Michael Westerburg

Performance Implications of Supply Chain Risk and Risk Management

Michael Westerburg
Endowed Chair of Procurement
Business School
University of Mannheim

Performance Implications of Supply Chain Risk and Risk Management

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M.Sc. Michael Westerburg
Mannheim

Dekan:	*Prof. Dr. Dieter Truxius*
Referent:	*Prof. Dr. Christoph Bode*
Korreferent:	*Prof. Dr. Moritz Fleischmann*

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Summary

Firms operate in a complex world characterized by interdependencies among various factors which are difficult to anticipate and can pose a risk to a firm's operations. On the one hand, prior research has identified major categories of supply chain risk. On the other, it has established that supply chain disruptions do indeed negatively affect a firm's performance once they materialize. However, prior research has not explained which external uncertainties actually turn into what type of risk exposure. Moreover, such research has not yet explained under what conditions external events are extraordinarily harmful, and whether firms should have managed these potential risks. In order to fill in this lack of knowledge, this dissertation has developed a new measurement of a firm's exposure to risk. To this end, it scrutinizes a firm's 10-K reports and transforms the unstructured textual data into quantitative information. The resulting novel data set is augmented by financial and other publicly available secondary data. The results suggest that the industry is an important moderator of how external threats affect a firm's performance. Furthermore, external threats always increase a firm's exposure to risk, while internal strategies partly increase and partly decrease such an exposure. Finally, a firm must carefully analyze the type of risk to which it is exposed, because the efficiency of the mitigation strategy employed depends on the type of risk exposure. In sum, this dissertation suggests exploiting a firm's self-disclosed textual information by means of linguistic computer analysis. As a result, it provides new answers to new research questions and hence extends the existing knowledge in the field of supply chain risk management.

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1 Introduction

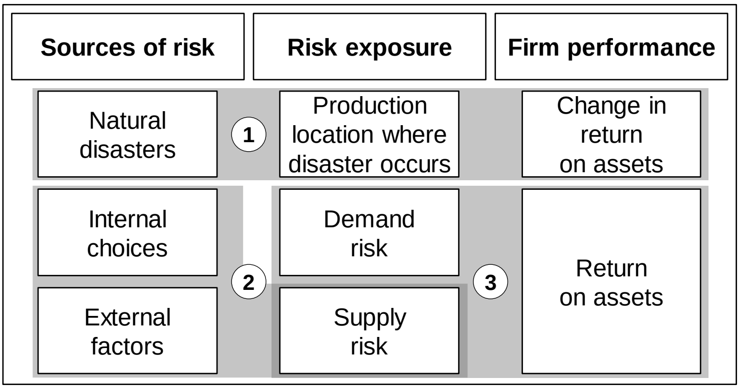
In an ideal business world, a firm possesses assured finances, receives a steady flow of supply for its operations, runs its operations without interruptions, and satisfies customer demand successfully which materializes as forecasted. In other words, a firm operates smoothly in an accommodating world. In reality, the external environment, however, poses challenges which are difficult to anticipate and can interfere with a firm's planned operations. For example, both the supply and the demand side of a firm are susceptible to risk which can materially influence a firm's performance. The suppliers that provide key raw materials and components in accordance with a firm's specifications might go bankrupt or fail in other ways with the result that they can no longer deliver the required products. Likewise, customers who buy the final product might have new or changing needs with the result that they stop buying the firm's product. In the same way, the further external environment beyond the supply or demand side can also exert a strong negative influence on a firm's success: Natural disasters may damage or even destroy production facilities if a firm operates in areas where such risks occur; market dynamics can render a successful product obsolete if a new entrant develops a convincing substitute; direct competitors can alter their competitive activities in such a way that a firm's profit margins are substantially eroded.

While these challenges may well harm a firm's performance, the true risk exposure depends on the strategies selected by the firm, the alternatives available, and the industrial environment in which a firm operates. Although firms are exposed to a theoretically unlimited number of challenges, in reality only a minority of these potential challenges or risks presents a serious problem. Most importantly, some risks may be totally irrelevant for a given firm. For example, a firm which operates far from the coastline can never be exposed to the risk of a tsunami destroying its production facilities. Similarly, a monopolist can ignore the risk of a price war in the short term because there are effectively no competitors in the market. Yet, if a firm is confronted with a risk, it can actively decrease its vulnerability to such a risk. Typical risk management strategies that address a firm's potential vulnerability include preventative and avoidance strategies. A firm can establish a relationship with a second-source supplier, for instance, to reduce the risk of supply interruptions (prevention). Alternatively, it can modify the specifications of a purchased product in such a way that the product represents a commodity for which several suppliers come into question (avoidance). Nevertheless, some circumstances may make it impossible for a firm to reduce its vulnerability completely, either because this is infeasible or economically prohibitive. This residual risk is subsequently denoted as risk exposure and limits the overall risk to one which a firm has recognized but neither prevented nor avoided. This risk exposure can potentially have a negative effect on a firm's performance, should some event materialize. Typical risk management strategies that address the consequences of materialized risk include risk mitigation and risk transfer strategies. Considering the above example of a supply interruption, a firm can maintain additional safety stock in order to be able to resume production in the event of supplier failure (mitigation). Alternatively, it can cover financial losses due to a supply shortage by a production interruption insurance (transfer). Although these strategies lower the negative effect should some event materialize, they also lead to immediate cost without return should no damaging event occur. Finally, a firm can simply decide to do nothing about its exposure at all (acceptance) which is for free should no event occur but can result in high cost otherwise. As a result, firms face some kind of lottery: Should they incur some sure cost now to reduce future possible negative effects or should they avoid the sure cost now and accept possible higher payouts in the future? In order to make a sensible decision, firms must understand the sources of their risk exposure, the conditions under which events lead to extraordinarily negative consequences, and the strategies that efficiently tackle their risk exposure.

Despite its importance, risk exposure has up to now been largely neglected: On the one hand, researchers have categorized the different types of risk that firms might face. To this end, different categories such as supply risk, demand risk, technology risk, infrastructure risk, or catastrophic risk have been specified.

However, these studies only explain what type of risk a firm might face in general terms, but do not explain specifically which uncertainties turn into what type of risk exposure. On the other hand, researchers have investigated the effect of actual materialized events in depth. If a firm announces that it has experienced a shortfall in supply or its operations are otherwise disturbed, its performance – measured in terms of several dimensions (e.g., share price, net income, or operating profit) – declines on average. This observation may lead to the conclusion that these actual materialized events do evidently pose a threat to a firm and should have been managed accordingly. Although the subsequent analysis of actual materialized events provides important evidence that disruptions do really matter, it cannot explain, however, whether a firm is potentially exposed to a given type of risk, whether this risk exposure possesses negative implications as far as a firm's performance is concerned, and whether the mitigation of the respective risk would have been beneficial in expectancy. Very few studies have actually attempted to measure a firm's potential exposure to risk. One notable exception is the study by Wagner and Bode (2008) which investigates the relationship between risk exposure and operating performance based on a survey among executives.

Figure 1-1: Relationships between sources of risk, risk exposure, and performance outcomes as analyzed in this dissertation



Note: Shaded areas indicate separate paper projects, overlap indicates common variables.

This dissertation now focuses on a firm's potential risk exposure and sheds light on the relationships between exposure to supply chain risk on the one hand and sources of risk or performance outcomes on the other in three separate essays. Figure 1-1 illustrates linkages between the constructs investigated and highlights the core of each essay. The first essay focuses on the risk of natural disasters and how this affects a firm's performance under different conditions. It addresses the following research question: To what extent do industry attributes mitigate or exacerbate the negative effect of a natural disaster? The second essay focuses on supply risk in particular and evaluates the sources of supply risk with the result that the following research question is answered: What environmental uncertainties and which internal strategic choices turn into an exposure to risks in the supply chain? The third essay explores supply and demand risk, how the exposure to these risks affects a firm's performance, and what a firm can do about these risks. Specifically, it provides an answer to the last research question: How do firms deal efficiently with an exposure to such supply chain risk?

In an attempt to provide answers to these research questions, this dissertation has constructed – based on publicly available secondary data – new measurements of a firm's exposure to supply chain risk. To this end, firms' annual reports (Form 10-K) were scrutinized. Annual reports are arguably among the most important means of communication for firms and a crucial source of information for share- and other stakeholders. The main objective of a firm's financial reporting is to inform investors on the amount, timing, and degree of uncertainty about future cash flows. By publishing information in their annual reports, firms legitimize their position vis-à-vis stakeholders, gain access to financial capital or other resources from outside the firm, and put themselves in an advantageous position over competitors. 10-K reports are composed of several elements, such as the income statement, the cash flow statement, the balance sheet, and qualitative descriptions of the firm's situation. The great advantage of 10-K reports is their standardized structure and the set order of topics mandated by the United States Securities and Exchange Commission (SEC). Each relevant topic is dealt with in a separate chapter which is headed as an "Item". Information in the 10-K report comprises both descriptions of the current and past financial years as well as forward-looking statements concerning future prospects. The information content, style, and language of 10-K reports have been investigated in the course of numerous studies in the fields of accounting and finance. In general, 10-K reports have been found to be adequately informative about a firm's competitive position (Gao et al., 2016). In particular, firms also provide operations-related information in their 10-K reports. In Item 1.A of a firm's 10-K report, the SEC mandates firms to disclose those factors that “make the offering speculative or risky” (SEC, 2005). Among all the risk factors that firms disclose in Item 1.A they also report on supply chain risk factors. In Item 2 a firm must describe the significant properties (e.g., plants, mines, other physical properties) that it controls. This description comprises both self-owned and leased property and hence provides a detailed picture of a firm’s production network. As one of the first in the field of operations management, this dissertation relies on 10-K reports as a valuable source of information. For the analysis on a large scale, it employs automated text mining algorithms to elicit the desired information. The information from the 10-K reports is augmented by financial data (e.g., balance sheet, income statement) from secondary data sources describing the industry in which a firm operates, the strategies it pursues, and the overall performance it delivers.

Contingency theory has been applied as theoretical lens to investigate the relationships which exist between a firm’s risk exposure, its environment, and its strategies. In a nutshell, contingency theory posits that firms must be designed to cope with the uncertainties in their environment and must change appropriately in order to remain effective. The more drastic and unforeseen such changes in the environment are, the more difficult becomes the identification of appropriate decisions by managers in response to these changes. Throughout this dissertation, a firm’s environment is characterized by contextual factors like competitive intensity, sales growth, demand volatility, or pace of technological change within the industry in which a firm operates. A firm’s effectiveness in coping with changes in the environment is described by its profitability, whereas managerial decisions are depicted by inventory levels and spare capacity as well as business and geographic diversification. The findings suggest that the analysis of risk exposure contributes to the understanding of a firm’s competitive position, its decisions, and ultimately its performance.

Chapter 2 presents an empirical study on the moderating effect of the industrial environment on the negative association between the effect of a natural disaster on a firm’s production network and its subsequent performance. The study has been motivated by the observation that economies can rebound quickly from the destruction caused by natural disasters provided that aid is directed to the right recipients. Just as people differ with respect to their need for help, the same holds good for firms. If financial aid is directed to the right firms after a disaster has damaged or destroyed their assets, firms can recover more quickly and the economic repercussions of the natural disaster are reduced to such an extent that the overall welfare losses are kept to a minimum. However, the question still remains which firms exactly require disaster relief aid. Applying the conceptual model of contingency theory, the study argues that the effect of a natural disaster on a firm's performance is primarily contingent on the industrial environment in which a firm operates. Firms that operate in certain industrial environments may require aid, while others in a different environment do not. For this study, Item 2 was extracted from a firm's 10-K report. It presents the significant physical properties controlled by a firm. Thus, Item 2 describes where a firm may be vulnerable to the destruction of its assets by natural disasters. For the identification of locations in Item 2, a named entity recognition (NER) tagger from computational linguistics was deployed. Subsequently, data on natural disasters collected by the Center for Emergency Management and Homeland Security at the Arizona State University were matched to the location information in order to identify those firms that had actually been hit by a natural disaster. Finally, these data were augmented by financials which described a firm's industrial environment in terms of its three generally accepted attributes: complexity, munificence, and dynamism. A difference-in-difference regression model was then employed to test the hypothesized relationships. The empirical results suggest that the occurrence of a natural disaster does indeed have a negative effect on a firm's performance. More importantly, this negative effect is intensified in high-complexity and high-munificence industries. These results support the conclusion that disaster relief aid should be first of all directed to firms operating in such industries in order to mitigate negative performance repercussions. The provision of aid is less important in low-complexity and low-munificence industries. This article has been written jointly with Christoph Bode[1].

The study in Chapter 3 empirically investigates the sources of supply risk exposure. It has been motivated by the observation that the interplay between the industrial environment in which a firm operates and the strategic decisions which it actively makes strongly influence a firm's performance. Primarily conceptual models postulate that risk is in reality a function of how a strategy is likely to perform in an unexpected scenario (Porter, 1985) or a function of the

[1] Westerburg, M. and Bode, C., 2018. Relief or burden? The role of the economic environment after a natural disaster. *Unpublished Working Paper,* 1-32.

interaction of strategy and industry (Baird and Thomas, 1985). Although supply chain risk exposure in particular is a highly critical factor, it has not yet received sufficient attention. Moreover, time may exhibit other effects those those of differences between firms. On the basis of the literature dealing with strategic management and organizational theory, the main factors from the industrial environment affecting a firm and the strategic decisions made by the firm are delineated and their effect on the supply risk exposure is hypothesized. This study has used the disclosure of risk factors in Item 1.A of a firm's 10-K report for the measurement of a firm's risk exposure. A risk is defined as a possible loss caused by future events (FASB, 1975). The risk disclosed can cover a wide range of topics, such as the risk from a firm's supply or operations, its employee risk, refinancing risk, or regulatory risk (FASB, 1975). A previously developed sentence latent Dirichlet allocation (sLDA) algorithm was employed to identify only supply-related risk items within Item 1.A and quantify a firm's exposure to such risks. The factors characterizing a firm's industrial environment were technological change and complexity. A firm's strategic decisions comprehended business and geographic diversification strategies. The empirical analysis utilizing a multi-level regression model explicitly distinguishes different levels present in the data set. The results suggest that the industrial environment increases a firm's exposure to supply risk in both the short and the long term. In contrast, business diversification appears to be an appropriate strategy for actively managing a firm's exposure to supply risk in the long term, although it does increase a firm's exposure to supply risk in the short term. Also, the results provide an indication of what type of risk a firm can expect from operations in an industry characterized by a certain set of factors or the pursuit of a certain set of business strategies. This article has been written jointly with Christoph Bode[2].

Chapter 4 deals in more detail with risk mitigation strategies to tackle risk exposure. This study has been motivated by the observation that firms are under severe pressure to simultaneously lower their operating costs and their risk exposure. If a firm accepts too much risk, then disruptions and consequential

[2] Westerburg, M. and Bode, C., 2018. Sources of supply risk: Environment or strategic choice?. *Unpublished Working Paper,* 1-42.; an earlier version was nominated for the Chan Hahn Best Paper Award of the Operations and Supply Chain Management Division of the Academy of Management at the Annual Meeting in Chicago, IL in 2018; abbreviated paper published as: Westerburg, M. and Bode, C., 2018. Sources of supply chain risk: External environmental factors or strategic choice?. In Guclu Atinc (Ed.), *Proceedings of the Seventy-eighth Annual Meeting of the Academy of Management.*

operational losses are almost certain. By contrast, if a firm invests too much in risk management, its operations become inefficient and profit margins decline. Only a few guidelines exist which indicate what risk management strategies firms should employ against a given type of risk. Against the backdrop of information processing theory, the study posited that firms could introduce operational slack to meet outside uncertainties. However a contingency perspective suggests that the type of operational slack must be matched to the type of uncertainty in order to be efficient (i.e., minimum negative impact on performance). This study also derived its risk exposure from Item 1.A of the 10-K reports. In this study, the sLDA algorithm was employed to identify and quantify two types of risk, demand and supply. The types of operational slack investigated were inventory and capacity. Utilizing a fixed effects regression model, this study first demonstrates a negative relationship between the two types of risk exposure and firm performance. Second, the effect of operational slack was investigated. In line with arguments from contingency theory, operational slack effectively mitigates the association between supply risk exposure and performance, but exacerbates the effect of demand risk on firm performance. Third, the joint effect of both types of operational slack on the link between risk exposure and performance is greater than the sum of their parts. By the "right" combination of the two types of operational slack, a firm can further decrease the negative performance implications of risk while not incurring additional costs. This article has been written jointly with Christoph Bode[3].

[3] Westerburg, M. and Bode, C., 2018. Supply chain risk and risk mitigation: Which strategies tackle identified risks most efficiently?. *Working Paper*, 1-40. Available at SSRN: https://ssrn.com/abstract=3215155.; an earlier version received the ISM Best Paper Award in Supply Chain Management of the Operations and Supply Chain Management Division of the Academy of Management at the Annual Meeting in Atlanta, GA in 2017; abbreviated paper published as: Westerburg, M. and Bode, C., 2017. Supply chain risk and risk mitigation: Which strategies tackle identified risks most efficiently?. In Guclu Atinc (Ed.), *Proceedings of the Seventy-seventh Annual Meeting of the Academy of Management.*

2 Relief or Burden? The Role of the Economic Environment after a Natural Disaster

Co-author:

Christoph Bode

Endowed Chair of Procurement, Business School, University of Mannheim, Germany

Abstract:

Natural disasters can have severe negative effects on people, businesses, and the environment. However, empirical evidence suggests that some countries are less affected by a disaster compared to others, which has been attributed to various country-specific characteristics. The present paper investigates whether this phenomenon also exists at the firm level and how certain characteristics of the industrial environment, specifically the three attributes of complexity, munificence, and dynamism, influence the relationship between disaster occurrence and firm performance. The locations of firms' production networks were identified in annual reports using a named entity recognition tagger from computational linguistics and linked with disaster occurrences. Based on these data, a negative association between natural disaster occurrence and firm performance could be established employing a difference-in-difference regression estimation. Furthermore, this observed negative relationship was found to be exacerbated by industry complexity and munificence.

2.1 Introduction

Natural disasters pose a serious threat to people, businesses, and the environment alike. They are among the top risks worldwide in terms of impact and likelihood of occurrence (WEF, 2018). For 2017, total losses of US-$ 340bn were recorded, exceeding the record losses of US-$ 163bn in 2005 with hurricanes Katrina, Rita, and Wilma (MunichRe, 2018). Additionally, the number of weather-related disasters causing billion-dollar damages has been on a constant rise since 1985 (NOAA, 2018). For firms, the negative effects of natural disasters are twofold. On the one hand, natural disasters can directly destroy a firm's productive assets (Belasen and Polachek, 2009, Strobl, 2011). On the other hand, natural disasters are a major cause of business interruptions (Allianz, 2018) with negative indirect repercussions, such as a delay of product introductions (Reuters, 2011) or a decline in firm performance (Hendricks and Singhal, 2005a).

Yet, under certain conditions, natural disasters have a less severe negative effect on economies. If the economic development level of a country is high, if its institutional quality is high, or if societal resilience measures are in place, the negative effect of a disaster on a country's welfare is lower (e.g., Cuaresma et al., 2008, Felbermayr and Gröschl, 2014, Kahn, 2005, Noy, 2009). Furthermore, the long-term negative economic loss from natural disasters can be decreased if assets and profitability are restored quickly after the disaster occurred (Leiter et al., 2009, Okuyama, 2003). Similar moderation mechanisms might also exist at the firm level. Under certain conditions, the effect of a natural disaster on a firm's performance might be stronger or weaker. It is important to identify such conditions because they hint at firms that require urgent aid. The more quickly the most severely affected firms of a country's economy are identified and receive aid, the less negative the country's economic outlook becomes due to the natural disaster. As a result, firms stay in business and provide jobs; thus, people are less likely to move away after the disaster (Belasen and Polachek, 2009). An important level of analysis is the industry (Ketokivi, 2006). According to extant literature, industries can be characterized by three attributes: (a) munificence, (b) dynamism, and (c) complexity (Dess and Beard, 1984, Keats and Hitt, 1988). Our research questions address these three industry attributes. Specifically, we asked, (1) Do natural disasters have a negative influence on firm performance? and (2) To what extent do the industry attributes – (a) munificence, (b) dynamism, and (c) complexity – exacerbate (mitigate) the negative association? The answers to these research questions respond to calls for further research on the relationship between natural disasters and their effect on firms (Cavallo and Noy, 2011, Zhou and Botzen, 2017).

To address these research questions empirically, we collected and analyzed a unique set of data. First, a firm's production network was identified in its 10-K report using a named entity recognition (NER) tagger from computational linguistics. Second, places where natural disasters occurred were linked to the firm's production locations. Third, financial information of firms was merged with the production and disaster location data. This novel data set allowed us to clearly link disaster occurrences to production plants and firms. After establishing a negative direct effect of natural disasters on firm performance, we explored different industry attributes that moderated the negative relationship between natural disasters and firm performance.

This study contributes to the extant research in several important ways. To begin with, we contribute to the literature by showing that the negative effect of natural disasters on performance is highly dependent on the industry context. If firms face severe competition or operate in munificent industries, they face more severe losses compared to firms operating in less competitive or munificent industries. Thus, the provision of disaster relief aid to these firms would directly alleviate their performance losses and would efficiently mitigate the negative performance effect of a disaster on a country's economy. Furthermore, the focus on the United States (US) as geographical area and the empirical estimation strategy of a difference-in-difference approach preclude alternative explanations of the identified effect and establish a strong empirical foundation. Finally, this study applies computational linguistics to establish a convincing link between the location of plants and the location of disaster occurrences. Recent studies have used primarily the location of a firm's headquarters (e.g., Dessaint and Matray, 2017) or the location of patent filings (Ryu et al., 2018).

This essay is structured as follows. In section 2.2, we present the background on natural disasters and the effect of industry attributes in the empirical operations management literature. Subsequently (section 2.3), hypotheses are developed for the direct effect of natural disaster occurrence and performance as well as the moderating effect of the industry. Next, the construction of the data set is explained, followed by the presentation of the analysis and the results (section 2.4). Finally, the results are discussed in section 2.5 before the conclusion (section 2.6).

2.2 Background

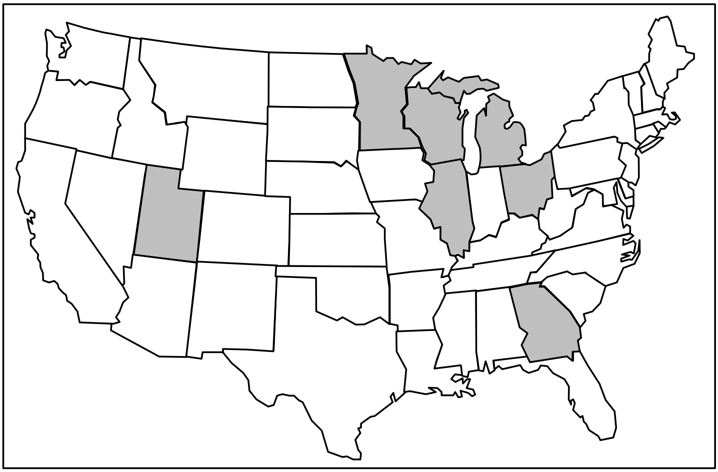
2.2.1 Effect of natural disasters

Risk can be conceptualized either as fluctuations around an expected value (Arrow, 1965) or as a purely negative deviation from an expected outcome (Mao, 1970). Although both are found in the literature, the latter more accurately reflects managerial perceptions (March and Shapira, 1987) and is hence predominantly found in management in general (e.g., Miller and Leiblein, 1996). Among the most prominent and most severe causes of an unexpected negative deviation are natural disasters. For the purpose of this study, a natural disaster is a "natural event that causes a perturbation to the functioning of the economic system, with a significant negative impact on assets, production factors, output, employment, or consumption" (Hallegatte and Przyluski, 2010, p. 2). Examples of natural events are earthquakes, storms, and hurricanes as well as intense rainfall, heat waves, and cold spells. A country's economy can suffer from natural disasters directly and indirectly (Kousky, 2014). As direct effect, natural disasters destroy the factors of production, labor, and physical capital. As indirect effect, they provoke but do not directly cause losses. Such losses include the cost of business interruptions due to destroyed public infrastructure or private assets (Hallegatte and Przyluski, 2010). The consequences of natural disasters have been studied extensively at the level of a country's economy. Although the empirical evidence of a negative association between the occurrence of natural disasters and economic growth is still inconclusive (Cavallo et al., 2013, Strobl, 2011), it dominates empirical research (e.g., Cavallo and Noy, 2011, Lazzaroni and van Bergeijk, 2014). The main reason for this observed negative association is that natural disasters destroy physical assets required for the production of goods and services, shifting an economy's production possibility frontier inwards (Felbermayr and Gröschl, 2014). If the destroyed assets are not replaced, the level of production is permanently lowered (Leiter et al., 2009), particularly if the natural disasters evoke major political changes or turmoil (Cavallo et al., 2013). Furthermore, the effect of a natural disaster is strongly associated with its severity (Kousky, 2014). Comparing the growth rates of different countries and using geophysical and meteorological data, the worst 1 % of disasters decrease the growth-rate of the gross domestic product by 6.8 % while a disaster in the lowest quartile still decreases the growth-rate of the gross domestic product by 0.01 % (Felbermayr and Gröschl, 2014). Other US-centric studies revealed similar results. Counties hit by a natural disaster were found to experience a decline in the growth-rate of the gross domestic product by 0.45 percentage points compared to an average growth-rate of the gross domestic product of 1.68 % in counties that were not hit by a disaster (Strobl, 2011). Such negative effects also propagate to other states through linkages of firms (Bernile et al., 2017b). Besides economic losses, natural disasters cause societal disruptions, as people tend to leave areas affected by a natural disaster (Belasen and Polachek, 2009). Various factors moderate the intensity of the negative effects of natural disasters on a country's economic performance (Kousky, 2014), including the country's current development level (Cuaresma et al., 2008, Kahn, 2005), overall government effectiveness (Lazzaroni and van Bergeijk, 2014), institutional quality, openness to trade, and financial openness (Felbermayr and Gröschl, 2014), and societal resilience that comprises measures such as early warning systems, evacuation plans, building codes, or other preventive actions (Kahn, 2005, Noy, 2009, Zhou and Botzen, 2017). In addition, several studies have focused on major single events to illustrate their negative effect on the growth rate of the gross domestic product: the Kobe earthquake in 1995 (Chang, 2010, Horwich, 2000), hurricane Katrina in 2005 (Cashell and Labonte, 2005, Vigdor, 2008), the Great East Japan Earthquake in 2009 (Carvalho et al., 2016) or the earthquake in Haiti in 2010 (Cavallo et al., 2010). Such single, although major, events were found to be negatively associated with a country's overall economic performance.

As natural disasters in general and single events in particular have negative economic repercussions, researchers have started to investigate their effect on smaller units within an economy, such as firms. Studies of major single natural disasters have indeed shown that in the short term, natural disasters harmed firms that operated in the affected areas. A major event, like Hurricane Katrina in 2005, destroyed important assets, threatening the firm's existence (Runyan, 2006). After the Great East Japan Earthquake in 2011, operational performance and stock returns of the affected firms declined (Hendricks et al., 2017, Todo et al., 2015). Moreover, the effect of this earthquake also propagated through the value chain (Carvalho et al., 2016). While these major single events have demonstrated the potential negative effects of natural disasters, they are luckily relatively rare. Thus, an understanding of the effect of a broader range of events is necessary. In particular, four studies have investigated the effect of natural disasters on firm level data. First, firms that operated in European NUTS-II regions hit by a flooding in 2000 experienced a decline in productivity but growth in employment and total assets (Leiter et al., 2009). Second, the effect of a disaster on a firm's performance depends on its position in the value chain (Altay and Ramirez, 2010). As measurement, Altay and Ramirez (2010) used the product of a binary variable (assigning the value of 1 if a firm's headquarters were located in a country that had been hit by a natural disaster and 0 otherwise) and a composite variable measuring the effect of the disaster. They further classified each firm into one out of four different industry categories. They found that the strength of the effect of a natural disaster on cash flow, leverage, and asset turnover depended on the industry in which the firm operated without further characterizing the industry. Third, the effect of major natural disasters propagates through the value chain (Barrot and Sauvagnat, 2016). Barrot and Sauvagnat (2016) constructed buyer-supplier dyads, showing that a buyer's growth of sales and cost of goods sold declined if a firm had at least one supplier with headquarters located in a state hit by a natural disaster. This effect was stronger if the supplier provided specific inputs (Barrot and Sauvagnat, 2016). Fourth, firms with headquarters located in proximity to regions hit by a hurricane increase their cash holdings and report more frequently about hurricane related risk in their annual report (Dessaint and Matray, 2017). In their study, Dessaint and Matray (2017) connected disaster data with the location of firms' headquarters. Utilizing a difference-in-difference regression estimation, they compared the cash holding of firms that were located in the immediate vicinity to a disaster occurrence with those of firms located further away from the disaster occurrence. They found that firms close to disasters had higher cash holdings and reported on natural disasters in their annual reports more frequently. In line with prospect theory, they concluded that the firms' managers were more strongly influenced by risks that were more salient to them.

Common to all these studies is that they usually rely on the location of a firm's headquarters to identify a firm hit by a natural disaster. However, a firm can operate a dispersed production network of plants independent from its headquarters' location, as the example in Figure 2-1 illustrates. An empirical investigation of the effect of natural disasters on firm performance based on plant locations would be more accurate and more relevant for operations management. Furthermore, these studies do not investigate whether this effect is stronger for certain groups of firms compared to others. Country characteristics have been found to moderate the relationship between disaster occurrence and a country's economic performance. Similarly, certain attributes of an industry might moderate the relationship between disaster occurrence and a firm's performance.

Figure 2-1: Production network of Apogee Enterprises, Inc. (CIK: 6845) as reported in its annual report for the fiscal year ended March 2, 2013



Note: Shaded states indicate a production location, no production locations in Alaska or Hawaii.

2.2.2 Industrial environment

Firms operate in industries that they cannot easily influence (Bourgeois, 1980) but which play an important role as a moderator of the relationship between organizational strategies and performance outcomes (Keats and Hitt, 1988, Ketokivi, 2006). Three general attributes characterize the industrial environment (Dess and Beard, 1984). First, complexity is a function of the number, diversity, and distribution of external factors and parties with which a firm must interact (Dess and Beard, 1984, Heeley et al., 2006). Industry complexity is characterized by many firms with equal market shares (Palmer and Wiseman, 1999). Second, munificence is reflected in the degree to which resources support sustained growth for all the firms of a specific industry (Dess and Beard, 1984). A munificent industry provides sufficient growth opportunities for all firms and is characterized by a constant growth in terms of overall industry sales (Heeley et al., 2006). Third, dynamism pertains to the degree of instability or the turbulent nature of the industry in which a firm competes. This instability is especially characterized by random occurrences of changes and new developments (Dess and Beard, 1984, Heeley et al., 2006). Although munificence and dynamism scores are drawn from the same data, they focus on unique aspects of the industry (Heeley et al., 2006). Munificence focuses on an industry's sales trend, whereas dynamism explains the fluctuation in sales over time.

In operations management, numerous empirical studies have documented the moderating effect of the industry on the relationship between operational decisions and performance. Using primary data, many researchers have highlighted that the fit between operational strategies and the environment is crucial for firm performance (e.g., Jambulingam et al., 2005, Ketokivi, 2006, Patel, 2011). Various empirical studies have demonstrated the moderating effect of industry attributes on the relationship between operational strategies and financial performance outcomes. Previous studies have investigated operational strategies, such as operating flexibility (Anand and Ward, 2004), top-level communication and strategy making (Demeester et al., 2014), service innovation (Prajogo and Oke, 2016), and the success of exploratory innovation (Jansen et al., 2006). Industry attributes also moderate the relationship between operational strategies and operational performance (like quality, delivery, speed). Examples for operational strategies that were investigated pertain to lean practices (Chavez et al., 2013) and e-collaboration (Rosenzweig, 2009). Finally, these industry variables have been found to influence not only the strength of the effect, but also its functional form, specifically, the link between team autonomy and new product development performance (speed, cost, success) becomes inversely U-shaped in turbulent industries while it is U-shaped in constant industries (Chen et al., 2015).

Other studies have relied on secondary data to measure the industry attributes of complexity, munificence, and dynamism. These moderate at least partly the relationship between financial performance as dependent variable and operational strategies, such as lean operations and lean purchasing (Azadegan et al., 2013b), product quality and product cost (Terjesen et al., 2011), or operational slack (Eroglu and Hofer, 2014) as the independent variable. Industry attributes also moderate the link between operational slack as independent variable and other performance indicators like product safety

(Wiengarten et al., 2017) or the likelihood of venture survival (Azadegan et al., 2013a) as dependent variable. Furthermore, the industry attributes moderate the link between operational strategies, like realized absorptive capacity and stock market performance (Setia and Patel, 2013).

2.3 Hypotheses

The literature review has revealed that natural disasters negatively affect the production network operated by a firm and consequently firm performance. Industry attributes might moderate this negative association. Such a moderation would hint at boundary conditions to the negative effect of natural disasters. In the following subsections, the direct effect of natural disasters on firm performance is elucidated first (2.3.1). Subsequently, the extent to which the three industry attributes, (a) complexity, (b) munificence, and (c) dynamism, influence the association between natural disaster occurrence and firm performance is posited (2.3.2).

2.3.1 Direct effect of natural disasters

Natural disasters have a severe negative effect on the performance of firms that operate plants in regions hit by these disasters. First, a firm’s assets (e.g., property, buildings, machinery, raw material, unfinished and finished goods, and other supplies) might be damaged or destroyed. Depending on the damage, the firm must depreciate the assets’ book values. Similarly, a firm may have to replace fully depreciated assets with the result that these have to be written off again and a firm incurs depreciation cost. Higher depreciation costs directly affect a firm’s bottom line, its net income. Indeed, after hurricane Katrina, small businesses reported the largest losses in terms of inventory and equipment (Runyan, 2006). Second, prior studies have shown a negative relationship between the unpredictability and instability of demand and firm performance (e.g., Kovach et al., 2015, Patel et al., 2012). On the one hand, the precise occurrence of natural disasters in terms of time and place is unpredictable. On the other hand, natural disasters cause instability along the supply chain (e.g., Allianz, 2017, Kleindorfer and Saad, 2005, Norrman and Jansson, 2004). As natural disasters are both unpredictable and cause instability, they are likely to lead to a decline in performance. In sum, the replacement of assets in a firm’s production network as well as the unpredictability of the disaster itself and the instability it causes decrease a firm’s performance.

Hypothesis 1: *Firms whose production network is affected by a natural disaster face a decline in return on assets compared to the previous quarter.*

2.3.2 Moderating effects: Complexity, munificence, and dynamism

Complex industries are characterized by many firms with equally sized market shares (Palmer and Wiseman, 1999). Complexity has two major implications that affect the disaster-performance relationship. First, high complexity of an industry creates causal ambiguity for managers, which impedes their precise understanding of the effectiveness of a chosen strategy (King, 2007, Kunc and Morecroft, 2010, Teece et al., 1997). Firms' managers must identify various influencing factors and the interplay among them in a complex industry. They must also estimate the consequences for their firm's operations and product offerings and draw conclusions from their analysis for their firm's strategy. Given managers' bounded rationality, they focus primarily on the response to immediate competitive pressures in their markets and may overlook more distant external threats (Kocabasoglu et al., 2007). Thus, they are likely to be surprised and caught off guard by natural disasters if their firms operate in complex industries. Second, high industry complexity implies the presence of many competing firms that offer similar products. However, these competing firms have different "operating footprints". If a disaster hits a specific region, the production location of some firms within an industry will be destroyed; thus, their production will be disrupted. However, other firms will operate in distant states not affected by the disaster and will continue to produce. Due to the high number of competing firms with similar product offering, customers can switch from the disrupted to other available producers. Additionally, competitors will attempt to exploit the weakness of the disrupted firm and actively target its customers (Sirmon et al., 2010). Consequently, firms not affected by the disaster can enlarge their sales at the expense of firms with disrupted production (Hallegatte and Przyluski, 2010). In sum, surprise and seizure of market share by competitors will exacerbate the negative relationship between the effect of a natural disaster on a firm's production network and its performance if a firm operates in a complex industry.

Hypothesis 2: *Firms whose production network is affected by a natural disaster face a stronger decline in performance if they operate in a complex industry than if they operate in a less complex industry.*

An industry's munificence indicates that sales are growing for all firms, like a rising tide that lifts all boats (Pagell and Krause, 2004). In such an industry, speed and efficiency matter in strategy execution (Demeester et al., 2014). Additionally, managers focus more on the opportunities than on the threats of a decision (Wiengarten et al., 2017). Hence, they are willing to consider potentially risky investments to take advantage of the growth opportunities while neglecting low-probability events, like natural disasters. As a result, firms in munificent industries are more likely to operate a production network that is exposed to hits from a natural disaster. Second, such industries call for the rapid accumulation of operations resources and capabilities to seize the largest share of the market growth (Demeester et al., 2014). Thus, in anticipation of strong market growth, such firms have typically invested more resources into property, plant, and equipment or inventory compared to firms that did not anticipate such strong growth. If a disaster hits the production locations of a firm that anticipated strong growth, the resulting damage is larger compared to the damage to a firm that anticipated only slow growth. Third, to keep its market share constant in a munificent industry, a firm's sales and the industry's growth must expand at the same rate. Being hit by a disaster, however, obstructs important internal resources. Human resources attempt to keep the business operational and cannot focus on the firm's strategic development; capital assets are destroyed and not available for production anymore; financial resources are required for the disaster response and not available for the expansion of the business. As a result, a firm hit by a disaster cannot execute its strategic business plans in line with the market development and consequently loses market share. In sum, firms' managers are less aware of the probability of a natural disaster and crucial resources are obstructed, thus, the negative relationship between the effect of a natural disaster on a firm's production network and its performance becomes exacerbated for firms operating in munificent industries.

<u>*Hypothesis 3*</u>: *Firms whose production network is affected by a natural disaster face a stronger decline in performance if they operate in a munificent industry than if they operate in a less munificent industry.*

In a dynamic industry, change occurs at a faster pace and with greater magnitude (Rosenzweig, 2009). First, firms that operate in dynamic industries typically implement adaptable production approaches to react flexibly to unforeseen changes (Anand and Ward, 2004). In the aftermath of a disaster, such firms can capitalize on their flexible production systems and can easily switch parts of their production to non-disrupted plants in their production network. As a result, these firms are less vulnerable and they can resume production more quickly. Second, dynamic industries require firms to include contingency schemes in their supply contracts, ensuring that agreed upon procedures are in place to handle design or volume changes (Kaufmann and Carter, 2006). In addition, these industries require firms to build close and stable supply chain partnerships with suppliers and customers (Kocabasoglu et al., 2007). The aforementioned two aspects, flexible contracts and close relationships with suppliers and customers render a firm's operations more flexible. Third, firms that operate in a dynamic, fast-changing industry have developed capabilities to quickly respond to change, adapt the organization, and learn from the new situation. Since a natural disaster affects the supply situation, production, and demand pattern, such capabilities are also beneficial: A firm that is accustomed to unforeseen change is more capable of dealing with it. In short, in dynamic industries, firms apply more flexible production and sourcing approaches and are more used to sudden changes. Thus, these firms can better accommodate the effect of changes following a natural disaster on their production network.

Hypothesis 4: *Firms whose production network is affected by a natural disaster face a weaker decline in performance if they operate in a dynamic industry than if they operate in a less dynamic industry.*

2.4 Data

2.4.1 Construction of the data set

The data necessary for analyzing the hypothesized negative association between natural disasters and firm performance and the moderation of industry were compiled from three databases. Production location data were extracted from a firm's annual reports filed in the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. Data on natural disasters were downloaded from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) database. Financials were derived from the archival database in Compustat (Capital IQ North America Fundamentals Quarterly).

Annual reports are arguably the most important communication channel for the presentation of business performance and firm development (Gao et al., 2016). Disclosures therein affect shareholder behavior (e.g., Staw et al., 1983). As annual reports are widely accepted to be accurate, relevant, and representative, their semantics have been used to extend industry classifications (Hoberg and Phillips, 2016) or to detect competitive forces (Hoberg et al., 2014). According to Generally Accepted Accounting Principles in the US (US-GAAP), a firm's major property is described in Item 2 of its annual report (Form 10-K) (17 CFR 229.102). The section states the location of the significant physical properties (fixed assets, property, plant, and equipment) of a firm. Intellectual property and intangible assets are not described in this section (SEC, 2018).

The location information in Item 2 was extracted from the annual reports in a multi-step procedure. First, Item 2 itself was separated from the entire report. The start and end of Item 2 were identified by a combination of text and visual features. In the 10-K report, its start is marked by the header that contains the terms "Item 2" or "Properties" while its end is marked by the header of the subsequent section that contains the terms "Item 3", "Legal Proceedings", "Item 4" or "Mine safety regulations". When such a term was found, its font-style was checked (whether it was printed in bold letters) to determine whether the found term indeed was a header. If two headers were identified as start and end, the text in between them was extracted. Second, html-code had to be deleted and the text cleansed. As firms are only required to present the information in a structured format, they employ different structuring elements in html, such as lists, tables, or just paragraphs. Tables were identified by their html-tags and the entire text of a single table cell was extracted. After the extraction of the text from all cells of all the tables, the remaining text of the section was extracted. This text was then further cleansed (e.g., deletion of digits, replacement of multiple white spaces, substitution of defined abbreviations by full names, replacement of capitalized words). Third, the location information was separated using a NER tagger. A named entity is a "real-world object" to which a name is assigned (e.g., person for Martin Luther King, country for United Kingdom or product for Galaxy Note). The detection of a named entity in text is not trivial, because named entities can comprise several words (e.g., West Virginia). Additionally, the assignment of the type of named entity can be ambiguous because different objects can be assigned to the same word (e.g., the types of product, person, or company can be assigned to the word Ford). Therefore, each tag is predicted based on a statistical model. Due to the complexity and the potential ambiguity, spaCy's trained and well-calibrated NER tagger was used to identify the major geographic entities (countries, states, counties, cities) in the text extracted from the annual reports (Choi et al., 2015, Honnibal and Johnson, 2015, Honnibal and Montani, 2017). The text other than the geographic entities was discarded. Fourth, additional geographic information was aggregated and standardized to a common notation for US-states. Most importantly, all US counties that could be uniquely matched to a US-state were manually replaced by the respective state. As the same town and city names were found in various states (e.g., Portland in Arkansas, Georgia, Kansas, Michigan, Texas, and other states), they did not provide additional information and were not included in the further analysis. Based on this aggregation, a location vector was created that contained a binary variable for each of the 50 US-states and the District of Columbia. The binary variable associated with a state was set to 1 if a firm operated at least one major location in the respective state and 0 otherwise. For the sake of reliability, frequencies were neglected. The reason for this was twofold. On the one hand, some firms mentioned the same location several times because different business segments produced at the same plant. On the other hand, other firms used a hierarchical structure and only mentioned the state once, although they operated several plants in several cities of the respective state.

SHELDUS collects disaster incidents that occur across the US. These include thunderstorms, hurricanes, floods, wildfires, and tornados as well as flash floods or heavy rainfall. For each county and month, the database contains direct losses caused by the disaster (property and crop losses as well as injuries and fatalities). Data from SHELDUS have been used to detect the propagation of natural disasters through the supply chain or to investigate the extent to which early-life disasters affect a CEO's risk attitude (e.g., Barrot and Sauvagnat, 2016, Bernile et al., 2017a). In the present study, relevant disasters were identified by their financial effect on counties because disasters were found to exert strong effects at county-level (Strobl, 2011). Specifically, counties were considered to be hit by a disaster if the disaster lasted for less than 30 days and all disasters in the respective quarter caused a total loss of at least US-$ 25mil (in 2016-US-$). Injuries or fatalities were not considered as indicators of a relevant disaster because the focus was on losses in infrastructure or property of firms. Different disaster types were not distinguished because they are usually intertwined (Kousky, 2014). Hurricanes like Katrina or Sandy also caused severe floods in large areas. Finally, a disaster vector was created for each quarter that contains a binary variable for each of the 50 US-states and the District of Columbia. The binary variable associated with a state was set to 1 if at least one county of the state was hit by at least one natural disaster in the respective quarter that met the criteria defined above and 0 otherwise.

The quarterly disaster occurrence was matched to the production locations based on the fiscal quarter end because most damage occurs immediately after the disaster (Raddatz, 2009). Thus, for each firm and quarter, a vector of production locations and a vector of disaster occurrences were created, both of the same dimensionality, with one dimension for each state. Financials for industries and firms were derived from Compustat and merged into this data set.

2.4.2 Variables

The dependent variable is firm i's delta of the return on assets $\Delta ROA_{i,t,q}$ from the previous quarter $q-1$ to the current quarter q in year t. The delta of returns allows to focus on the immediate effect of the disaster and avoids a distortion by any firm-specific differences in the returns. The return on assets $ROA_{i,t,q}$ of firm i in quarter q of year t was operationalized by dividing a firm's net income $ni_{i,t,q}$ in quarter q of year t by its book value of assets $bva_{i,t,q}$ in quarter q of year t.

$$\Delta ROA_{i,t,q} = \frac{ni_{i,t,q}}{bva_{i,t,q}} - \frac{ni_{i,t,q-1}}{bva_{i,t,q-1}}$$

Negative values indicate a decline in performance compared to the previous quarter, positive values indicate performance growth.

To derive the measure of disaster occurrence $dis_{i,t,q}$ by which firm i is hit in quarter q in year t, first the transposed vector of production locations $PL_{i,t,q}^{T}$ of firm i in quarter q of year t was multiplied with the vector of disaster occurrences $DL_{t,q}$ in quarter q of year t. If a firm only maintained production locations in states not hit by a natural disaster or if disasters happened in states in which a firm did not operate production locations, the resulting scalar was zero. Depending on the number of states with production locations that were hit by a disaster, the dot product between $PL_{i,t,q}^{T}$ and $DL_{t,q}$ was positive. Second, this value was coded as 1 for any positive value of the dot product. This measure captures whether in quarter q of year t, firm i operates at least one production location in any US-state that was hit by a natural disaster in the same period.

$$dis_{i,t,q} = \begin{cases} 1 \;\; if \; PL_{i,t,q}^{T} \cdot DL_{t,q} \geq 1 \\ 0 \;\; otherwise \end{cases}$$

The variables describing the industry are based on Dess and Beard (1984) and were operationalized similar to numerous studies across strategic and operations management (e.g., Azadegan et al., 2013a, George, 2005, Heeley et al., 2006, Keats and Hitt, 1988). In this study, an industry is described by its four-digit SIC code. Industry complexity $comp_{j,t,q}$ was approximated by the reverse of industry concentration, because a higher concentration corresponds to a lower complexity (e.g., Palmer and Wiseman, 1999). Industry concentration was measured by an industry's Herfindahl index of sales that is defined as the sum of the squared quarterly market shares of each firm operating in the industry. This measure has been widely used in strategic and operations management to account for industry complexity (e.g., George, 2005).

$$comp_{j,t,q} = 1 - \sum_{i=1}^{N_{j,t,q}} \left(\frac{s_{i,j,t,q}}{s_{j,t,q}} \right)^2$$

$s_{i,j,t,q}$ equals the quarterly sales of firm i in industry j in quarter q of year t and $s_{j,t,q}$ the sum of sales of all firms $N_{j,t,q}$ in industry j in quarter q of year t. Industry complexity is computed as 1 minus sales concentration with higher values indicating higher complexity.

For munificence and dynamism, first the sum of industry sales in industry j in quarter q of year t, $s_{j,t,q}$, was computed. Second, industry sales were regressed on time using ordinary least squares (OLS) regressions on moving 20-quarter-windows with the following equation: $s_{j,t,q} = b_0 + b_1 * time_{q,t} + \varepsilon_{t,q}$, in which b_0 was the common intercept, b_1 the estimate of time and $\varepsilon_{t,q}$ the error term. The 20-period time horizon corresponds to the commonly used five-year time horizon used in empirical operations management studies. For the measurement of munificence $munif_{j,t,q}$ of industry j in quarter q of year t, the estimate of time (b_1) was divided by the industry-average sales of the same 20-quarter time horizon. For the measurement of dynamism $dyna_{i,t,q}$ in industry j in quarter q of year t, the standard error of the estimate of time (b_1) was divided by the industry-average sales of the same 20-quarter time horizon. This operationalization is common in empirical research (e.g., Azadegan et al., 2013a).

Several variables controlled for differing firm characteristics. To begin with, firm fixed effects accounted for heterogeneity among firms. Year-dummy-variables absorbed any general trend of returns (e.g., due to economic downturns). Quarter-dummy variables captured any seasonality in returns. State-dummy-variables accounted for unobservable heterogeneity among locations in the states, because some states are more disaster-prone and at the same time more disaster-experienced. One firm can operate in several states. Furthermore, larger firms usually operate more production locations (i.e. are more likely to be hit by a disaster), but are less dependent on a single plant. The natural logarithm of firm sales was used to control for firm size. Finally, leverage has an influence on the net income for which a firm's leverage ratio controlled. The leverage ratio was computed as quotient of the book value of debt and the sum of the book values of debt and equity.

2.4.3 Sample

The unit of analysis was the firm-quarter that a firm's Global Company Key (GVKEY) and the quarter of its quarterly reporting date uniquely identified. The investigated period covered the twelve-year time horizon from 2005 until 2016.

Table 2-1: Means (*M*), standard deviations (*SD*), and pairwise correlations

	M	***SD***	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
(1) ΔROA	0.001	0.057	1.000						
(2) Disaster	0.236	0.425	–0.013	1.000					
(3) Complexity	0.751	0.176	0.009	–0.017	1.000				
(4) Munificence	0.045	0.077	–0.003	0.043	0.119	1.000			
(5) Dynamism	0.023	0.019	0.006	–0.002	–0.225	–0.030	1.000		
(6) Size	5.820	1.969	–0.013	0.131	0.034	–0.011	–0.005	1.000	
(7) Leverage	0.238	0.249	0.006	0.059	–0.001	–0.085	0.019	0.323	1.000

Note: n = 48,314; Pearson product-moment correlation coefficients are shown; all pairwise correlations $|r| > 0.01$ are significant at $p < 0.05$. Complexity, munificence, and dynamism standardized by mean and standard deviation, size was transformed using the natural logarithm.

In order to derive meaningful and comparable results, only firms of the manufacturing sector (SIC codes 20 to 39) were retained. Furthermore, we restricted the sample by minimum values of assets (US-$ 1mil), quarterly sales (US-$ 0.5mil) and quarterly returns on assets (larger than –1.5 and smaller than 1.5). In addition, firms that operate production locations in more than 15 states were dropped. Moreover, we required at least two observations per firm and three observations per industry-quarter. The total sample comprised 48,314 firm-year-quarters (2,254 firms). Thus, we observed on average 21.4 quarters per firm (min: 2; max: 48). Last but not least, all variables were winsorized at the 99-percentile to address outliers (Aguinis et al., 2013). Means, standard deviations, and pairwise correlations coefficients for all key variables are displayed in Table 2-1. Details of firms hit by a disaster (i.e., treatment group) and of those not hit by a disaster (i.e., control group) are presented in Table 2-2.

Table 2-2: Summary statistics for control and treatment group

	Disaster = 0		**Disaster = 1**	
	M	***SD***	***M***	***SD***
ΔROA	0.001	0.059	–0.001	0.049
ROA	–0.014	0.086	–0.005	0.071
Sales	455.516	1,555.641	569.498	1,634.951
Total assets	2,295.883	8,517.472	2,755.947	8,651.098
Complexity	0.753	0.176	0.745	0.177
Munificence	0.043	0.076	0.051	0.08
Dynamism	0.023	0.019	0.023	0.019
Number of observations	36,903		11,411	

Note: The control group (Disaster = 0) comprehends observations of firms not hit by a natural disaster in the respective quarter, whereas the treatment group (Disaster = 1) comprehends firm-quarters in which a firm is hit by a disaster.

2.5 Analysis

2.5.1 Model specification

The effect of having a production location in at least one state that was affected by a natural disaster on the change in return on assets was investigated using a difference-in-difference estimation which is common practice to answer such questions (e.g., Dessaint and Matray, 2017). The control model (CM) served as benchmark and includes control variables only. The base model (BM) also included the variables of the disaster occurrence and of the industry attributes (munificence, dynamism, complexity). The estimate b_1 in the BM measured how much the performance of a firm hit by a disaster has changed relative to firms not hit by a disaster. The interaction model (IM) also included the interaction terms between the disaster and the three industry attributes complexity, munificence, and dynamism respectively (estimates of interest: b_5, b_6, and b_7 in the IM). These estimates measured whether the identified change in performance varied with the respective attribute of the industry. To facilitate the interpretation of the interactions, the three industry variables were standardized by mean and standard deviation (Aiken et al., 1991).

Control model (CM)

$$\begin{aligned} \Delta ROA_{i,t,q} = {} & b_{0,i} + b_1 * size_{i,t,q} + b_2 * lev_{i,t,q} + b_{3,t} * year_t \\ & + b_{4,q} * quarter_q + b_{5,s} * state_s + \varepsilon_{i,t,q} \end{aligned} \tag{1}$$

Base model (BM)

$$\begin{aligned} \Delta ROA_{i,t,q} = {} & b_{0,i} + b_1 * dis_{i,t,q} + b_2 * comp_{i,t,q} + b_3 * munif_{i,t,q} \\ & + b_4 * dyna_{i,t,q} + b_5 * size_{i,t,q} + b_6 * lev_{i,t,q} + b_{7,t} * year_t \\ & + b_{8,q} * quarter_q + b_{9,s} * state_s + \varepsilon_{i,t,q} \end{aligned} \tag{2}$$

Interaction model (IM)

$$\begin{aligned} \Delta ROA_{i,t,q} = {} & b_{0,i} + b_1 * dis_{i,t,q} + b_2 * comp_{i,t,q} + b_3 * munif_{i,t,q} \\ & + b_4 * dyna_{i,t,q} + b_5 * dis_{i,t,q} * comp_{i,t,q} \\ & + b_6 * dis_{i,t,q} * munif_{i,t,q} + b_7 * dis_{i,t,q} * dyna_{i,t,q} \\ & + b_8 * size_{i,t,q} + b_9 * lev_{i,t,q} + b_{10,t} * year_t \\ & + b_{11,q} * quarter_q + b_{12,s} * state_s + \varepsilon_{i,t,q} \end{aligned} \tag{3}$$

In these regression equations, i indexes firms, t years, q quarters, and s states. $\Delta ROA_{i,t,q}$ measures a disaster's impact on firm performance for firm i in quarter q of year t as difference of the return on assets to the previous period $q-1$. $dis_{i,t,q}$ is the main variable of interest capturing whether a disaster occurs in a state in which firm i operates a production location in quarter q of year t. $comp_{i,t,q}$, $munif_{i,t,q}$, and $dyna_{i,t,q}$ describe the industry attributes complexity, munificence, and dynamism in industry j in quarter q of year t respectively in which firm i operates according to its primary SIC code. $size_{i,t,q}$ and $lev_{i,t,q}$ control for a firm's size and leverage, respectively. $year_t$, $quarter_q$, and $state_s$ are year, quarter, and state fixed effects. $b_{0,i}$ is the firm-specific intercept. $\varepsilon_{i,t}$ is the error term that is clustered at the firm level to account for potential serial correlation. Multicollinearity is unlikely to be present, because variance inflation factors ranged between 1.0 and 1.1.

2.5.2 Endogeneity

Endogeneity poses a serious threat to the validity of empirical results. Its most frequent causes are reverse causality, measurement error, or omitted variable bias (Wooldridge, 2002). Although the absence of endogeneity cannot be proven, this study fulfills reasonable standards for the plausible exogeneity of the regressors (cf. Ketokivi and McIntosh, 2017). The arguments revolve around the exogeneity of the natural disaster occurrence, the measurement of variables, and the specification as a difference-in-difference regression model. First, natural disasters represent independent events which are not directly caused by a firm's operations or strategic decisions. Thus reverse causality is unlikely to be present. Second, measurement error was addressed by minimizing the risk of common method bias which is one of the main sources of measurement error (Podsakoff et al., 2003). The dependent and independent variables were not only calculated from secondary data sources, but had even been obtained from three different data sources. The disaster occurrence variable was derived from disaster data independent from companies (SHELDUS) as well as the textual analysis of Item 2 of a firm's 10-K report. Performance and industry variables were derived from a firm's financial data that have been widely applied in strategic and operations management (e.g., Azadegan et al., 2013a, Heeley et al., 2006). Third, omitted variable bias was addressed by the specification as difference-in-difference model. Two groups of firms were constructed. In one group, firms experienced a natural disaster during quarter q of year t (treatment group), whereas in the other group, firms did not experience a disaster during the same quarter (control group). As only the difference in returns has been considered, any firm-specific effects that were constant over time were controlled for. Given the parallel trend assumption of treatment and control group, all the time effects on the level of the performance were also controlled for. Nonetheless, firms may have different capabilities to react to disasters. Furthermore, some years may be more sensitive to external events. These are controlled for by firm and year fixed effects. Any seasonality is controlled for by quarter fixed effects. As firm size and leverage could also affect the difference in trends as time varying covariates, these were also controlled for. As one firm can be hit multiple times by a disaster, robust standard errors, combined with the clustering option, relaxed the assumption of independence of observations within the cluster of a firm.

2.5.3 Results

While the CM included only the control variables ($F = 4.47, p < 0.001$), the BM has also included the main variable of interest (disaster occurrence in a state with production location) and the industry variables as controls ($F = 4.50, p < 0.001$). The IM ($F = 4.43, p < 0.001$) also comprised the interaction terms. Table 2-3 presents the results of the analysis for the three models. The hypothesized relationship between the negative effect of a natural disaster on a firm's production network and the change in firm performance received support from the data.

Table 2-3: Results of difference-in-difference regression analysis

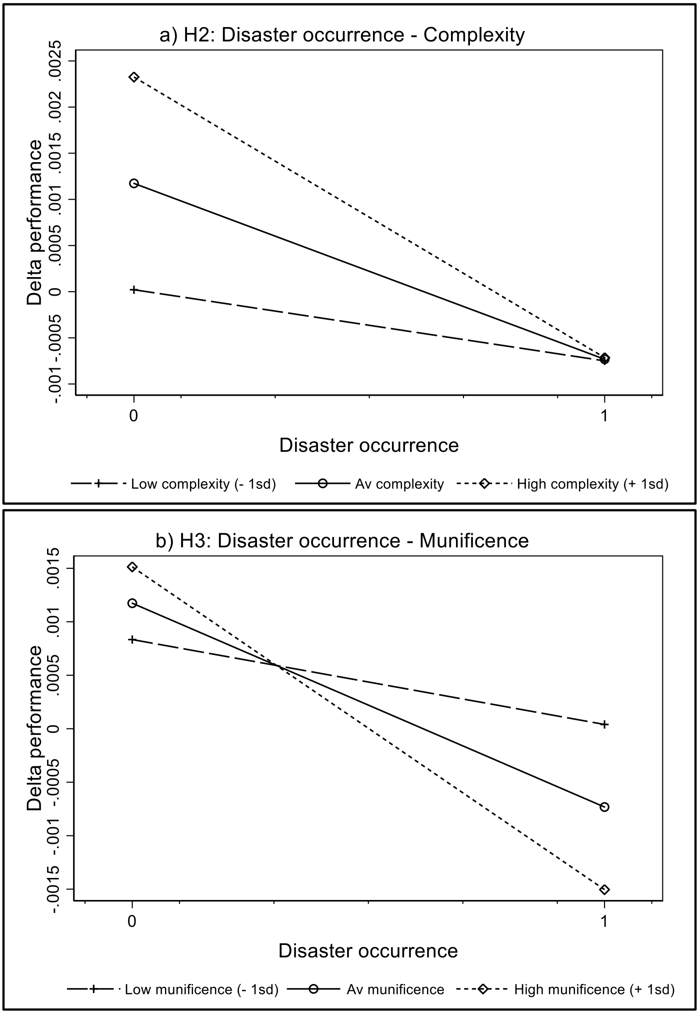
	Control model		Base model		Interaction model	
	Estimate	***SE***	**Estimate**	***SE***	**Estimate**	***SE***
Disaster			–0.002 **	(0.001)	–0.002 **	(0.001)
Complexity			0.001	(0.001)	0.001	(0.001)
Munificence			0.000	(0.000)	0.000	(0.000)
Dynamism			0.001 *	(0.000)	0.001 *	(0.000)
Disaster × Complexity					–0.001 *	(0.001)
Disaster × Munificence					–0.001 *	(0.001)
Disaster × Dynamism					0.000	(0.000)
Size	0.002 ***	(0.001)	0.002 **	(0.001)	0.002 **	(0.001)
Leverage	0.000	(0.002)	0.000	(0.002)	0.000	(0.002)
Constant	–0.011 **	(0.004)	–0.011 **	(0.004)	–0.011 **	(0.004)
Firm FE	YES		YES		YES	
Time FE	YES		YES		YES	
State FE	YES		YES		YES	
R^2 (within)	0.006		0.006		0.006	
Observations	48,314		48,314		48,314	
Number of firms	2,254		2,254		2,254	

Note: Robust standard errors (*SE*) in parentheses (clustered at firm-level).
† p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001 (two-tailed).

The base model estimate suggests that a natural disaster in a state in which major property is located lowers firm performance (*Hypothesis 1*). As expected, the coefficient (BM: $b_1 = -0.002$, $p = 0.01$) is significantly negative. A firm that experienced a natural disaster in a state in which it operated major property faced a decline of 0.2 basis points in the return on assets in a single quarter compared to a firm that was not affected by a disaster in the same quarter.

Given the mean and median close to 0 (*M* = 0.0004, *SD* = 0.055, median = 0.00003) and the typical size of quarterly return on assets, this is an economically meaningful result.

Figure 2-2: Interaction plots for complexity and munificence on the disaster-performance link



Note: The plots are based on standardized estimates reported in Table 2-3. The interactions are plotted at one standard deviation above ("high") and below ("low") the mean values of the moderator variables.

When looking at the interaction model, the estimates indicated some support for the moderating effect of industry attributes on the relationship between disaster occurrence in a state with major property and performance decline. *Hypothesis 2* predicted that higher industry complexity would exacerbate this relationship. Indeed, the results of the interaction model confirm this expectancy (IM: $b_5 = -0.001$, $p < 0.05$). Figure 2-2a illustrates this relationship. Firms that have operated a major plant in a state hit by a natural disaster face a decline in performance. While this relationship is only weakly existent in industries characterized by low complexity (–1 *SD*), this relationship becomes more negative, the more complex the industry becomes (+1 *SD*).

Hypothesis 3 posited that higher industry munificence would also exacerbate the relationship between disaster occurrence in a state with a major property and performance decline. In line with *Hypothesis 3*, industry munificence negatively moderates the suggested relationship (IM: $b_6 = -0.001$, $p < 0.05$). Figure 2-2b illustrates that firms that operate a major property in a state hit by a disaster experience a decline in performance. Again, in industries characterized by low munificence (–1 *SD*), the occurrence of a disaster in a state in which a firm has operated major property hardly matters. However, with increasing munificence (+1 *SD*), the negative relationship becomes more pronounced and clearly negative. Finally, *Hypothesis 4* predicted that industry dynamism mitigates the negative influence of a natural disaster in a state in which a firm has operated major property on performance. However, the data do not provide empirical support for this hypothesis (IM: $b_7 = -0.0003$, $p = 0.47$).

2.6 Discussion

This study investigated the effect of natural disasters on firms under several industry conditions. More specifically, firms that operated major plants in states that were hit by a natural disaster faced a decline in performance. This decline in performance was found to be even more pronounced in complex (i.e., highly competitive) or munificent (i.e., growing) industries. These results contribute to our understanding of the negative effects of external threats on firm performance.

First, we developed a new empirical measurement to determine the effect if a firm is hit by a natural disaster. Recent studies have noted that the information on the location of production facilities was not available (Dessaint and Matray, 2017, Ryu et al., 2018). To obtain this information from publicly available data, we suggest employing a NER tagger as automated text analysis method to systematically scrutinize Item 2 of a firm's annual report. This empirical contribution is crucial for understanding a firm's distribution of assets because not only a firm's headquarters but also its plants are significant assets. Several studies provide empirical evidence that even the slightest disruption of production facilities can have severe detrimental effects on stock market and operational performance. Thus, the empirical measurement of a firm's production locations based on publicly available data opens several avenues for further research.

Second, employing this new measurement, we were able to accumulate further empirical evidence that natural disasters have a detrimental effect on firm performance. We found that when a firm is hit by a disaster, this is bad news without potential positive outcome in the same quarter. Thus, we contribute to the ongoing debate about the extent to which natural disasters destroy a firm's operating base and harm its profits.

Third, just as country characteristics have been found to moderate the relationship between natural disaster occurrence and a country's economy, industry attributes have been found to moderate the relationship between a disaster occurrence and firm performance. Natural disasters have only a minor effect on firm performance in low complexity industries. Low complexity industries are characterized by the existence of few players or one dominant player or both. In each case, competitors are not able to scale up their production and to replace the product offering of the affected firm. As a result, a firm operating in a low complexity industry can delay the fulfillment of the demand without diverting it to its competitors. In contrast, highly complex industries comprise many independent firms. If a firm is disrupted in such an industry by a natural disaster, its competitors can replace the disrupted firm's products, fulfill market demand, and consequently take over its market share. Our findings for munificent industries revealed a similar picture. Firms that operate in highly munificent industries suffer more from natural disasters compared to firms that operate in less munificent industries. Our results are in line with prior studies, which have shown that firms operating in munificent industries focus on the expansion of production networks in order to fulfill the increasing demand. Furthermore, these firms appear to be less aware of potential small probability risks, such as the risk of natural disasters that they may face when making their location decisions. Once these firms are affected, they cannot keep up with the market growth and consequently lose market share.

These results have major implications for managers and policy makers. First, managers must be aware of natural disasters which have a direct negative effect on their company's performance. To cope with them, managers can either reduce the susceptibility of being hit or lower the exposure to such events. On the one hand, managers should consider the probability of being hit by a natural disaster and reduce it where appropriate. To this end, they could find locations that are less prone to the occurrence of disasters or perform more crucial activities at locations that are less likely to be hit by a natural disaster. On the other hand, managers can try to reduce the effects of a disaster by preparing for emergencies (e.g., backup power, water drainage) or by developing contingency plans if they are hit by a disaster. Moreover, managers must consider the conditions in which their firm operates. If their firm faces fierce competition, they should take the risk of potential natural disasters more seriously than if the firm faced low competition. Additionally, if a firm faces a strongly growing (i.e., munificent) market, its managers should always account for potential risks in their location decisions.

Although this study makes important contributions to theory and has important implications for managers, it should be considered in light of its limitations. First, we examined Item 2 of a firm's annual report by means of a NER-tool to identify its major production locations. Although annual reports are generally regarded as valuable source of information, regulation only mandates firms to disclose information about a major property. However, firms have some discretion about what constitutes a major property. Thus, just as accounting studies investigate whether specific sections of annual reports provide valuable information, future studies should also assess this particular section to confirm the source of information. Furthermore, we focus on whether a firm operates a property in a given state. Thus, our data neither quantify the production network nor identify product flows. Further research should be conducted to identify product flows among plants to further refine the analysis.

2.7 Conclusion

This study investigated conditions under which a natural disaster causes more severe performance losses in affected firms. To this end, a firm's production locations, as mentioned in Item 2 of its annual report, have been matched to disaster occurrences. Subsequently, industry and firm financial information have been merged in the data set. The results of a difference-in-difference regression estimation suggested not only that natural disasters were associated with performance declines, but also that industry attributes had a moderating effect on this relationship. Complexity and munificence both exacerbated the negative relationship between disaster occurrence and performance development. These results provide evidence for the conclusion that firms operating in complex or munificent industries require disaster relief aid quicker to allow them a quicker rebound from the negative repercussions of the natural disaster.

3 Sources of Supply Risk: Environment or Strategic Choice?

Co-author:

Christoph Bode

Endowed Chair of Procurement, Business School, University of Mannheim, Germany

Abstract:

The interplay between the external environment in which a firm operates, the strategies it pursues, and the context in which it makes decisions together determine a firm’s success or failure. As all these interdependencies are impossible to evaluate ex-ante, some strategies may have unforeseen and unintended consequences. They can even jeopardize lower-level functional strategies such as the sourcing strategy. However, little is known about the extent to which the environment (outside-in) and high-level corporate strategic decision making (inside-out) increase supply risk. This is surprising, because the availability of supply has a strong influence on corporate performance. This paper investigates the extent to which the external environment and corporate strategies contribute to a firm’s exposure to supply risk. Their effects are investigated over time and between firms. To this end, a hybrid regression model is estimated, capturing time- and firm-effects in a single empirical model. The results suggest that an outside-in perspective explains supply risk exposure better than an inside-out perspective can. Furthermore, the distinction between time- and firm-effects explains different directions of several sources of a firm’s exposure to supply risk.

3.1 Introduction

Firms must formulate their performance goals, identify the industries in which they compete, and define their competitive strategies against rival firms. These complex and difficult strategic decisions are critical determinants of a firm's survival or failure (Eisenhardt and Zbaracki, 1992). These decisions can also have potentially detrimental effects on different levels and in different functions of a firm. For instance, an internationalization strategy can generate additional revenue in a new geographic market, but also necessitate relationships with new suppliers in that market. However, if the phasing in of the new suppliers fails, the internationalization strategy and consequently overall firm performance might be at risk. Another difficulty stems from possible opposing interpretations of the same situation. For instance, a competitive industry may hint at an attractive market volume on the one hand, but on the other may also impede the supply of a firm operating in that industry with the result that its operational, financial, and stock market performance is weakened (e.g., Hendricks and Singhal, 2005a). However, we do not know how the unexpected and unintended consequences of corporate strategies and the environment affect or even put at risk different subordinated hierarchies of a firm. This study focuses on supply risk and integrates supply risk in the literature on strategic decision making; despite its importance, this topic has been largely neglected (van der Vegt et al., 2015).

Quite a few studies describe the phenomenon of supply risk by taxonomies and typologies (Wagner and Bode, 2006). For example, the supply- and demand-side risk as well as catastrophic risk which a firm faces can stem from different sourcing initiatives. However, these studies neither investigate the extent to which initially well-intended corporate strategies contribute to a firm's exposure to supply risk nor do they evaluate how strongly the environment contributes to a firm's exposure to supply risk. Therefore, this essay addresses this important gap and investigates how a firm's own strategic decisions and the external environment translate into its exposure to downside supply risk.

To tackle this research question, we propose a new measurement for a firm's ex-ante exposure to supply risk based on secondary data sources. Supply risk exposure is a firm's acknowledgement of a supply-related issue in the risk disclosure section of its annual report (Item 1.A in 10-K filings). For the detection of these issues, we use a topic modeling approach previously developed for the analysis of Item 1.A. The derived exposure to supply risk is investigated from the angle of external factors and internal strategic choices on two levels: change within and between firms. Regarding external factors, new entrants disrupt existing product offerings and reshape industry boundaries. As a result, a firm's competitive position reshapes in comparison to its industry peers or in comparison to its past operations. Our results confirm the belief that external factors substantially contribute to supply risk within and between firms. With regard to internal strategic choices, firms extend their product offering and the global reach of their sales. As a result, they must adopt their operations, comply with regulatory requirements, and deal with a larger scope of suppliers which again strains a firm's resources. The results suggest that internal strategic choices partly increase (within firms) and partly decrease (between firms) a firm's exposure to supply risk.

3.2 Background

Organizational situations are complex, path-dependent, and determined by a myriad of interdependent factors. There is a large body of literature, particularly in strategic management and organization, which proposes and tests theories that explain why performance differs among firms and how specific organizational situations lead to corporate success or failure (Child, 1972, MacKay and Chia, 2013, Thietart, 2016).

Two major streams can be distinguished. The market-based view of the firm (outside-in perspective) emphasizes the importance of the market environment and of other external factors for a firm's performance after a specific organizational situation (Thietart, 2016). The focus is on the suppliers' and buyers' power, the threat of new entrants and substitute products, or the competitive intensity as drivers of a firm's performance (Porter, 1980). Once a firm has opted to compete in a given industry, this choice pre-determines its profitability. For instance, Bayer's takeover of Monsanto lowered the relative importance of the pharmaceutical business and increased the one of the crop science business, resulting in a new profit mix. However, a narrow view of external factors does not sufficiently explain performance differentials between firms, because resource endowments are heterogeneous and immobile among firms of the same industry (Barney, 1991). The resource-based view of the firm (inside-out perspective) emphasizes the role of superior resources and their deployment for performance. This stream of research argues that firms can shape their bundle of resources and change the conditions in which they operate (de Rond and Thietart, 2007). For example, when Pfizer developed Viagra, its management team allocated resources to the exploration of Viagra's key ingredient and thus created new market opportunities. While external factors and internal choices were regarded as competing explanations for performance in the past, they have become more integrated for strategy formulation and the explanation of firm performance. Performance variations can be explained by the interplay among internal choice, external factors, and the context of the choices (de Rond and Thietart, 2007).

These studies have demonstrated that the interplay among internal choice, external factors, and context can also lead to inferior performance (MacKay and Chia, 2013). MacKay and Chia (2013) found that the purposeful and well-intended strategic decisions of a Canadian automotive company often had detrimental effects on its performance after unexpected changes in the environment. For example, the firm's management had decided to liquidate a nickel hedge to improve its financial position. Shortly after this decision, however, the price of nickel rose, resulting in a greater loss than gain from the liquidation. Besides explaining the failure of the automotive company, the study showed that organizational actions and the external environment changed the firm's exposure to downside supply risk. The prior decision to rely on American banks as creditors put the supply at risk because these banks withdrew credit lines required to finance shipments of supply from China. This example underlines the importance of understanding the downside potential inherent in every business decision. Moreover, studying downside risk is important, because the failure to perform at a desired level substantially influences managerial decision making and characterizes a decision maker's risk preferences (Hoskisson et al., 1991, Miller and Leiblein, 1996).

This study offers an intuitive explanation for a firm's exposure to downside supply risk, broadly defined as a firm's inability to meet customer demand (Manuj et al., 2014). On the one hand, external factors affect a firm's exposure to supply risk (Rao and Goldsby, 2009, Zsidisin, 2003). With the plethora of supply risk categorizations, this study focuses on technology change and industry complexity as external sources of supply risk. Product change is a key determinant of the supply chain strategy (Trkman and McCormack, 2009). In a case study of a multinational manufacturing company, its distributors identified technological development yielding new products as one of the main risk sources (Ritchie and Brindley, 2007). In addition, industry complexity greatly contributes to supply risk. In a complex environment caused by high competition, a firm's supply chain cannot adapt quickly to a competitor's moves, because cost reduction was chosen over flexibility (Jüttner et al., 2003).

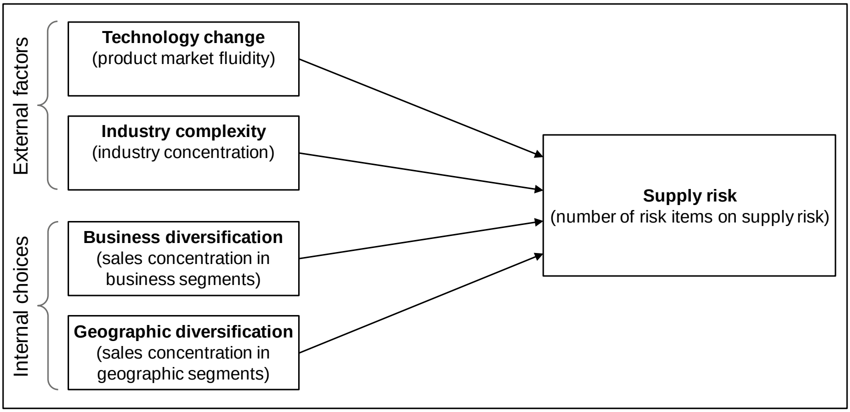
At the same time, a firm's internal strategic choices affect its exposure to supply risk. Firms choose the product domains or geographic regions in which they operate and compete (Hitt et al., 1994). In this context, the direction of the effects remains unclear. Serving additional markets increases the complexity of a firm's supply chain (Hendricks et al., 2009). The more complex a firm's supply chain, the more likely disruptions are to emerge (Bode and Wagner, 2015). Besides, the more geographic markets a firm serves, the more negative is the stock market reaction to announced supply chain disruptions (Hendricks et al., 2009). Thus, these strategies may increase a firm's exposure to supply risk. In contrast, the same internal strategic choices can also reduce a firm's exposure to supply risk as increased product and geographic scope reduce the negative effect of unpredictable markets (Kovach et al., 2015). Furthermore, investments are more likely to be recouped if they are made in adjacent domains, reducing the risk of an investment in a specific supplier relationship (Lieberman et al., 2017).

While the distinction between external factors and internal strategic choices provides an intuitive structure for the analysis of downside supply risk, their effects (size and direction) may also differ by level (Klein et al., 1994). The "lower" level (firm-year) captures the effect of changes in external factors or internal strategic choices on a firm's exposure to supply risk over time and corresponds to within-firm-variance in econometric analyses. The "higher" level (firm) distinguishes cross-sectional differences of external factors and internal strategic choices between firms and their effect on supply risk exposure. This corresponds to between-firm-variance in econometric analyses. Although the same variables are investigated at the different levels, they measure different constructs (Firebaugh, 1978). The intuition is that a given degree of external uncertainty may be high for one firm, but low for another, while both firms face an increase with corresponding associations with supply risk. Assuming that the two levels of effects are equal is known as the "ecological fallacy" (Robinson, 1950) and can lead to errors in inferences made from data (Curran and Bauer, 2011) and confusion in theory development (Klein et al., 1994). Hence, the distinction of different levels in the present data promises additional interesting insights to understand the phenomenon of downside supply risk exposure better.

3.3 Hypotheses

As delineated above and illustrated in Figure 3-1, a firm's exposure to supply risk originates from external factors and its internal strategic choices (Garg et al., 2003). With regard to the former, we focus on technology change and industry complexity, which are the key environmental factors (Daft et al., 1988): Product markets change due to rival firms' technological developments (Hoberg et al., 2014) and industry complexity results from the interplay of many firms within an industry sector (Palmer and Wiseman, 1999). With regard to the latter, business and geographic diversification are key strategic choices of firms (Hitt et al., 1994).

Figure 3-1: Conceptual model for the analysis of the exposure to supply-related risk



Furthermore, external factors and strategic decisions may affect a firm's exposure to supply risk at different levels. Therefore, hypotheses are developed for both, the effect of change within a firm (*Hypotheses a*) and the effect of cross-sectional differences between firms (*Hypotheses b*). Change over time is predicted to be positively associated with supply risk exposure for all constructs, because it requires a firm to alter its supply chain structure. The effect of cross-sectional differences between firms on supply risk exposure is more nuanced. While higher degrees of uncertainty from external factors increase a firm's supply risk exposure, a firm accumulates experience, has higher reputation and power over its supply base, and gains greater flexibility from its previous internal strategic choices. On this basis, higher degrees of diversification are supposed to reduce a firm's supply risk exposure.

3.3.1 External factors

Technological development represents the rate of change in underlying technologies of a purchased product (Stump et al., 2002). As technology changes, firms have to adapt their sourcing strategy (Mahapatra et al., 2010). This imposes additional risk for three reasons.

First, firms can process only a limited amount of information (Galbraith, 1973). The more quickly technology evolves, the more likely a firm's management is to miss or misinterpret important events. For example, Ericsson misinterpreted the information of a fire in its supplier's semiconductor plant while Nokia shifted orders to other suppliers (Norrman and Jansson, 2004). This example highlights that timely processing and interpretation of information is crucial to cope with external factors, but may be impeded in fast-paced markets. Second, firms have not only problems in processing and interpreting existing information, but they even lack information on the past development in fast-paced markets. This makes their proper demand forecast and production planning more difficult. Consequently, a firm's own demand forecast will be prone to errors resulting in erratic ordering behavior which can escalate along the supply chain. This leads to an inefficient supply chain with higher cost and to discrepancies between supply and demand. Third, for the efficient management of technological change, a firm relies more on loose coupling and lower relationship continuity implying that suppliers are switched more frequently (e.g., Choi et al., 2001, Heide and John, 1990). However, selecting a new supplier is risky (Riedl et al., 2013). The reasons are that challenges arise from a firm's inexperience in assessing the quality and future capabilities of a supplier (Krause et al., 2000). In addition, there is no accumulated relational capital between a firm and its supplier that could improve the outcomes of buyer-supplier relationships (Cousins et al., 2006). Finally, there might be no alternative suppliers (Krause et al., 2000) so supplier switching is impossible. In sum, technology change overwhelms internal information processing, makes planning more difficult, and may necessitate more frequent supplier switching with the result that overall supply risk increases on both levels.

<u>*Hypothesis 1a*</u>: *On the time-level, an increase in technology change is associated with an increase in supply risk exposure.*

<u>*Hypothesis 1b*</u>: *On the firm-level, a higher degree of technology change is associated with a firm's higher supply risk exposure.*

Complex industries are characterized by many firms with equally sized market shares (Palmer and Wiseman, 1999). In such an industry, firms face competition not only in their product offering but also in the supply of raw materials (e.g., Wilhelm, 2011). Just as a buying firm instills competition among its suppliers to improve their performance (Krause et al., 2000), suppliers can encourage competition among their customers to obtain better prices. Competition in the market reduces not only a customer's power but also the supplier's dependence on its customer (Emerson, 1962). As a result, the supplier is able to select the customer that offers the most favorable terms (Blenkhorn and Banting, 1991) and a buyer's failure to offer favorable terms to the supplier results in lack of supply. Furthermore, competition increases the risk of information and knowledge leakage through the supplier. Just as two firms learn from each other through joint ventures (Inkpen, 2000), suppliers gain access to their customers' knowledge in joint projects. This knowledge concerns not only the immediate exchange episode, but also the relationship as such and potential future exchanges (e.g., Gulati and Gargiulo, 1999). Yet, if a supplier enters into a relationship with the buying firm's competitor, unintended knowledge leakage may have substantial negative effects on the buying firm's performance (Day, 1995). What is more, suppliers may also engage in business relationships with several competing buying firms at the same time. Although direct knowledge transfers are usually prohibited and protective governance mechanisms often in place, spillovers of tacit knowledge can never be precluded. In sum, greater industry complexity favors growing competition for resources and potential information leakage through the supply base with the result that the overall supply risk increases (on both levels).

<u>Hypothesis 2a</u>: *On the time-level, an increase in industry complexity is associated with an increase in supply risk exposure.*

<u>Hypothesis 2b</u>: *On the firm-level, a higher degree of industry complexity is associated with a firm's higher supply risk exposure.*

3.3.2 Internal strategic choice

Firms that enter a new business segment are confronted with increased supply risk due to their unfamiliarity with and the complexity of the corresponding sourcing decisions. First, firms entering a new market must make unfamiliar decisions concerning their supply and production in a new business segment. Those decisions not only require additional effort (Grant et al., 1988), but also make the proper distinction of relevant from irrelevant information more difficult (Alba and Hutchinson, 1987). For example, new and unknown resources of which a diversifying firm may not be able to accurately evaluate the quality are sourced from other suppliers with whom the firm has not previously collaborated. Similarly, the new products are produced in a new production process. During ramp-up (i.e., the transition from a research and development-oriented to a steady-state production process) discrepancies between the planned and the actual production process must be resolved (Terwiesch and Xu, 2004). This results in the reconfiguration of product or logistics requirements and the production process leading to potential surprises for a firm's suppliers to which they cannot react. Second, the complexity of the decisions increases with the number of interactions among different decisions as a result of diversification (Simon, 1955). Consequently, a firm may miss critical issues along its supply chain until those suddenly materialize and disrupt its operations. In sum, the increase in business diversification leads to more unfamiliar decisions with respect to sourcing and production as well as more complex decisions that induce supply-related risk.

Hypothesis 3a: *On the time-level, an increase in the business diversification is associated with an increase in supply risk exposure.*

While an increase in business diversification is hypothesized to be associated with an increase in supply risk, we predict that a high degree of business diversification is associated with a low degree of supply risk. Experience can be acquired on novel tasks or on tasks that have been performed repeatedly in the past (Katila and Ahuja, 2002) and can be measured in terms of the cumulative number of task performances. Task performance experience is converted into industry-specific knowledge (Argote and Miron-Spektor, 2011). Hence, highly diversified firms have a broader knowledge base and can use it to react quickly to operational contingencies. This aids not only in managing product diversification but also in taking effective mitigation measures against different types of risk, including supply risk.

In contrast to non-diversified firms that have more at stake with a single business, highly diversified firms achieve a lower revenue share from a single business. They can balance out risk (Carroll, 1984) because their less than perfectly correlated income streams from multiple businesses result in a more stable overall cash flow. This enables a firm to shift funds between businesses in response to a disruption (Hendricks et al., 2009). Besides greater independence from funds, highly diversified firms have a more diverse set of suppliers and several supply chains in place and thus, a larger supply base. These suppliers might have an overlapping product offering which is delivered to different businesses of a firm. If a supplier needs to be replaced, highly diversified firms can address their existing supply bases whether one supplier is able to deliver the desired good. As a result, an urgent need for the supply of a good could be fulfilled in a timelier manner because suppliers are pre-qualified.

Finally, a multi-product firm can leverage its reputation to increase the sales of a new product (e.g., Wernerfelt, 1988). For supply, a multi-business firm can use its reputation in one business division to attract suppliers. Suppliers are more responsive, more anticipatory, and provide more high-quality resources towards attractive customers (Hüttinger et al., 2012). As a result, a firm faces low supply risk if its reputation makes it attractive. In sum, firms with a high degree of business diversification face a low supply risk exposure compared to firms with a low degree of business diversification, because they have accumulated experience, are able to pool different risks, and leverage size to attract more qualified suppliers.

<u>*Hypothesis 3b*</u>*: On the firm-level, a higher degree of business diversification is associated with a firm's lower supply risk exposure.*

Like an increase in business diversification, a firm's increase in geographic diversification increases its exposure to supply risk. To begin with, an increase of geographic diversification implies that a product will be sold to other markets in larger quantities than before. The further the distance between customer market and production facilities (i.e., the spatial distance), the more complex the distribution logistics become (Marucheck et al., 2011). The consequences are twofold: the likelihood of supply disruptions increases (Bode and Wagner, 2015) and quality risks that are attributable to suppliers become more likely (Marucheck et al., 2011). In addition, countries impose regulatory restrictions like local content requirements or tariffs to protect local industry against imports. Locally produced components or local assembly circumvent such tariffs. Airbus's recent acquisition of the equity interest in the Bombardier C-series and the announced partial relocation of the production to Mobile, Alabama, prevents excess import duties into the United States (US). This example illustrates that a firm is often forced to change its supply chain design due to regulatory requirements of the foreign countries to which they export. To summarize: As an increase in geographic diversification usually increases the spatial distance between production and distribution and may lead to changes in the configuration of the supply chain, supply risk exposure similarly increases.

<u>Hypothesis 4a</u>: *On the time-level, an increase in the geographic diversification is associated with an increase in supply risk exposure.*

In contrast to an increase in geographic diversification, a high degree of geographic diversification will be associated with a low supply risk exposure. Just like business diversification, knowledge has been accumulated with each entry into a foreign market. A part of this knowledge is universally valuable to all international entries. Hence, a firm with a high degree of geographic diversification benefits from a larger pool of generalizable knowledge than a firm which is not so diversified (Lu and Beamish, 2004). Through the accumulation of general knowledge, firms are better prepared to deal with supply-related issues stemming from international supply such as cross-border regulation. In addition, a high degree of geographic diversification is associated with a firm's market power over its suppliers, distributors, and customers (Kogut, 1985). As previously argued, power and dependence are two sides of the same coin. If a firm exerts power over its suppliers, its suppliers are dependent on the firm (Emerson, 1962). Suppliers that are highly dependent are willing to accept price reductions or to accelerate deliveries if requested by their customer (e.g., Buchanan, 1992). Firms may even increase their purchasing volume and leverage their buying power (Vereecke and Muylle, 2006) if they are able to standardize parts across different geographic areas. Hence, geographically diverse firms have more buying power that can protect them against supply risk. Finally, an expanded multi-national network increases a firm's strategic flexibility (Kogut, 1985). A highly diversified firm can shift sales from one region to another in response to unanticipated threats in ways not possible for a single-business firm without such investments already in place (e.g., Lee and Makhija, 2009). In addition, firms hedge against currency fluctuations by ramping up purchases of production inputs from the same nations as they sell their final products to (Hoberg and Moon, 2017). Taking this one step further, firms can explicitly source from those countries that offer the most favorable exchange rates. Furthermore, a firm that operates in several geographic regions has multiple supply chains in place. If one supply chain is disrupted, a firm can redeploy resources from one region to another, effectively reducing supply risk. In sum, a firm's high degree of geographic diversification lowers its supply risk exposure through learning opportunities, higher purchasing power and increased operational flexibility.

Hypothesis 4b: *On the firm-level, a higher degree of geographic diversification is associated with a firm's lower supply risk exposure.*

3.4 Data

3.4.1 Construction of the data set

Data on supply risk stem from the risk section of annual reports that are available for download from the electronic data gathering, analysis, and retrieval system (EDGAR) of the SEC. Annual reports are arguably the firm's most important communication channel for the presentation of their business performance and development (Gao et al., 2016). The disclosures therein affect shareholder behavior (e.g., Staw et al., 1983). As annual reports are widely accepted as accurate, relevant, and representative, their semantics were used to extend industry classifications (Hoberg and Phillips, 2016) or to detect competitive forces (Hoberg et al., 2014). According to the Generally Accepted Accounting Principles in the US (US-GAAP), annual reports must disclose the material risks facing a firm (FASB, 2010), with risk being defined as possible loss caused by future events (FASB, 1975). A risk is material if the disclosure of a possible future loss "significantly altered the 'total mix' of information made available" (TSC Industries vs. Northway, 1976). The risk can be associated with the supply and operations side of a firm, such as the loss or damage of enterprise property by fire, obligations related to product warranties, and losses from catastrophes (FASB, 1975). This definition of risk in accounting corresponds to the definition of risk in supply chain management.

Since 2005, the US Securities and Exchange Commission (SEC) has required firms to disclose risks in a single, dedicated section, the Item 1.A ("Risk Factors") (SEC, 2005). Risks are the factors that "make the offering speculative or risky" (SEC, 2005). In Item 1.A, each risk is presented under a sub-caption that summarizes the risk and that is subsequently denoted as a "risk item." Following prior studies, the risk item serves as source of information on supply risk. Although the risk is then discussed below this sub-caption, the discussion does not contain additional information necessary for the risk's classification.

Table 3-1: Risk items (extract) disclosed by "LS Starrett Company" (CIK 93676) in 2013 and 2014 after receiving comments from the SEC on the corporate risk disclosure

Fiscal year ended 06/30/2013	Fiscal year ended 06/30/2014
Risks Related to Raw Material and Energy Costs	Volatility in the price of energy and raw materials could negatively affect our margins.
Risks Related to Technology	Technological innovation by competitors could adversely affect financial results.
Risks Related to Foreign Operations	International operations and our financial results in those markets may be affected by legal, regulatory, political, currency exchange and other economic risks.
Risks Related to Information Systems	Any inadequacy, interruption, integration failure or security failure with respect to our information technology could harm our ability to effectively operate our business.

Each risk item should focus on a single risk that the SEC enforces. Frequently mentioned criticisms by the SEC are ambiguous risk items that could apply to any firm, inconsistencies with other parts of the report, and omitted or irrelevant risk items. For example (as illustrated in Table 3-1), the L.S. Starrett Company changed the risk items in the wake of criticism from the SEC. A study of SEC staff comments on prospectuses of initial public offerings reveals similar results (Robbins and Rothenburg, 2005). Firms even modify their risk disclosure if a close rival, the industry leader, or numerous industry peers receive such comment letters (Brown et al., 2018).

The specific section of Item 1.A discusses a wide range of topics from general market risk down to idiosyncratic risk that affects only the supply of a single firm (SEC, 2005). Studies that focus on Item 1.A show that investors regard the risk disclosure as relevant. In general, risk items reflect the risk that a firm faces (Campbell et al., 2014). The information content of the qualitative part of the risk disclosure is associated with quantitative information from financials (Beatty et al., 2018). Although the general risk disclosure is associated with higher stock return volatility (Israelsen, 2014), disclosing firm-specific risk reduces volatility by reducing the information asymmetry between firms and their investors (Bao and Datta, 2014). In this regard, more specific risk items lead to a stronger market reaction (Hope et al., 2016). Besides triggering a market reaction, the risk items reflect a firm’s operational exposure: The disclosure of oil-related risk approximates the risk associated with the price of oil (Israelsen, 2014). In addition, the disclosure of cybersecurity risk is associated with the occurrence of such incidents (Li et al., 2018). Thus, the disclosure of other risks can be used to proxy other risks that cannot be measured (Israelsen, 2014) such as supply risk. Furthermore, first studies have already exploited Item 1.A. Firms with greater exposure to key employee risk disclosed are smaller and more innovation-oriented. They have higher total and idiosyncratic stock return volatilities (Israelsen and Yonker, 2017). This again demonstrates that a firm’s risk disclosure in its annual report contains relevant and validated information that can be used for the measurement of supply risk. For the purpose of this study, we used a combination of keywords and visual features to detect Item 1.A in and to truncate it from the annual reports. Specifically, we used the regular expressions “Item 1.A” and “Risk Factors” without punctuation and white spaces to detect the beginning of Item 1.A and the headlines of Item 2 and Item 3 to detect the end of Item 1.A. For each hit, we checked whether this was a headline (font-style in bold). All text between headlines was extracted. Previous studies have deployed similar approaches (e.g., Li et al., 2018).

Table 3-2: Means (*M*), standard deviations (*SD*), and pairwise correlations

	M	***SD***	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
(1) Techn. change	6.99	3.64	1.00											
(2) Ind. complexity	0.77	0.16	0.30*	1.00										
(3) Business div.	0.19	0.26	–0.22*	–0.16*	1.00									
(4) Geographic div.	0.33	0.29	–0.28*	–0.13*	0.21*	1.00								
(5) Size	6.39	1.94	–0.05*	0.03*	0.31*	0.30*	1.00							
(6) Leverage	0.12	0.14	0.02*	0.07*	0.11*	–0.07*	0.37*	1.00						
(7) Book-to-market	0.64	0.60	–0.10*	–0.04*	0.02*	–0.08*	–0.10*	–0.04*	1.00					
(8) Return on assets	–0.03	0.20	–0.27*	–0.10*	0.18*	0.21*	0.43*	0.01	–0.07*	1.00				
(9) Risk in cf	0.35	3.94	–0.03*	–0.01	0.02*	0.01	0.07*	0.02*	0.02*	0.10*	1.00			
(10)Readability	1.00	0.35	0.01	0.07*	0.16*	0.11*	0.44*	0.29*	–0.02*	0.09*	0.06*	1.00		
(11)Analyst follow	1.56	1.06	0.05*	0.08*	0.11*	0.24*	0.64*	0.12*	–0.27*	0.28*	0.05*	0.25*	1.00	
(12)Big-4 auditing	0.75	0.44	0.07*	0.06*	0.12*	0.19*	0.51*	0.18*	–0.20*	0.13*	0.02	0.20*	0.41*	1.00

Note: n = 10,502; Pearson product-moment correlation coefficients are shown; size, readability, and analyst following were transformed using the natural logarithm, big-4 auditing is a binary variable; correlations flagged with * are significant at $p < 0.05$.

From the extraction, the risk items themselves were parsed using visual features. Specifically, the formatting of each sentence in the extraction is investigated. Building on the SEC’s requirement to present each risk as risk item and subsequent discussion, the longest part is the discussion. Hence, we extract the second-longest part of the risk section as measured by the count of the occurrence of a visual feature (i.e., bold, italics, underlining, and/or capitalization). Although the extraction of risk items is not trivial, the high correlation (0.90) of the number of risk items extracted to a previous study by Bao and Datta (2014) confirms the quality of our extraction approach.

Financials were obtained from Compustat (Capital IQ North America Fundamentals Annual and Historical Segment) and the Hoberg-Phillips data library (http://hobergphillips.usc.edu/), and matched to the information from the annual reports. The unit of analysis was the firm-year that a firm's central index key (CIK) and its date of the fiscal year end uniquely identify. Due to data availability, the period investigated covers the 10-year time horizon from 2006 until 2015. Industries in which operational strategies do not play a major role (e.g., banking, insurance, or services) were dropped. In total, 10,502 firm-years (1,599 firms, on average 6.6 (minimum: 3, maximum: 10) observations per firm) were retained for the analysis. Descriptive statistics and pairwise correlations among the variables are reported in Table 3-2.

3.4.2 Supply risk

Each risk item that was extracted consists of one or two sentences describing a single risk as described above. As these risks cover a broad range of different themes, a sentence latent Dirichlet allocation (sLDA) was employed to identify supply-related risk items and to quantify a firm's exposure to such risks. Bao and Datta (2014) developed this algorithm as extension of the original LDA by Blei et al. (2003) for the analysis of the risk disclosure in Item 1.A. The rationale behind the sLDA is that the risk items in the risk disclosure section are a blend of different topics, each of which is composed of distinct words. To exploit the unique structure of the risk disclosure, all words of one risk item are assumed to be sampled from the same topic. The sLDA achieves high quality in assigning and quantifying common topics in the risk disclosure: It has highest predictive power measured by perplexity and best cluster quality measured by the silhouette coefficient (Bao and Datta, 2014). According to extensive numerical studies conducted by Bao and Datta (2014), the sLDA has a comparable quality to supervised algorithms but is far more reliable. They found that it had highest precision for 30 to 40 topics.

Appendix B describes how the texts were preprocessed prior to building the topic model. Then, a metric similar to the "term frequency inverse document frequency" (tf-idf) was used as indicator for the most meaningful words characterizing a distinctive topic in preparation for the analysis. For the purpose of the present study, the nominator is the percentage of firms using a specific word. The denominator is the natural logarithm of the average fraction of a firm's risk items that contain the word. Words with a high score are potentially relevant. These are used by several firms in a small fraction of their risk items. In contrast, words that score low are less relevant. These are either used by very few firms or in a large fraction of risk items. All words that score lower than two were excluded from the relevant words of the period. In total, the corpus of relevant words comprises 981 distinctive terms ranging from 344 terms in 2006 to 847 in 2016.

Figure 3-2: Computation of the scores for the exposure to supply-related risk

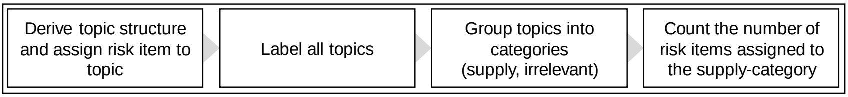


Figure 3-2 describes the computation of the supply risk score. The sLDA simultaneously identifies the underlying topic structure of the documents and assigns each risk item to a topic (Bao and Datta, 2014). The topic model is run with 34 topics on the corpus of relevant words present in the respective risk items. Its output is twofold: Each risk item is assigned to a topic and each topic is described by the words that occur the most frequently. The number of 34 topics serves as compromise between a higher granularity of topics (like 40 or 50) and the robustness of the assignment of risk item to topic. The key words per topic are robust to the number of topics.

Two researchers manually labeled all topics based on each topic's most frequent words and each topic's compilation of risk items, because automated labeling were not applicable (Mei et al., 2007). After discussions with other scholars in seminars and workshops, all supply-related topics were grouped into the broader category supply and the assigned risk items were counted for each firm and year. All other topics detected cover risks unrelated to supply management. The risk items assigned to these topics were discarded. Table 3-3 describes the supply-related sLDA-topics.

Table 3-3: Supply-related topics extracted from 10-K reports' Item 1.A using the sLDA

Topic	Topic label	Key words	Sample
0	**Disruption in production**	*natural facility production disaster manufacturing*	The impact of natural disasters could negatively impact our supply chain and customers resulting in an adverse impact to our revenues and profitability.
3	**Dependence on contract manufacturing**	*party rely development manufacture delay*	We have no capacity to manufacture supplies of our product candidates and intend to rely solely on third parties to manufacture supplies of all of our product candidates.
17	**Dependence on joint development**	*license agreement contract development right*	We are dependent on technology systems and third-party content that are beyond our control.
22	**Supply issues**	*supplier supply component party raw*	As we rely on a limited number of third parties to manufacture, assemble and test our IC products and to supply required parts and materials, we are exposed to significant supplier risks.
23	**International risks**	*foreign currency international fluctuation rate*	We manufacture a significant portion of our products outside the United States, and political, societal or economic instability may present additional risks to our business.

Let R_{Sup} denote the set of supply-related risk items. $1_{RI_{itk} \in R_{Sup}}$ is an indicator function indicating the membership of the kth risk item of firm i in year t ($RI_{i,t,k}$) in the set of supply-related risk items R_{Sup}.

$$1_{RI_{i,t,k} \in R_{Sup}} = \begin{cases} 1 & if\ RI_{i,t,k} \in R_{Sup} \\ 0 & otherwise \end{cases}$$

The risk exposure to supply-related risk of firm i in year t is then calculated as the sum of the indicator function values for the $K_{i,t}$ risk items RI_{itk} of firm i in year t.

$$Exp_{Sup,i,t} = \sum_{k=1}^{K_{i,t}} 1_{RI_{i,t,k} \in R_{Sup}}$$

The measurement for the exposure to supply-related risk is validated by computing the Spearman's rank correlation coefficient between the Standard & Poor's (S&P) credit rating and the measurement of supply-related risk. The Spearman's rank correlation coefficient is necessary, because the variables are not continuous. Its value of 0.19 illustrates that the disclosure of supply-related risk items is associated with bankruptcy probability and hence proxies a firm's exposure to risk.

3.4.3 External factor variables

Technology change ($TC_{i,t}$) is operationalized by product market fluidity (Hoberg et al., 2014). The variable is based on the product description sections in firm 10-K reports and measures the change in a firm's product descriptions due to competitors' moves in the firm's product markets. Technically, it measures the overlap between words in a firm's product description and the change in words describing the product market universe and is computed as dot product between the vector indicating the words a firm uses and the normalized vector indicating the words that changed from the previous year. This measure has been widely applied in the finance and accounting domains (e.g., Boone et al., 2016).

$$TC_{i,t} = N_{i,t} \cdot \frac{D_{t-1,t}}{\left\|D_{t-1,t}\right\|}$$

$N_{i,t}$ represents the vector indicating the words a firm i uses in year t and $D_{t-1,t}$ the vector indicating the words that have changed from year $t-1$ to t. Data are available for download from the Hoberg-Phillips data library homepage (http://hobergphillips.usc.edu). Higher values of product market fluidity indicate higher technology change.

Industry complexity ($IC_{i,t}$) is approximated by the reverse of industry concentration, because a higher concentration corresponds to a lower complexity (e.g., Palmer and Wiseman, 1999). An industry is thereby described by its four-digit SIC-code. Its concentration is measured by an industry's Herfindahl index of sales that is defined as the sum of the squared annual market shares of each firm operating in the industry. This measure has been widely used in strategic and operations management to account for industry complexity (e.g., George et al., 2016).

$$IC_{i,t} = 1 - \sum_{i=1}^{N_{j,t}} \left(\frac{s_{i,j,t}}{s_{j,t}}\right)^2$$

$s_{i,j,t}$ equals the annual sales of firm i in industry j in year t, $s_{j,t}$ the sum of sales of all firms $N_{j,t}$ in industry j in year t. Industry complexity is computed as 1 minus sales concentration with higher values indicating higher industry complexity.

3.4.4 Internal strategic choice variables

Publicly listed firms are required to disclose significant segment information (FASB, 1997). A separate segment needs to be reported if it covers 10 % of revenues, profits, losses, or assets. The segments can pertain to business or geographic segments. The measure of business diversification ($BD_{i,t}$) is based on computing the Herfindahl index for each firm i in year t based on the sales reported by its different business segments. It is defined as 1 minus the sum of the squared business segments' shares of sales of a firm.

$$BD_{i,t} = 1 - \sum_{b=1}^{B_{i,t}} \left(\frac{s_{b,i,t}}{s_{i,t}}\right)^2$$

$s_{b,i,t}$ is the annual sales of business segment b of firm i in year t and $s_{i,t}$ is the sum of sales of all $B_{i,t}$ business segments in which firm i operates in year t. Firms with values closer to 1 are more diversified while firms closer to 0 are less diversified.

As for business segments, firms must disclose significant geographic segment information. The measure of geographic diversification ($GD_{i,t}$) is based on computing the Herfindahl index for each firm i in year t based on the sales reported by its different geographic segments. It is defined as 1 minus the sum of the squared geographic segments' shares of sales of a firm.

$$GD_{i,t} = 1 - \sum_{g=1}^{G_{i,t}} \left(\frac{s_{g,i,t}}{s_{i,t}}\right)^2$$

$s_{g,i,t}$ is the annual sales of geographic segment g of a firm i in year t and $s_{i,t}$ is the sum of sales of all $G_{i,t}$ geographic segments in which firm i operates in year t. Firms with values closer to 1 are more diversified while firms closer to 0 are less so. Both measures of diversification assume a value of 0 for single-segment firms and have been widely applied in prior operations management research (e.g., Hendricks et al., 2009).

3.4.5 Control variables

Several variables control for differing firm characteristics and disclosure incentives. The natural logarithm of the book value of assets controls for firm size as larger firms tend to disclose more risks. Moreover, leverage ratio (book value of debt to book value of equity), book-to market ratio (book value of equity to market value of equity), and return on assets (net income to assets) control for differences in firm success and future growth options. Firms that are more successful or have more future growth options were found to disclose less risk in their annual reports (Hope et al., 2016, Israelsen and Yonker, 2017). Furthermore, the 5-year standard deviation of annual cash flows controls for risk inherent in a firm's business model. Firms with a higher standard deviation of cash flows were found to disclose more risks in their annual reports (Hope et al., 2016). Besides, the length of the annual report controls for a firm's internal disclosure orientation. The natural logarithm of file size serves as general measure for many dimensions of readability and serves as indicator for the clarity of the provided information (Hope et al., 2016, Loughran and McDonald, 2014). In addition, the natural logarithm of the number of analysts following a firm and a big-four auditing company control for differences in disclosure that is imposed by external auditing. Higher analyst following and a big-four auditing company were found to influence the disclosure quality (e.g., Nelson and Pritchard, 2016). Finally, firm-specific random intercepts and the time-dummy-variables control for firm-specific (e.g., differences in operating model, industry, or long-term strategy) and time-specific effects (e.g., overall economic development), respectively.

3.5 Analysis

3.5.1 Model specification

As firms are observed over time, two levels are present in the dataset. Standard approaches for the analysis of such data are fixed or random effects models for the two-level and multi-level models for more level cases. As multi-level and random effects models have the similar underlying equations and yield to almost identical results for the two-level case (e.g., Wooldridge, 2002), only fixed effects and random effects models are distinguished here. In fixed effects models, higher level variance (i.e., variance between firms) is controlled out by a group-wise demeaning of the variables. While this has the advantage of providing unbiased estimates in the presence of unobserved cross-level heterogeneity, it fails to measure the effect of any time-invariant variables (Bell and Jones, 2015). In contrast, random effects models combine within- and between-variance in a single estimate. If the within- and between-effects are different, the estimator is an uninterpretable weighted average of these two effects (e.g., Raudenbush and Bryk, 2002). This can be thought of as omitted variable bias because unaccounted variance will be absorbed by the error terms (group-error and random error).

The solution to this issue is to split each variable into a group-centered and a group-mean variable (Mundlak, 1978). By including the group-means into the regression equation, the between-effect is explicitly modeled and captures group-level heterogeneity (Bell and Jones, 2015, Certo et al., 2017). This approach has two major advantages. It yields unbiased estimates for the group-centered variables. Besides, it provides interesting information about the group-means (Bell and Jones, 2015). Thus, within- and between-variance of external factors and internal strategic choices can be used to explain differences in supply risk exposure in a single model.

The intra-class correlation coefficient (ICC) as measure of the relative importance of between-firm variance ranges from 0.75 for technology development to 0.95 for industry complexity, indicating that a large fraction of variance is attributable to differences between firms. In other words, between 75 % and 95 % of variance would be lost if a standard fixed effects model was estimated. At the same time, a Hausman test suggests that a random effects model is inappropriate ($p < 0.001$) (Hausman, 1978). Thus, this study also explicitly models the heterogeneity of the between-effect. To this end, all variables are split into two variables: a group-centered variable for the within- and the group-mean for the between effect. The group-mean is calculated as average over all observations of a firm. The group-centered variables are computed as difference of the firm-year observation and the firm average. These variables are used in a random effects estimation model with panel-clustered robust standard errors to account for the heteroscedasticity and autocorrelation which are present in the dataset. To control for period effects across firms ($p < 0.001$), year dummies were used, as this method is the most efficient for short panel data (Petersen, 2009). If the model is correctly specified, the estimates derived with a fixed effects model are the same as the estimates for the demeaned variables in the random effects model as delineated above. For the sake of brevity, only the complete model with random effects is described.

Operationally, the *xtreg*-routine with random effects in *Stata 15* was used to estimate the following model:

$$\begin{aligned} Exp_{Sup,i,t} = {} & b_1^C * TC_{i,t}^C + b_2^C * IC_{i,t}^C + b_3^C * BD_{i,t}^C + b_4^C * GD_{i,t}^C \\ & + b_1^M * TC_{i,t}^M b_2^M * IC_{i,t}^M + b_3^M * BD_{i,t}^M + b_4^M * GD_{i,t}^M \\ & + b_5^C * size_{i,t}^C + b_6^C * lev_{i,t}^C + b_7^C * roa_{i,t}^C + b_8^C * b2m_{i,t}^C \\ & \quad + b_9^C * big4_{i,t}^C \ + b_{10}^C * read_{i,t}^C + b_{11}^C * analyst_{i,t}^C \\ & \quad + b_{12}^C * cf_{i,t}^C \\ & + b_5^M * size_{i,t}^M + b_6^M * lev_{i,t}^M + b_7^M * roa_{i,t}^M + b_8^M * b2m_{i,t}^M \\ & \quad + b_9^M * big4_{i,t}^M + b_{10}^M * read_{i,t}^M + b_{11}^M * analyst_{i,t}^M \\ & \quad + b_{12}^M * cf_{i,t}^M \\ & + \sum_{j=2008}^{2016} \left(b_{13,j}^C * year_j^C + b_{13,j}^M * year_j^M \right) + b_0 + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{4}$$

In this equation, $Exp_{Sup,i,t}$ represents the dependent variable of supply risk exposure. $TC_{i,t}$ and $IC_{i,t}$ refer to the external factors of technology change and industry complexity respectively. $BD_{i,t}$ and $GD_{i,t}$ measure the internal strategic choices of business and geographic diversification respectively. $size_{i,t}$, $lev_{i,t}$, $roa_{i,t}$, and $b2m_{i,t}$ account for firm size, leverage ratio, return on assets, and book-to-market value. $big4_{i,t}$ is an indicator variable equal to 1 for firms being audited by a big-four auditing company, $read_{i,t}$ represents the file size and controls for the overall readability of a firm's annual report, and $analyst_{i,t}$ accounts for the number of analysts following a firm. $cf_{i,t}$ controls for variation in a firm's cash flows. All these variables are measured for firm i in year t. $year_j$ accounts for time-effects, with $year_j = 1$ if $j = t$ and 0 otherwise. The superscript C indicates a centered variable and estimate while the superscript M denotes the group mean variable and estimate. $\varepsilon_{i,t}$ is the random error term for shared errors between firm i and year t, μ_i accounts for unobserved firm-level random effects, and b_0 is the common intercept shared by all firms.

All independent variables are winsorized at the 99th percentile to address outliers (Aguinis et al., 2013). For an additional robustness check, the model was estimated in a pooled regression to derive variance inflation factors (VIFs). VIFs ranged from 1.02 to 3.18 for the final estimation model. This indicates that multicollinearity is unlikely to be a problem.

3.5.2 Endogeneity

Endogeneity poses a serious threat to the validity of empirical results. Its most frequent causes are reverse causality, measurement error, or omitted variable bias (Wooldridge, 2002). Although the absence of endogeneity cannot be proven, this study fulfills reasonable standards for plausible exogeneity of the regressors (cf. Ketokivi and McIntosh, 2017). The arguments revolve around theoretical arguments, the measurement of variables, and the use of panel data. First, reverse causality is unlikely to be present. As noted above, theory and prior empirical studies offer quite a few arguments, why external factors or internal strategic choices contribute to supply risk. The opposite is rather difficult to imagine. A firm has only limited influence on external factors such as technology change or industry complexity in the short run. An alternative but equally unlikely explanation may be that a firm, which identifies additional risks in its supply chain, deliberately seeks global sales or extends its product range.

Second, measurement error is addressed by minimizing the risk of common method bias as a main source of measurement error. The dependent and independent variables are not only calculated from secondary data sources, but were also obtained from different data sources. The measurement problem persists in the sense that firms can strategically disclose or withhold information in their annual reports. However, numerous studies have confirmed that a firm’s risk disclosure reflects its overall risk (e.g., Campbell et al., 2014, Israelsen and Yonker, 2017, Li et al., 2018). Thus, we believe that a firm’s disclosure of supply risk provides a good proxy for its downside risk exposure.

Third, omitted variable bias is addressed by the specification as a hybrid model (Certo et al., 2017). The demeaned variables provide robust estimates that are equal to the estimates of a fixed effects model. As a result, they are robust to omitted variable bias. In order to gain additional insights into the intercepts, the between-firm heterogeneity is explicitly modeled by the group means of the variables. The study includes several control variables which have been found to influence a firm’s risk disclosure to address the issue of omitted variable bias.

Table 3-4: Results of fixed effects (FE) and random effects (RE) regression analysis

	Fixed effects				Random effects			
	Control model		Full model		Control model		Full model	
Variables	**Estimate**	***SE***	**Estimate**	***SE***	**Estimate**	***SE***	**Estimate**	***SE***
External factors (group-centered for RE model, uncentered for FE model)								
Techn. change			0.045***	(0.012)			0.045***	(0.012)
Ind. complexity			0.777†	(0.433)			0.777†	(0.433)
External factors (group-means, for RE model only)								
Techn. change							0.245***	(0.021)
Ind. complexity							0.512	(0.382)
Internal strategic choice (group-centered for RE model, uncentered for FE model)								
Business div.			0.384*	(0.188)			0.384*	(0.188)
Geographic div.			0.079	(0.231)			0.079	(0.231)
Internal strategic choice (group-means, for RE model only)								
Business div.							–0.611*	(0.259)
Geographic div.							0.635**	(0.229)
Control variables (group-centered for RE model, uncentered for FE model)								
Size	0.318***	(0.069)	0.299***	(0.069)	0.318***	(0.069)	0.299***	(0.069)
Leverage	0.079	(0.272)	0.062	(0.268)	0.079	(0.272)	0.062	(0.269)
Book-to-market	0.041	(0.040)	0.034	(0.040)	0.041	(0.040)	0.034	(0.040)
Return on assets	–0.319*	(0.138)	–0.272*	(0.137)	–0.319*	(0.138)	–0.272*	(0.137)
Risk in cf	0.000	(0.003)	0.001	(0.003)	0.000	(0.003)	0.001	(0.003)
Readability	0.176†	(0.095)	0.153	(0.094)	0.176†	(0.095)	0.153	(0.095)
Analyst follow	0.007	(0.051)	0.006	(0.051)	0.007	(0.051)	0.006	(0.051)
Big-4 auditing	0.197	(0.141)	0.187	(0.139)	0.197	(0.141)	0.187	(0.139)
Control variables (group-means, for RE model only)								
Size					–0.218***	(0.057)	–0.168**	(0.056)
Leverage					–0.415	(0.514)	–0.479	(0.498)
Book-to-market					0.320**	(0.123)	0.473***	(0.117)
Return on assets					–2.490***	(0.444)	–0.567	(0.458)
Risk in cf					0.018	(0.031)	0.020	(0.029)
Readability					1.397***	(0.284)	0.957***	(0.273)
Analyst follow					0.440***	(0.089)	0.222**	(0.083)
Big-4 auditing					0.501**	(0.180)	0.414*	(0.169)
Constant	1.495***	(0.442)	0.626	(0.570)	2.684**	(0.945)	0.716	(0.968)
Firm FE	YES		YES		NO		NO	
Firm RE	NO		NO		YES		YES	
Time FE	YES		YES		YES		YES	
R^2	0.102		0.107		0.745		0.746	
AIC	30,796.47		30,744.35		37,725.78		37,518.17	
BIC	30,919.88		30,897.80		37,994.38		37,844.84	
Observations	10,502		10,502		10,502		10,502	
Number of CIK	1,599		1,599		1,599		1,599	

Note: Robust standard errors (*SE*) in parentheses (clustered at firm-level); the estimates of RE models were derived using the generalized least squares estimator; AIC and BIC of RE models were calculated using the maximum-likelihood estimator; R^2 (within) is reported for FE model, R^2 (adjusted) is reported for RE model.
† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

3.5.3 Results

While the control model adds control variables, the full model integrates the independent variables of external factors and internal strategic choices. As shown in Table 3-4, the R^2 increases when the control and independent variables are added. Finally, both Akaike's (AIC) and Schwarz's (BIC) Bayesian information criteria indicate that the full model fits the data better as their respective values become smaller. This offers statistical and empirical support for the effect of external factors and internal strategic choices on the exposure to supply risk. The discussion of the results is divided into three parts: The first part shows the results of the centered variables. The second part describes the results concerning the group means. The third part contrasts the estimates of the centered variables with the ones of the group means. The estimates of the centered variables model lend some support to the hypotheses. An increase in supply risk exposure was predicted to stem from an increase in external factors and change in the internal strategic choices. While *Hypothesis 1a* suggested that an increase in technology change is associated with an increase in supply risk exposure, *Hypothesis 2a* claimed that an increase in industry complexity is associated with an increase in supply risk. The coefficient of technology change is significantly positive ($b_1^C = 0.045$, $p < 0.001$) providing support for *Hypothesis 1a*. The positive coefficient of industry complexity ($b_2^C = 0.777,\ p = 0.08$) provides weak support for *Hypothesis 2a*. In sum, change induced by external factors (technology change and industry complexity) contributes heavily to an increase in supply risk. Furthermore, the risk from internal strategic choices was investigated. An increase in business diversification (*Hypothesis 3a*) and geographic diversification (*Hypothesis 4a*) were hypothesized to increase the supply risk exposure. In line with expectancy, the coefficient of business diversification is significant and positive ($b_3^C = 0.384$, $p < 0.05$) in support of *Hypothesis 3a*. The results do not support *Hypothesis 4a* ($b_4^C = 0.079$, $p = 0.725$).

In addition, estimates for the group means are investigated, because the intra-class correlation suggested a considerable amount of variance on the group-level. The hypotheses predicted that supply risk stems from a high degree of external factors but a low degree of diversification. More specifically, a high degree of technology change (*Hypothesis 1b*) and a high degree of industry complexity (*Hypothesis 2b*) were both hypothesized to be related to a high supply risk. As predicted by *Hypothesis 1b*, the coefficient for technology change is positive and significant ($b_1^M = 0.245,\ p < 0.001$). However, the results do not support *Hypothesis 2b* ($b_2^M = 0.512,\ p = 0.562$). Furthermore, *Hypothesis 3b* predicted that firms with a high degree of business diversification face low supply risk and *Hypothesis 4b* claimed that firms with a high degree of geographic diversification are exposed to a low supply risk. The results provide partial support for the hypotheses as the coefficient of business diversification ($b_3^M = -0.611,\ p < 0.05$) is significant and negative. In contrast to expectancy, the coefficient for geographic diversification is positive ($b_4^M = 0.635,\ p < 0.01$). Firms with a high degree of geographic diversification are associated with a high supply risk exposure. While risk pooling effects across regions and segments were expected, they are observed only for the latter.

Finally, the within-effects are contrasted to the between-effects to further investigate the differences between the effects. Of the four independent variables, three have indeed different estimates for within- and between-effects. The estimates of business diversification ($\chi^2(1) = 9.97,\ p < 0.01$) and technology change ($\chi^2(1) = 72.63,\ p < 0.001$) were significantly different from each other while the estimates of geographic diversification ($\chi^2(1) = 2.96,\ p = 0.085$) were weakly different from each other. For industry complexity ($\chi^2(1) = 0.22,\ p = 0.641$), the estimates were not significantly different.

As robustness check, the above model was run as fixed effects model. As displayed in Table 3-4, the estimates for the group-centered variables from the random effects models are equal to the respective estimates from the fixed effects model. Furthermore, the random effects model was run as multi-level model (2 levels). The results are almost equal. Moreover, a third level was added capturing industry effects. The intra-class correlation coefficient shows that only 17 % of the total variance in the dependent variable were explained by industry effects, 53 % by firm effects and 30 % by time effects. However, the inclusion of the industry-level had only minor influence on the size of the estimates for the group mean of geographic diversification leading to the conclusion that these effects do not play a major role. For the sake of brevity, they are not presented here.

3.6 Discussion

This study investigated factors that contribute to a firm's supply risk exposure. The results make several important theoretical, methodological, and empirical contributions and have important implications for managers. First, this study pursues a structured approach to delineate factors that contribute to a firm's supply risk exposure. Previous research has either relied on anecdotal or survey-based evidence to identify sources of risk (e.g., Wagner and Bode, 2006), however, the studies have not delivered a structured framework to explain which sources of risk turn into exposure to supply risk. This study's theoretical perspective builds on the strategic choice and environmental determinism literature which finds that both dimensions may contribute independently to negative firm performance (MacKay and Chia, 2013). This perspective also enhances the understanding of purely negative supply risk: Increases in supply risk stem from both the choices that a firm actively makes (such as increase business diversification) and external factors beyond that firm's direct control (such as increases in industry technology change). More importantly, external factors explain both higher degrees of and increases in supply risk to a larger extent than internal strategic choices indicating that an outside-in perspective (industry factors) explains a firm's supply risk exposure better than an inside-out perspective (resources and their deployment).

Second, from a methodological perspective, this study investigates within- and between-firm variance in a single empirical model. The approach has only recently gained management scholars' attention. The results confirm that changes over time are indeed not the same as differences between firms. This confirms that researchers must carefully specify the level for which a theory is valid (Klein et al., 1994). By accounting for both effects and avoiding ecological fallacy, this essay distinguishes the direction of each effect and draws the correct conclusions for each level, time and firm, which is crucial in multilevel theorizing and modelling (Paruchuri et al., 2018).

Combining this study's theoretical perspective with its methodological approach, further theoretical contributions can be carved out. Third, external factors always contribute to supply risk in the sense that both an increase and a higher degree lead to higher supply risk (with different effect sizes). Thus, uncertainty in a firm's environment translates into risk exposure that the firm cannot escape. In contrast, internal strategic choices exhibit a more nuanced finding. For business diversification, the sign is positive for the within-effect but negative for the between-effect. Thus, firms can counter their supply risk exposure in the long run by means of high degree of business diversification. One possible explanation of these results is that firms operating in several disciplines have access to a broader supply base and can leverage their power and reputation to mitigate their supply risk exposure.

Fourth, although geographic diversification was posited to provide operational flexibility and the resulting size power over its suppliers, such benefits do not seem to translate into a reduced exposure to supply risk. Prior conceptual and empirical papers have already discussed a more complicated or even negative relationship between geographic diversification and firm performance and found that most firms realize disadvantages – not advantages – from the degree of their global sourcing strategy (Lu and Shang, 2017). Transaction costs increase with the number of country-specific transactions with suppliers, customers, distributors, or government agencies (Hitt et al., 1997). In addition, firms that are more geographically diversified exhibit a more negative stock market reaction than do firms that are less diversified (Hendricks et al., 2009). Besides, from an operations management perspective, firms with greater geographic diversification have an increased likelihood of product recalls (Steven et al., 2014). This study not only accumulates further empirical evidence that a high degree of geographic diversification in sales is not necessarily beneficial for the operations, but also adds a risk perspective to the explanation that international operations increase the cost of managing a multinational network (Lee and Makhija, 2009).

Fifth, the difference of the "within-effect" of geographic diversification from its "between-effect" can explain opposing results found in empirical studies thus far. Hendricks et al. (2009) reported a negative moderating effect between geographical diversification and stock market reaction in an event study. In contrast, Kovach et al. (2015) found a positive moderating effect between unpredictability and operating performance in a longitudinal multi-level study. While the former identified differences between firms based on cross-sectional data, the latter found differences over time. Thus, the explicit modeling of the within-effect and between-effect explains these differences and advances the understanding of the multifaceted nature of supply risk.

Finally, this study contributes to the empirical measurement of ex-ante downside exposure to supply risks that firms face and for which no real measurement exists to date. The risk section of a firm's annual report is scrutinized by means of a sLDA to detect risks that deal with supply. One additional risk item about supply-related risk in a firm's annual report is interpreted as an increase in the ex-ante downside exposure to supply-related risk. The positive association between external factors and supply risk disclosure provides empirical evidence that a firm's disclosure with respect to supply risk reflects its exposure. This measurement is an improvement over those presented in previous studies that relied on ex-post information on materialized disruptions or that approximated the ex-ante risk exposure using either variables describing the environment or sales data. As the measurement derived from the corporate risk disclosure directly captures a firm's ex-ante downside exposure to supply risk, it more accurately concurs with managers' perceptions of risk (March and Shapira, 1987) and is more relevant to operations management researchers. Furthermore, this study introduces a new measurement of technology change which relates a firm's change to its industry's change (Hoberg et al., 2014). While the measurement has attracted broad attention in the fields of finance and accounting, operations management scholars have not been aware of it, yet.

For managers, our results have important implications. The results suggest that a high degree of geographic diversification is associated with a high supply risk exposure while a high degree of business diversification is associated with low supply risk exposure. From these results, we conclude that firms continued to rely on their existing supply base when entering foreign geographic markets but engaged in new supplier relationships when they entered new business segments. In order to fully exploit the mitigation potential of geographic diversification, firms should also diversify their supply base when they are active in different geographic markets. Furthermore, from a sole risk management perspective, firms should diversify their businesses (in terms of segments) and enlarge their supply base. Although this increases the supply risk exposure in the short run, more diversified firms benefit from risk pooling effects, thereby decreasing their supply risk exposure in the long run. Finally, technology change and industry complexity contribute to supply risk to a larger extent than changes in business diversification. This suggests that firms should hold some resources to tackle their risk exposure because they cannot escape from the uncertainty in their external environments.

While this study makes several contributions to theory and has important implications for practitioners, it has a few limitations which might serve as avenues for further research. First of all, this study identifies only the differences in within- and between effects as well as opposite directions of business diversification. Future studies can attempt to explain the differences and explicitly consider mediating and moderating factors between strategic decisions and supply risk exposure. In addition, this study can serve as starting point for the investigation of international sales, international procurement and how the two are related. Moreover, we suggest future research on the consequences of the exposure to supply risk. Future studies can investigate whether risk exposure has negative performance implications and how firms can actually tackle efficiently the risk that they anticipate. Finally, the same limitations that apply to any empirical study with secondary data pertain to this study. Data of firms that are publicly listed in the US and belong in the manufacturing sector were used to test the proposed relationships. Firms in other industries, operating in other countries, or not publicly listed might have other requirements or objectives. Consequently, the generalizability of the findings might be limited. Further research can explore these issues. Also, an important assumption underlying the use of secondary financial data and information from annual reports is that they accurately represent a firm's true financial condition and that there are no accounting misrepresentations or manipulations. Therefore, we suggest further research on this topic using other data sources.

3.7 Conclusion

This study distinguishes two types of supply risk sources. External factors beyond a firm's direct control contribute to its supply risk exposure. In response to changes in the industry, a firm has to adapt its value chain, identify new suppliers for innovative products, or counter competitive pressure within its industry. The empirical results suggest that both changes over time and differences between firms explain supply risk exposure. The second type, a firm's strategies, also contribute to its supply risk exposure. A firm's decision to extend the product or the geographic diversification has consequences for its supply chains. The empirical results provide evidence that an increase in business diversification contributes to an increased supply risk exposure whereas a high degree of business diversification leads to a pooling effect with the result that supply risk exposure decreases. These results are linked to prior findings in the operations management literature.

4 Supply Chain Risk and Risk Mitigation: Which Strategies are the Most Efficient?

Co-author:

Christoph Bode

Endowed Chair of Procurement, Business School, University of Mannheim, Germany

Abstract:

Firms face risks in their upstream and downstream supply chains. Although some operational strategies can fully or partially insulate a firm from the adverse effects of possible supply chain disruptions, implementing these strategies is costly. At the same time, firms face intense pressure on margins, forcing them to keep operating costs low. These conflicting goals require further investigation on whether and to what extent different operational strategies can mitigate several types of risk. This paper delineates and tests how operational strategies mitigate the exposure to supply chain risks with minimum negative influence on performance. To measure a firm's exposure to supply chain risk, we analyzed corporate qualitative risk disclosures in annual reports (Form 10-K) using an adapted latent Dirichlet allocation approach from computational linguistics. The results suggest that operational strategies mitigate the negative association between supply-related risk and performance, but not the negative association between demand-related risk and performance.

4.1 Introduction

"Risk is a function of how poorly a strategy will perform, if the 'wrong' scenario occurs."

Michael E. Porter (1985: 476)

Over the past two decades, many firms have implemented many supply chain initiatives, from single sourcing or vendor-managed inventory all the way to just-in-time logistics concepts, to reduce inventory levels and increase the utilization of fixed assets (e.g., Chen et al., 2005). In stable environments, these initiatives have a positive effect on firm performance. In volatile, uncertain, complex, and ambiguous (VUCA) environments, however, they also make firms more vulnerable to exogenous disruptive events. Both the supply and the demand sides of supply chains are susceptible to such disruptions. For example, the 2011 earthquake in Japan disrupted Toyota's supply for months, while a fire in a Primark distribution center threatened the company's run-up for the Christmas sales season (Gibson and Savage, 2013). Once materialized, such disruptions have a severe effect on a firm's operating performance, stock price, as well as short- and long-term shareholder value (Hendricks and Singhal, 2003, 2005a, b, 2014).

Professionals are aware of the increased vulnerability of their supply chains and associated negative consequences: 42 % of global chief procurement officers have reported an increase in supply-related risk (Deloitte, 2016) and 60 % of chief supply chain officers consider risk management a crucial activity (IBM, 2009). However, the same managers have also reported that pressure on margins and savings remains high (Deloitte, 2016) and that cost containment is a top priority (IBM, 2009). This trade-off between costly risk management and cost containment is a key challenge for supply chain managers: For every type of risk, they have to decide in advance between taking the risk of a possible loss (lottery) or incurring the cost of a risk management intervention which prevents extreme losses (sure payout) (Bakshi and Kleindorfer, 2009, Blome and Schoenherr, 2011). If managers accept too much risk, then a disruption and operational losses are almost certain. In contrast, if managers invest too much on risk management, the firm's operations become inefficient and profit margins decline. Precise guidance on the trade-off on risk acceptance vs. risk management is scarce, because neither a measurement for ex-ante downside risk exists nor is there deep knowledge about the efficiency of risk mitigation activities.

Chopra and Sodhi (2004) have suggested implementing risk mitigation strategies that have minimum impact on efficiency. To the best of our knowledge, only two studies have investigated conditions under which certain operational strategies are efficient. The empirical results of Kovach et al. (2015) suggested that capacity slack strengthens firm performance in unstable markets. Talluri et al. (2013) illustrated that operational risk mitigation strategies improve supply chain performance in the presence of distinct types of supply chain risk. While the former study focuses on demand variability as sole source of risk, the latter considers only operational performance. Hence, there is still no clear guidance on the conditions under which costly risk management provides benefits on the corporate level, leading to our research question: Which operational strategies mitigate different types of supply chain risk in the least costly manner?

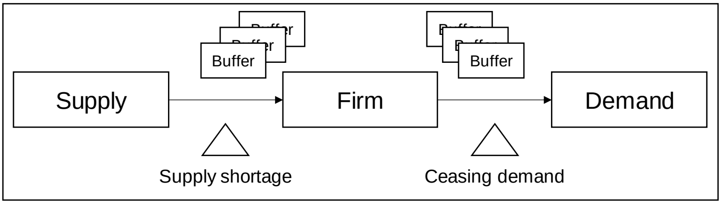
We investigate how firms operate if they are exposed to supply chain risk. Risk exposure is a firm’s acknowledgement that a risk exists. For its measurement, we use the textual risk descriptions in corporate annual reports (Item 1.A in 10-K filings). The risk exposure is matched to financial data on operational strategies and performance. This data set allows us to answer our research question in response to calls to incorporate performance metrics for the evaluation of risk management approaches (Manuj et al., 2014) and to investigate conditions under which operational risk management is beneficial (Kovach et al., 2015).

4.2 Background

4.2.1 Supply chain risk exposure

Risk can be conceptualized either as fluctuations around an expected value (Arrow, 1965) or as a purely negative deviation from an expected outcome (Mao, 1970). Although both are found in the literature, the latter more accurately reflects managerial perceptions (March and Shapira, 1987) and is hence predominantly found in management in general (e.g., Miller and Leiblein, 1996) and in supply chain management in particular (e.g., Käki et al., 2015). In this study, risk is conceived as the possible threat of a negative deviation from an expected performance outcome. On the one hand, risk comprises the negative-only deviation of the realized result from the anticipated one. Such deviation is often triggered by an event in a firm’s environment. On the other hand, risk contains the probability that such an event actually occurs (Wagner and Bode, 2008).

Figure 4-1: Sources of risk along the supply chain and operational mitigation strategies



As Figure 4-1 illustrates, this study assumes a supply chain perspective and focuses on risk caused by potential disruptions that affect supply and demand (Manuj et al., 2014). Supply risk is the possibility of a disruption associated with inbound supply or operations, such that a firm is unable to meet customer demand (Manuj et al., 2014). One example of a supply disruption is the complete breakdown of production if a single-sourced supplier fails to deliver a critical component. Demand risk is the possibility of an event that is associated with outbound flows or with variance in customer demand and may affect the likelihood of customers placing orders with the focal firm (Manuj and Mentzer, 2008). With regard to variance in customer demand, both the product mix and the volume offered by a firm can be affected (Tang and Tomlin, 2008). Examples of events affecting the outbound logistics are truck driver strikes or fires in distribution warehouses (Wagner and Bode, 2008). Examples affecting the customer demand are a lack of market acceptance of new products or the introduction of new products by competitors, rendering a firm’s product obsolete (Manuj and Mentzer, 2008).

4.2.2 Risk disclosure

Annual reports are arguably the most important communication channel that firms have to present their business performance and development to shareholders and other stakeholders (Gao et al., 2016). Disclosures therein significantly affect shareholder behavior (e.g., Staw et al., 1983). According to the Generally Accepted Accounting Principles in the United States (US-GAAP), annual reports must disclose the material risks facing a firm (FASB, 2010), with risk being defined as possible loss caused by future events (FASB, 1975). A risk is material if there is a “substantial likelihood that the disclosure of the omitted fact would have been viewed by the reasonable investor as having significantly altered the 'total mix' of information made available" (TSC Industries vs. Northway, 1976). The risk can be associated with either the supply or demand side of a firm, such as the loss or damage of enterprise property by fire, obligations related to product warranties, and losses from catastrophes (FASB, 1975). This definition of risk corresponds to the definition of risk in supply chain management.

Although managers can choose which risks to disclose based on what they believe to be significant, risk disclosures reflect the risk to which firms are exposed (Rajgopal, 1999). Additionally, the selection of risks disclosed is in itself informative about the firm strategy and the risks on which managers focus their attention (Schrand and Elliott, 1998). Consequently, the risk disclosure in annual reports has been of longstanding interest to researchers, especially with the rise of computational linguistics. In general, textual disclosures are informative with respect to both fundamentals and market reactions (Li, 2010). Increases in textual risk disclosures are associated with higher stock return volatility, trading volume, investor's risk perceptions, and more dispersed forecast revisions (Kravet and Muslu, 2013). Negative news is more strongly weighted (Kothari et al., 2009). As the annual reports are widely accepted to be accurate, relevant and representative, their semantics were used to extend industry classifications (Hoberg and Phillips, 2016) or to detect competitive forces (Hoberg et al., 2014).

In accounting and finance, common methodological approaches are to compare the semantics of annual reports (Hoberg and Phillips, 2016), assess their readability (Loughran and McDonald, 2016), assess their sentiment (Kearney and Liu, 2014), or detect common topics in risk disclosure (e.g., Campbell et al., 2014). To achieve the latter, researchers have applied various methods of automated text analysis from computational linguistics ranging from dictionary-based and supervised to unsupervised text mining algorithms. In contrast to the former two methods which have the drawback that the criteria for the categories have to be defined a priori, unsupervised text mining algorithms require only a specific number of topics. They are particularly useful to infer unknown connections from text (Agarwal et al., 2017). One example of an unsupervised text mining algorithm is the latent Dirichlet allocation (LDA) proposed by Blei et al. (2003). The LDA is part of probabilistic generative models and can be used to infer a hidden thematic structure in documents. Documents arise from a generative process based on distributions of words and topics. To generate a document, its words are assumed to be picked from the distribution of a document’s topics and the distribution of words given the topic drawn. While all documents cover the same topics and all topics use the same words, their respective probabilities are different. From the observed set of documents, the documents’ hidden distributions of topics and each topic’s distribution of words are computed by maximizing the likelihood of observing the documents.

Table 4-1: Risk items (extract) disclosed by "LS Starrett Company" (CIK 93676) in 2013 and 2014 after receiving comments from the SEC on the corporate risk disclosure

Fiscal year ended 06/30/2013	Fiscal year ended 06/30/2014
Risks Related to Raw Material and Energy Costs	Volatility in the price of energy and raw materials could negatively affect our margins.
Risks Related to Technology	Technological innovation by competitors could adversely affect financial results.
Risks Related to Foreign Operations	International operations and our financial results in those markets may be affected by legal, regulatory, political, currency exchange and other economic risks.
Risks Related to Information Systems	Any inadequacy, interruption, integration failure or security failure with respect to our information technology could harm our ability to effectively operate our business.

Since 2005, the United States Securities and Exchange Commission (SEC) has required firms to disclose risks in a single, dedicated section, Item 1.A (“Risk Factors”) (SEC, 2005). Risks are the factors that “make the offering speculative or risky” (SEC, 2005). In this section, each risk must be presented under a sub-caption that summarizes the risk and that is subsequently denoted as a “risk item”. The risk must then be discussed below this sub-caption. Each risk item and its accompanying discussion should focus on a single risk. The SEC enforces these requirements. Frequently mentioned criticisms by the SEC are unspecific risk items that could apply to any firm, inconsistencies with other parts of the report, and omitted or irrelevant risk items. For example (as illustrated in Table 4-1), the L.S. Starrett Company changed the risk items after having received critical comments from the SEC. A study of SEC staff comments on prospectuses of initial public offerings reveals similar results (Robbins and Rothenburg, 2005).

Table 4-2: Sample supply- and demand related risk items disclosed in annual reports (Form 10-K, Item 1.A)

Supply-related risk	Demand-related risk
If we fail to maintain or expand our relationships with our suppliers, in some cases single-source suppliers, we may not have adequate access to new or key technology necessary for our products, and, as a result, our ability to deliver leading-edge products may be impaired.	Unfavorable legislation in the hearing health market may decrease the demand for our products, and may negatively impact our financial condition.
We depend on highly specialized equipment to manufacture our products and loss of or damage to our manufacturing facilities could result in significant losses.	The competitive nature of our business results in significant price concessions to our customers and increased pressure to reduce our costs.
We have increased our dependence on external sources of wood pulp, which subjects our business and results of operations to potentially significant fluctuations in the price of market pulp.	The uncertainty of acceptance of products developed through biotechnology could affect our profitability.

Item 1.A discusses a wide range of topics from general market risk down to idiosyncratic risk that affects only the supply or demand of a single firm (SEC, 2005). Table 4-2 shows a sample of supply- and demand-related risk items. Studies focusing on Item 1.A show that investors regard the information disclosed as relevant. In general, risk items reflect the risk that a firm faces (Campbell et al., 2014). The qualitative risk factor section has additional explanatory power for financials (Huang, 2010) and is associated with higher stock return volatility (Israelsen, 2014). In particular, disclosing firm-specific risk reduces information asymmetry between firms and their investors (Bao and Datta, 2014). The information content of the qualitative part of the risk item disclosure is associated with quantitative information from financials (Beatty et al., 2018). In this regard, more specific risk items lead to a stronger market reaction (Hope et al., 2016). The information content of risk factors has also been validated: As the disclosure of oil-related risk can serve as proxy for risk associated with the oil price, the disclosure of other risks can be used to proxy those risks for which well-accepted proxies do not exist (Israelsen, 2014) such as supply chain risk. First studies rely on the information content revealed in the risk disclosure. Firms with greater exposure to key employee risk disclosed are smaller and more innovation-oriented. They have higher total and idiosyncratic stock return volatilities (Israelsen and Yonker, 2017). This again demonstrates that the firms' risk disclosure in their annual report not only contains relevant and validated information, but is also explored from other angles.

4.2.3 Risk management

Researchers have identified several operational strategies that reduce either the risk's probability of occurrence or its loss (Ho et al., 2015). The strategies cover the development of robustness or resilience (e.g., Brandon-Jones et al., 2014), supply chain agility (e.g., Braunscheidel and Suresh, 2009), multi-sourcing (e.g., Tomlin, 2006), information sharing (e.g., Dehning et al., 2007), or supplier development (e.g., Talluri et al., 2010). While these risk mitigation strategies can be effective, they involve coordinating activities across several stages of the supply chain and increase a firm's dependence on its suppliers or customers. However, increasing the dependency on suppliers or customers is in itself a driver of a firm's exposure to supply chain risk (Wagner and Bode, 2006). In addition, if risk is transferred from one firm to another, risk can accumulate at one member of the supply chain or its different members might follow individual and possibly contradicting strategies (Hallikas et al., 2004). Hence, the focus of this study is on strategies that a firm can implement independently from other firms in its supply chain to manage supply chain risk.

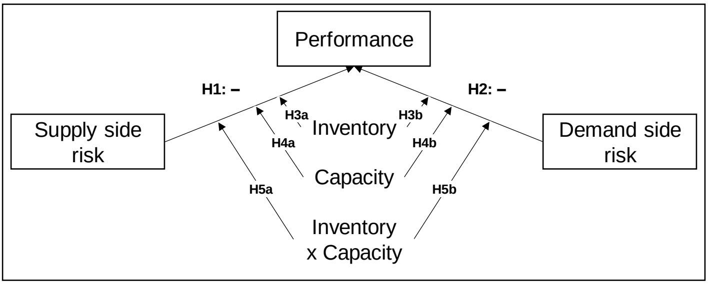
The discussion of such strategies typically revolves around redundancy or operational slack (Chopra and Sodhi, 2014). Slack refers to resources available to a firm in excess of actual requirements and serves as cushion to adapt to internal or external pressures (Bourgeois, 1981). Operational slack can be categorized as absorbed slack (Singh, 1986) because it is of low discretion (George, 2005). Inventory and capacity are two common forms of operational slack (Chopra and Sodhi, 2014). If the normal flow of goods is disrupted, operational slack does not address the corresponding root causes of disruptions, but rather mitigates the disruption's immediate negative effects (Field et al., 2006). It enables a firm to buy time such that the attention can be diverted from immediate firefighting to identifying a workaround as remediation. Operational slack can be employed to maintain operations, repair facilities, or obtain supplies from different sources, when severe disruptions materialize in the supply chain (MacKenzie et al., 2014). Consequently, the association between the level of operational leanness (as the inverse of operational slack) and firm performance or credit ratings exhibits a curvilinear relationship indicating that less slack is not always better (Bendig et al., 2017, Modi and Mishra, 2011). In contrast, operational slack can be beneficial for firm performance. Firms with more operational slack experience less negative stock market reactions to supply chain disruptions announced (Hendricks et al., 2009) and exhibit superior performance if they operate in unstable environments (Kovach et al., 2015). Besides these benefits on firm performance, operational slack lowers the likelihood of new venture failure (Azadegan et al., 2013a), has a positive (negative) effect on product exploitation (exploration) (Voss et al., 2009) and improves worker safety (Wiengarten et al., 2017).

A second operational strategy is flexibility. It reflects a firm's ability to adapt or respond effectively to change (Jack and Raturi, 2002). However, the two concepts of slack and flexibility are interwoven. Operational slack is an antecedent of flexibility because most firms derive their short-term flexibility from redundant operational resources like inventory or capacity (Jack and Raturi, 2002). To avoid conceptual ambiguity, this study's focus is on how firms can invest in operational slack to manage identified risks.

4.3 Conceptual Framework

This essay studies the link between corporate supply chain risk exposure, operational slack, and firm performance. From an information processing perspective, firms require appropriate information processing capabilities to operate effectively in an uncertain environment (Tushman and Nadler, 1978). Firms can reduce the information processing requirements by the creation of self-contained tasks leading to slack and the introduction of slack into the firm's operations (Galbraith, 1974). The most prominent forms of operational slack are inventory and redundancy as outlined in subsection 4.2.3. Figure 4-2 depicts the conceptual framework and the relationships that are hypothesized.

Figure 4-2: Conceptual framework guiding the analysis



4.3.1 Supply and demand side risk

When risk is conceptualized as the possible threat of a negative deviation from the expected performance, an increase in risk exposure implies that additional negative deviations from the expected result can occur. Events triggering a deviation are key suppliers who cannot deliver input required for production (supply risk exposure) or customers who may refuse a new product (demand risk exposure). A firm with higher risk exposure faces more potential deviations and consequently a higher probability that at least one event materializes than a firm with lower risk exposure. Prior research has shown that the actual occurrence of such events has a severe negative effect on operational performance (Hendricks and Singhal, 2005a). These also reduce stock returns, increase stock price volatility, and reduce customer satisfaction. Therefore, a higher risk exposure increases the likelihood that the operational performance of a firm decreases. Exposure to risk requires a firm's managers to monitor their firm's current situation in the light of environmental developments. In addition, the managers must assess the extent to which the developments are relevant or irrelevant for their firm. The execution of such tasks requires resources. For example, the Procurement Risk Management Group at Hewlett Packard developed a suite of software tools to support risk management practices (Nagali et al., 2007). Moreover, firms develop potential action plans in anticipation of potential future disruptions as Mattel did to deal with potential disruptions (Pyke and Tang, 2010). These examples show that firms exposed to risk commit costly resources to risk management activities which harms operational performance. Finally, higher risk exposure leads to more variability in a firm's cash flow (Lubatkin and Chatterjee, 1994). To smooth out the cash flow, the firm's management may seek to decrease the corporate exposure at the expense of higher cost (Miller, 1998). On the one hand, slack resources can be introduced into a firm's operations which is costly. On the other hand, tasks can be re-planned, re-adjusted, and re-aligned throughout an organization. This reduces operational efficiency as employees have to deviate from established working procedures and change existing production steps. Therefore, a higher risk exposure increases costs and reduces revenue, leading to lower profit:

Hypothesis 1: *The higher the exposure to supply risk, the lower the financial performance.*

Hypothesis 2: *The higher the exposure to demand risk, the lower the financial performance.*

4.3.2 Risk mitigation strategies

Slack absorbs external shocks and (partially) decouples a firm's operations from the environment (Bourgeois, 1981). However, it reduces operational efficiency, is costly, and may have only limited benefits. As shown in Figure 4-2, firms must evaluate whether operational slack actually mitigates the effects of the exposure to a given set of perceived operational risks (Galbraith, 1973) and whether the resources fit to the environment (Tushman and Nadler, 1978). As discussed above, we focus on capacity and inventory as operational slack resources in response to exposure to supply and demand risk.

4.3.2.1 Inventory slack

In practice firms carry inventory for several well-documented reasons, such as the risk inherent in the timing or rate of supply and demand. Inventories ensure the availability of goods despite delivery or production delays, serve as a hedge against price fluctuations, or smooth production if huge bulk orders are placed (e.g., Nahmias, 2009, Slack et al., 2007). Hence, they can improve the operational flow. The drawback of additional costs stemming from storage, loss, or obsolescence is also well documented (e.g., Nahmias, 2009, Slack et al., 2007). The production/manufacturing literature reveals comparable results: additional buffers of costly work-in-process inventory increase the capacity of production flow-lines (Conway et al., 1988). The cost-benefit trade-off of inventory has generated numerous empirical studies investigating inventory as well as the link of inventory to performance. Several studies have rejected the idea that firms with the smallest inventories perform best (e.g., Chen et al., 2005, Eroglu and Hofer, 2011). One reason for this is environmental uncertainty. If the exposure to risk is low, the operational flow can be ensured at very low levels of inventory. In contrast, high inventory levels would result in increased cost only. However, if exposure to risk is high, inventory is required to ensure the operational flow. The cost for inventory is lower than cost from production interruptions. This view is supported by empirical results: They suggest that firms with more slack in their supply chain experience less pronounced stock market reactions to announced operational disruptions (Hendricks et al., 2009). Inventory is especially favorable if the disruption is short (Tomlin, 2006). These arguments suggest that firms holding higher levels of inventory in the presence of supply risk exhibit a lower performance decline than those with lower levels of inventory.

Hypothesis 3a: *The negative association between a firm's exposure to supply risk and its financial performance is weaker if the firm has high levels of inventory slack than if the firm has low levels of inventory.*

In contrast, the usefulness of inventory in the presence of demand risk is not as clear as in the presence of supply risk. Higher inventory can be counterproductive. Exposure to demand risk implies that the trend of demand carries risk in the sense that demand does not materialize as planned. If in this case raw materials continue to be sourced or finished goods produced, this introduces automatically slack. But more slack does not absolve a firm from re-planning when demand does not materialize. On the contrary, a high level of inventory in the presence of demand risk leads to higher risk of obsolescence. If demand risk materializes (i.e., demand lower than expected), then inventory accumulates. The longer inventory has been stored, the greater the probability that either expiration dates have passed or products have become technically outdated. As a result, inventory is obsolete. It does not only lose value but may also be disposed at cost. Therefore, a higher exposure to demand risk leads to the higher risk of costly obsolete inventory. These arguments suggest that if firms are exposed to demand risk, they have a stronger performance decline with high inventory slack than firms with low inventory slack.

Hypothesis 3b: *The negative association between a firm's exposure to demand risk and its financial performance is stronger if the firm has high levels of inventory slack than if the firm has low levels of inventory.*

4.3.2.2 Capacity slack

Although a high utilization of capacity is good, the inverse-U-shaped relationship between production resource efficiency and performance indicates that a certain minimum level of resources is even better (Modi and Mishra, 2011). Similar to the line of argument for inventory, a firm can use capacity slack to buffer its operations against outside contingencies (Chopra and Sodhi, 2004). Empirical results suggest that capacity slack mitigates effects from the exposure to supply risk. Firms with high capacity experience less severe stock market reactions after they announce a supply chain disruption because they recover more quickly (Hendricks et al., 2009). Excess capacity is extraordinarily valuable in markets that are characterized by a high degree of demand instability (Kovach et al., 2015). In daily operations, if a disruption actually hits a firm and leads to the consumption and depletion of inventory, production must be halted, creating a backlog of orders. After the normal flow of goods is restored, excess capacity not only enables a firm to catch up more quickly on its production schedule, but allows it to reschedule and shift production between sites or production flow lines. Customer orders can be fulfilled with only minor delays and backlogs cleared. Especially in service operations, capacity serves as a buffer to scale up production quickly (Ellram et al., 2004). In the healthcare industry, capacity is used to react quickly if tasks require more time than anticipated (Jack and Powers, 2004). Hence, we posit that firms that are exposed to supply-related risk but possess excess capacity have a lower performance decline than firms that have more capacity tied up.

Hypothesis 4a: The negative association between a firm's exposure to supply risk and its financial performance is weaker if the firm has high levels of capacity slack than if the firm has low levels of capacity.

If some product is not approved or if a major customer goes bankrupt and cancels all its orders, a previously defined production plan becomes obsolete. On short notice, the reserved production capacity is idle, resulting in cost only. Production capacity or knowledge exclusively utilizable for a single product or customer even becomes obsolete and the investment is consequently sunk. Cost for capacity remains. As demand does not materialize, no revenue can be generated. Therefore, a higher exposure to demand risk results in idle capacity and lack of revenue:

Hypothesis 4b: The negative association between a firm's exposure to demand risk and its financial performance is stronger if the firm has high levels of capacity slack than if the firm has low levels of capacity.

4.3.2.3 Interaction of slack resources

The upshot of the preceding analysis is that operational strategies mitigate the exposure to supply-related risk. Inventory or capacity slack ensures the operational flow in the presence of uncertainty. Raw material inventory provides resources to maintain production despite of a supplier failure or additional finished goods inventory can be sold to keep up sales despite of a production interruption. In addition, capacity slack helps to increase production after the occurrence of a disruption to reduce the backlog of sales. However, the two operational strategies are not likely to act in isolation, but interdependently (Ennen and Richter, 2010). Firms that hold both, inventory and capacity slack can use both simultaneously to bridge the time between the occurrence of a disruption and its final resolution more efficiently. Although capacity enables a firm to catch up its production schedules after a supply disruption, additional inventory then helps to boost capacity utilization by keeping additional work-in-process buffers to reduce idle time of machinery. In the same vein, although inventory alone enables a firm to continue to sell finished products, additional capacity can be used to continue production at other locations or to dedicate other capacity to the disrupted product line. This suggests that simultaneous high levels of inventory and capacity slack create additional remedies to the exposure to supply-related risk. Due to the interaction of the operational strategies, a firm profits from the presence of both, inventory and capacity slack at the same time more than from the presence of a single resource.

Hypothesis 5a: *The total positive effect of joint inventory and capacity slack on the negative association between a firm's exposure to supply risk and its financial performance is stronger than the sum of its parts.*

While capacity and inventory have a mitigating effect on the exposure to supply risk, they are presumed to have an exacerbating effect on the demand side. Investments in inventory or capacity in anticipation of a demand surge bear the risk of cost from obsolescence. However, again, inventory and capacity are likely to act interdependently. A firm that has only plenty of inventory, but little excess capacity can accept the inventory holding cost until demand resurges, while a firm with capacity but no inventory can continue to utilize its production capacity and produce to stock until demand surges. If inventory and capacity slack are both present, capacity is idle for a longer time. Before resuming production, inventory has to be used up. At the same time, costs are not only incurred for inventory holding but also for idle workers and machinery for production. Hence, such a firm will suffer more than if it only had one operational strategy in place.

Hypothesis 5b: *The total negative effect of joint inventory and capacity slack on the negative association between a firm's exposure to demand risk and its financial performance is stronger than the sum of its parts.*

4.4 Data

4.4.1 Construction of the data set

Data were obtained from the archival database in Compustat (Capital IQ North America Fundamentals Annual) and the electronic data gathering, analysis, and retrieval system (EDGAR) of the SEC. The starting point was SEC release 33-8591 effective December 2005, which introduced Item 1.A as delineated above. The unit of analysis was the firm-year that a firm's central index key (CIK) and its date of the fiscal year end uniquely identify. The period investigated covers the fiscal years from 2006 until 2016. Industries in which operational strategies do not play a major role (e.g., banking, insurance, or services) were dropped from the analysis.

Table 4-3: Means (*M*), standard deviations (*SD*), and pairwise correlations

Variable	*M*	*SD*	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Return	0.07	0.17	1.00						
(2) Supply	4.20	2.56	–0.11	1.00					
(3) Demand	3.53	2.45	–0.25	0.31	1.00				
(4) Inventory	–0.01	0.90	–0.08	0.01 +	0.02 +	1.00			
(5) Capacity	–0.01	0.89	–0.18	0.00 +	0.00 +	0.08	1.00		
(6) Size	6.19	2.10	0.53	–0.03	–0.17	–0.15	–0.12	1.00	
(7) Leverage	0.26	0.24	0.06	–0.00 +	–0.01 +	–0.05	0.03	0.37	1.00

Note: n = 10,771. Pearson product-moment correlation coefficients are shown; correlations flagged with + are not significantly different from zero ($p > 0.05$), all others are significant at the $p < 0.001$ level; supply and demand are lagged by 1 period, inventory and capacity are standardized by industry-mean and standard deviation; size was transformed using the natural logarithm.

Based on this scope, Appendix A delineates the multi-step-procedure in which the risk items were extracted from the annual reports and relevant financial data was matched to the extracted risk items. The results were compared to a previous study by Bao and Datta (2014) to investigate the quality of the extraction of risk items. The numbers of extracted risk items from both studies are highly correlated (0.90). In total, 10,771 firm-years (1,574 firms, on average (minimum, maximum) 6.8 (3, 10) observations per firm) were retained for the analysis. The number of observations, their mean and standard deviation, as well as all pair-wise correlations are displayed in Table 4-3.

4.4.2 Risk exposure

All risk items extracted formed the corpus of texts to be analyzed. This corpus reflected the structure of the risk items. Each risk item consists of one or two sentences describing a single risk. Many risks items reoccur over subsequent years. This corpus was analyzed by means of a sentence latent Dirichlet allocation (sLDA) algorithm that Bao and Datta (2014) developed for the analysis of the risk disclosure in Item 1.A. They adopted the original LDA by Blei et al. (2003) to exploit the unique structure of the risk items. As each risk item deals with only one single topic, the sentence boundaries provide additional information on which words constitute one topic. As a result, instead of sampling words independently, all words of a sentence are sampled from the same topic (Bao and Datta, 2014). As the risk disclosure discusses a broad range of different topics, the sLDA was employed to identify supply- and demand related risk items and to quantify a firm's exposure to such risks which allows to analyze the research question at finer granularity (George et al., 2016). The sLDA achieves high quality in assigning and quantifying common topics in the risk disclosure: It has highest predictive power measured by perplexity and best cluster quality measured by the silhouette coefficient (Bao and Datta, 2014). Results of their extensive numerical studies show that the sLDA has a comparable quality to supervised algorithms but is far more reliable. It has highest precision for 30 to 40 topics.

To build the topic model, the textual data was processed to extract the most meaningful words characterizing a distinctive topic. In addition to the steps outlined in Appendix B, a metric indicating the distinctiveness of a word was calculated. The purpose of the metric is to identify the words that are used by firms across different industries to capture rather broad themes of risk but not firm-specific ones. At the same time, the words should not be boilerplate (i.e., applicable to any situation). The computed metric is similar to the "term frequency inverse document frequency" (tf-idf). The tf-idf reflects the importance of a word in a corpus of documents. The counted number of appearances of a term in a document is divided by the number of documents in which the term occurs. The intuition of this calculation is that the more frequently a word occurs, the more important it is. However, if many documents use the word, then it is less distinctive. The metric applied in this study is calibrated to the data structure present. Other studies have also developed their metrics to distillate the most important words (e.g., Hasan et al., 2015). The nominator is the percentage of firms using a specific word. The denominator is the natural logarithm of the average fraction of a firm's risk items that contain the word. The firm's fraction of risk items containing a word is used instead of the absolute value in order to avoid distortions by very long risk disclosures. The intuition of the metric is as follows. The more firms use a specific word, the more likely it is to be relevant for a broad group of firms. However, the higher is the percentage of risk items of a firm that contain the word, the more likely it is that the word applies to a wide set of different situations. Words that score high are used by several firms in only few risk items on average. These words are potentially relevant. In contrast, words that score low are either used by very few firms or in a large fraction of risk items. The former case excludes words on firm-specific risks while the latter case excludes words that are used in many situations. All words that score lower than two were excluded from the relevant words of the period. In total, the corpus of relevant words comprises 981 distinctive terms ranging from 344 terms in 2006 to 847 terms in 2016.

Figure 4-3: Computation of the scores for the exposure to supply- and demand-related risk

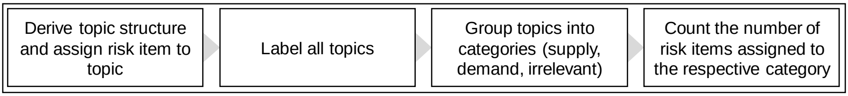


Figure 4-3 describes the computation of the supply and demand risk scores. After preparing the corpus of texts, the topic model is run with 34 topics. The algorithm simultaneously identifies the underlying topic structure of the documents and assigns each risk item to a topic (Bao and Datta, 2014). Its output is twofold: On the one hand, the topics are characterized by the most frequent words describing the topic. On the other hand, each risk item is assigned to a topic. The number of 34 topics serves as compromise between a higher granularity of topics (like 40 or 50) and the robustness of the assignment of risk item to topic. The key words per topic are robust to the number of topics. Two researchers manually labeled all topics based on each topic's most frequent words and each topic's compilation of risk items. Although automated labeling procedures exist, they are not applicable if solid background knowledge is required (Mei et al., 2007). All supply- and demand-related topics were then grouped into the two broader categories supply and demand, after discussions with other scholars in seminars and workshops. All other topics detected cover risks unrelated to supply chain management. Examples for these topics are the lack of human resources, volatility in the stock price, or lack of refinancing. The risk items assigned to these topics were not further considered.

Table 4-4: Supply- and demand-related topics extracted from 10-K reports' Item 1.A using sLDA

Cat	Topic	Topic label	Key words	Sample
Supply	0	**Disruption in production**	*natural facility production disaster manufacturing*	The impact of natural disasters could negatively impact our supply chain and customers resulting in an adverse impact to our revenues and profitability.
	3	**Dependence on contract manufacturing**	*party rely development manufacture delay*	We have no capacity to manufacture clinical or commercial supplies of our product candidates and intend to rely solely on third parties to manufacture clinical and commercial supplies of all of our product candidates.
	17	**Dependence on joint development**	*license agreement contract development right*	We are dependent on technology systems and third-party content that are beyond our control.
	22	**Supply issues**	*supplier supply component party raw*	As we rely on a limited number of third parties to manufacture, assemble and test our IC products and to supply required parts and materials, we are exposed to significant supplier risks.
	23	**International risks**	*foreign currency international fluctuation rate*	We manufacture a significant portion of our products outside the United States, and political, societal or economic instability may present additional risks to our business.
Demand	4	**Market competition**	*competition competitive industry compete competitor*	We face intense competition and rapid technological change that could result in products superior to the products we are developing.
	9	**Product approval**	*approval regulatory obtain requirement regulation*	We may be unable to complete our BTT study or obtain regulatory approvals, which will prevent us from selling our products and generating revenue.
	25	**Market acceptance**	*party reimbursement marketing revenue acceptance*	MelaFind may not be commercially viable if we fail to obtain an adequate level of reimbursement by Medicare, Medicaid and other third party payers.
	26	**Product approval**	*approval regulatory delay development clinical*	Ethical and other concerns surrounding the use of stem cells may negatively affect regulatory approval or public perception of our product candidates.
	31	**Industry demand**	*economic industry demand global downturn*	Current uncertainty in global economic conditions makes it particularly difficult to predict demand for our products and forecast revenues, and makes it more likely that our actual results could differ materially from expectations.

Both the supply-related risk category and the demand-related risk category consist of five topics each from the sLDA. As a result, every risk item is either assigned to the category of supply-related risk, to the category of demand-related risk or discarded. Table 4-4 describes the relevant sLDA-topics and their mapping to the categories of supply- and demand-related risk. Other studies in the field of accounting that have applied the LDA to annual reports have also aggregated the number of topics to broad categories (e.g., Dyer et al., 2016).

Let R_{Dem} and R_{Sup} denote the sets of demand- and supply-related risk items respectively. $\mathbf{1}_{RI_{itk} \in R_{Dem}}$ is an indicator function indicating the membership of the kth risk item of firm i in year t (RI_{itk}) to the set of demand-related risk items R_{Dem}.

$$1_{RI_{i,t,k} \in R_{Dem}} = \begin{cases} 1 & if\ RI_{i,t,k} \in R_{Dem} \\ 0 & otherwise \end{cases}$$

The risk exposure to demand-related risk of firm i in year t is then calculated as the sum of the indicator function values for the $K_{i,t}$ risk items RI_{itk} of firm i in year t.

$$Exp_{Dem,i,t} = \sum_{k=1}^{K_{i,t}} 1_{RI_{itk} \in R_{Dem}}$$

The exposure to supply-related risk is calculated analogously based on the set of supply-related risk items R_{Sup}. The measurements for the exposure to supply- and demand-related risk as well as the total number of extracted risk items are then compared to the Standard & Poor's (S&P) credit rating that is available in the Compustat database. In the case of S&P credit rating in Compustat there are seven rating categories, the highest credit quality being A+, and the lowest C. The credit ratings reflect the default probability of the bonds issued (A+: low default probability, C: high default probability). A bond is in default (D), if the issuer is not able to redeem either a coupon or the underlying principal. The literal ratings are recoded as numeric values with 1 corresponding to the A+ rating and 8 corresponding to C rating. Hence, the lower the value of the credit rating the lower is the default probability. The Spearman's rank correlation coefficient between the measurement of demand- and supply-related risk as well as the total number of risk items and the credit rating is computed because all variables are not continuous. The correlation of

0.25 between the total number of risk items and the S&P credit rating indicates that the number of risk items reflects some information of the credit rating. This reinforces the view that the number of risk items disclosed is a meaningful proxy for the risk exposure of a firm. The correlation between the credit rating and supply- and demand-related risk is 0.15 and 0.12, respectively. The results illustrate that while supply- and demand-related risk items are associated with bankruptcy probability, exposure to them is not as severe as it is to the full bundle of risk items including stock market risk, refinancing risk, or regulation risk.

4.4.3 Risk mitigation and performance

The return on assets proxies the performance of a firm. The return on assets $roa_{i,t}$ of firm i in year t is operationalized by dividing a firm's earnings before interest, tax, depreciation, and amortization $ebitda_{i,t}$ by its book value of assets $bva_{i,t}$:

$$roa_{i,t} = \frac{ebitda_{i,t}}{bva_{i,t}}$$

The higher a firm's return on assets $roa_{i,t}$, the higher its performance. On the one hand, this metric is highly aggregated and generated on the same corporate level as the independent variables of supply- and demand-related risk exposure. On the other hand, it encapsulates the efficiency in employing the given assets. Furthermore, previous studies have also used the $ebitda$ to capture the performance (e.g., Paeleman and Vanacker, 2015).

A firm's inventory slack $invsl_{i,t}$ was measured as the days of inventory of firm i in year t. The variable is calculated as a firm's inventory position at the end of the current year t, $inv_{i,t}$, divided by its annual cost of goods sold $cogs_{i,t}$ (for firm i in year t):

$$invsl_{i,t} = \frac{inv_{i,t}}{cogs_{i,t}}$$

Firms with higher values of inventory slack $invsl_{i,t}$ have more days of inventory available and can utilize this to decouple from outside contingencies. Previous studies have used these measurements for inventory slack (Hendricks et al., 2009).

To measure a firm's capacity slack $capsl_{i,t}$, we use the ratio of a firm's gross property, plant, and equipment at the end of year t, $ppe_{i,t}$, to annual sales $sale_{i,t}$ (for firm i in year t):

$$capsl_{i,t} = \frac{ppe_{i,t}}{sale_{i,t}}$$

Firms with higher values of capacity slack $capsl_{i,t}$ have more capacity to achieve their sales. They can use this as an additional buffer in their operations to produce at different locations or catch up production after an unavailable supply incident. We followed prior studies in using the metric (Hendricks et al., 2009).

Both slack measures were industry-adjusted (4-level SIC code). First, period t's industry-mean was subtracted from each observation. The difference was then divided by the period's industry standard deviation. The industry-adjusted slack measures reflect the extent to which a firm has above or below industry average levels of slack measured by industry standard deviations. Consequently, the slack measures are comparable across the different industries. Such standardization is common practice in empirical studies (e.g., Hendricks et al., 2009).

Firm-specific intercepts account for the influence of any time-constant factors that affect a firm (as discussed in subsection 4.5.1). They absorb a firm's long-term strategies and its disclosure orientation, as well as control for industry fixed effects. In addition, cross-sectional time fixed effects account for any economic events affecting all firms. Therefore, only time-varying firm individual factors with an influence on performance must be controlled for. Prior studies have considered the leverage ratio and the firm size as such factors (e.g., Mishra et al., 2013, Paeleman and Vanacker, 2015). The leverage ratio represents the financial health and strength that a firm has in a certain period. A higher leverage indicates financial distress which limits the firm's room for mobility to exploit future market opportunities (Opler and Titman, 1994). The leverage ratio of firm i in year t is calculated from the firm's book value of debt divided by its sum of the book values of debt and equity. In addition, bigger firms were found to be more profitable. The natural logarithm of a firm's annual total sales controls for firm size.

4.5 Analysis

4.5.1 Model specification

Due to the longitudinal data structure of firms observed over years, the estimation model was specified as a firm- and period fixed effects model with panel-clustered robust standard errors. The Lagrange multiplier test suggested by Breusch and Pagan (1980) indeed indicated a firm-specific intercept ($p < 0.001$); hence, the firm-effects could not be pooled. As the predictors are correlated with the unit effects, the Hausman test was rejected and, consequently a fixed effects estimator was chosen (Mundlak, 1978). The t-statistics were computed using panel-clustered robust standard errors because these are unbiased and produce correctly-sized confidence intervals (Stock and Watson, 2008) in the presence of heteroscedasticity (Wald test for group-wise heteroscedasticity, $p < 0.001$) and autocorrelation (Wooldridge's test, $p < 0.001$). To control for period effects across firms ($p < 0.001$), year dummies were used, as this method is the most efficient for short panel data (Petersen, 2009).

Apart from the methodological arguments, a fixed effects estimator allows us to concentrate on variance within a firm. Specifically, factors explaining various levels of performance were controlled to focus on the firm-individual effect of additional risk exposure on performance. Operationally, the *xtreg*-routine with fixed effects in *Stata 14.2* was used to estimate the following models:

Null model (NM):

$$roa_{i,t} = b_{i,0} + b_1 * size_{i,t} + b_2 * lev_{i,t} + \sum_{j=2008}^{2016} b_{3,j} * year_j + \varepsilon_{i,t} \tag{5}$$

Base model (BM):

$$\begin{aligned} roa_{i,t} = {} & b_{i,0} + b_1 * exp_{sup,i,t-1} + b_2 * exp_{dem,i,t-1} + b_3 * invsl_{i,t} \\ & + b_4 * capsl_{i,t} + b_5 * size_{i,t} + b_6 * lev_{i,t} + \sum_{j=2008}^{2016} b_{7,j} * year_j \\ & + \varepsilon_{i,t} \end{aligned} \tag{6}$$

Interaction model (2IM):

$$
\begin{aligned}
roa_{i,t} = {} & b_{i,0} + b_1 * exp_{sup,i,t-1} + b_2 * exp_{dem,i,t-1} + b_3 * invsl_{i,t} \\
& + b_4 * capsl_{i,t} + b_5 * exp_{sup,i,t-1} * invsl_{i,t} \\
& + b_6 * exp_{dem,i,t-1} * invsl_{i,t} + b_7 * exp_{sup,i,t-1} * capsl_{i,t} \\
& + b_8 * exp_{dem,i,t-1} * capsl_{i,t} + b_9 * size_{i,t} + b_{10} * lev_{i,t} \\
& + \sum_{j=2008}^{2016} b_{11,j} * year_j + \varepsilon_{i,t}
\end{aligned}
\tag{7}
$$

Three-way interaction model (3IM):

$$
\begin{aligned}
roa_{i,t} = {} & b_{i,0} + b_1 * exp_{sup,i,t-1} + b_2 * exp_{dem,i,t-1} + b_3 * invsl_{i,t} \\
& + b_4 * capsl_{i,t} + b_5 * exp_{sup,i,t-1} * invsl_{i,t} \\
& + b_6 * exp_{dem,i,t-1} * invsl_{i,t} + b_7 * exp_{sup,i,t-1} * capsl_{i,t} \\
& + b_8 * exp_{dem,i,t-1} * capsl_{i,t} \\
& + b_9 * exp_{sup,i,t-1} * invsl_{i,t} * capsl_{i,t} \\
& + b_{10} * exp_{dem,i,t-1} * invsl_{i,t} * capsl_{i,t} \\
& + b_{11} * size_{i,t} + b_{12} * lev_{i,t} + \sum_{j=2008}^{2016} b_{13,j} * year_j + \varepsilon_{i,t}
\end{aligned}
\tag{8}
$$

In these equations, $roa_{i,t}$ represents the dependent variable of firm i in year t. The intercept $b_{i,0}$ accounts for firm-specific time-constant effects. $exp_{sup,i,t-1}$ and $exp_{dem,i,t-1}$ measure the lagged exposure to supply- and demand-related risks of firm i in year $t-1$. $invsl_{i,t}$ and $capsl_{i,t}$ refer to inventory and capacity slack of firm i in year t standardized by industry mean and standard deviation. $size_{i,t}$ and $lev_{i,t}$ control for firm size and leverage ratio of firm i in year t. $year_j$ accounts for time-effects, with $year_j = 1$ if $j = t$ and 0 otherwise. $\varepsilon_{i,t}$ is the random error term for shared errors between firm i and year t. All variables are winsorized at the 99th percentile to address outliers (e.g., Aguinis et al., 2013, Chen et al., 2005, Dehning et al., 2007). For an additional robustness check, the model was estimated in a pooled regression to derive variance inflation factors (VIFs). These serve as upper limits to identify any variance-induced biases. VIF values ranged from 1.03 to 2.04 for the estimation models, indicating that multicollinearity is unlikely to be a problem.

4.5.2 Endogeneity

Endogeneity poses a serious threat to the validity of empirical results. Its most frequent causes are reverse causality, measurement error, or omitted variable bias (Wooldridge, 2002). Although the absence of endogeneity cannot be proven, this study fulfills reasonable standards for plausible exogeneity of the regressors (cf. Ketokivi and McIntosh, 2017). The arguments revolve around the lagging of the independent variables, the measurement of variables, and the specification as fixed effects panel data estimator.

First, the time lag between the independent risk variables and the dependent performance variable addresses reverse causality. Hence, retrospective justifications of performance declines are not an issue. Although one could claim that an anticipated performance decline leads to an increase in risk disclosure, this is exactly the purpose of the risk disclosure: to inform investors about possible future threats. In addition, the time lag between the independent variables and the moderators ensures that firms do not use the risk disclosure as post-hoc means to defend wrong operational decisions. The time lag supports the view that firms learn about their environment and then take actions which are reflected in their performance.

Second, measurement error is addressed by minimizing the risk of common method bias which is one of the main sources of measurement error (Podsakoff et al., 2003). The dependent and independent variables are not only calculated from secondary data sources, but were obtained from different data sources. The risk variables are derived from qualitative descriptions of the risk disclosure in annual reports which can be used to proxy a firm's exposure to specific categories of risk (Israelsen, 2014). On the other hand, the operational strategies and performance are derived from a firm's financial data that have been widely applied in operations management (Hendricks et al., 2009, Kovach et al., 2015). The measurement problem persists in the sense that firms can strategically disclose or withhold information in their annual reports. However, this problem is not limited to textual disclosures but is also found in other forms of financial reporting. The major argument is that the cross-sectional size of the data set helps to average out this firm-individual strategic behavior.

Third, omitted variable bias is addressed by the specification as a fixed effects model with firm-specific intercepts. These intercepts absorb any unobserved heterogeneity that is stable over time. The fixed- instead of a random effects model allows the firm-specific effects to be correlated with the regressors which is the case as previously discussed. The model only assumes that the independent variables are uncorrelated with each other and with the residual disturbance. We find that the independent variables and moderating variables are uncorrelated (Table 4-3). To address concerns of time-varying confounders, time-fixed as well as time- and firm-variant controls are included. These controls are discussed in subsection 4.4.3.

4.5.3 Results

The variables were standardized before creating the interaction terms to facilitate the interpretation of the results. While the BM includes the main effects and the control variables ($F = 35.63,\ p < 0.001$), the 2IM integrates the moderating effects of inventory and capacity ($F = 28.82,\ p < 0.001$) and the 3IM also captures the interaction of the two operational slack strategies ($F = 26.61, p < 0.001$).

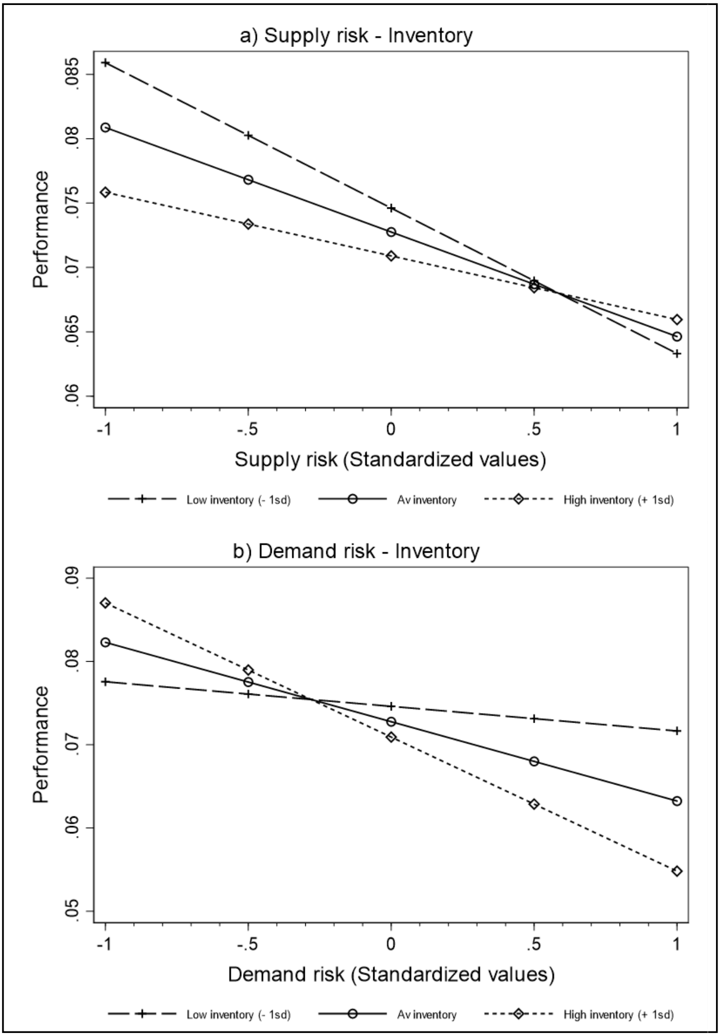
Table 4-5: Results of fixed effects regression analysis

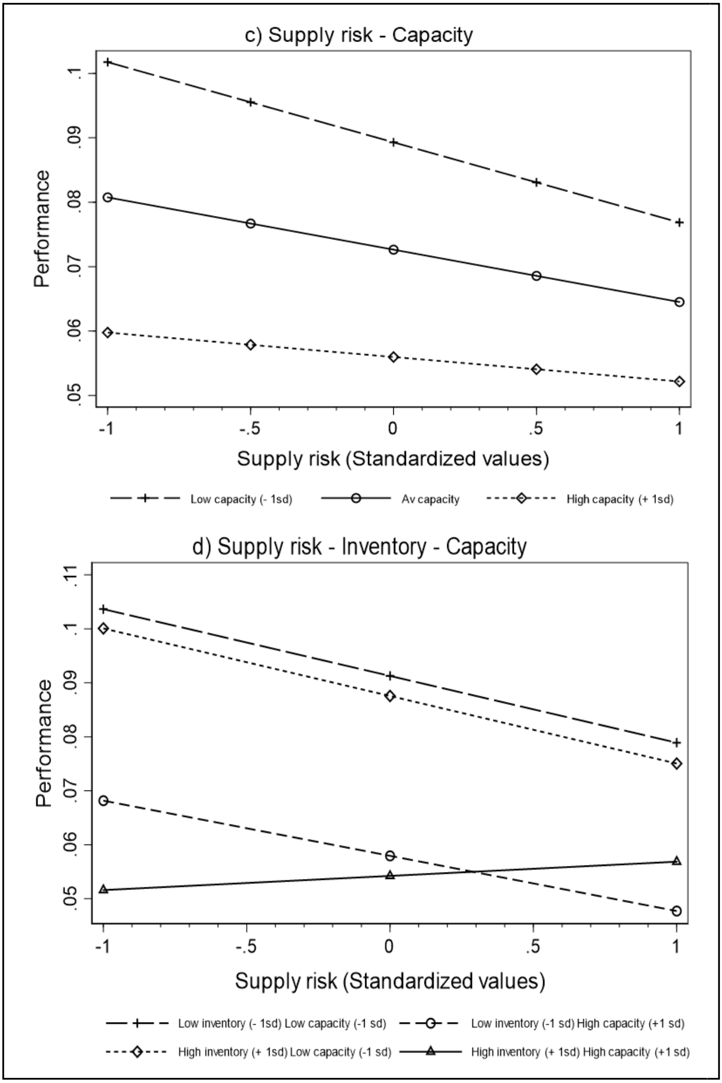
Variable	Base model Estimate	Base model *SE*	2-way model Estimate	2-way model *SE*	3-way model Estimate	3-way model *SE*
Supply	–0.007*	(0.003)	–0.008*	(0.003)	–0.008**	(0.003)
Demand	–0.009*	(0.004)	–0.010*	(0.004)	–0.010*	(0.004)
Inventory	–0.002	(0.003)	–0.002	(0.003)	–0.002	(0.003)
Capacity	–0.016***	(0.003)	–0.016***	(0.003)	–0.017***	(0.003)
Supply × Inventory			0.004*	(0.002)	0.003	(0.002)
Demand × Inventory			–0.006**	(0.002)	–0.007**	(0.002)
Supply × Capacity			0.005*	(0.002)	0.004†	(0.003)
Demand × Capacity			0.000	(0.003)	0.000	(0.003)
Supply × Inventory × Capacity					0.003*	(0.002)
Demand × Inventory × Capacity					0.000	(0.001)
Size	0.098***	(0.006)	0.099***	(0.006)	0.099***	(0.006)
Leverage	–0.103***	(0.012)	–0.103***	(0.012)	–0.104***	(0.012)
Constant	–0.493***	(0.035)	–0.498***	(0.035)	–0.498***	(0.035)
Firm FE	YES		YES		YES	
Time FE	YES		YES		YES	
R^2 within (R^2 adjusted)	0.201 (0.709)		0.205 (0.710)		0.206 (0.710)	
AIC	–24,505.68		–24,551.19		–24,562.45	
BIC	–24,425.26		–24,449.32		–24,449.86	
Observations	10,771		10,771		10,771	
Number of firms	1,574		1,574		1,574	

Note: *SE* refers to robust standard errors clustered at the firm level; BIC calculated with number of firms.
† p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001 (two-tailed).

As shown in Table 4-5, the R^2 (within) increases from 0.201 to 0.206 (adjusted R^2 from 0.709 to 0.710) when the interaction effects are added. Finally, both Akaike's (AIC) and Schwarz's (BIC) Bayesian information criteria indicate that the IMs fit the data better as their values become smaller. This is statistical and empirical support for the moderating effects of operational strategies in the presence of supply- and demand-related risks. The hypothesized relationships between a firm's performance and its exposure to supply chain risk received support from the data. The base model estimates suggest that firms facing more risk related to supply (*H1*) and demand (*H2*) exhibit a lower performance. As expected, supply side risk (BM: $b_1 = -0.007, p < 0.05$) and demand side risk (BM: $b_2 = -0.009$, $p < 0.05$) are negatively associated with return on assets. A one-standard-deviation (*SD*) increase in supply (demand) risk is related to a decrease of roa of 70 (90) basis points. In addition, capacity (BM: $b_4 = -0.016$, $p < 0.001$) is negatively associated with return. These results are in line with prior research (e.g., Modi and Mishra, 2011). When looking at the results of the interaction models, the estimates indicate support for the mitigating effect of inventory slack on the relationship between supply- and demand-related risks and performance. Specifically, firms with high inventory slack were hypothesized to have a weaker negative association between supply-related risk and return (*H3a*) but a stronger negative association between demand-related risk and return (*H3b*) than firms with low inventory slack. As predicted by *Hypothesis 3a*, inventory positively moderates the relationship between supply risk and return (2IM: $b_5 = 0.004$, $p < 0.05$). The interaction plot in Figure 4-4a highlights that as supply risk increases, firms with both high (+1 *SD*) and low (–1 *SD*) inventory experience a decline in performance. However, firms with high inventory slack have a flatter performance decline compared to firms with low inventory if supply risk increases. As a result, in the presence of high supply-related risk, firms with high inventory exhibit a higher performance than firms with low inventory. The effect hypothesized in *Hypothesis 3b* was also found. In line with *Hypothesis 3b*, inventory negatively moderates the relationship between demand risk and return. Figure 4-4b illustrates that firms with both high (+1 *SD*) and low (–1 *SD*) inventory exhibit a lower performance as demand risk increases. Similar to supply-related risk, more inventory-efficient firms exhibit a higher performance than less inventory-efficient firms for an average level of demand-related risk. In contrast to supply-related risk but in line with the hypothesized moderating effect of inventory on the association of demand risk and performance, firms with high inventory have a much steeper performance decline than firms with low levels of inventory as demand risk increases (2IM: $b_6 = -0.006, p < 0.01$).

Figure 4-4: Interaction plots between types of risk (supply and demand) and operational mitigation strategies (inventory and capacity)





Note: The plots are based on standardized estimates reported in Table 4-5. The interactions are plotted at one standard deviations above ("high") and below ("low") the mean values of the moderator variables.

The results provide partial support for the idea that capacity slack moderates the relationship between supply- and demand-related risks and performance. Firms with high levels of capacity slack were hypothesized to have a weaker negative association between supply-related risk than firms with low levels of capacity slack (*H4a*). In contrast to supply risk, the negative association between demand-related risk and return was hypothesized to be stronger for firms with high levels of capacity slack than for firms with low levels of capacity slack (*H4b*). In line with *Hypothesis 4a*, the results suggest that capacity slack positively moderates the relationship between supply risk and return (2IM: $b_7 = 0.005$, $p < 0.05$). As supply risk increases, firms with high (+1 *SD*) and low (–1 *SD*) capacity realize a decline in performance (cf. Figure 4-4c). The slopes are different though. Firms with low levels of capacity have a steeper decline in performance than firms with high levels of capacity if supply risk increases. However, firms with low levels of capacity always exhibit a higher performance than firms with high levels of capacity. In *Hypothesis 4b*, capacity slack was expected to increase the negative effect of demand-related risk on performance. The results do not support *Hypothesis 4b* (2IM: $b_8 = 0.000$, $p > 0.10$).

Finally, the results partially support the prediction that inventory and capacity slack amplify each other's positive (negative) effect on the association between supply-related (demand) risk and return. More specifically in *Hypothesis 5a*, it was expected that the existence of joint inventory and capacity slack weakens the negative association between a firm's supply-related risk and its performance stronger than their sum while the opposite was expected for their effect on the association between demand-related risk and performance (*Hypothesis 5b*). The results provide support for *Hypothesis 5a* (3IM: $b_9 = 0.003$, $p < 0.05$). Figure 4-4d illustrates that the slope is positive if both levels of capacity and inventory are high (+1 *SD*), but negative if either or both levels of capacity and inventory are low (–1 *SD*). In other words, if a firm has both inventory and capacity slack then the performance is higher than if either is missing. Therefore, the joint effect of inventory and capacity slack on the association between supply-related risk and performance is larger than its parts. A comparison of slopes reveals that the slope of inventory and capacity slack is indeed different from other cases. The results do not provide support for *Hypothesis 5b* (3IM: $b_{10} = 0.000$, $p > 0.10$). The hypothesized joint negative effect of inventory and capacity on the association between demand-related risk and performance is not confirmed.

As all variables of interest were winsorized at the 99th percentile, all results were also computed with a data set in which variables were not winsorized and in which observations above the 99th percentile were dropped. Results are robust in direction and size. In addition, robustness checks were conducted for different performance outcome measures and different controls of firm size. Again, results remain robust in direction and size.

4.6 Discussion

This study investigates how the exposure to supply- and demand-related risk influences performance and which operational strategies mitigate the negative association with the lowest negative performance impact. The results provide additional empirical support for the claim that the success of operational risk mitigation strategies depends on their fit to the environment: Firms that operate in VUCA environments, as highlighted in the introduction, can use different operational strategies to mitigate negative performance impacts. These results make several important contributions to the literature related to operational strategies.

First, we propose a novel approach to measure the ex-ante downside exposure to supply- and demand-related risks firms face. The risk section of a firm's annual report is scrutinized by means of a sLDA to detect risks that deal with supply or demand. One additional risk item about supply- or demand-related risk in a firm's annual report is interpreted as an increase in the ex-ante downside exposure to supply- or demand-related risk. This measurement is an improvement over those presented in previous studies that rely on ex-post information on materialized disruptions (e.g., Hendricks and Singhal, 2005b), and that do not allow for an ex-ante evaluation of the effectiveness of operational strategies (Wagner and Bode, 2008). Others have approximated the ex-ante risk exposure using either variables describing the environment (e.g., Azadegan et al., 2013a) or sales data (Kovach et al., 2015). However, both ways of measuring ex-ante risk also contain upside potentials. As the measurement derived from the corporate risk disclosure directly captures the ex-ante downside risk exposure of a firm, it more accurately reflects managers' perceptions of risk (Mao, 1970, March and Shapira, 1987). The results suggest that an increase in the exposure to supply or demand risk has a negative influence on firm performance. This finding is in line with prior research on materialized supply chain disruptions (Hendricks and Singhal, 2003).

Second, the results of this study contribute to a better understanding of the conditions under which certain operational strategies are beneficial, responding to calls for further research (Kovach et al., 2015, Schoenherr et al., 2012, Talluri et al., 2013). Although the exposure to supply risk has a negative impact on firm performance, operational slack can alleviate it. Firms that have more inventory or capacity exhibit a lower performance decline than firms with less inventory or capacity. This result is in line with prior research (Hendricks et al., 2009). However, inventory is more efficient than capacity. While firms with high level of inventory outperform firms with low level of inventory if the exposure to supply-related risk is high, this does not hold for capacity. Even if firms are exposed to supply-related risk, low-capacity-firms still outperform high-capacity-firms. Moreover, the right mix of operational strategies influences the performance. Operating in environments characterized by high exposure to supply risk, firms with joint higher levels of inventory and capacity outperform firms that have only one or none of the risk mitigation strategies in place.

In contrast, the negative association between the exposure to demand-related risk and performance is exacerbated by high inventory slack. This result might appear contradictory to prior results which suggest that supply chain slack mitigates the influence of instability on performance (Kovach et al., 2015). However, the conceptualization of risk strongly affects a firm’s optimal decision of the short-term cost structure (Banker et al., 2014). If risk is conceptualized as a variation around an expected value, then firms should accept higher fixed costs to be able to exploit the upside potential from variability. If risk is conceptualized as a negative deviation from an expected outcome, firms should aim at reducing fixed costs. In this regard, fixed and variable cost are distinguished in terms of cost for adjusting prior decisions (Banker and Byzalov, 2014), which corresponds to the notion of operational slack as absorbed slack (Singh, 1986). These can be incurred for either ill-planned inventory or capacity. In contrast to Kovach et al. (2015) who measured risk as variation around an expected value, our study conceives risk as potential downside threat. The results suggest that a firm’s investment into operational slack is not beneficial for a firm exposed to demand-side risk. An economic example that illustrates the logic is changed customer preferences that render a product obsolete. If a firm invested in inventory solely usable for the production of that product, this inventory would become obsolete and would have to be salvaged at cost.

Third, this essay proposes a new idea for the measurement of corporate risk exposure. While this study focuses on exposure on supply chain risk, the risk disclosure section of annual reports discusses all the material risk that a firm faces and hence covers a broader range of topics like risk from innovation, financing problems, or regulatory issues. In subsequent research, strategy scholars can scrutinize the risk disclosure in annual reports to identify topics that are relevant for their research. To this end, a new approach and data source is proposed to gain direct insights about managers' risk perceptions that reflect recognized developments in the external environment (Bansal et al., 2018). Furthermore, measurements like expenditures for research and development have been shown to be problematic (Bromiley et al., 2017).

For managers, the results provide additional empirical evidence that the effective management of supply chain risks provides a competitive advantage and contributes to superior firm performance. On the one hand, operational managers must carefully investigate the sources of the risk to which they are exposed. While operational strategies effectively tackle supply-related risk and reduce its negative effect on performance, they exacerbate the association between demand-related risk and performance. Only if managers find that supply-related risk is present, they should consider operational slack. However, if supply-related risk is present, operational managers must choose an operational strategy. Based on the results of this study, operational managers should prefer investments in inventory because this appears to have a less negative effect on performance than investments in capacity. A firm's managers should try to reduce inventory levels if their firm is facing severe downstream risk.

This study must be considered in light of its limitations pertaining to data and methodology. First, the limitations of large-scale empirical research apply. Data of firms that are publicly listed in the United States and belong in the manufacturing sector were used to test the proposed relationships. Firms in other industries, operating in other countries, or not publicly listed might have different requirements or pursue different objectives. Consequently, the generalizability of the findings might be limited. Further research can explore these issues. Second, an assumption underlying the use of secondary financial data and information from annual reports is that they accurately represent a firm's true financial condition and that there are no accounting misrepresentations or manipulations. Further research is suggested using other data sources. Third, the data are highly aggregated at the firm level. Many of the firms have different business units with several products involving different suppliers, investment alternatives, and inventory policies. The measures for inventory and capacity slack are also distant from the real business world, although scholars have frequently used the same or similar constructs in previous studies. An analysis on product level with more fine-grained constructs might result in more nuanced results. We leave these issues to further research. Fourth, apart from these drawbacks on data and the variables' measurements, this study utilizes qualitative textual data to measure a firm's exposure to supply chain risk. Although annual reports have previously been used as source of information in operations management (e.g., Davies and Joglekar, 2013) and tools are applied that have been developed for other studies, textual analysis yields soft information (Tsai and Wang, 2017). Different text extraction methods might lead to different extracted risk disclosures, which then might be clustered and labeled differently. A fixed effects model was used for the regression analysis. Although such models produce robust estimates in the presence of heteroscedastic and auto-correlated data, all variance between groups is henceforth neglected. Further research on these data is suggested to apply different text mining algorithms or regression methods to extract more information from the data. Finally, mitigation strategies to tackle demand side risk remain unexplored. By integrating ideas from marketing or strategy, future research can develop additional mitigation strategies that then resolve demand-related risks.

4.7 Conclusion

In this study, the risk qualitatively disclosed in firms' annual reports was used to measure the risk to which the firms are exposed. These data allow the differentiation between the sources of supply chain risk, which are supply side and demand side risks. The derived results suggest a negative relationship between supply- and demand-related risks and performance. This negative relationship between risks on the one hand and performance on the other is partially alleviated by operational strategies. Operational strategies only mitigate supply-related risk, leaving demand-related risk unaddressed at best. This study's findings are linked to prior results in accounting and operations management.

5 Conclusion and Outlook

5.1 Summary

Firms do not operate in an accommodating world, but in reality are confronted with challenges which are difficult to anticipate and can interfere with a firm’s planned operations. However, not every firm faces the same challenges. The number and types of potentially relevant challenges and consequently the potential risk exposure will depend on prior decisions (e.g., operating location decisions), the industrial environment (e.g., competitors’ activities), and current and past strategies (e.g., internationalization strategy). Moreover, should a given risk materialize, the firms affected can employ operational strategies to cope with the consequences in such a way that they can swiftly resume production. Despite its importance, the potential risk exposure has been largely neglected in research up to now. On the one hand, previous research has only specified various categories of supply chain risk without explaining which external uncertainties might turn into a given type of risk for an individual firm. On the other, it has provided abundant empirical evidence that actual events indeed do pose a real threat to a firm and should have been managed accordingly. However, such research was unable to explain to what extent the firms affected were potentially exposed to this risk prior to its occurrence, and whether the mitigation of the potential risk exposure would have made economic sense. On order to remedy this negligence of a firm’s potential risk exposure, this dissertation builds on the contingency theory and information processing theory literatures and presents a new approach for the measurement of a firm’s risk exposure based on a textual analysis of the publicly available 10-K reports for a given firm. Inter alia, firms provide operations-related information in their 10-K reports (e.g., risk factors in Item 1.A, locations in Item 2). By linking additional data on a firm’s financial performance and natural disaster occurrences with the data from the 10-K reports, this dissertation empirically analyzes whether firms remain effective if they are confronted with sudden and unforeseen change in their environment and how they respond to such changes.

The study in Chapter 2 investigates empirically the moderating effect of the industrial environment on the relationship between the effect of a natural disaster on a firm's production network and its subsequent performance. The study has been motivated by the observation that economies rebound quickly from the destruction caused by natural disasters, provided that aid is directed to the right recipients and the economy's original production capabilities are restored. Transferring these insights to the firm level, the industrial environment, and specifically its three attributes of complexity, munificence, and dynamism, is presumed to play a role for the negative association between the effect of a natural disaster on a firm's production network and its subsequent performance: In particular, the performance of firms that operate in industrial environments characterized by high complexity, high munificence, or low dynamism is presumed to be more negatively affected by a natural disaster than that of firms operating in industrial environments where the conditions are precisely the opposite. The key arguments revolve around competitive forces, the managers' risk preferences, and the accumulated experience in coping with change in the said industry. For the development of the required data set, a NER tagger has been deployed to analyze Item 2 of a firm's 10-K report and to identify the locations of the firm's plants. These data have been augmented by data on disaster occurrences and financials. Based on the resulting data set, the hypotheses developed are tested utilizing a difference-in-difference regression model. The results suggest that natural disasters are definitely harmful for firms and that their negative impact is indeed moderated by the two industrial environment's attributes of complexity and munificence. The study makes several important contributions. To begin with, the textual analysis of Item 2 presents a novel approach for constructing a firm's production network which is based on publicly available data. Up to now, studies have approximated production networks based on the subsidiaries' names or the location of patent filings. In addition, this study accumulates further knowledge which confirms that natural disasters do have a negative effect on a firm's performance. Based on this negative relationship, the study identifies two boundary conditions for this negative relationship. If a firm operates in industrial environments characterized by low complexity or munificence, disasters have much less effect on its performance. By contrast, if it operates in industrial environments characterized by high complexity or munificence, natural disasters have a stronger negative effect on the firm's performance. These results have important implications for managers and policymakers. Managers must not only be aware of the risk of natural disasters when deciding on the geographic location of their production facilities but must also take into account the industrial environment in which their firm operates. When policymakers decide on the allocation of disaster relief aid after a natural disaster has occurred, they should also consider the industrial environments in which firms affected operate.

Chapter 3 presents an empirical study on the sources of supply risk. The study has been motivated by the observation that the interplay between strategic choices, industrial environment, and context not only has strong implications for a firm's performance, but also contributes to its exposure to supply risk. On the one hand, exposure to supply risk is assumed to stem from the industrial environment (outside-in) in which a firm operates. These factors comprise complexity and technological change. On the other hand, supply risk is hypothesized as stemming from the major strategic decisions that a firm can take (inside-out) such as business and geographic diversification strategies. Moreover, the hypotheses distinguish the effect of change over time within a firm on supply risk exposure (positive) from the effect of differences between firms on supply risk exposure (positive and negative). The main arguments for the positive association between change over time and supply risk exposure revolve around the uncertainties associated with the necessary alteration of the supply chain structure in response to the change. With respect to differences between firms, the same arguments hold for the positive association between the industrial environment and a firm's exposure to supply risk, whereas for the negative association between strategic decisions and exposure to supply risk, the arguments reflect the accumulated experience, the higher reputation and power of these firms, as well as their greater operational flexibility. To shed light on the relationships information on supply risk has been extracted from a firm's risk disclosure as presented in Item 1.A of its 10-K report and quantified by means of a sLDA previously developed for this purpose. This information has been augmented by the financial data describing the firm's strategic decisions and its industrial environment. The predicted relationships are tested by means of a multi-level regression model which explicitly distinguishes different levels (time and firm) which are present in the data set. The results suggest that the industrial environment to a large extent determines a firm's exposure to supply risk, while the strategic decisions are a less important factor for the explanation of a firm's risk exposure. More importantly, the distinction of a "within-effect" from a "between-effect" is crucial for strategic decisions. While an increase in business diversification is positively associated with a firm's exposure to supply risk, a higher degree is negatively associated with it. These results provide several important contributions to the literature on supply risk. First, the distinction of the different levels allows the integration of those opposing empirical results reported on thus far and exemplifies the necessity to be clear on the level for which a given theory is valid. Second, the results explain that the exposure to supply risk is pre-determined by the industrial environment which a single firm cannot alter. This result accumulates further empirical evidence that firms must be prepared for the need to respond to such external uncertainty. Third, this study proposes a new measurement of a firm's potential exposure to supply risk based on a textual analysis. Although 10-K reports have been extensively studied in the accounting and finance literature, they have not been exploited as a source of information in operations management. For managers the implications of this study are twofold: Managers must be aware of the double-edged sword offered by business diversification. Although an increase in business diversification may increase their firm's exposure to supply risk in the short term, such business diversification is nevertheless an eminently suitable strategy for tackling supply chain risk in the long term. Furthermore, the observation that exposure to supply risk largely stems from the industrial environment means that firms must keep sufficient resources on hand in order to react to unforeseen changes.

Chapter 4 deals in more detail with the interplay among factors like a firm's exposure to supply chain risk, its risk mitigation strategies, and its performance. The study has been motivated by the observation that firms are under severe pressure to simultaneously lower their operating costs and also manage their risk exposure. This study analyzes the kind of risk management strategy a firm should deploy against a given type of risk to ensure that performance is not (or only weakly) impaired. Against the backdrop of information processing theory, this study investigates supply- and demand-related risks as typical types of risk and capacity and inventory as types of operational slack in response to these types of risks. From a contingency perspective, operational slack must be matched to the type of risk in order to be efficient. More specifically, operational slack mitigates the negative relationship between a firm's exposure to supply risk and its performance, but inevitably exacerbates the negative relationship between demand risk and performance. What is more, inventory and capacity are hypothesized to have a joint effect on the relationship between the type of risk and performance which is larger than the sum of their parts. To shed light on these relationships, the previous sLDA has been employed to quantify supply- and demand-related risks in Item 1.A. Inventory and capacity, as well as performance, have been measured on the basis of a firm's financial data. The hypothesized relationships are tested utilizing a fixed effects regression model. The results suggest that exposure to supply- and demand-related risks is indeed negative for a firm's performance. The effect of supply-related risk on a firm's performance is, however, mitigated by both, inventory and capacity, whereas the effect of demand-related risk on a firm's performance is exacerbated only by inventory. Finally, if a firm is exposed to supply risk and simultaneously holds adequate inventory and capacity, both their mitigating effects on the association between supply risk exposure and performance of a firm amplify each other in such a way that their joint effect is greater than the sum of their parts and a firm's supply risk exposure is reduced even further. These results represent a number of important contributions to the literature on supply chain risk management. First, this study develops a new empirical measurement of a firm's potential exposure to two distinct types of supply chain risk based on secondary data which has not been considered, yet. To this end, the study relies on Item 1.A as prime source of information. Second, this study accumulates evidence that the type of supply chain risk and the respective mitigation strategy must be carefully matched to each other. Third, balancing inventory and capacity against each other appears more beneficial than relying only on a single type of slack. For managers, this study presents important guidelines for the decision on which risk mitigation strategy should be pursued. If a firm's managers identify mainly supply-related risk, then they should select operational slack as the best policy. However, if their main fear is demand-related risk, then they should avoid operational slack. Furthermore, just focusing on one type of slack is an inefficient policy. A firm which selects the right level of inventory and capacity slack will be more successful compared to a firm which just maintains a single type of slack in response to supply-related risk.

Overall, these three essays taken together make an important contribution to the literature on supply chain risk management. From an empirical perspective, this dissertation suggests positive impetus for future research relying on the qualitative sections of 10-K reports as a source of information. Automated text analysis tools greatly facilitate the analysis and allow the reliable information extraction on a large scale. The information extracted deepens the understanding of a firm's exposure to various types of risk. On the basis of these new empirical measurements, this dissertation can advance the theoretical understanding of supply chain risk and provide new insights on the sources of a firm's potential risk exposure while also suggesting how a firm can efficiently cope with its risk exposure.

5.2 Limitations

Although this dissertation makes an important contribution to theory and practice, its results must be viewed in the light of certain limitations with respect to the data and the methodology. First, the dissertation heavily depends on the corporate risk disclosure in 10-K reports. However, the risk disclosure reflects only the risk that a firm has identified and found sufficiently probable. In this regard, firm may evaluate incorrectly or be even unaware of some risks. Furthermore, managers have considerable discretion in deciding what constitutes a material risk. Other incentives might lie behind the decision on what risk to disclose. Quite a few drivers for this decision have been identified (e.g., the number of following analysts and their opinion, auditors' reports, prior managerial experience), though this list is far from being exhaustive. Thus although studies in the field of accounting support the assumption that a firm's risk disclosure reflects its real risk exposure, this assumption requires critical examination. Second, the dissertation uses advanced text mining tools for the analysis of the 10-K reports. Although these tools have been developed by prior research and do lead to reliable results, they nevertheless build on stochastic models and make predictions accordingly (e.g., is a given term a location, or what topic does a certain term belong to). Moreover, the application of these tools is highly case-specific. In this dissertation, a measurement similar to the tf-idf-metric has been used to identify the most important words in a firm's risk disclosure. There are no clear guidelines as to which parts of speech or how many terms should be considered for the automated analysis of texts. Consequently, some researchers even refer to the application of text mining tools as an art, even though the tools themselves are built on scientific models.

The implication is that different researchers might come to different conclusions if they apply the same tools using a different set of words or other modeling assumptions. Third, the dissertation relies on secondary data only of manufacturing firms publicly listed in the United States. In other countries, other challenges might be regarded as a risk. Also, privately owned firms may have different values and pursue other objectives, with the result that different risks are relevant. Finally, other industries might have a different risk exposure, may be unable to employ operational slack, or find that other risks are relevant. Therefore the results are only generalizable within these boundaries and other studies with a different scope might come to different conclusions. Fourth, the dissertation uses regression models to derive its conclusions. The estimation models deployed (difference-in-difference, fixed effects) apply a robust specification (clustered robust standard errors, time controls, firm controls) and provide robust estimates even if the model was misspecified (e.g., due to omitted variable bias, heteroscedasticity, serial correlation, wrong functional form). Nevertheless, misspecifications might still distort the results. Besides, the results only indicate a correlation between the independent and the dependent variables, but not necessarily the direction of this effect. As a result, the dissertation can only provide empirical evidence on the association between the constructs but is not in a position to make causal claims about the direction of the effects identified.

5.3 Future research directions

Despite its shortcomings, this thesis sheds light on supply chain risk management from a new angle. Scrutinizing unstructured texts, converting the data into information, and using this as input for advanced empirical analyses allows the derivation of new insights into supply chain risk management. The data provide the opportunity to generate additional knowledge for future research. First, future researchers can further explore the disclosure of supply chain-related risks. Since this dissertation has identified the major supply chain-related risks, as in the next step these risks can be further clustered to derive a taxonomy of these risks. One potential approach could be to also include more detailed sections of the textual disclosure on supply chain risk in the analysis utilizing a topic model. Such an analysis would identify different topics within the disclosure of supply chain risk. Each of these “second level” topics could then be interpreted as one element in an empirical taxonomy of the overall supply chain risk. Second, a list of keywords could be defined to validate existing risk typologies. In such a project, the potential exposure of firms as disclosed in the 10-K report could be compared to the exposure suggested by existing typologies. In addition, the frequency of types of risk could be used to enrich the information content. Third, prior research clusters firms based on the strategies that they pursue. One prominent example is the distinction between product-differentiation and cost-leadership firms. The same idea could be pursued, but based on supply chain risk. It would be possible to compute pairwise similarities among all the textual descriptions of the supply chain-related risks that firms have disclosed. Based on the resulting pairwise similarity matrix, several clusters of firms could be identified. Intra- and inter-group analyses could well generate important insights. As regards the former, the coherence of a group could be assessed with respect to other relevant variables such as performance or operational slack. If they differ, a theory on the reasons for these differences could be developed. The inter-group analysis could reveal whether firms with different risk exposures are inclined to make different strategic decisions. Fourth, the production location data could be further refined by including physical distances or product flows. To derive such distances, the states' geographic positions can be looked up and the distances between them computed. For the derivation of product flows, the production locations could be linked to the names of subsidiaries which often reveal the product segment to which the respective subsidiary belongs. As a result, the production networks of firms could be analyzed on a more fine-grained level. Fifth, scanning the entire 10-K report of a firm instead of merely dedicated sections, all the firm names could be identified. The occurrence of a firm name would hint at a relationship between these firms. This would allow the construction of a network of interrelated firms which could be used to investigate the innovation potential of such firm networks. Sixth, and moving one step further away from 10-K reports, other firm publications such as sustainability reports or news releases could be explored using text mining tools. For example, one could try to find similar news releases. If two firms publish two very similar news releases, these firms are likely to announce either a joint project or are competitors offering a very similar product and addressing similar customer needs.

In sum, this dissertation mines the texts of 10-K reports in order to construct a measurement of the potential risk exposure of a firm. Such a measurement allows new insights into what type of external contingencies could turn into risk exposure, which conditions make a firm extraordinarily vulnerable to external threats, and how firms can deal efficiently with such a potential risk exposure. The dissertation finally highlights that the analysis of textual data in general and of 10-K reports in particular represent promising avenues for further empirical research in operations management.

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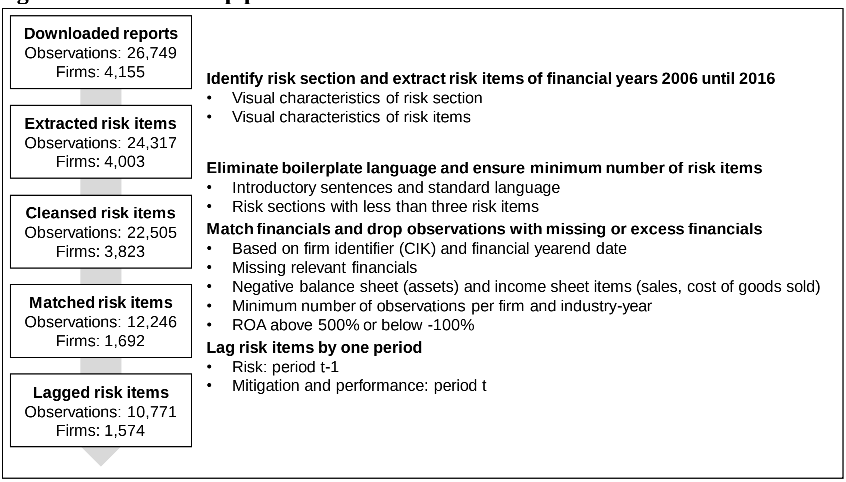
Appendix

Appendix A: Derivation of the data set analyzed in chapter 4

The final data set was derived in a five-step procedure as Figure A-1 illustrates. In the first step, 26,749 annual reports of 4,155 firms meeting the selection criteria were downloaded via the SEC's EDGAR database. In the second step, the risk items were extracted. To do so, Item 1.A was identified by a combination of text search and visual characteristics and was subsequently truncated from 24,317 (91 %) annual reports (4,003 firms). The remaining parts and all other annual reports were discarded. Furthermore, visual features (i.e., bold, italics, underlined, and capital letters or a combination thereof) that fulfilled the SEC's requirement of presenting the information clearly and concisely were used to then identify and extract the risk items from these risk sections.

Figure A-1: Multi-step procedure for the derivation of the final data set

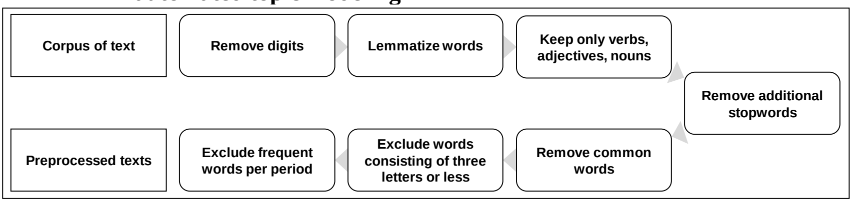


In the third step, the risk extraction was further cleansed, leaving 22,505 firm-years (3,823 firms). Firm-years which contained less than three risk items were dropped, and boilerplate language and introductory sentences were deleted. The reason for this cleansing is twofold. On the one hand, these firms were likely to state that they were not required to disclose a risk section. On the other hand, focus was on keeping a high data quality by being overly conservative. Fourth, a firm's financials from Compustat were matched to the risk disclosure from EDGAR based on the CIK and the date of the fiscal year end (+/–7 days). Observations with relevant financials that were missing or implausible (i.e., negative book value of assets, negative cost of goods sold, negative sales) were dropped. In addition, firms with a return on assets of below –100 % and above 500 % were discarded, because such returns do not represent a sustainable long-term profit. Finally, all firms with less than three observations or operating in industries with less than three firms in a given year were also dropped. Remaining were 12,246 firm-years from 1,692 firms over the time period between 2006 and 2016. Fifth, additional observations were lost because the risk variables are lagged by one period to relieve endogeneity concerns in the estimation model.

Appendix B: Preprocessing of text

In order to derive meaningful topics, the text from the risk items had to be further cleansed. All digits were removed and all words were lemmatized reducing inflected verbs to infinitive or nouns in plural to singular. In contrast to stemming, lemmatizing bases on morphological rules and is less aggressive. Furthermore, only verbs, adjectives, and nouns (with the exception of proper nouns) were considered. In addition, several words were eliminated using the following rules. First, all stopwords (i.e., words that are very common in the English language) were eliminated. Besides already excluded determiners or prepositions, the list of stopwords (319 in total) comprises verbs like “describe” or “become”. Second, additional 34 words that are very common to the risk disclosure were disregarded (e.g., risk, uncertainty, negative). Third, all words consisting of three letters or less were excluded. Fourth, the 15 most frequently occurring words in the risk disclosure of a given year were neglected (e.g., business, product, result, affect, or operation). The following example illustrates the necessity for a time-dependent corpus of relevant words: In 2008, the word “condition” enters the list of the most common words. This coincides with the risk of worsening economic conditions due to the financial crisis in 2008 which many firms mention. Using a static list across all periods would have resulted in the exclusion of “condition” in all periods.

Figure A-2: Preprocessing of the corpus of text from the risk items to enable automated topic modeling



Curriculum Vitae

Professional Experience

02/2015 – 09/2018	Research Assistant, Endowed Chair of Procurement University of Mannheim, Germany

Education

02/2015 – 09/2018	Doctoral Candidate in Operations Management University of Mannheim, Germany
09/2010 – 08/2012	Business Administration (M.Sc.) University of Mannheim, Germany
09/2007 – 07/2010	Business Administration (B.Sc.) University of Mannheim, Germany
06/2006	Abitur Gymnasium Wolbeck, Münster, Germany