813431		1813431		1813431		1813431	
	R-squared	0.14930		0.14940		0.14880		0.14880	
	Variable	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF
(1)	Review valence frame	0.0120⁑	1.36	0.0120⁑	1.36	0.0130⁑	1.36	0.0130⁑	1.36
(2)	Review variance	−0.00011	1.29	−0.00011	1.29	−0.00037	1.29	−0.00037	1.29
(3)	Review quality	0.0658⁑	1.72	0.0657⁑	1.72	0.0669⁑	1.72	0.0668⁑	1.72
(4)	Review votes (likes)	−0.0267⁑	2.47	−0.0266⁑	2.47	−0.0286⁑	2.47	−0.0286⁑	2.47
(5)	Review length	−0.0198⁑	1.54	−0.0198⁑	1.54	−0.0241⁑	1.51	−0.0241⁑	1.51
(6)	Review picture	0.0027⁑	1.51	0.0027⁑	1.51	0.0019*	1.52	0.0019*	1.52
(7)	Review age	−0.0053⁑	1.40	−0.0053⁑	1.40	−0.0077⁑	1.41	−0.0078⁑	1.41

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Table 2 (continued)

	Variable	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF
(8)	Reviewer expertise	−0.0553⁑	1.93	−0.0553⁑	1.93	−0.0404⁑	1.51	−0.0404⁑	1.51
(9)	Reviewer-User similarity	0.1601⁑	1.46	0.1602⁑	1.46	0.1592⁑	1.46	0.1593⁑	1.46
(10)	User following Reviewer recently	0.0134⁑	1.05	0.0134⁑	1.05	0.0135⁑	1.05	0.0135⁑	1.05
(11)	User disliked Reviewer	−0.0054⁑	1.05	−0.0054⁑	1.05	−0.0053⁑	1.05	−0.0053⁑	1.05
(12)	Reviewer following User recently	0.0129⁑	1.06	0.0128⁑	1.06	0.0135⁑	1.06	0.0134⁑	1.06
(13)	Reviewer disliked User	−0.0068⁑	1.05	−0.0068⁑	1.05	−0.0069⁑	1.05	−0.0069⁑	1.05
(14)	Reviewer social connectedness	0.0289⁑	2.19	0.0288⁑	2.19	0.0176⁑	1.99	0.0176⁑	1.99
(15)	Reviewer locality	0.0029⁑	1.01	0.0029⁑	1.01	0.0037⁑	1.01	0.0037⁑	1.01
(16)	Reviewer-User common locality	0.0128⁑	1.02	0.0128⁑	1.02	0.0138⁑	1.02	0.0138⁑	1.02
(17)	Brand strength (busAvgRating)	−0.00112	1.11	−0.00111	1.11	0.0017*	1.10	0.0017*	1.10
(18)	Review variance × Reviewer expertise	0.0098⁑	1.03	0.0098⁑	1.03	0.0072⁑	1.03	0.0072⁑	1.03
(19)	Lagged user-review affinity (7 days)	0.2869⁑	1.05	0.2868⁑	1.05	0.2871⁑	1.05	0.2870⁑	1.05

Note:
Model 1 uses the total count of (good) reviews, photos, and followers to measure (8). Model 2 uses the average count per day for (8). Model A uses the unweighted scale for user's and reviewer's recent votes for each other in measuring (9). Model B uses the weighted score for (9). ⁑ significance at the 1% level; * significance at the 5% level.

Let p_x, p_y and p_z denote the proportion of observations where users liked, commented on, and re-read reviews within seven days of initial reads, respectively.

Then, user-review affinity weighted by softmax with positive base is equal to:

$$\frac{x \cdot \exp(p_x) + y \cdot \exp(p_y) + z \cdot \exp(p_z)}{\exp(p_x) + \exp(p_y) + \exp(p_z)}$$

Table 3: Additional path analyses by linear regression with user-review affinity weighted by softmax with positive base

	Dependent variable = User-review affinity	Model 1A		Model 1B		Model 2A		Model 2B	
	Number of observations	1813431		1813431		1813431		1813431	
	R-squared	0.14750		0.14750		0.14700		0.14700	
	Variable	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF
(1)	Review valence frame	0.0124***	1.36	0.0124***	1.36	0.0133***	1.36	0.0133***	1.36
(2)	Review variance	−0.00021	1.29	−0.00021	1.29	−0.00024	1.29	−0.00024	1.29
(3)	Review quality	0.0621***	1.72	0.0620***	1.72	0.0632***	1.72	0.0631***	1.72
(4)	Review votes (likes)	−0.0243***	2.47	−0.0243***	2.47	−0.0262***	2.47	−0.0261***	2.47
(5)	Review length	−0.0194***	1.54	−0.0194***	1.54	−0.0235***	1.51	−0.0235***	1.51
(6)	Review picture	0.0025***	1.51	0.0025***	1.51	0.0019*	1.52	0.0019*	1.52
(7)	Review age	−0.0050***	1.40	−0.0050***	1.40	−0.0074***	1.41	−0.0075***	1.41

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Table 3 (continued)

	Variable	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF
(8)	Reviewer expertise	−0.0543⁑	1.93	−0.0543⁑	1.93	−0.0405⁑	1.51	−0.0405⁑	1.51
(9)	Reviewer-User similarity	0.1516⁑	1.46	0.1517⁑	1.46	0.1508⁑	1.46	0.1509⁑	1.46
(10)	User following Reviewer recently	0.0127⁑	1.05	0.0127⁑	1.05	0.0128⁑	1.05	0.0128⁑	1.05
(11)	User disliked Reviewer	−0.0050⁑	1.05	−0.0050⁑	1.05	−0.0049⁑	1.05	−0.0049⁑	1.05
(12)	Reviewer following User recently	0.0118⁑	1.06	0.0117⁑	1.06	0.0124⁑	1.06	0.0123⁑	1.06
(13)	Reviewer disliked User	−0.0063⁑	1.05	−0.0063⁑	1.05	−0.0064⁑	1.05	−0.0064⁑	1.05
(14)	Reviewer social connectedness	0.0285⁑	2.19	0.0285⁑	2.19	0.0177⁑	1.99	0.0177⁑	1.99
(15)	Reviewer locality	0.0029⁑	1.01	0.0028⁑	1.01	0.0036⁑	1.01	0.0036⁑	1.01
(16)	Reviewer-User common locality	0.0129⁑	1.02	0.0129⁑	1.02	0.0139⁑	1.02	0.0139⁑	1.02
(17)	Brand strength (busAvgRating)	−0.000127	1.11	−0.00126	1.11	0.0015*	1.10	0.0015*	1.10
(18)	Review variance × Reviewer expertise	0.0097⁑	1.03	0.0097⁑	1.03	0.0073⁑	1.03	0.0073⁑	1.03
(19)	Lagged user-review affinity (7 days)	0.2923⁑	1.05	0.2922⁑	1.05	0.2925⁑	1.05	0.2924⁑	1.05

Note:
Model 1 uses the total count of (good) reviews, photos, and followers to measure (8). Model 2 uses the average count per day for (8). Model A uses the unweighted scale for user's and reviewer's recent votes for each other in measuring (9). Model B uses the weighted score for (9). ⁑ significance at the 1% level; * significance at the 5% level.

Let p_x, p_y and p_z denote the proportion of observations where users liked, commented on, and re-read reviews within seven days of initial reads, respectively.

Then, user-review affinity weighted by softmax with negative base is equal to:

$$\frac{x \cdot \exp(-p_x) + y \cdot \exp(-p_y) + z \cdot \exp(-p_z)}{\exp(-p_x) + \exp(-p_y) + \exp(-p_z)}$$

Table 4: Additional path analyses by linear regression with user-review affinity weighted by softmax with negative base

	Dependent variable = User-review affinity	Model 1A		Model 1B		Model 2A		Model 2B	
	Number of observations	1813431		1813431		1813431		1813431	
	R-squared	0.15120		0.15120		0.15060		0.15060	
	Variable	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF
(1)	Review valence frame	0.0117***	1.36	0.0117***	1.36	0.0127***	1.36	0.0127***	1.36
(2)	Review variance	−0.00000	1.29	−0.00000	1.29	−0.00051	1.29	−0.00050	1.29
(3)	Review quality	0.0697***	1.72	0.0696***	1.72	0.0707***	1.72	0.0706***	1.72
(4)	Review votes (likes)	−0.0292***	2.47	−0.0291***	2.47	−0.0312***	2.47	−0.0311***	2.47
(5)	Review length	−0.0203***	1.54	−0.0203***	1.54	−0.0247***	1.51	−0.0247***	1.51
(6)	Review picture	0.0029***	1.51	0.0029***	1.51	0.0020*	1.52	0.0020*	1.52
(7)	Review age	−0.0056***	1.40	−0.0057***	1.40	−0.0080***	1.41	−0.0081***	1.41

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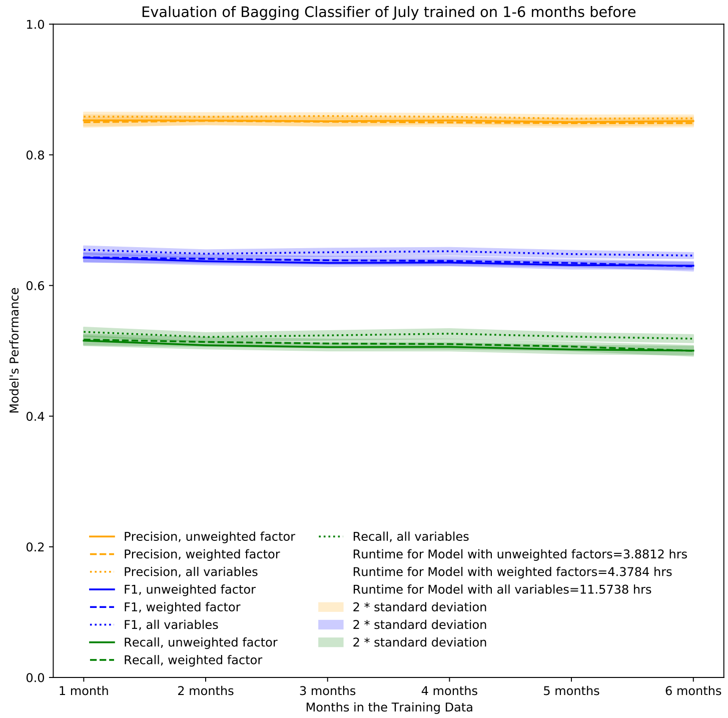
Table 4 (continued)

	Variable	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF	Coeff.	VIF
(8)	Reviewer expertise	−0.0562⁑	1.93	−0.0562⁑	1.93	−0.0402⁑	1.51	−0.0402⁑	1.51
(9)	Reviewer-User similarity	0.1687⁑	1.46	0.1688⁑	1.46	0.1678⁑	1.46	0.1679⁑	1.46
(10)	User following Reviewer recently	0.0142⁑	1.05	0.0141⁑	1.05	0.0143⁑	1.05	0.0142⁑	1.05
(11)	User disliked Reviewer	−0.0059⁑	1.05	−0.0059⁑	1.05	−0.0058⁑	1.05	−0.0058⁑	1.05
(12)	Reviewer following User recently	0.0140⁑	1.06	0.0139⁑	1.06	0.0147⁑	1.06	0.0146⁑	1.06
(13)	Reviewer disliked User	−0.0072⁑	1.05	−0.0072⁑	1.05	−0.0073⁑	1.05	−0.0073⁑	1.05
(14)	Reviewer social connectedness	0.0292⁑	2.19	0.0292⁑	2.19	0.0176⁑	1.99	0.0175⁑	1.99
(15)	Reviewer locality	0.0030⁑	1.01	0.0030⁑	1.01	0.0038⁑	1.01	0.0038⁑	1.01
(16)	Reviewer-User common locality	0.0127⁑	1.02	0.0127⁑	1.02	0.0138⁑	1.02	0.0138⁑	1.02
(17)	Brand strength (busAvgRating)	−0.00097	1.11	−0.00095	1.11	0.0019⁑	1.10	0.0020⁑	1.10
(18)	Review variance × Reviewer expertise	0.0099⁑	1.03	0.0099⁑	1.03	0.0072⁑	1.03	0.0072⁑	1.03
(19)	Lagged user-review affinity (7 days)	0.2809⁑	1.05	0.2808⁑	1.05	0.2812⁑	1.05	0.2811⁑	1.05

Note:
Model 1 uses the total count of (good) reviews, photos, and followers to measure (8). Model 2 uses the average count per day for (8). Model A uses the unweighted scale for user's and reviewer's recent votes for each other in measuring (9). Model B uses the weighted score for (9). ⁑ significance at the 1% level; * significance at the 5% level.

Figure 4: Evaluation of Bagging Classifier (BC) trained on 1–6 months before (30 runs)

(a)



(b)

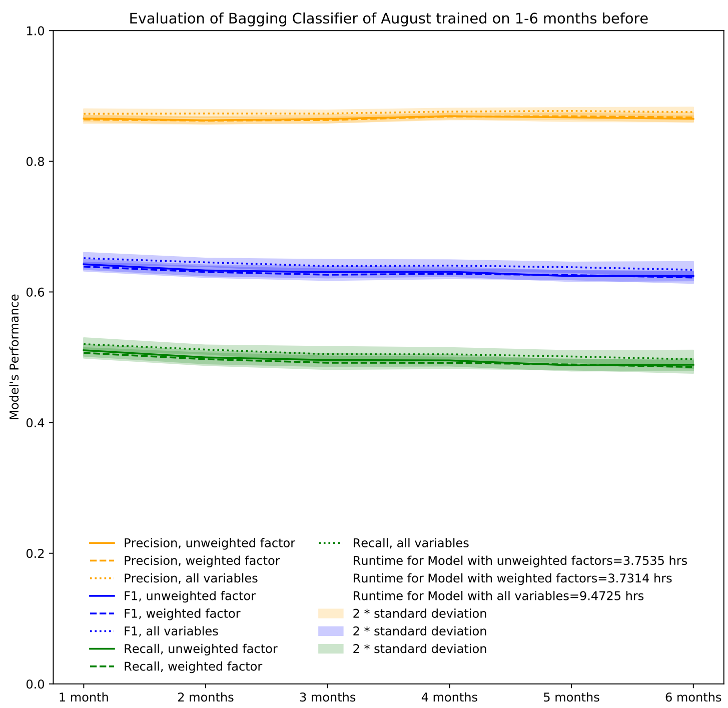
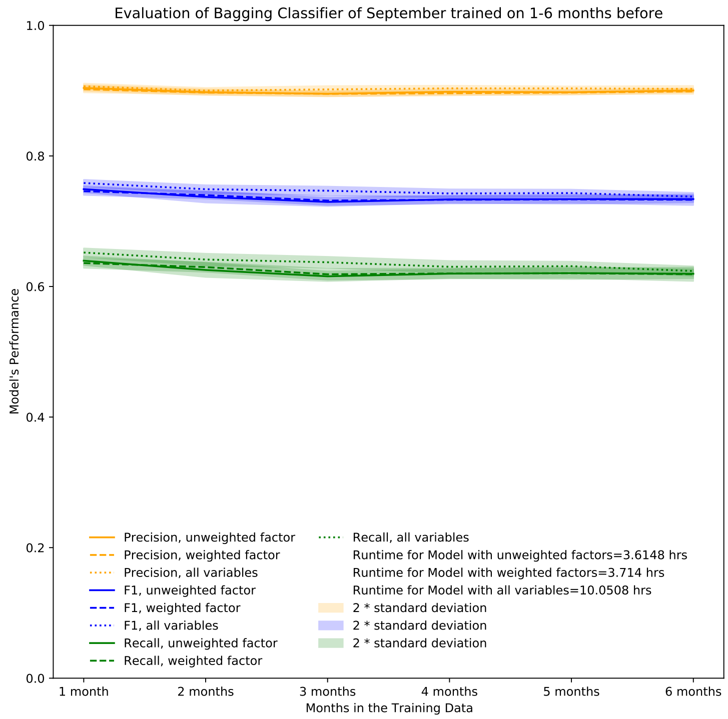


Figure 4: Evaluation of BC (cont'd)

(c)



(d)

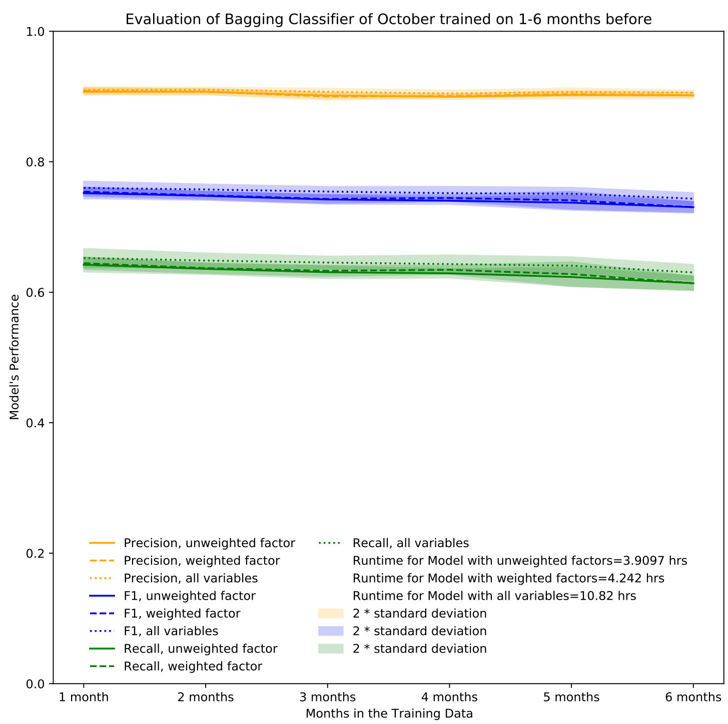
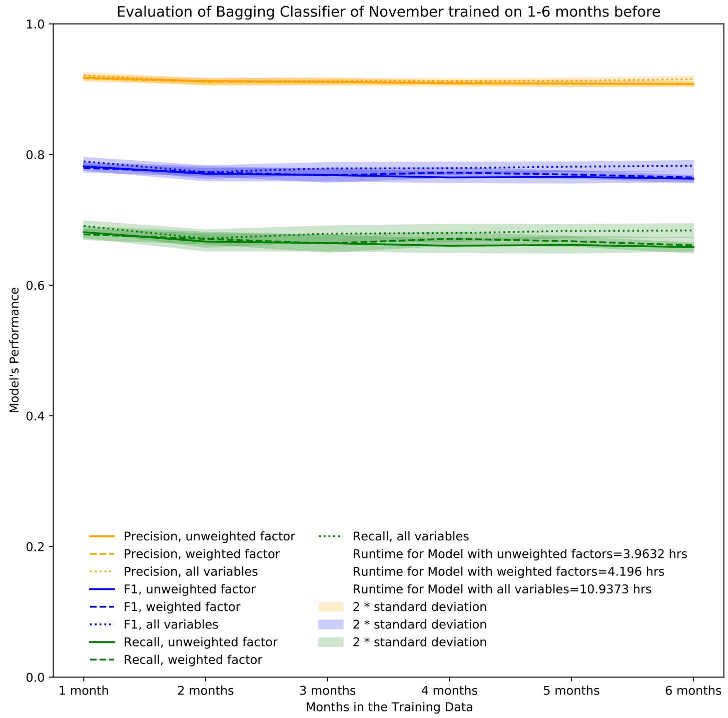


Figure 4: Evaluation of BC (cont'd)

(e)



(f)

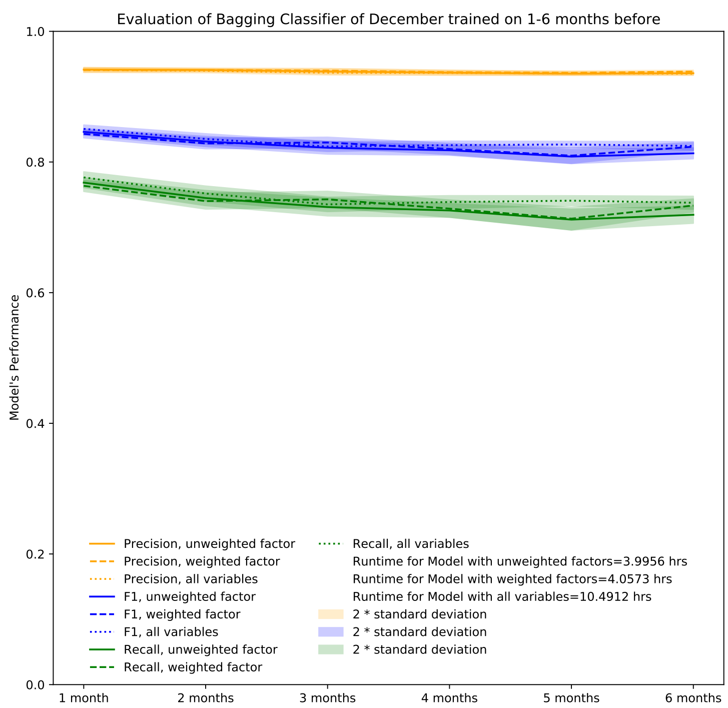
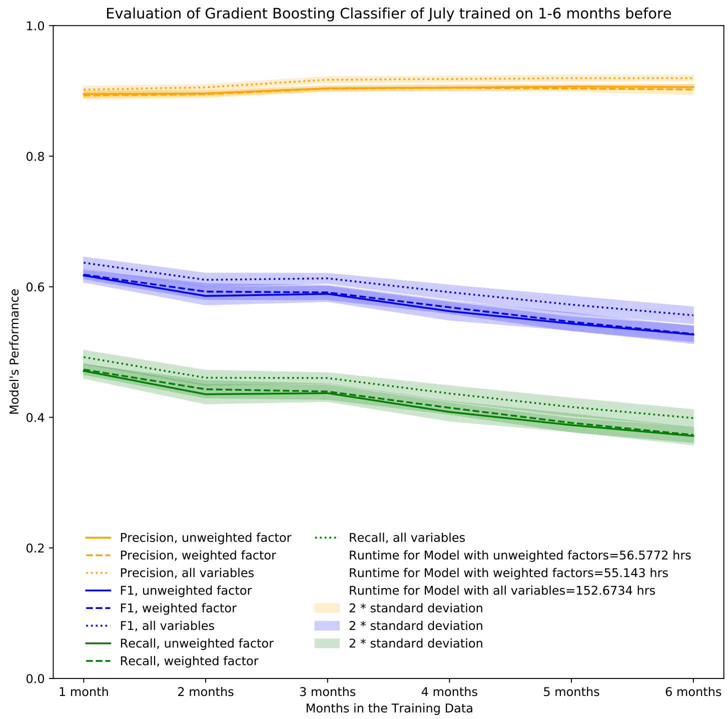


Figure 5: Evaluation of Gradient Boosting Classifier (GBC) trained on 1–6 months before (30 runs)

(a)



(b)

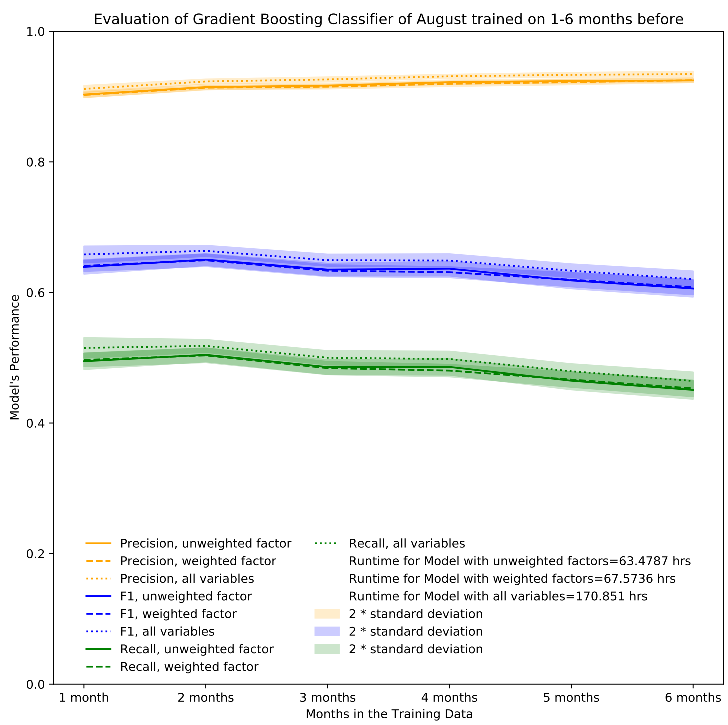
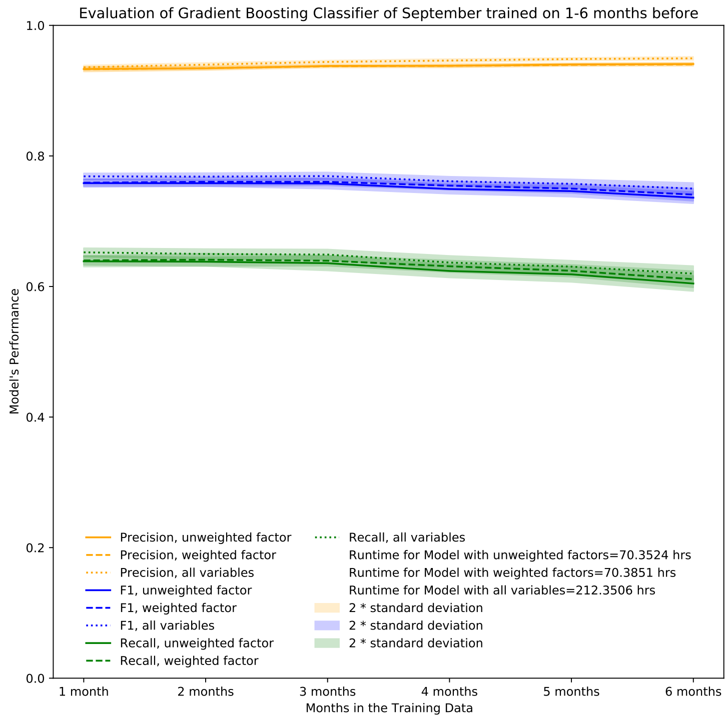


Figure 5: Evaluation of GBC (cont'd)

(c)



(d)

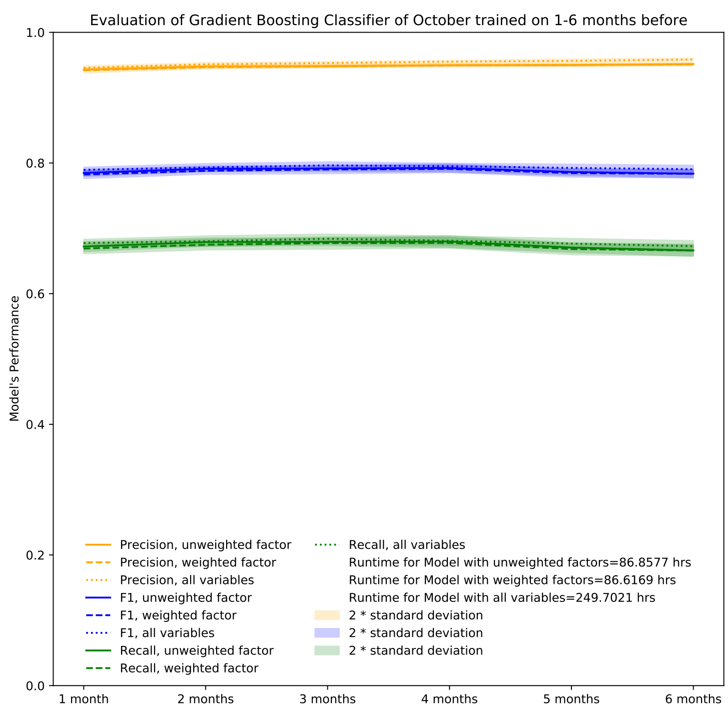
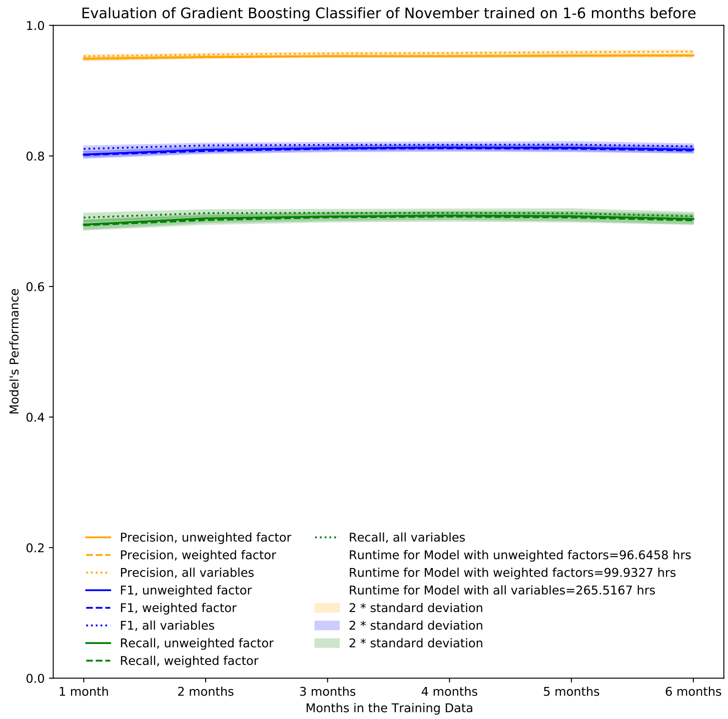


Figure 5: Evaluation of GBC (cont'd)

(e)



(f)

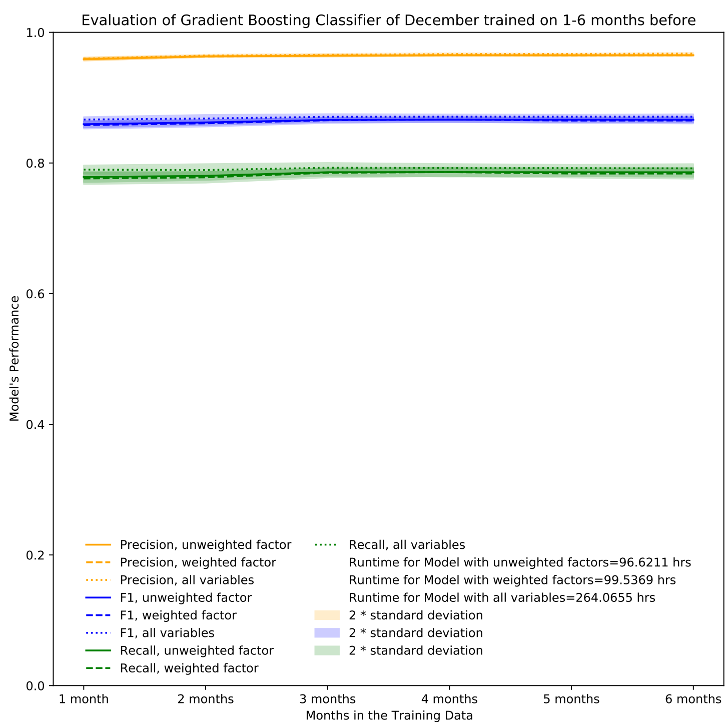
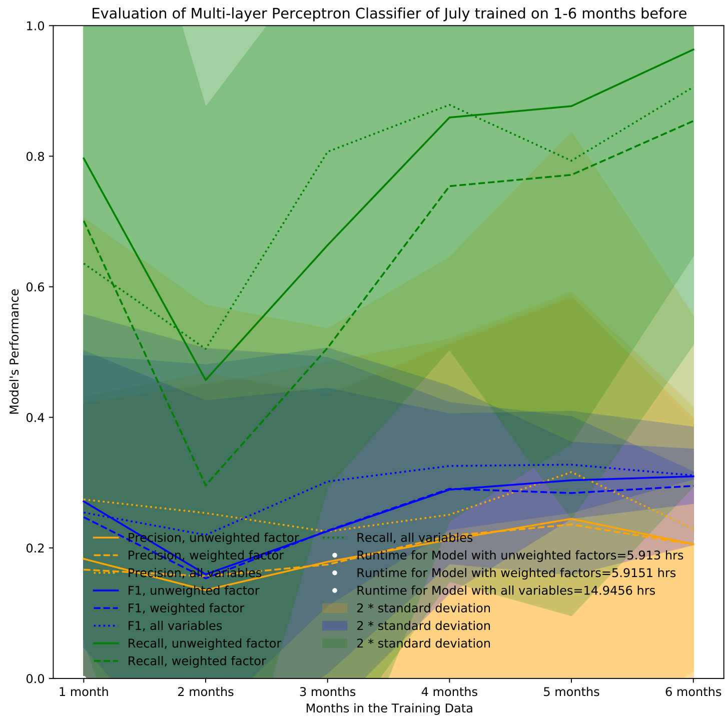


Figure 6: Evaluation of Multi-layer Perceptron Classifier (ANN) trained on 1–6 months before (30 runs)

(a)



(b)

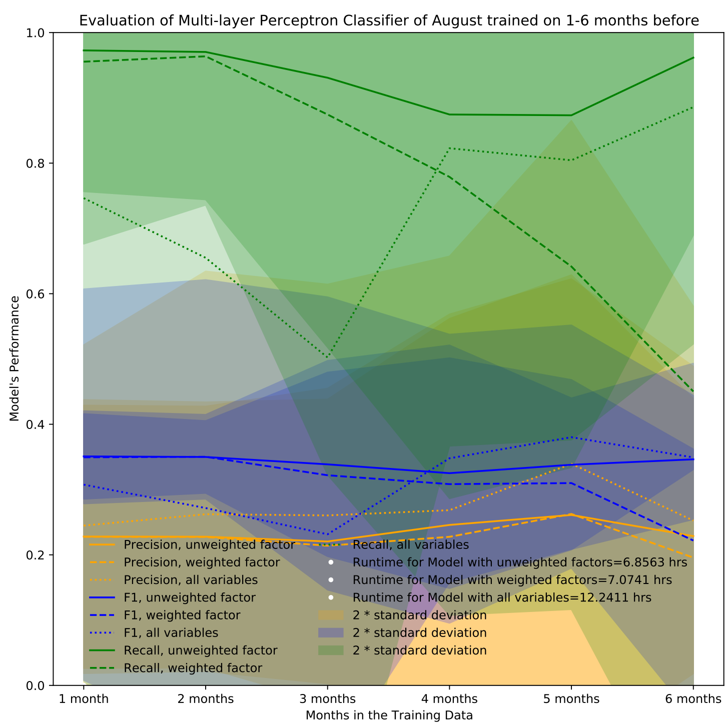
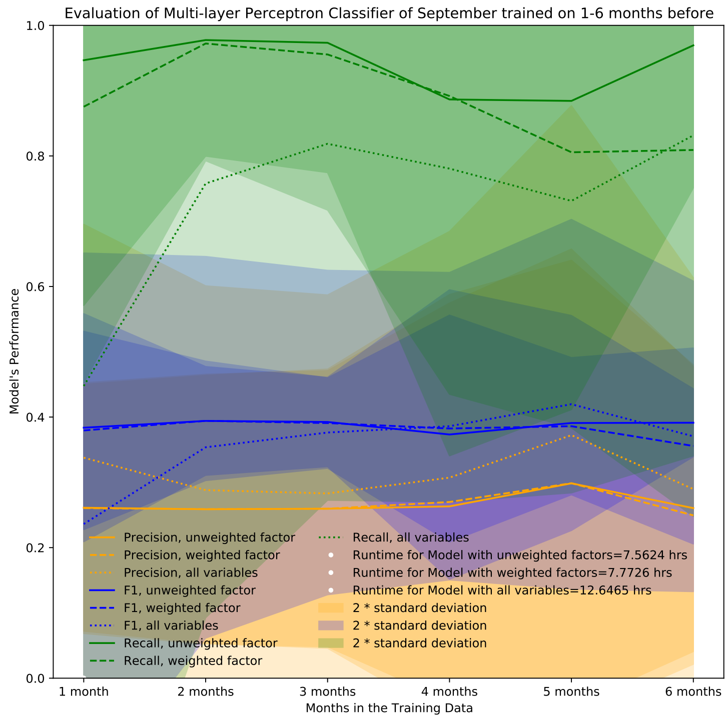


Figure 6: Evaluation of Multi-layer Perceptron Classifier (ANN) (cont'd)

(c)



(d)

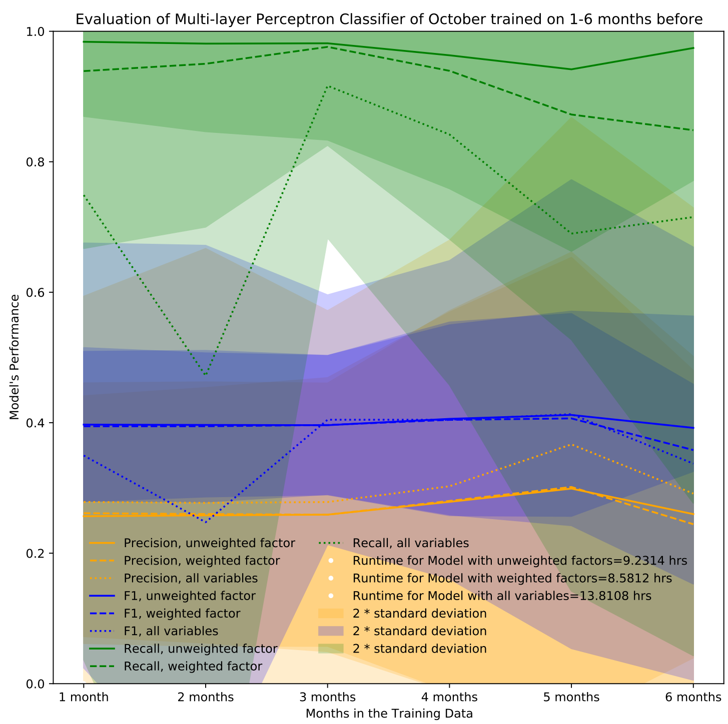
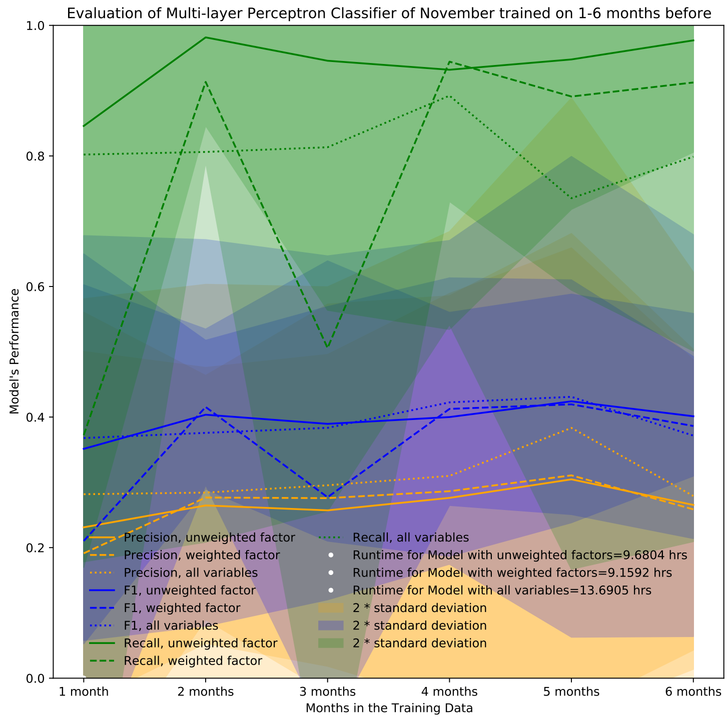


Figure 6: Evaluation of Multi-layer Perceptron Classifier (ANN) (cont'd)

(e)



(f)

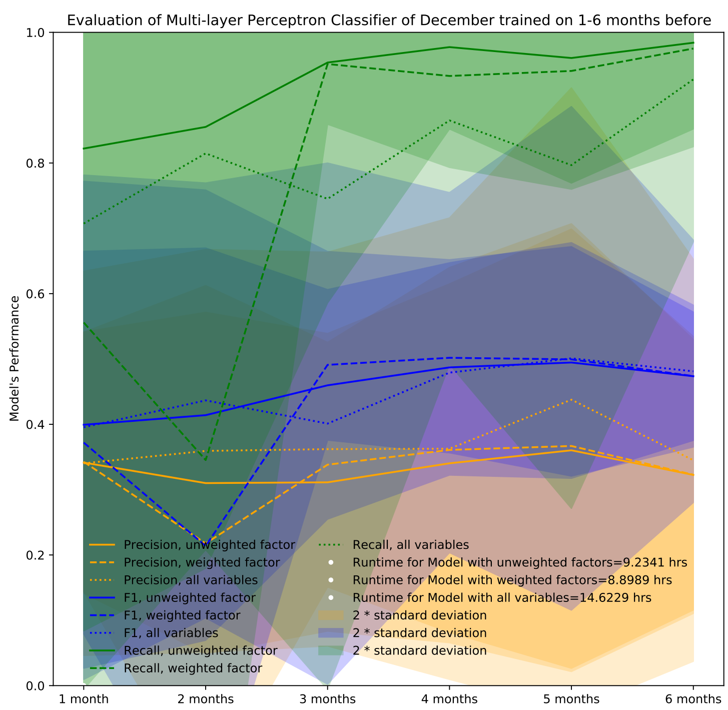
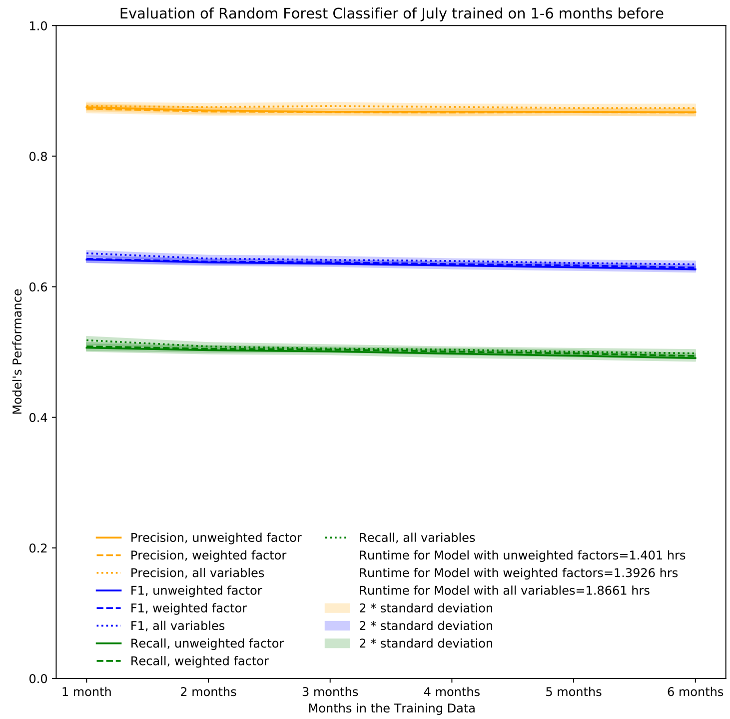


Figure 7: Evaluation of Random Forest Classifier (RFC) trained on 1–6 months before (30 runs)

(a)



(b)

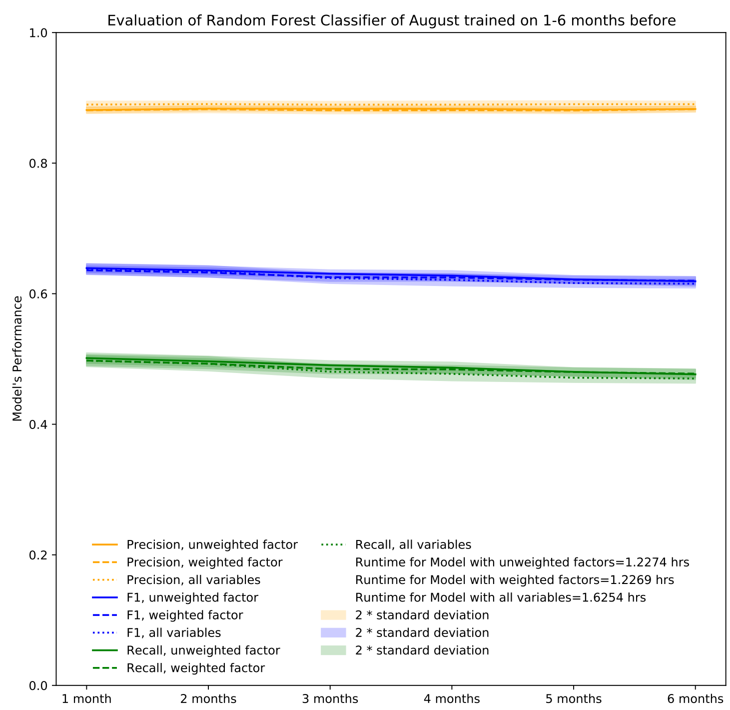
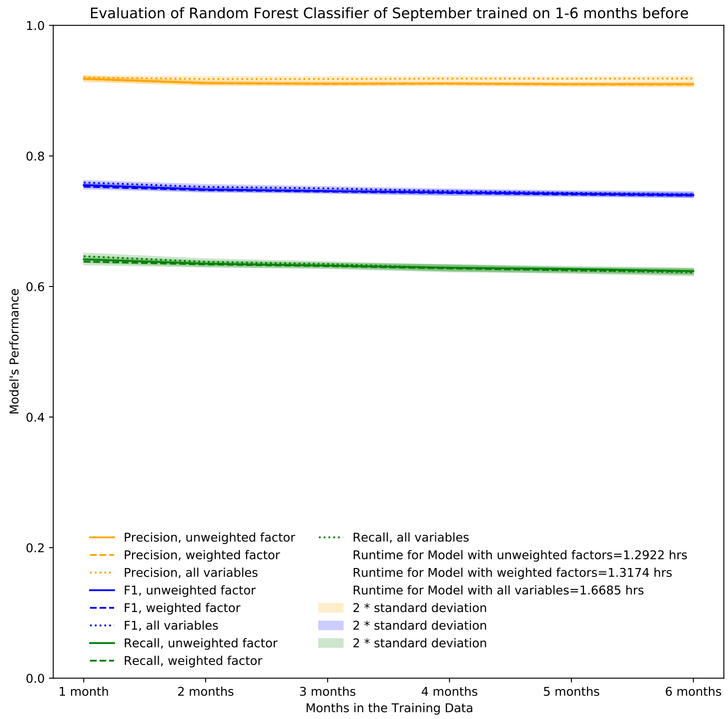


Figure 7: Evaluation of RFC (cont'd)

(c)



(d)

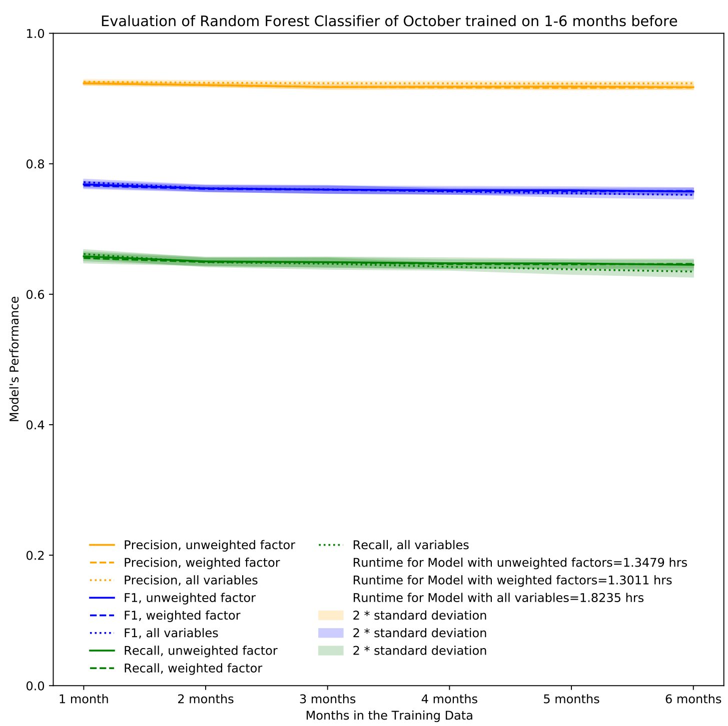
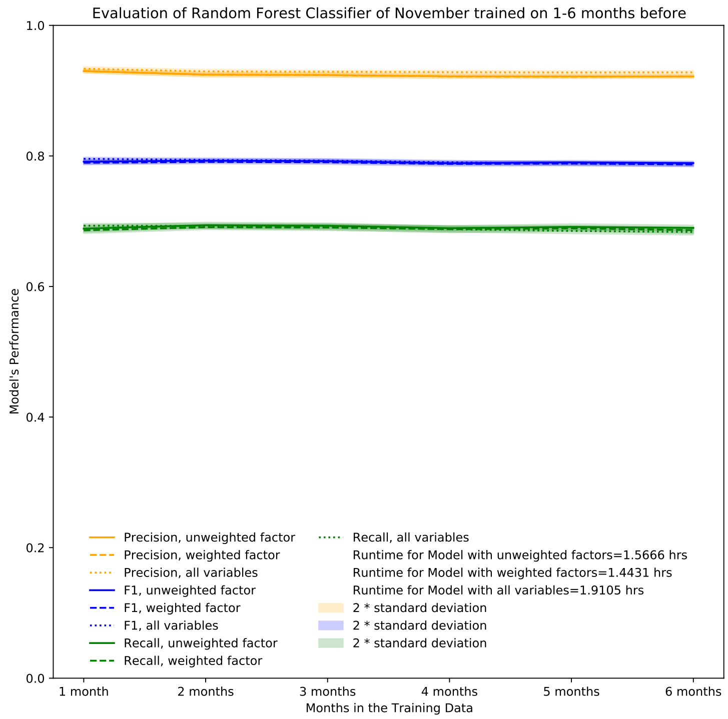
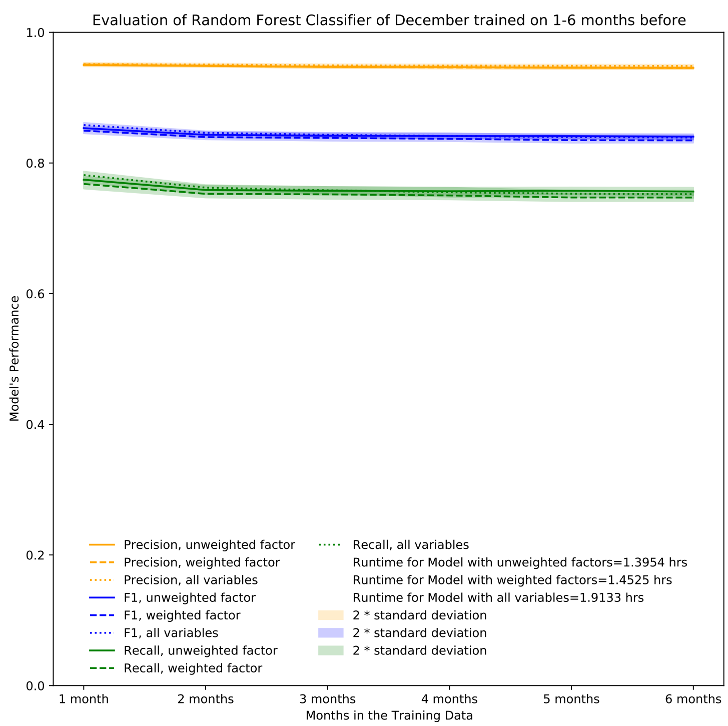


Figure 7: Evaluation of RFC (cont'd)

(e)



(f)



Appendix C – Chapter 3's material

Descriptive statistics

This section of Appendix C provides descriptive statistics supplementary to Table 3.1 in Chapter 3.

Table 5: Number of countries, firms, and observations retained during data collection

Step	Number of countries	Number of firms	Number of observations
Supplier relationships from the FactSet database	211	111,136	360,824
Firm-level control variables from the FactSet and Orbis databases	119	36,074	117,382
Country-level control variables from the WB website	115	35,156	113,771
Trade policies from the GTA database	114	35,153	113,739
Economic nationalist sentiments from MPD	47	n/a	18,535

Table 6: Firm and observation distribution by country

No.	Country name	Country ISO code	Number of firms	Number of observations	MPD
1	United States of America	USA	4103	19404	*
2	China	CHN	3724	10873	

(continued next page)

Table 6 (continued)

No.	Country name	Country ISO code	Number of firms	Number of observations	MPD
3	Great Britain	GBR	3361	8635	*
4	Japan	JPN	3084	11463	*
5	South Korea	KOR	2039	5810	*
6	India	IND	1925	5864	
7	Germany	DEU	1685	4649	*
8	Italy	ITA	1253	3233	*
9	France	FRA	1203	3500	*
10	Australia	AUS	1087	3381	*
11	Canada	CAN	907	3167	*
12	Sweden	SWE	899	2568	*
13	Singapore	SGP	592	1725	
14	Spain	ESP	580	1560	*
15	Thailand	THA	574	1745	
16	Malaysia	MYS	540	1607	
17	Norway	NOR	472	1345	*
18	Indonesia	IDN	414	1820	
19	Russia	RUS	406	1315	*
20	Finland	FIN	398	1120	*
21	Brazil	BRA	397	1328	
22	Netherlands	NLD	356	1062	*
23	Poland	POL	356	1128	*
24	Belgium	BEL	349	1011	*
25	Israel	ISR	263	1030	*
26	Vietnam	VNM	250	552	

(continued next page)

Table 6 (continued)

No.	Country name	Country ISO code	Number of firms	Number of observations	MPD
27	Denmark	DNK	249	670	*
28	Switzerland	CHE	217	941	*
29	Austria	AUT	199	578	*
30	Philippines	PHL	193	654	
31	Turkey	TUR	161	467	*
32	South Africa	ZAF	159	716	*
33	Chile	CHL	150	683	
34	Ireland	IRL	145	437	*
35	New Zealand	NZL	143	447	*
36	Hong Kong	HKG	136	588	
37	Mexico	MEX	135	588	*
38	Pakistan	PAK	122	393	
39	Luxembourg	LUX	113	301	*
40	Portugal	PRT	104	261	*
41	Romania	ROU	102	273	*
42	Colombia	COL	97	257	
43	Saudi Arabia	SAU	93	395	
44	Greece	GRC	88	285	*
45	Czechia	CZE	80	202	*
46	Sri Lanka	LKA	62	183	
47	Peru	PER	60	233	
48	Estonia	EST	58	118	*
49	Bangladesh	BGD	55	132	
50	Argentina	ARG	54	201	

(continued next page)

Table 6 (continued)

No.	Country name	Country ISO code	Number of firms	Number of observations	MPD
51	United Arab Emirates	ARE	49	197	
52	Kuwait	KWT	48	145	
53	Egypt	EGY	45	157	
54	Bermuda	BMU	44	234	
55	Croatia	HRV	43	124	*
56	Jordan	JOR	43	77	
57	Hungary	HUN	34	76	*
58	Iran	IRN	34	58	
59	Lithuania	LTU	34	89	*
60	Slovenia	SVN	34	80	*
61	Cyprus	CYP	33	85	*
62	Morocco	MAR	33	60	
63	Ukraine	UKR	33	86	*
64	Oman	OMN	32	131	
65	Bulgaria	BGR	31	85	*
66	Iceland	ISL	30	77	*
67	Serbia	SRB	29	75	*
68	Nigeria	NGA	28	132	
69	Malta	MLT	27	74	
70	Kazakhstan	KAZ	26	70	
71	Qatar	QAT	24	129	
72	Slovakia	SVK	21	36	*
73	Cayman Islands	CYM	19	63	
74	Latvia	LVA	20	58	*

(continued next page)

Table 6 (continued)

No.	Country name	Country ISO code	Number of firms	Number of observations	MPD
75	Mauritius	MUS	19	44	
76	Bahrain	BHR	12	45	
77	Tunisia	TUN	10	22	
78	Kenya	KEN	9	37	
79	Panama	PAN	9	31	
80	Ecuador	ECU	8	10	
81	Trinidad and Tobago	TTO	8	24	
82	Zambia	ZMB	8	18	
83	Zimbabwe	ZWE	8	33	
84	Algeria	DZA	6	16	
85	Botswana	BWA	6	20	
86	Ghana	GHA	5	12	
87	Ivory Coast	CIV	5	6	
88	Jamaica	JAM	5	16	
89	Uruguay	URY	5	12	
90	Tanzania, United Republic of	TZA	4	13	
91	Venezuela	VEN	4	7	
92	Bolivia, Plurinational State of	BOL	3	6	
93	Bosnia and Herzegovina	BIH	3	13	*
94	Macedonia, the former Yugoslav Republic of	MKD	3	6	*
95	Uganda	UGA	3	7	
96	Dominican Republic	DOM	2	3	
97	Georgia	GEO	2	3	

(continued next page)

Table 6 (continued)

No.	Country name	Country ISO code	Number of firms	Number of observations	MPD
98	Kyrgyzstan	KGZ	2	7	
99	Malawi	MWI	2	5	
100	Montenegro	MNE	2	5	*
101	Albania	ALB	1	5	
102	Azerbaijan	AZE	1	4	
103	Barbados	BRB	1	4	
104	Costa Rica	CRI	1	8	
105	Ethiopia	ETH	1	2	
106	Fiji	FJI	1	2	
107	Honduras	HND	1	1	
108	Lebanon	LBN	1	1	
109	Moldova, Republic of	MDA	1	5	*
110	Mongolia	MNG	1	1	
111	Rwanda	RWA	1	2	
112	Senegal	SEN	1	3	
113	Seychelles	SYC	1	2	
114	Uzbekistan	UZB	1	2	

Note: Highlighted are the countries where the number of firms available in our data is above the 25th percentile. *: included in the Manifesto Project Database (MPD).

Additional robustness checks

In this section of Appendix C, additional robustness checks are presented to reinforce the findings in Section 3.4 of Chapter 3. The results are all in accord with those discussed in the main text. Tables 7–10 use multilevel modeling while Tables 11 and 12 employ panel-data linear regression estimated by maximum likelihood to show that the results reported are robust across model specifications. The Wald tests of zero coefficients, both nonlinear and linear, support the statistical significance of each of our variables of interest.

Table 7: Test results with domestic sourcing days and implemented economic nationalist policies for Hypotheses 1–2

Dependent variable	Domestic sourcing days			
	(1)	(2)	(3)	(4)
$ENpolicies$			.0274⁑	.0263⁑
			(.0025)	(.0025)
$ENpolicies \times essentialgoods$				.0185*
				(.0076)
Essential goods				−.2263⁑
				(.0643)
GDP growth rate		−.00311	−.00206	−.00206
		(.0023)	(.0023)	(.0023)
GDP per capita		−.0365⁑	−.01673	−.01662
		(.0088)	(.0090)	(.0090)
Operating revenue (Turnover)		−.00381	−.00388	−.00383
		(.0026)	(.0026)	(.0026)
Net assets turnover		−.00170	−.00172	−.00172
		(.0016)	(.0016)	(.0016)
Constant	.3236⁑	.4819⁑	.5104⁑	.5100⁑
	(.0200)	(.0535)	(.0547)	(.0547)
Country $var(cons), \sigma^2_{\mathscr{C}}$	.03458	.03405	.03211	.03221
	(.0057)	(.0057)	(.0054)	(.0054)
Firm $var(cons), \sigma^2_{\mathscr{F}}$	.12943	.11740	.11742	.11742
	(.0011)	(.0010)	(.0010)	(.0010)
Time $var(residual), \sigma^2$	.03697	.03702	.03696	.03696
	(.0002)	(.0002)	(.0002)	(.0002)
Number of observations	113,739	113,739	113,739	113,739
Log likelihood (with group means)		−12,909	−12,846	−12,843
Log likelihood (without group means)	−14,341	−12,927	−12,862	−12,859
Likelihood ratio test $\left(Prob > \chi^2\right)$		.000	.000	.000
Akaike information criterion (AIC)	28,691	26,165	26,042	26,038
Bayesian information criterion (BIC)	28,730	27,833	27,729	27,735

$*p$<0.05; ⁑p<0.01.
Standard errors are shown in parentheses. Continuous independent variables are standardized. The models reported here are those with group means.

Table 8: Test results with implemented economic nationalist policies for Hypotheses 1–3 in a subset of countries

Dependent variable	Domestic sourcing				*ENpolicies*
	(1)	(2)	(3)	(4)	(5)
ENpolicies			.0245⁑	.0234⁑	
			(.0024)	(.0025)	
ENpolicies				.0175*	
$\times$*essentialgoods*				(.0075)	
Essential goods				−.2436⁑	
				(.0653)	
GDP growth rate		−.00108	−.00015	−.00015	
		(.0022)	(.0022)	(.0022)	
GDP per capita		−.0292⁑	−.01154	−.01144	
		(.0086)	(.0088)	(.0088)	
Operating revenue		−.00431	−.00440	−.00435	
(Turnover)		(.0025)	(.0025)	(.0025)	
Net assets turnover		−.00178	−.00179	−.00180	
		(.0016)	(.0016)	(.0016)	
ENsentiment					.1419⁑
					(.0038)
Constant	.3574⁑	.5295⁑	.5506⁑	.5504⁑	−.5344⁑
	(.0207)	(.0538)	(.0544)	(.0544)	(.1014)
Country $var(cons), \sigma^2_{\mathscr{C}}$	.03311	.02809	.02638	.02642	.41625
	(.0056)	(.0048)	(.0046)	(.0046)	(.0905)
Firm $var(cons), \sigma^2_{\mathscr{F}}$	.12784	.11599	.11601	.11601	
	(.0011)	(.0010)	(.0010)	(.0010)	
Time $var(residual), \sigma^2$	.03515	.03520	.03515	.03515	.04412
	(.0002)	(.0002)	(.0002)	(.0002)	(.0005)
Observations	113,576	113,576	113,576	113,576	18,531
Log likelihood (with group means)		$-10,590$	$-10,537$	$-10,534$	2,470
Log likelihood (without group means)	$-12,023$	$-10,607$	$-10,555$	$-10,552$	2,470
Likelihood ratio test $\left(Prob > \chi^2\right)$		.000	.000	.000	.781
Akaike information criterion (AIC)	24,055	21,526	21,424	21,421	$-4,929$
Bayesian information criterion (BIC)	24,093	23,194	23,111	23,117	$-4,882$

$*p<0.05$; ⁑$p<0.01$.
Standard errors are shown in parentheses. Continuous independent variables are standardized. The models reported here are those with group means.

Table 9: Test results with domestic sourcing days for Hypotheses 1–2 in a subset of countries

Dependent variable	Domestic sourcing days			
	(1)	(2)	(3)	(4)
$ENpolicies$			.0245⁑	.0233⁑
			(.0024)	(.0024)
$ENpolicies \times essentialgoods$				.0184*
				(.0073)
Essential goods				$-$.2477⁑
				(.0659)
GDP growth rate		$-$.00305	$-$.00198	$-$.00197
		(.0023)	(.0023)	(.0023)
GDP per capita		$-$.0363⁑	$-$.0184*	$-$.0184*
		(.0088)	(.0090)	(.0090)
Operating revenue (Turnover)		$-$.00379	$-$.00389	$-$.00384
		(.0026)	(.0026)	(.0026)
Net assets turnover		$-$.00171	$-$.00172	$-$.00173
		(.0016)	(.0016)	(.0016)
Constant	.3572⁑	.5245⁑	.5458⁑	.5455⁑
	(.0208)	(.0542)	(.0548)	(.0548)
Country $var(cons), \sigma^2_{\mathscr{C}}$	.03321	.02824	.02653	.02658
	(.0056)	(.0048)	(.0046)	(.0046)
Firm $var(cons), \sigma^2_{\mathscr{F}}$	.12954	.11748	.11751	.11750
	(.0011)	(.0010)	(.0010)	(.0010)
Time $var(residual), \sigma^2$	.03701	.03706	.03701	.03701
	(.0002)	(.0002)	(.0002)	(.0002)
Number of observations	113,576	113,576	113,576	113,576
Log likelihood (with group means)		$-12,929$	$-12,874$	$-12,871$
Log likelihood (without group means)	$-14,366$	$-12,947$	$-12,892$	$-12,889$
Likelihood ratio test $\left(Prob > \chi^2\right)$		.000	.000	.000
Akaike information criterion (AIC)	28,740	26,204	26,098	26,093
Bayesian information criterion (BIC)	28,779	27,872	27,785	27,790

$*p$<0.05; ⁑p<0.01.
Standard errors are shown in parentheses. Continuous independent variables are standardized. The models reported here are those with group means.

Table 10: Test results with domestic sourcing days and implemented economic nationalist policies for Hypotheses 1–2 in a subset of countries

Dependent variable	Domestic sourcing days			
	(1)	(2)	(3)	(4)
$ENpolicies$			.0275⁑	.0264⁑
			(.0025)	(.0025)
$ENpolicies \times essentialgoods$				.0189*
				(.0076)
Essential goods				$-.2480$⁑
				(.0659)
GDP growth rate		$-.00305$	$-.00201$	$-.00201$
		(.0023)	(.0023)	(.0023)
GDP per capita		$-.0363$⁑	$-.01642$	$-.01631$
		(.0088)	(.0090)	(.0090)
Operating revenue (Turnover)		$-.00379$	$-.00389$	$-.00384$
		(.0026)	(.0026)	(.0026)
Net assets turnover		$-.00171$	$-.00173$	$-.00173$
		(.0016)	(.0016)	(.0016)
Constant	.3572⁑	.5245⁑	.5460⁑	.5457⁑
	(.0208)	(.0542)	(.0548)	(.0548)
Country $var(cons), \sigma^2_{\mathscr{C}}$	.03321	.02824	.02649	.02654
	(.0056)	(.0048)	(.0046)	(.0046)
Firm $var(cons), \sigma^2_{\mathscr{F}}$	.12954	.11748	.11751	.11751
	(.0011)	(.0010)	(.0010)	(.0010)
Time $var(residual), \sigma^2$	.03701	.03706	.03701	.03700
	(.0002)	(.0002)	(.0002)	(.0002)
Number of observations	113,576	113,576	113,576	113,576
Log likelihood (with group means)		$-12,929$	$-12,866$	$-12,863$
Log likelihood (without group means)	$-14,366$	$-12,947$	$-12,884$	$-12,881$
Likelihood ratio test $\left(Prob > \chi^2\right)$		.000	.000	.000
Akaike information criterion (AIC)	28,740	26,204	26,082	26,077
Bayesian information criterion (BIC)	28,779	27,872	27,769	27,774

$*p<0.05$; ⁑$p<0.01$.
Standard errors are shown in parentheses. Continuous independent variables are standardized. The models reported here are those with group means.

Table 11: Test results for Hypotheses 1–2 with panel-data linear regression estimated by maximum likelihood

Dependent variable	Domestic sourcing		Domestic sourcing days	
ENpolicies measured by	implemented policies	announced policies	implemented policies	announced policies
ENpolicies	.0233⁑	.0198⁑	.0263⁑	.0232⁑
	(.0025)	(.0023)	(.0025)	(.0024)
ENpolicies	.0176*	.0175*	.0190*	.0185*
$\times$*essentialgoods*	(.0075)	(.0071)	(.0076)	(.0072)
Essential goods	−.2374⁑	−.2371⁑	−.2416⁑	−.2414⁑
	(.0645)	(.0645)	(.0650)	(.0650)
GDP growth rate	−.00004	−.00004	−.00188	−.00184
	(.0022)	(.0022)	(.0023)	(.0023)
GDP per capita	−.01166	−.01408	−.01652	−.0186*
	(.0088)	(.0087)	(.0090)	(.0090)
Operating revenue	−.00433	−.00433	−.00383	−.00384
(Turnover)	(.0025)	(.0025)	(.0026)	(.0026)
Net assets turnover	−.00179	−.00179	−.00173	−.00172
	(.0016)	(.0016)	(.0016)	(.0016)
Constant	.8860⁑	.8877⁑	.8896⁑	.8910⁑
	(.1931)	(.1931)	(.1948)	(.1948)
Panel-level standard	.33983	.33982	.34203	.34202
deviation σ_υ	(.0015)	(.0015)	(.0015)	(.0015)
Standard deviation of	.18738	.18741	.19225	.19227
the idiosyncratic error σ_ε	(.0005)	(.0005)	(.0005)	(.0005)
Fraction of variance due to	.76685	.76679	.75991	.75987
panel effect (ρ)	(.0019)	(.0019)	(.0020)	(.0020)
Observations	113,739	113,739	113,739	113,739
Log likelihood	$-10,311$	$-10,321$	$-12,641$	$-12,649$
Akaike information criterion (AIC)	21,188	21,207	25,848	25,863
Bayesian information criterion (BIC)	23,917	23,936	28,577	28,592
B-P LM test $\left(Prob > \chi^2\right)$	.000	.000	.000	.000
Hausman test $\left(Prob > \chi^2\right)$	.000	.000	.000	.000

$*p$<0.05; ⁑p<0.01. B-P LM: Breusch-Pagan Lagrange multiplier.
Standard errors are shown in parentheses. Continuous independent variables are standardized. The models reported here are those with group means.

Table 12: Test results for Hypotheses 1–2 in a subset of countries with panel-data linear regression estimated by maximum likelihood

Dependent variable	Domestic sourcing		Domestic sourcing days	
ENpolicies measured by	implemented policies	announced policies	implemented policies	announced policies
ENpolicies	.0234⁑	.0198⁑	.0264⁑	.0232⁑
	(.0025)	(.0023)	(.0025)	(.0024)
ENpolicies	.0178*	.0177*	.0191*	.0186*
$\times$*essentialgoods*	(.0075)	(.0071)	(.0076)	(.0073)
Essential goods	−.2381⁑	−.2378⁑	−.2423⁑	−.2421⁑
	(.0653)	(.0653)	(.0659)	(.0659)
GDP growth rate	−.00005	−.00005	−.00191	−.00187
	(.0022)	(.0022)	(.0023)	(.0023)
GDP per capita	−.01159	−.01402	−.01646	−.0185*
	(.0088)	(.0088)	(.0090)	(.0090)
Operating revenue	−.00435	−.00434	−.00384	−.00384
(Turnover)	(.0025)	(.0026)	(.0026)	(.0026)
Net assets turnover	−.00179	−.00179	−.00173	−.00172
	(.0016)	(.0016)	(.0016)	(.0016)
Constant	.8862⁑	.8880⁑	.8898⁑	.8913⁑
	(.1933)	(.1933)	(.1950)	(.1950)
Panel-level standard	.34010	.34009	.34229	.34228
deviation σ_υ	(.0015)	(.0015)	(.0015)	(.0015)
Standard deviation of	.18749	.18751	.19236	.19238
the idiosyncratic error σ_ε	(.0005)	(.0005)	(.0005)	(.0005)
Fraction of variance due to	.76693	.76687	.75998	.75993
panel effect (ρ)	(.0019)	(.0019)	(.0020)	(.0020)
Observations	113,576	113,576	113,576	113,576
Log likelihood	$-10,357$	$-10,367$	$-12,686$	$-12,694$
Akaike information criterion (AIC)	21,222	21,241	25,880	25,896
Bayesian information criterion (BIC)	23,671	23,690	28,329	28,344
B-P LM test $\left(Prob > \chi^2\right)$	.000	.000	.000	.000
Hausman test $\left(Prob > \chi^2\right)$	.000	.000	.000	.000

$*p$<0.05; ⁑p<0.01. B-P LM: Breusch-Pagan Lagrange multiplier.
Standard errors are shown in parentheses. Continuous independent variables are standardized. The models reported here are those with group means.