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Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions

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ABSTRACT

A great deal of research has focused on supply chain risk management, but the question "Which supply chain characteristics increase the frequency of supply chain disruptions?" has not received much attention from empirical research. This is a relevant question, because firms seek stability in their operations, and therefore managers need to know how the structure of their supply chains affects the occurrence of disruptions. The present study addresses this issue with a specific focus on upstream supply chain (supply-side) disruptions. Drawing on the literature on supply chain complexity, we devise and test a model that predicts the frequency of supply chain disruptions based on a multi-dimensional conceptualization of upstream supply chain complexity. Not only do the empirical findings suggest that all of the three investigated complexity drivers – horizontal, vertical, and spatial complexity – increase the frequency of disruptions, but also that they interact and amplify each other's effects in a synergistic fashion.

1. Introduction

"If you are in supply chain management today, then complexity is a cancer you have to fight." This statement from a former vice president of supply chain operations from Coca-Cola North America (Gilmore, 2008), expresses the commonly held belief both among practitioners and scholars that supply chain complexity is one of the most pressing problems in modern supply chains and a key impediment to performance (Bozarth et al., 2009; Choi and Krause, 2006; Mariotti, 2008). High levels of complexity in the inter-connected flows of materials, funds, and information between firms have not only been blamed for decreasing supply chain efficiency, but also identified as a key precursor of supply chain disruptions (Chopra and Sodhi, 2004; Craighead et al., 2007; Narasimhan and Talluri, 2009). For example, Toyota's recent product recall crisis has been explained, at least in part, as the result of a surge in supply chain complexity (Cole, 2010).

Supply chain disruptions have the potential to cause heavy short- and long-term losses in shareholder value, sales, and reputation; they may also damage relationships between customers and suppliers (Hendricks and Singhal, 2003; Sheffi, 2005). Consequently, many scholars have advised firms to tackle the risk of supply chain disruptions as aggressively as they do financial risks and to reassess their supply chain designs from a risk perspective (Sodhi et al., 2012). So far, however, relatively little is known about the link between the *structural characteristics* of supply chains and the risk of disruptions. From an empirical perspective, only a few studies have examined this relationship. Papadakis (2006), for example, suggested that when a disruption strikes, make-to-order (MTO) supply chains are more vulnerable than make-to-forecast (MTF) supply chains are. Hendricks et al. (2009) found negative stock market reactions to supply chain disruptions to be more severe for firms that are more geographically diversified, less vertically related (i.e., high level of outsourcing), and equipped with little operational slack. Using a similar methodology, Schmidt and Raman (2012) reported that supply chain disruptions are more damaging to shareholder value if shareholders attribute the disruption to factors within the focal buying firm or its supplier network. All three studies identify several supply chain characteristics that affect a firm's losses *if* a disruption actually occurs. While these are valuable insights, they address only the magnitude of impact of disruptions (Holton, 2004). The other important element of risk remains largely unexplored: How frequent (or likely) are supply chain disruptions, given a certain supply chain structure? This is an important question, because firms seek stability in their operations (Katz and Kahn, 1978; Thompson, 1967), and therefore managers

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need to know how the organization of their supply chains affects the occurrence of supply chain disruptions. To the best of our knowledge, only the recent study by Marley et al. (2014) has investigated this relationship using a normal accident theory perspective to predict the occurrence of "every-day" downstream supply chain (demand-side) disruptions.

The purpose of this study is to advance our understanding of the relationship between supply chain characteristics and the frequency of supply chain disruptions. We address this issue within a manufacturing industry context and with a specific focus on upstream supply chain (supply-side) disruptions. Based on the initially highlighted complexity perspective, we hypothesize and test a proposed theoretical model that links structural drivers of upstream supply chain complexity with the number of supply chain disruptions experienced by buying firms over a 12-month period. Drawing on the literature on supply chain complexity (Bozarth et al., 2009; Choi and Hong, 2002; Choi and Krause, 2006; Manuj and Sahin, 2011), our model identifies three structural drivers (or dimensions) of upstream supply chain complexity – horizontal, vertical, and spatial complexity – and suggests that not only each of these variables increases the frequency of supply chain disruptions, but also that each one also intensifies the effects of the other two in a synergistic (superadditive) fashion. The results, received from count regression analyses, offer support for our model and yield relevant theoretical and managerial implications.

Given that the phenomena under investigation are supply chain disruptions, the following section discusses this term and defines it within the scope of this study. Further, to understand the linkage between supply chain structure and disruptions, we review the literature on supply chain complexity, which will be the basis for the subsequent development of hypotheses. The research methodology and the results are then presented. The remaining sections discuss the results from both scholarly and managerial perspectives. We conclude by describing the limitations of the study and by making recommendations for future research.

2. Background

2.1. Supply chain disruptions

Of the numerous risks that firms face, the risk of supply chain disruptions arises from the vulnerabilities of the inter-connected flows of materials, information, and funds in inter-firm networks. To some extent, all firms depend on external sources and supply chain relationships (Pfeffer and Salancik, 1978), and are consequently exposed to this type of risk.

The extensive corresponding literature is not always consistent in its terminology, but several studies have advanced the conceptual clarity of the terms used in the fields of supply chain risk management (e.g., Bode et al., 2011; Craighead et al., 2007; Ellis et al., 2011; Rao and Goldsby, 2009). In these works, a *supply chain disruption* is typically viewed as a discrete event that causes the losses for the affected firms. Craighead et al. (2007, p. 132), for example, defined supply chain disruptions as "unplanned and unanticipated events that disrupt the normal flow of goods and materials within a supply chain [...] and, as a consequence, expose firms within the supply chain to operational and financial risks." Supply chain disruptions involve at least two tiers in a supply chain, but, beyond this commonality, they may be highly heterogeneous in their characteristics and may emerge from a variety of sources, internal and external to a supply chain (Rao and Goldsby, 2009; Sodhi et al., 2012). A delayed shipment of non-critical material on the supply side, for example, may represent a less serious disruption than a major product recall on the demand side. For this reason, it is conceptually helpful to distinguish minor, repetitive problems of coordinating supply and demand from more major events that significantly threaten the normal course of business operations of a focal firm (Chopra and Sodhi, 2014; Kleindorfer and Saad, 2005).

For the purpose of this study, we restrict our focus to the latter and to the upstream supply chain. Based on the related literature (Bode et al., 2011; Craighead et al., 2007), we define a supply chain disruption as the combination of an unintended and unexpected triggering event that occurs somewhere in the upstream supply chain (the supply network), the inbound logistics network, or the purchasing (sourcing) environment, and a consequential situation which presents a *serious* threat to the normal course of business operations of the focal firm. This scope sets the stage for a large set of issues, including quality problems with suppliers, delivery outages, supplier defaults, labor strikes, or plant fires; all of which can vary considerably in their causes, characteristics, and effects.

2.2. Supply chain complexity

Complexity is an elusive construct that plays an important role in many academic disciplines. The term is usually discussed in connection with a system of elements and referred to as a system attribute (e.g., ecosystems, stock markets, the human brain), but it has a variety of different measurements and conceptualizations depending on the specific research field (for a detailed overview, see Jacobs and Swink, 2011). In the social sciences, an influential definition was provided by Simon (1962, p. 468) who stated that a socio-technical system is complex if it is "made up of a large number of parts that interact in a nonsimple way." This definition, which has become core to many subsequent conceptualizations of complexity, highlights two defining qualities of complexity: structure and behavior (Anderson, 1999; Burnes, 2005; Perrow, 1984; Senge, 2006). The former is often termed *structural complexity* (also *static* or *detail complexity*) and refers to the number and variety of elements defining the system. The latter is often called *dynamic complexity* (or *operational complexity*) and refers to the interactions between the elements of the system. In practice, these aspects are often closely interrelated, because the larger the number of varied elements, the greater is the possible number of interactions and thus the variety of behaviors and states the system may exhibit. This is especially true of supply chains (Bozarth et al., 2009; Manuj and Sahin, 2011; Skilton and Robinson, 2009).

Complexity is an important theme in the supply chain literature[2] in which there is a general consensus that supply chains have become increasingly complex over the last decades and that this complexity is not a desirable feature. Supply chain complexity has been argued to decrease the performance of operations (Bozarth et al., 2009), complicate decision making (Manuj and Sahin, 2011), and precipitate disruptions (Chopra and Sodhi, 2014; Craighead et al., 2007; Narasimhan and Talluri, 2009). Within this literature, there are two sub-streams that take a unique perspective on complexity in supply chains. One stream investigates supply chains as complex adaptive systems that have the capability to learn and adapt to changes in their environments (Choi et al., 2001; Pathak et al., 2007). Here, the specific focus is on the interactions of the autonomous elements defining the supply chain system, with the goal of understanding the principles and the adaptive behavior of the entire system (Dooley and Van de Ven, 1999). A second stream examines supply chains as complex social networks and uses methods from social network analysis to understand how relational ties are formed and how these ties affect social capital, resource access, convergence, and contagion in supply chains

[2] For example, in 10% percent of all articles (56 out of 547, without editorials) published in the *Journal of Operations Management* from 2001 to 2013, the terms *complexity* or *complex* appear at least once in the abstract or title.

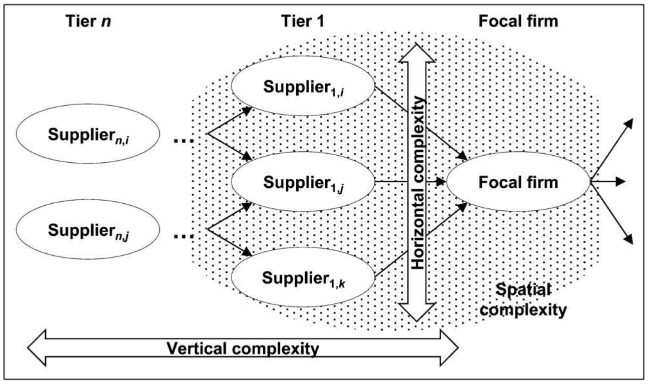


Fig. 1. Horizontal, vertical, and spatial complexity of the upstream supply chain.

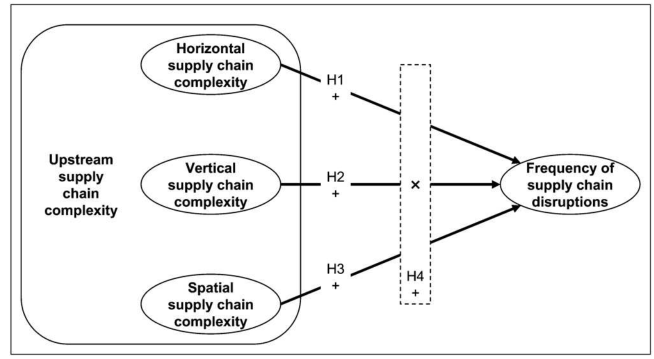


Fig. 2. Conceptual framework.

and networks (Borgatti and Li, 2009; Kim, 2014; Lomi and Pattison, 2006).

Although this research offers very helpful insights into the nature and effects of supply chain complexity, there is still no universally accepted definition of what actually constitutes or determines supply chain complexity (Manuj and Sahin, 2011; Milgate, 2000). Most studies have viewed supply chain complexity as a multi-faceted, multi-dimensional phenomenon that is driven by several sources (for a detailed overview of these sources, see Table I in Manuj and Sahin, 2011). For example, Milgate (2000) described three key sources of supply chain-related complexity (uncertainty, technological intricacy, and organizational systems), Vachon and Klassen (2002) identified two (complicatedness and uncertainty), Rao and Young (1994) proposed three (product, process, and network complexity), Choi and Krause (2006) described three (number of suppliers, the differentiation among those suppliers, and the relationships among the suppliers in the supply base), and Bozarth et al. (2009) identified two (detail and dynamic complexity). The reason for these differences lies partly in the differences in the scopes of the studies. Some authors were interested in the complexity of an entire supply chain (e.g., Bozarth et al., 2009) while others looked only at the complexity of specific parts or segments (e.g., Choi and Krause, 2006).

As stated above, the scope of this study is decidedly restricted to the upstream supply chain and particularly to its structure (or organization). In this regard, Choi and Hong's (2002) study is most relevant, because it provides the most fine-grained conceptualization of upstream supply chain complexity from a structural perspective. From the point of view of a buying firm, the upstream supply chain can be viewed as an organization. In organizational theory, the structural complexity of organizations is typically measured along three drivers: horizontal, vertical, and spatial complexity (Anderson, 1999; Daft, 2006; Jablin, 1987; Tolbert and Hall, 2009). Choi and Hong (2002) transferred this framework to the supply chain context and suggested that *horizontal complexity* corresponds to the number of suppliers in each tier; *vertical complexity* corresponds to the number of tiers; and *spatial complexity* corresponds to the extent of the dispersion among members within the network (i.e., geographic distance between a focal firm and its suppliers).

Fig. 1 visualizes this conceptualization of upstream supply chain complexity from the perspective of a focal buying firm, which we will adopt for the development of our hypotheses.

3. Conceptual framework and hypotheses

Supply chain scholars are not alone in trying to understand the association between complexity and system performance (including performance exceptions caused by disruptive events). The question of how accidents, crises, disruptions, or errors unfold has been examined by a multitude of research streams, and especially by researchers in the fields of organization (e.g., Perrow, 1984), engineering (e.g., Leveson, 2004), and psychology (e.g., Reason, 1990). Organizational theorists found that due to their complex and technology-oriented processes, inter-firm networks are becoming more susceptible to accidents (Lin et al., 2006). This prediction is supported by Perrow (1984), a sociologist who developed normal accident theory (NAT) to explain why complex socio-technical systems fail. NAT has become a very influential theoretical lens through which to assess the vulnerability of socio-technical systems, because it links the occurrence of accidents to the structure and technology of the underlying system. As Shrivastava et al. (2009, p. 1357) have put it: "It is hardly possible for organizational theorists to write about accidents without referring to Normal Accident Theory." According to NAT, complexity is a key factor in the higher accident rates in socio-technical systems. From this broad literature, we can delineate two distinct mechanisms by which complexity affects the occurrence of disruptive events in systems such as supply chains.

The first mechanism is related to the *emergence of disruptive events* in complex systems: A system comprising a large number of elements can be expected to produce more disruptions than a smaller system (Perrow, 1984). For illustration purposes, this can be easily demonstrated with Bernoulli random variables. Assume that for every element j ($j = 1,\ldots, n$) in a system there is an independent probability p_j of producing a disruption within a certain finite time horizon. If, for convenience, corresponding Bernoulli disruption indicators 1_{D_j} are defined so that $P[1_{D_j} = 1] = p_j$, the expected value of disruptions (which the focal firm will have faced at the end of the time horizon) is equal to $E(D) = \sum_{j=1}^{n} 1_{D_j}$ which clearly increases with the number of elements n. Furthermore, due to the interactions and relationships among the elements in a complex system, small, independent failures can interact in unplanned ways and produce unfamiliar, unexpected event sequences that are not immediately comprehensible. This makes the behavior of complex systems surprising and unpredictable (Anderson, 1999).

The second mechanism is related to the *managerial ability to detect and prevent disruptive events* shortly prior to or very soon after their occurrence. In fact, many disruptive events send out early warning signals (Mitroff, 2000). If these accident precursors are detected and correctly interpreted, disruptions can be averted or at least their impact contained by resorting to quick preventive interventions. For example, receiving two months' advance notice of a supplier becoming financially distressed would enable a buying firm to adapt its sourcing arrangements or to financially support the distressed supplier in order to preserve the supply chain. However, a system consisting of a large number of varied elements becomes more opaque to those who manage and control it, implying that it becomes difficult to properly identify and interpret early warning signals (Sagan, 1993; Skilton and Robinson, 2009). In addition to this challenging information-processing task (Galbraith, 1973), the system's reaction to interventions is hard to predict, because feedback loops may propagate, attenuate, or even reverse the intended effect in an unforeseeable manner (Choi and Krause, 2006).

In the next sections, we will use the two delineated mechanisms to develop hypotheses that link the drivers of upstream supply chain complexity suggested by Choi and Hong (2002) with the occurrence of supply chain disruptions. Fig. 2 shows the model of predicted relationships. The model's unit of analysis is the upstream supply chain of a buying firm and the number of serious disruptions incurred by this firm within a finite time horizon.

3.1. Horizontal supply chain complexity

In organizational theory, *horizontal complexity* is associated with the specialization of skills and knowledge in an organization (Daft, 2006). For example, a firm with many departments or business units has a greater degree of horizontal complexity than a firm with only a few. In an upstream supply chain, horizontal complexity has been linked to the number of direct suppliers in a focal firm's supply base (Choi and Hong, 2002; Choi and Krause, 2006). We expect horizontal complexity to drive both of the disruption mechanisms discussed above.

First, because no supplier is perfectly reliable, the frequency of disruptions will likely increase with the number of direct suppliers (e.g., Babich, 2006; Chaturvedi and Martínez-de-Albéniz, 2011). However, as discussed by Choi and Krause (2006), the *severity* of these supply chain disruptions is affected by the chosen sourcing strategy (single-, dual-, or multi-sourcing). The intensive use of dual/multi-sourcing arrangements will increase horizontal complexity and the frequency of disruptions, but can mitigate the severity of the experienced disruptions.

Second, larger supply bases are also associated with more coordination and administrative tasks which may impair a buying firm's ability to proactively identify disruptions (Boulding, 1953; Kasarda, 1974). The more direct suppliers a focal firm has, the greater the number of interfaces that need to be managed, monitored, and coordinated (Choi and Krause, 2006). With such increasing task complexity, the boundary-spanning employees (logistics, purchasing, supply chain management) are less likely to sustain a sufficiently broad view to manage the risk of disruptions (Campbell, 1988; Vachon and Klassen, 2002; Wood, 1986). Indeed, task complexity has been reported to reduce the quality of decisions and slow the pace of decision-making (Wally and Baum, 1994). Given the two mechanisms, we predict:

Hypothesis 1. There is a positive relationship between *horizontal supply chain complexity* and the frequency of supply chain disruptions.

3.2. Vertical supply chain complexity

Organizations with more hierarchical levels exhibit greater complexity than organizations with fewer. Organizational theory terms this *vertical complexity* (or *hierarchical complexity*) (Jablin, 1987; Tolbert and Hall, 2009). In a supply chain context, this type of complexity corresponds to the number of tiers which has been argued to drive supply chain complexity (Blackhurst et al., 2005a; Choi and Hong, 2002; Mentzer et al., 2001).

First, vertical supply chain complexity is related to the potential for chain reactions (i.e., cascading disruptions from upstream supply chain tiers) (Choi et al., 2001). For example, in January 2005, the automotive OEMs Audi, BMW, and Daimler experienced a severe supply chain disruption due to defective diesel injection pumps. The supplier, Robert Bosch, failed to detect a defect in the Teflon coating on an inexpensive half-inch socket that went into these diesel injection pumps. The interesting aspect of this incident is that the socket was not produced by Bosch itself, but by its US supplier Federal Mogul that had in turn sourced a contaminated batch of Teflon from the US chemical company DuPont. Downstream in the supply chain, the contaminated Teflon brought the automotive OEMs' assembly lines to a standstill, triggered a product recall of several thousand cars costing millions of dollars, and damaged the reputation of Bosch and the OEMs (Wagner and Bode, 2006). This example illustrates that a change in a single tier may trigger a rapid change in related ones. Similar to the domino effect, small failures can interact in unforeseen ways and produce major disruptions further downstream in the supply chain (Chopra and Sodhi, 2014). The more tiers there are, the more chances there are for these ripple effects. Thus, the greater the vertical complexity, the more likely a firm is to experience disruptions as a result of problems that occurred upstream the supply chain (events that spread throughout the supply chain).

Second, uncertainty in the upstream supply chain increases with vertical supply chain complexity (Beamon, 1999; Milgate, 2000). Choi and Hong (2002, p. 490) conjectured that many focal firms have only limited transparency and knowledge "regarding what lies beyond the top-tier supplier (e.g., who the second- and third-tier suppliers are)." Upper supply chain tiers are often not actively managed, and emerge over time. This makes it hard to detect and identify early warning signals. In this regard, Simchi-Levi et al. (2014) cited the example of Evonik Industries, a German second-tier supplier to the automotive industry, which caused a major disruption to many automotive OEMs after one of its production plants exploded in 2012. In sum, we predict:

Hypothesis 2. There is a positive relationship between *vertical supply chain complexity* and the frequency of supply chain disruptions.

3.3. Spatial supply chain complexity

Spatial complexity is the geographical spread of an organization and/or a supply base (Choi and Hong, 2002; Vachon and Klassen, 2002; Wilding, 1998) which complicates the supply chain structure. High levels of spatial complexity in the upstream supply chain are typically associated with global sourcing. Prior research stressed that spatial complexity contributes to the complexity of supply chains and increases the risk of supply chain disruptions (Blackhurst et al., 2005b; Das and Handfield, 1997; Kraljic, 1983; Lorentz et al., 2011).

First, a geographically dispersed supply chain implies a physically elongated flow of goods with longer paths and longer and more variable lead times which creates more possibilities for disturbances (Crone, 2006; Simchi-Levi et al., 2014). For example, longer paths usually involve more logistics touch points and greater reliance on critical infrastructures (e.g., ports, airports) which are vulnerable to risk sources such as cargo theft, rough handling, and environmental conditions (e.g., condensation, contamination with fresh or sea water, fire, or natural disasters). Using agent-based simulation, Nair and Vidal (2011) showed that longer average paths between supply chain nodes decrease a supply network's robustness.

Second, and as in the case of horizontal complexity, information-processing needs and monitoring costs increase with geographic distance from the suppliers (Stock et al., 2000). In comparison to sourcing from local or domestic markets, global sourcing is typically associated with increased uncertainty and less transparency due to, for example, trade restrictions, customs barriers, exchange rate fluctuations, and institutional differences (Wagner and Bode, 2006). The coordination of operations, control of consistency, and sharing of activities also become costly when there is a great geographic distance between a buyer and a supplier, because of likely time-zone and language differences as well as difficulties of face-to-face communications (Madhavan et al., 2004). Although modern technologies have substantially reduced the costs of information exchange and monitoring, it is still difficult to constantly monitor suppliers in terms of opaque issues such as their financial health or even their specific exposure to natural hazards if the geographic distance is large. Furthermore, longer geographical distances interfere with the timely detection, interpretation, and implementation of countermeasures. These arguments lead us to expect:

Hypothesis 3. There is a positive relationship between *spatial supply chain complexity* and the frequency of supply chain disruptions.

3.4. Interaction of supply chain complexity dimensions

The upshot of the preceding analysis is that horizontal, vertical, and spatial complexity are likely associated with increased uncertainty and with poorer transparency and visibility, leading to an increasing frequency of supply chain disruptions. Horizontal, vertical, and spatial complexities create their own information-processing needs that the focal firms must meet. However, the three drivers of upstream supply chain complexity likely do not act in isolation, but interdependently (Ennen and Richter, 2010). Supply chains are not mechanistic structures whose behavior can be easily predicted by knowing the elements of which it is composed. This is a typical feature of complex systems (Anderson, 1999). In a seminal article on complex systems, Simon (1962, p. 467) argued that "[i]n such systems, the whole is more than the sum of the parts, not in an ultimate, metaphysical sense, but in the important pragmatic sense that, given the properties of the parts and the laws of their interaction, it is not a trivial matter to infer the properties of the whole." This suggests that simultaneous high levels of horizontal, spatial, and vertical complexity create additional potential for unfamiliar cause-effect sequences caused by non-linear interactions, dependencies (e.g., supplier default dependencies) (Wagner et al., 2009), or complicated feedback loops (e.g., supplier-supplier relationships) (Choi et al., 2002). Due to these interactions, the supply chain will likely exhibit nonlinear behavior (Perrow, 1984) and create additional information-processing needs (Skilton and Robinson, 2009). For example, managing a large number of suppliers is demanding (horizontal complexity), but if these suppliers are also distributed across the globe (spatial complexity), the coordination tasks become even more complicated. These arguments suggest that the effects produced by the three supply chain complexity dimensions amplify each other's effects, thus:

Hypothesis 4. The total effect of horizontal, vertical, and spatial supply chain complexity on the frequency of supply chain disruptions is greater than the sum of the effects of each individual complexity dimension.

4. Method

4.1. Data and procedure

The empirical context for this study is the manufacturing sector and our unit of analysis is a buying firm that experienced at least one disruption in its upstream supply chain during a period of 12 months. Primary data were collected in 2007 by means of a self-administered Internet-based survey of 3945 firms in Germany, Austria, and Switzerland (Bode et al., 2011). We followed a key informant approach and targeted senior managers with responsibilities for purchasing or supply management who are likely to have

Table 1
Industry breakdown.

Industry sector	f	%
Industrial machinery, machine tools	64	16
Electronics, optics, medical devices	59	15
Automotive	57	14
Chemicals, plastics, rubber	46	12
Metals, metal working	40	10
Pharmaceuticals, healthcare	27	7
Consumer goods	23	6
Paper, packaging	23	6
Engineering, construction	18	5
Textiles, clothing	16	4
Food, beverages	11	3
Aerospace, defense	6	2
Telecommunications	6	2

an overarching, boundary-spanning view of their firms' upstream supply chains and supplier activities. To this end, contact addresses were obtained from a commercial business data provider, with each respondent selected on the basis of job function, firm size (number of employees > 50), and industry sector (SIC code). Respondents were asked to base their answers on the supply chain of one of their major product lines and their experience with disruptions in this specific supply chain in the year 2006. In exchange for their participation, respondents were offered a summary of the results and a practitioner-oriented purchasing book. Three follow-up e-mails and reminder phone calls resulted in 462 questionnaires (i.e., an overall response rate of 11.71%). Due to missing values (particularly in the measures for horizontal and spatial supply chain complexity, see below), the number of cases usable to test our hypotheses was reduced to 396.

This data set covers a broad range of manufacturing industry sectors and firm sizes and revealed no indication of systematic bias. Table 1 presents the composition of the sample. The total annual revenues of the respondents' firms in 2006 ranged from US $1 million to US $14.5 billion ($M$ = US-$491.98 million, SD = 1474.32 million) and the number of employees ranged from fewer than 100 to 40000 (M = 1388.63, SD = 3803.15). Most of the respondents were senior managers in purchasing who had been in their current positions for an average of 6.90 years (SD = 5.90) and with their firms for 11.57 years (SD = 9.30). Their work experience consisted of purchasing, logistics, or supply chain management for an average of 14.37 years (SD = 8.42).

We used two strategies to assess whether non-response bias was present in the sample (Wagner and Kemmerling, 2010). First, we inspected the differences between early (initial invitation) and late respondents (second and third reminders) on all survey items in our model by means of a multivariate analysis of variance. No significant mean differences were found ($p < 0.05$), either at the multivariate or at the univariate level. Second, we compared the full survey data with a sample of 100 non-responding firms randomly drawn from the initial sampling frame (N = 3945) on the basis of firm size (number of employees) and firm age (as per 2006). The performed t-tests for these variables indicated no statistically significant differences between the two groups ($p < 0.05$). In sum, the performed analyses did not suggest that non-response bias poses a significant threat to the validity of the results.

To verify the quality of our data, we gathered objective secondary data from two commercial databases (Bloomberg Professional Service and AMADEUS from BvDEP). We were able to obtain secondary data on firm size (number of employees) and firm age for all cases in the survey data set. As both variables were also included in the survey instrument, we were able to perform a rough check on the data quality. The variables were highly correlated ($r > 0.80$), suggesting that the primary data was of good quality.

4.2. Survey instrument and measures

The survey instrument was developed in several stages following standard scale and survey instrument development techniques (DeVellis, 2003; Dillman et al., 2009). This process included a number of preliminary interviews with purchasing managers, an extensive review of the literature, in-person pretesting, as well as a small pretest study with purchasing executives from manufacturing firms. For the survey instrument we ensured the ease of use, low burden on respondents, and that respondents maintained interested until completion of the survey. The survey instrument offered anonymity (on the level of the respondent) and stated that the confidentiality of the responses would be protected to the maximum extent allowable by law. In addition, the survey instrument provided only general information about the study's objectives, and no clues about the actual relationships under investigation.

Prior research suggested using single-item scales for constructs that are doubly concrete, meaning that they are concrete and unidimensional in both their content and their attributes (Bergkvist and Rossiter, 2007). Given that the number of supply chain disruptions and the three complexity variables studied are factual and easily and uniformly imagined, we avoided the use of multi-item psychometric scales and relied on single items. Descriptive statistics for the employed measures and correlations appear in Table 2.

4.2.1. Dependent variable

For the dependent variable *frequency of supply chain disruptions* (*D*), we asked the respondents for the number of supply chain disruptions experienced for the 12 months from January 1 through December 31, 2006. To engender a common understanding, the respondents were presented with our definition of supply chain disruptions: An event that materialized in the upstream supply chain and that led to a situation that had the potential for severe negative consequence for the focal firm. The distribution of this variable was highly positively skewed with a mean of 13.89 (SD = 55.19), and a minimum of 1 and a maximum of 1000. To fix the minimum at the value of 0 (a desirable feature for the count regression approach, see below) this variable was subtracted by 1 (i.e., a linear left shift of the distribution).

4.2.2. Independent variables

In congruence with previous studies (e.g., Bozarth et al., 2009), *horizontal supply chain complexity* (*HC*) was measured as the number of direct suppliers of the focal firm.

To measure *vertical supply chain complexity* (*VC*), we used the analogy of a typical automotive supply chain and asked the respondents: "If one compared your firm with an automotive supply chain which of the following would be your supply chain position?" Similar to Wynstra et al. (2010), the answer cues ranged from "1: 4th tier supplier of raw material" ("far upstream") to "5: OEM/ Final product manufacturer" ("far downstream"). Thus, the higher this variable's score, the longer the upstream supply chain. Given the heterogeneity of purchased items and individual supply chains (even within a single firm), this approach showed itself to be substantially more robust in our pretests than directly asking the respondent for the number of upstream supply chain tiers.

To measure *spatial supply chain complexity* (*SC*) we followed Stock et al. (2000) and Lorentz et al. (2011) and asked how each firm's purchasing volume (in monetary units) is spread over five geographic regions: Home countries (Austria, Germany, Switzerland), other European countries, North America (US, Canada, and Mexico), Asia/Pacific region, and the rest of the world (e.g., Latin America). The spatial complexity measure was then derived as the summation of the share of firm *i*'s purchasing volume in each region *j* multiplied by region-specific distance weights: $SC_i = \sum_{j=1}^{5} d_{ij} \times \left(V_{ij}/V_{i,\,\mathrm{Total}}\right)$. The distance weights d_{ij} were derived by calculating the geographical distance (the great-circle path in kilometers) between the location of a respondent's firm and the geographic centers (based on the center of gravity method) of the five regions (e.g., Rugby, ND for North America). Similar to Coval and Moskowitz (1999), we computed d_{ij} for each region *j* (and each focal firm *i*) as follows:

$d_{ij} = \frac{2\pi r}{360} \arccos\left[\cos\left(lat_j\right)\cos\left(lon_j\right)\cos\left(lat_i\right)\cos(lon_i) + \cos\left(lat_j\right)\sin\left(lon_j\right)\cos\left(lat_i\right)\sin\left(lon_i\right) + \sin\left(lat_j\right)\sin\left(lat_i\right)\right]$ where *lat* and *lon* are latitudes and longitudes (measured in degrees) and *r* is the radius of the earth (~6378 km or 3959 mi). While this is a rather simple measure, it provides a relatively reasonable proxy for the geographic distances that must be managed by the buying firm (Awaysheh and Klassen, 2010). As a robustness check, we also conducted a sensitivity analysis using alternative geographic centers (based on methods different that the center of gravity method), but the results for our hypotheses tests remained entirely robust.

As shown in Table 2, the Pearson product–moment correlation coefficients between the three complexity variables are relatively low. However, due to their nature, there is a positive dependence structure among these three variables at the lower end of their variable range (tail dependence).

4.2.3. Control variables

In the hypothesis testing procedure, we control for firm size, firm age, competitive intensity, and industry. *Firm size* (*FS*), measured as the number of employees in the focal firm, was included because it seems plausible that larger firms would experience more supply chain disruptions than smaller firms would. *Firm age* (*FA*), measured as the difference between the founding year and the year of the data collection, was included as a proxy for knowledge, experience, and familiarity with supply chain processes which may have an attenuating effect of the frequency of disruptions. *Competitive intensity* (*CI*), the extent to which respondents perceive the competitive climate to be fierce, was included because firms facing high levels of competitive intensity might be pushed towards more vulnerable supply chain structures in the hope of tapping unused potentials and gaining more efficiency or responsiveness. When properly implemented, these structures may have a positive effect on firm performance in stable environments, but they may also increase the probability of disruptions in more turbulent competitive environments (Zsidisin et al., 2005). The construct was measured with a reflective, four-item scale (five-point Likert-type) adapted from Jaworski and Kohli (1993) (coefficient α = 0.75) (measurement items are listed in Appendix A). Finally, we controlled for *industry* by using 12 industry dummies (cf. Table 1), accounting for the effects of the 13 industry sectors within our sample.

5. Analysis and results

Our hypotheses state that the frequency of supply chain disruptions D_i (i.e., counts during a 12-month period) experienced by focal firm *i* depends on the structure of its upstream supply chain, particularly its supply chain complexity, measured along three structural drivers or dimensions: $D_i = f(HC_i, VC_i, SC_i)$. Other things being equal, the marginal contribution of each argument is expected to be positive, so that an increase in any argument increases the number of supply chain disruptions.

5.1. Estimation strategy

Given that the dependent variable takes on only nonnegative integer values, the hypotheses are best analyzed using count regression. The common starting point for count regression is the

Table 2
Descriptive statistics and bivariate correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Frequency of supply chain disruptions[a]	1						
	–						
(2) Firm size[a]	0.08	1					
	(0.10)	–					
(3) Firm age[a]	−0.06	0.13**	1				
	(0.21)	(0.01)	–				
(4) Competitive intensity	0.05	0.03	−0.02	1			
	(0.35)	(0.52)	(0.71)	–			
(5) Horizontal supply chain complexity	0.09	0.32***	0.07	−0.02	1		
	(0.06)	(0.00)	(0.19)	(0.69)	–		
(6) Vertical supply chain complexity	0.15**	0.07	0.03	−0.03	0.08	1	
	(0.00)	(0.19)	(0.54)	(0.60)	(0.12)	–	
(7) Spatial supply chain complexity	0.07	0.14**	−0.04	0.05	0.05	−0.00	1
	(0.18)	(0.00)	(0.40)	(0.31)	(0.29)	(0.97)	–
Mean (M)	1.49	5.98	3.71	3.29	242.20	3.93	2045.04
Standard deviation (SD)	1.30	1.40	0.92	0.76	342.47	1.27	2172.25

Note. Pearson product-moment correlation coefficients are shown with standard errors in parentheses. Number of observations (n) is 396.
* $p < 0.05$ (equals $|r| > 0.10$, two-tailed).
** $p < 0.01$ (equals $|r| > 0.13$, two-tailed).
*** $p < 0.001$ (equals $|r| > 0.16$, two-tailed).
[a] Transformed using the natural logarithm. *Frequency of disruptions* was transformed in order for this count variable to be admissible for Pearson correlation.

Poisson model (Cameron and Trivedi, 1998). Under the assumption that the data-generating process is Poisson, the distribution of disruptions D_i is given by

$$Pr\,(D_i = d_i) = \frac{e^{-\lambda_i}\lambda_i^{d_i}}{d_i!} \quad (\text{with}\, d_i = 0, 1, 2, \ldots),$$

where $E(D_i) = \mu_i = \lambda_i = Var(D_i)$. To explain the conditional expected value of D_i given the supply chain complexity and control variables $\mathbf{x}_i$, we need to parameterize the relation between λ_i and the independent variables $\mathbf{x}_i$. Using the canonical log-linear specification, the conditional mean for D_i is $E(D_i|\mathbf{x}_i) = e^{x_i'\mathbf{b}}$, where $\mathbf{b}$ is the vector of regression parameters. However, an examination of the data indicated that the data exhibits overdispersion. The unconditional mean of our outcome variable is significantly lower ($p < 0.001$) than its variance ($\sigma_{\text{observed}}/\mu_{\text{observed}} = 236.31$). The Poisson distribution contains the strong assumption that mean and variance are equal and, in the presence of overdispersion, the maximum likelihood t-values for the standard Poisson regression model may be considerably inflated. To account for the overdispersion, we followed prior studies (e.g., Bellamy et al., 2014; Hahn and Bunyaratavej, 2010) that opted for negative binomial regression[3] with a quadratic specification of the variance function (NB2) (Cameron and Trivedi, 1998; Hilbe, 2011). This approach has the same mean structure as the Poisson regression model ($E(D_i|\mathbf{x}_i) = \mu_i$), but allows the conditional variance to exceed the conditional mean by way of $Var(D_i|\mathbf{x}_i) = \mu_i + \alpha\mu_i^2$. A comparison of predicted and actual probabilities (using the "countfit" command in Stata by Long and Freese (2006)) revealed that the negative binomial model fits the probability mass better than the Poisson model. Likewise, a simple likelihood-based test ($p < 0.001$), the comparison of BIC and AIC values, and Dean's (1992) score test ($p < 0.001$) indicated that the negative binomial model should be preferred to the standard Poisson model. When estimating the negative binomial models, the (over)dispersion parameter α (estimated via maximum likelihood) was significantly positive ($p < 0.001$, likelihood ratio test) for all models, suggesting a substantial amount of overdispersion.

5.2. Hypothesis tests

We estimated the following models in hierarchical order:

$$\ln E\,(D_i|\cdot) = b_0 + b_1 FS_i + b_2 FA_i + b_3 CI_i + \sum_{k=1}^{12} b_{4,k}\text{Industry}_{k,i} + \varepsilon_i \quad (1)$$

$$\ln E\,(D_i|\cdot) = b_0 + b_1 FS_i + b_2 FA_i + b_3 CI_i + \sum_{k=1}^{12} b_{4,k}\text{Industry}_{k,i} + b_5 HC_i + b_6 VC_i + b_7 SC_i + \varepsilon_i \quad (2)$$

$$\ln E\,(D_i|\cdot) = b_0 + b_1 FS_i + b_2 FA_i + b_3 CI_i + \sum_{k=1}^{12} b_{4,k}\text{Industry}_{k,i} + b_5 HC_i + b_6 VC_i + b_7 SC_i + b_8 HC_i \times VC_i + b_9 HC_i \times SC_i + b_{10} VC_i \times SC_i + \varepsilon_i \quad (3)$$

$$\ln E\,(D_i|\cdot) = b_0 + b_1 FS_i + b_2 FA_i + b_3 CI_i + \sum_{k=1}^{12} b_{4,k}\text{Industry}_{k,i} + b_5 HC_i + b_6 VC_i + b_7 SC_i + b_8 HC_i \times VC_i + b_9 HC_i \times SC_i + b_{10} VC_i \times SC_i + b_{11} HC_i \times VC_i \times SC_i + \varepsilon_i \quad (4)$$

Control variables were entered as a block in Model 1, followed by the main effect variables in Model 2, the two-way (pair-wise) interaction terms in Model 3, and the three-way interaction term in Model 4 (simultaneous within blocks, stepwise across). Based on likelihood ratio tests, all models were statistically significant ($p < 0.001$) and model fit increased in each step. No indications for multicollinearity were found: zero-order correlations between the variables studied were relatively low (cf. Table 2) and both the variance inflation factors (maximum: 1.89) and the condition numbers (maximum: 19.84) were substantially below the commonly suggested thresholds for all models (Cohen et al., 2003). Our results are reported in Table 3.

In Model 1, we investigate whether the three drivers of upstream supply chain complexity increase the frequency of supply chain disruptions (i.e., the effects arising from the three individual complexity dimensions). To better understand the nature of these

[3] Assuming that the data-generating process is negative binomial, the distribution of the D_i is given by $\Pr(D_i = d_i) = \frac{\Gamma(\alpha^{-1}+d_i)}{\Gamma(\alpha^{-1})+\Gamma(d_i+1)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda}\right)^{\alpha^{-1}}\left(\frac{\lambda}{\alpha^{-1}+\lambda}\right)^{d_i}$ (with $d_i = 0$, 1, 2, ...) where $\Gamma(.)$ denotes the Gamma integral.

Table 3
Results of negative binomial regression.

Variable	Model 1 Control variables		Model 2 Main effects		Model 3 Two-way interactions		Model 4 Three-way interaction	
Controls								
Firm size [b_1]	0.13†	(0.07)	0.02	(0.08)	−0.01	(0.07)	−0.01	(0.07)
Firm age [b_2]	−0.19†	(0.10)	−0.21*	(0.10)	−0.17†	(0.10)	−0.17†	(0.10)
Competitive intensity [b_3]	0.37**	(0.12)	0.43***	(0.11)	0.41***	(0.11)	0.40***	(0.11)
Industry dummies[a] [$b_{4,\,1-12}$]								
Engineering, construction	−0.75	(0.48)	−0.77	(0.47)	−0.89†	(0.46)	−0.91*	(0.46)
Chemicals, plastics, rubber	−0.52	(0.37)	−0.59	(0.36)	−0.59†	(0.35)	−0.54	(0.35)
Electronics, optics, medical devices	−0.34	(0.33)	−0.36	(0.32)	−0.35	(0.31)	−0.30	(0.31)
Consumer goods	−0.63	(0.42)	−1.14**	(0.42)	−1.09*	(0.43)	−1.03*	(0.43)
Aerospace, defense	0.26	(0.71)	−0.03	(0.69)	0.00	(0.69)	0.00	(0.68)
Industrial machinery, machine tools	0.19	(0.32)	0.08	(0.32)	0.05	(0.31)	0.13	(0.31)
Metals, metal working	−0.81*	(0.36)	−0.57	(0.36)	−0.62†	(0.36)	−0.58	(0.35)
Food, beverages	−0.96†	(0.57)	−0.84	(0.57)	−0.87	(0.56)	−0.81	(0.56)
Paper, packaging	−1.09*	(0.45)	−1.10*	(0.43)	−1.24**	(0.43)	−1.22**	(0.42)
Pharmaceuticals, healthcare	1.14**	(0.40)	−0.22	(0.46)	−0.56	(0.42)	−0.60	(0.41)
Telecommunications	−0.96	(0.72)	−0.70	(0.71)	−0.36	(0.71)	−0.48	(0.71)
Textiles, clothing	−0.32	(0.49)	−0.28	(0.49)	−0.04	(0.50)	−0.25	(0.50)
Main effects								
Horizontal supply chain complexity [b_5]			0.35***	(0.10)	0.16	(0.10)	0.13	(0.10)
Vertical supply chain complexity [b_6]			0.27*	(0.11)	0.35**	(0.11)	0.35**	(0.11)
Spatial supply chain complexity [b_7]			0.22*	(0.10)	0.25*	(0.10)	0.27**	(0.10)
Two-way interaction effects								
Horizontal c. × Vertical c. [b_8]					0.28*	(0.13)	0.22†	(0.12)
Horizontal c. × Spatial c. [b_9]					0.26†	(0.14)	0.26*	(0.13)
Vertical c. × Spatial c. [b_{10}]					−0.09	(0.09)	−0.00	(0.10)
Three-way interaction effect								
Horizontal c. × Vertical c. × Spatial c. [b_{11}]							0.29*	(0.14)
Constant	1.27†	(0.72)	1.82**	(0.71)	1.90**	(0.70)	1.90**	(0.69)
−Log Likelihood	1222.62		1210.45		1204.19		1202.12	
Likelihood ratio (χ^2)	73.57***		97.91***		110.42***		114.57***	
$\Delta\chi^2$	–		24.33***		12.52**		4.15*	
McFadden's Pseudo R^2	0.03		0.04		0.04		0.05	
Cragg-Uhler (Nagelkerke) Pseudo R^2	0.17		0.22		0.24		0.25	

Note. Dependent variable is *frequency of supply chain disruptions* (count of disruptions during a 12-month period). Number of observations (n) is 396. Standard errors are shown in parentheses. The three complexity variables were standardized prior to estimation. All models were estimated in Stata 12.
† $p < 0.10$ (two-tailed).
* $p < 0.05$ (two-tailed).
** $p < 0.01$ (two-tailed).
*** $p < 0.001$ (two-tailed).
[a] "Automotive" served as the baseline category.

direct effects, Fig. 3 shows the corresponding plots and Table 4 reports the conditional marginal effects at mean values and the average marginal effects (both calculated using the Delta method) (Hilbe, 2011). As a result of the negative binomial model's non-linearity, the regression coefficients shown in Table 3 cannot be interpreted as marginal effects (Hoetker, 2007).

Hypothesis 1 suggests that the frequency of supply chain disruptions increases with horizontal complexity. The results for Model 1 support this hypothesis (standardized regression coefficient $\beta_5 = 0.35$, $p < 0.001$). All else being equal, the more direct suppliers there are, the more supply chain disruptions a firm will experience. As shown in Table 4, the average marginal effect (for the unstandardized variable) is 0.013, suggesting that a firm would experience 1.3 more disruptions per year (on average), if its supply base increased by 100 suppliers. When plotting this effect (Fig. 3A), we find that the relationship between horizontal complexity and

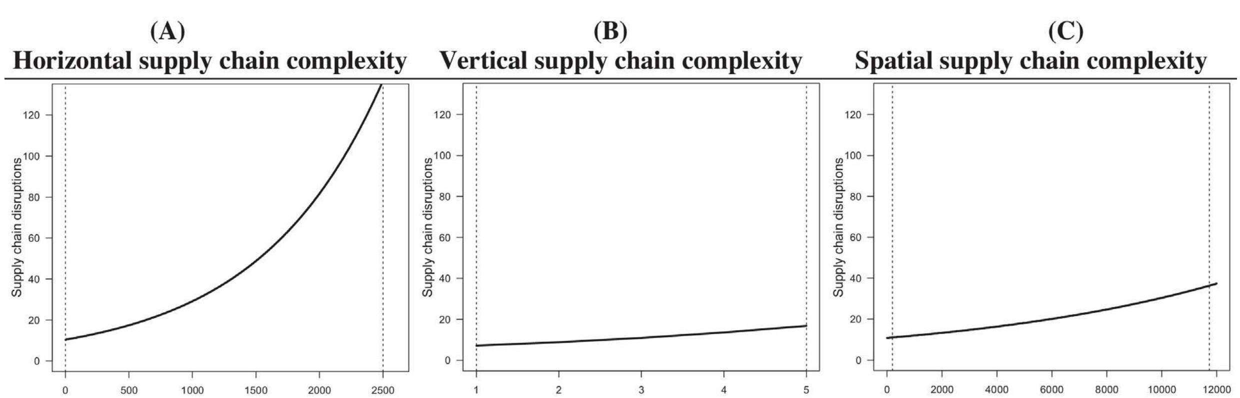


Fig. 3. Direct effects of horizontal, vertical, and spatial supply chain complexity.
Note: Dashed lines indicate minimum and maximum values of the observed independent variables.

Table 4
Marginal effects (ME) of the three supply chain complexity variables on the frequency of disruptions.

Variable		Unstandardized (change per 1 unit)		Standardized (change per 1 SD)	
		$\partial y/\partial x$	*SE*	$\partial y/\partial x$	*SE*
Horizontal supply chain complexity	Marginal effect at mean	0.01***	0.00	3.18***	0.91
	Average marginal effect	0.01**	0.00	4.47**	1.56
Vertical supply chain complexity	Marginal effect at mean	1.92*	0.79	2.43*	1.00
	Average marginal effect	2.69*	1.17	3.41*	1.48
Spatial supply chain complexity	Marginal effect at mean	0.00*	0.00	2.02*	0.90
	Average marginal effect	0.00*	0.00	2.84*	1.35

Note. Marginal effects are based on estimates of Model 2 ("Main effects" in Table 3) and calculated using the Delta method. For the conditional marginal effect at mean (MEM), all other model variables are held at their mean. For the average marginal effect (AME), the marginal effect is averaged across all values of the other model variables.
* $p < 0.05$ (two-tailed).
** $p < 0.01$ (two-tailed).
*** $p < 0.001$ (two-tailed).

the number of supply chain disruptions is not constant over the observed variable range. This suggests that the frequency of disruptions might increase even more than linearly with the number of suppliers.

Hypothesis 2 suggests that vertical supply chain complexity increases the number of supply chain disruptions. This is supported by the results which suggest that the number of upstream supply chain tiers has a positive effect on the frequency of supply chain disruptions ($\beta_6 = 0.27$, $p = 0.013$). As shown in Table 4, every additional upstream tier increases the frequency of disruptions by on average 2.69. Fig. 3B depicts the relationship which seems to be almost linear over the observed range.

Finally, the results lend empirical support for the third direct effect hypothesis which pertains to spatial supply chain complexity. The corresponding regression coefficient is significant and in the expected direction ($\beta_7 = 0.22$, $p = 0.023$), thus corroborating Hypothesis 3. Similar to Hypothesis 1, the corresponding plot (Fig. 3C) indicates that the rate of change in disruption frequency varies along the observed variable range. The number of supply chain disruptions seems to increase more than linearly with the total geographic distance within the supplier portfolio.

In general, the prediction that each of the three conceptualized supply chain complexity dimensions increases the frequency of supply chain disruptions is supported. The qualitative assessment of the graphs indicated that horizontal and spatial complexity dimension might increase the frequency of disruptions more than linearly.

Beyond these direct effects, the predictive power of the interaction effects is tested in Model 3 and Model 4. Hypothesis 4 suggests complementarities (or synergies) among the three complexity variables; that is, beyond their individual effects, the three complexity dimensions complementarily increase the frequency of supply chain disruptions. Hence, we are interested in the superadditive effects created when the three complexity dimensions act jointly. Interaction effect hypotheses that involve three or more variables are usually tested by including main variables and interaction terms in the same regression equation (e.g., Wiklund and Shepherd, 2005). Two-way interactions indicate the synergy at the level of the pairs of variables, whereas higher-order interactions (e.g., three-way) are able to detect additional multilateral effects implied by the interaction of the considered variables. Therefore, we test both two- and three-way interactions. Model 3 captures the pair-wise interactions and showed mixed results. Of the three interaction terms, we found one to be significant, one to be marginally significant, and one to be not significant. The results indicate a significant positive interaction effect between horizontal and vertical supply chain complexity ($\beta_8 = 0.28$, $p = 0.032$). The interaction between horizontal and spatial supply chain complexity is positive ($\beta_9 = 0.26$), but slightly above the 5% level of confidence ($p = 0.053$). For the effect between vertical and spatial supply chain complexity, we found a negative ($\beta_{10} = -0.09$), but substantially insignificant effect ($p = 0.317$). Simulation-based plots for the first and the second interaction effect are included in Appendix B (King et al., 2000; Zelner, 2009). The results suggest that the effect of horizontal complexity on the number of disruptions is weak at low and medium levels of vertical and spatial complexity, but strong at high levels ($M + 1SD$) of vertical and spatial complexity.

Model 4 introduces the important three-way interaction term formed by the three complexity dimensions. The results indicate a positive and significant coefficient for this interaction term ($\beta_{11} = 0.29$, $p < 0.036$). In sum, these results support the synergy posited in Hypothesis 4, that the total effect of the three drivers of upstream supply chain complexity is greater than the sum of the individual effects (superadditivity).

6. Discussion

This study contributes to a better understanding of the multidimensional nature of upstream supply chain complexity and its consequences for the frequency of supply chain disruptions. In essence, the proposed model posits positive direct relationships among horizontal, vertical, and spatial supply chain complexity and the frequency of supply chain disruptions. In addition, the model suggests that the three drivers or dimensions of complexity act synergistically which further amplifies the frequency of supply chain disruptions. The results provided support for our predictions and have several important scholarly and managerial implications.

6.1. Theoretical implications

The main research question we wished to investigate is whether structural characteristics of supply chains affect the frequency of disruptions experienced by buying firms. Several prior studies have suggested a relationship between certain supply chain characteristics and the occurrence of disruptions (e.g., Choi and Krause, 2006; Craighead et al., 2007), but empirical evidence is scarce. Our findings help to fill this important research gap. To understand this relationship, a theoretical perspective characterizing critical dimensions of a supply chain structure is needed. To this end, we applied the concept of supply chain complexity. The empirical results have supported the distinction of the three structural supply chain complexity dimensions in that our model provided explanatory power for the relationship between supply chain structure and frequency of disruptions. Specifically, the findings suggest that each of the three conceptualized drivers of upstream supply chain complexity is an individual source of disruption risk. In this respect, this study underscores the need for further investigations of supply chain complexity, particularly, for a further analysis of the interdependency between the three complexity dimensions. Future studies of supply chain complexity should consider its multi-dimensional nature.

Beyond the positive link between the complexity drivers and disruption frequency, the results indicate that the frequency of supply chain disruptions increases more than linearly with increasing horizontal and spatial complexity. For example, with regard to the former, the difference between a focal firm having 500 direct suppliers and one having 1000 direct suppliers is $\Delta D_{500\rightarrow 1000} = 11.75$ disruptions per year, whereas the difference between a firm having 1000 direct supplier and a firm having 1500 direct suppliers is $\Delta D_{1000\rightarrow 1500} = 19.67$ disruptions per year (cf. Fig. 3). In contrast, the results suggest a relatively linear relationship between vertical complexity and the frequency of disruptions.

A closer look at the effect sizes (standardized coefficients) reveals that the effect of horizontal supply chain complexity on the frequency of disruptions is considerably stronger than that of vertical supply chain complexity and spatial supply chain complexity. Hence, the number of suppliers in the supplier portfolio seems to have the largest effect on the frequency of disruptions.

Finally, the most important contribution of this study is that it examines the interactions among the three dimensions of complexity. Our results suggest that the frequency of supply chain disruptions is a superadditive function of the three supply chain complexity dimensions. Additional risk for supply chain disruptions emerges from the coexistence and interaction of the three complexity dimensions. Focusing solely on the direct effect relationships provides an incomplete picture of supply chain disruption frequency. Thus a proper understanding of how structural characteristics of supply chains affect the likelihood of supply chain disruptions requires a concomitant consideration of the three complexity dimensions.

6.2. Managerial implications

Supply chain managers design their supply chains according to principles that will presumably make their firms perform better. Many of the supply chain design principles that have become popular over the last twenty years have focused on increasing the efficiency and/or responsiveness of supply chain operations but only to a lesser extent to decreasing the risk of supply chain disruptions (Zsidisin et al., 2005). One reason could be that the literature offers few empirical justifications for supply chain design principles aimed at reducing the frequency of disruptions. The present study addresses this shortcoming and takes one step towards a better understanding of the relationship between supply chain structure and the occurrence of disruptions.

This study's main message for practice seems straightforward: simplify your supply chains (within the limits of your business model)! However, as discussed in the conceptual background section, complexity is a slippery concept. Therefore, the stated message may mean different things to different practitioners. Birkinshaw and Haywood (2010, p. 2) noted recently that "[D]espite widespread agreement that organizational complexity creates big problems by making it hard to get things done, few executives have a realistic understanding of how complexity actually affects their own companies." In this respect, our model highlights how complexity is driven by observable supply chain characteristics such as the number of direct suppliers or the geographic distances between a focal firm and its suppliers. These results offer hints to managers about the aspects of supply chain design that lead to more disruption-prone supply chains. All three structural drivers of supply chain complexity amplify the frequency of disruptions and decision-makers are well advised to be attentive to these aspects when they organize their supply chains. In other words, the study's insights may assist practitioners in assessing the impact of supply chain management strategies, like outsourcing or supply base reduction, on the exposure to supply chain risk.

In addition, our findings help supply chain managers to prioritize their supply chain risk management efforts. Particularly when there is a serious dearth of resources for supply chain risk management, firms should focus above all on horizontal supply chain complexity, because our results indicate that, on average, it has the strongest effect on the frequency of disruptions. Given the observed non-linear effects, this is particularly important if horizontal complexity is high. In cases where horizontal complexity is already low or where supply base reduction is not a valid option, other means of improving the supply chain robustness should be considered such as more rigorous control mechanisms or decentralized decision-making (Christopher and Lee, 2004; Perrow, 1999).

6.3. Limitations and future research directions

This study's findings need to be considered in light of its limitations. A few obvious limitations pertain to our data collection procedure: (1) the low response rate, (2) the concentration on manufacturing firms, (3) our reliance on single informants, (4) the estimated models are based on the simplified assumption that the surveyed firms' supply chain structures remain relatively stable during the considered time period, and (5) except for the control variables *firm size* and *firm age*, we were unable to draw on objective data for the main variables in our model. A replication of this study across other industries and based on multiple informants would augment the generalizability of the results.

In addition to and in line with our research objective to link supply chain structure with the frequency of disruptions, we "narrowly" conceptualized both our dependent and our independent variables. With regard to the dependent variable, we restricted our focus to major supply chain disruptions that had been triggered in the upstream supply chain. Supply chain disruptions may emerge from other sources such as the demand side or intra-firm operations which are not covered in our sample. Even more importantly, this study focusses on severe supply chain disruptions that are beyond a relevant severity threshold. However, the results do not say anything about the severity distribution beyond this threshold. For example, a buying firm with very low spatial complexity may experience very few major disruptions, but due to spatial concentration, one of these disruptions could be extreme ("showstopper" event).

With regard to the independent variables, we addressed only structural aspects of a supply chain. Other aspects of complexity such as dynamic (Bozarth et al., 2009; Rao and Young, 1994), cultural (Kaufmann and Carter, 2006), environmental (Cannon and John, 2007), or product complexity (Novak and Eppinger, 2001) may also affect the frequency of disruptions. Moreover, we used only proxies to measure the three complexity dimensions. Collecting large-scale and comprehensive supply chain network data on complexity would be a daunting task, but it would allow for a much more fine-grained empirical analysis.

Finally and most importantly, this study focused on "things that went wrong," not on how disruptions could have been prevented. Clearly, managers would prefer to avoid supply chain disruptions even in the presence of high levels of complexity. Perrow (1984) made an important contribution in identifying complexity as a major accident-increasing system characteristic. His conclusion, however, that accidents are inevitable in such systems has been criticized as overly pessimistic (Sagan, 1993). Some researchers have examined organizations that are exceptionally adept at responding to unexpected events and proposed a high reliability theory which argues that organizational and structural precautions can reduce the likelihood of accidents (e.g., Roberts, 1990; Weick, 1987). For example, organizational culture has been reported to play an important role in achieving superior performance in highly complex environments (Weick, 1987). Perhaps firms which possess the characteristics of highly reliable organizations are successful even in the presence of high levels of supply chain complexity. Thus, from a research perspective, the examination of such high reliability features alongside the dimensions of supply chain complexity seems promising.

7. Conclusion

A great deal of research has focused on supply chain risk management, but the question "Which supply chain characteristics increase the frequency of supply chain disruptions?" has not received much attention in the empirical literature. Driven by this question, this study extends literature in three significant ways. First, we present the first systematic empirical investigation of supply chain complexity to explain the frequency of disruptions triggered in the upstream supply chain. Second, the received results provide insights into the strength, form, and complementarity of the relationships between supply chain complexity dimensions and the frequency of disruptions. Finally, this study provides a basis for further investigations of the supply chain complexity concept, its dimensions, and the complementary effects of those dimensions.

Appendix A. Measurement items and scales

Frequency of disruptions (single item)

For the purpose of this study, a "supply disruption" is defined as the combination of:

1. An event that materialized in the upstream supply chain and that leads to. . .
2. . . .a situation that has the potential for severe negative consequences to your organization.

In 2006, approximately how many supply disruptions did you experience?

Horizontal complexity (single item)

Number of first tier suppliers?

Vertical complexity (single item)

If one compared your firm with an automotive supply chain which of the following would be your supply chain position: ("1: 4th tier supplier of raw material" ("far upstream") to "5: OEM/ Final product manufacturer" ("far downstream"))

Spatial complexity (single item)

How was the annual purchasing volume approximately split among the following geographic regions? 1: Austria, Germany, Switzerland, 2: other European countries, 3: North America (US, Canada, and Mexico), 4: Asia/Pacific region, 5: the rest of the world (e.g., Latin America)

Firm size (single item)

Total number of employees in 2006?

Firm age (single item)

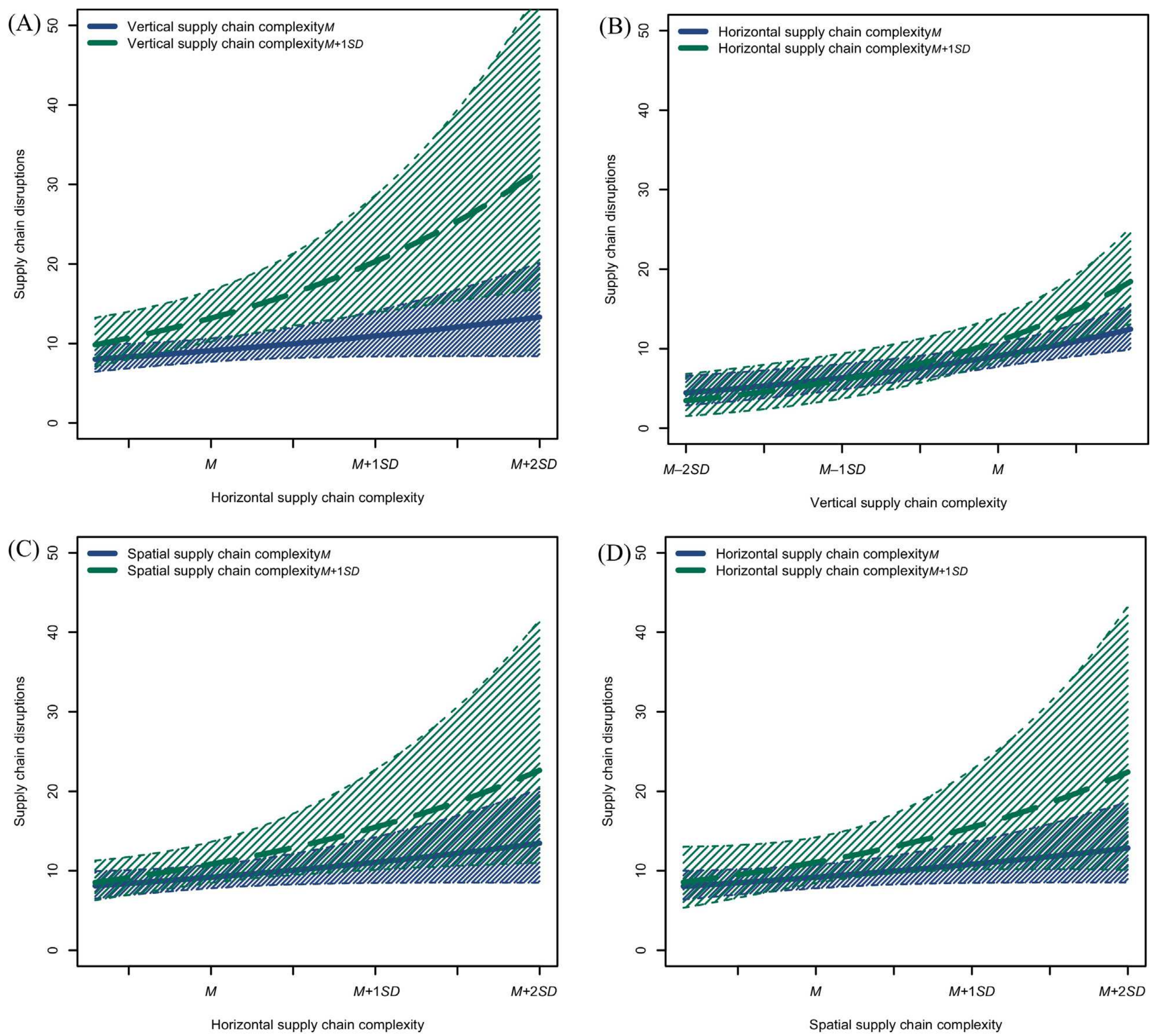
How long has your firm been in business? Since the year:

Competitive intensity (adapted from Jaworski and Kohli, 1993)

Please indicate your opinion on the following statements concerning the market for the given product line (1: not at all–5: to a very large extent):

Item 1	The business climate for the final product(s) is very competitive.
Item 2	Anything that one competitor can offer others can match readily.
Item 3	Competition in this industry is cutthroat.
Item 4	Winning in this marketplace is a tough battle.

Appendix B. Two-way interaction effects of supply chain complexity dimensions



Note. Moderator variables are underlined. Data were generated by means of simulation (100,000) using the "intgph" command in Stata 12 (King et al., 2000; Zelner, 2009).

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