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Stages of Supply Chain Disruption Response: Direct, Constraining, and Mediating Factors for Impact Mitigation

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ABSTRACT

It is well established that supply chain disruptions can have a severe negative impact on firms and general wisdom suggests that this impact can be mitigated by quick responses. Aside from a few anecdotes, however, little is known about the decision-making process that leads to speedy responses and about its impeding and supporting antecedents. Using the organizational information-processing perspective, this empirical study unravels the disruption management process along a sequence of four stages—disruption recognition, disruption diagnosis, response development, and response implementation—and hypothesizes constraining and mediating effects of these stages. The findings contribute to an improved understanding of the role that the decision stages play in mitigating supply chain disruptions, and confirm the prediction that the speed with which information is processed and the stages are worked through positively affects supply chain performance. In addition, the findings suggest that one of the stages, *diagnosis,* acts as a constraining factor to the other stages. The stages also play a mediating role between the impact that the disruption has and a firm's readiness (prior to a disruption), dependence on a key supplier, and supply chain complexity. This provides guidance to decision makers in the application of resources both prior to a negative event and during a disruption recovery. [Submitted: February 4, 2015. Revised: June 25, 2016. Accepted: July 6, 2016.]

Subject Areas: Decision response stages, Disruption management, Supply chain, and Supply chain risk.

INTRODUCTION

When the Eyjafjallajokull volcano in Iceland erupted in 2010, few supply chain managers initially thought that it would disrupt global supply chains. However, as

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information about the ash cloud spreading across Europe and about the implications for global aviation was disseminated, more and more managers recognized the threat and began developing responses to minimize the possible impact on their supply chains. All of them had to collect and interpret information while working through the response stages of recognizing the problem, diagnosing the problem, developing response alternatives, and implementing their choices. Yet, the speed or responsiveness of each firm to these consecutive stages was different, producing different impacts for each firm. For example, media reported that produce manufacturers in Africa who were slow to ship their product to Europe via alternative means of transportation had to dump tons of unsold product for a loss of US$1.3 million per day (Wadhams, 2010). While it seems straightforward from this example that the adage "you snooze, you lose" applies, it is less clear how firms should best work through the different decision-making stages and which of the stages is relatively more important (e.g., speed of recognizing the ash cloud as a risk vs. speed of implementing a specific response). Hence, the cited example also highlights an important call for unpacking the decision-making (or response) process and for a better understanding of how this process and the individual stages affect disruption impact.

Supply chain disruptions are events that interrupt the flow of materials between the raw materials' production and the end customer (Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007), and major disruptions occur to 85% of firms (Business Continuity Institute, 2011). In each case, supply chain decision makers must return the flow to the previous, uninterrupted state with minimal lasting impact (Sheffi, 2005). Disruption recovery is often measured through decreased performance related to operations, finance, and relationships. Supply chain disruptions may affect performance through lost sales, stockouts, production shutdowns, premium freight charges, and product substitutions (Hendricks & Singhal, 2005; Tomlin, 2006; Wu, Blackhurst, & O'Grady, 2007; Hendricks, Singhal, & Zhang, 2009). It is known, however, that the specific impact is often different from one firm to another, even for firms experiencing the same disruption cause. An oft-cited example is the impact difference that occurred to Nokia compared to Ericsson when a plant of their common supplier, Phillips, was hit by a lightning strike (Latour, 2001). Reasons for such differences may include the presence of slack resources (e.g., inventory, flexibility, time buffers) that act as mitigation for the negative effects of a disruption (Rice & Caniato, 2003), skills and experience of the involved managers (Ritchie & Marshall, 1993), and quick response processes (Sheffi, 2005). However, there should be other reasons that have not yet been investigated in detail. Examples include, but are not limited to, a firm's readiness (Macdonald & Corsi, 2013), relationships with suppliers (Grewal, Johnson, & Sarker, 2007), and supply chain complexity (Bode & Wagner, 2015; Habermann, Blackhurst, & Metcalf, 2015).

Although several authors have proclaimed the virtues of quick actions, the link between quick, responsive decision-making and reduced impact is assumed rather than tested and the supporting examples remain anecdotal in nature (Sodhi & Tang, 2009; Hopp, Iravani, & Liu, 2012; Macdonald & Corsi, 2013; Bode, Hübner, & Wagner, 2014). In fact, Sodhi and Tang (2009) left this link as future research. Referring back to the Eyjafjallajokull example, the affected firms were trying to understand how long the eruption would last, how this cloud would affect their supply chains, and what alternative modes of transportation could be used. This information was not presented to them in a spreadsheet or convenient table, hence the need for gathering and interpreting information. However, little is known about how these information processing tasks are linked to disruption recovery performance.

Using information processing theory as a lens, this study will address the following three key research questions: (1) Does quick decision-making make a difference to disruption impact? (2) Is it important to be responsive through all decision stages together, or are certain individual stages more important than others? And (3) what types of information affect the responsiveness of the firm and what is the recovery impact?

The remainder of this article will answer the above questions through a review of the literature, building and econometric testing of a model, and discussion of model results. Research and managerial implications will be discussed. Finally, limitations and future research directions are presented. A specific call to action for supply chain managers is provided in the conclusion.

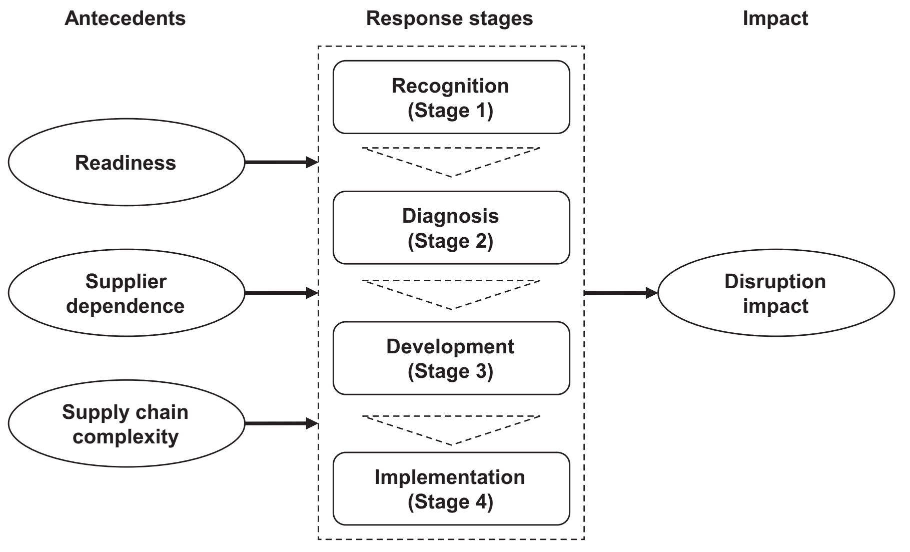
SUPPLY CHAIN DISRUPTIONS

Of the numerous risks that firms face, the risk of supply chain disruptions arises from the vulnerabilities of the interconnected flows of materials, information, and funds in interfirm networks (Narasimhan & Talluri, 2009; Rao & Goldsby, 2009; Garvey, Carnovale, & Yeniyurt, 2015). To some extent, all firms are dependent on external sources and supply chain relationships (Pfeffer & Salancik, 1978), and consequently exposed to this type of risk.

In the corresponding literature, a supply chain disruption is viewed as the discrete event that negatively affects a firm (e.g., Chopra & Sodhi, 2004; Blackhurst, Craighead, Elkins, & Handfield, 2005; Kleindorfer & Saad, 2005). 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." Based on the literature, 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 (Bode, Wagner, Petersen, & Ellram, 2011). This scope sets the stage for a large set of issues such as supplier quality problems, delivery outages, supplier defaults, labor strikes, or plant fires, all of which can vary immensely in their causes, characteristics, and effects.

Supply chain risk and disruption management seeks to address and manage a firm's exposure to supply chain risks either in a proactive or reactive fashion (Craighead et al., 2007). The overall objective is "to determine, implement, and monitor an optimal combination of measures to avoid, defer, reduce, or transfer all relevant risks" (Hofmann, Busse, Bode, & Henke, 2014, p. 162). The determined mix of activities is considered optimal, if the remaining amount of risk is in line

Figure 1: Conceptual framework.



with the firm's risk preference and its corporate strategy. Research in this field has proposed an array of specific activities to handle supply chain disruptions (e.g., Tang, 2006).

THEORETICAL BACKGROUND AND HYPOTHESES

The proposed conceptual framework (see Figure 1) draws on literature that views firms as information-processing systems (Thompson, 1967; Galbraith, 1977; Tushman & Nadler, 1978). The organizational information processing literature is rooted in the open systems perspective (Katz & Kahn, 1978) and suggests that organizational responses to external events are formed by a set of consecutive information-processing activities (Dutton, Fahey, & Narayanan, 1983; Isabella, 1990; Barr, 1998). These activities seek to reduce environmental uncertainty, which, for the involved managers, creates "a sense of doubt that blocks or delays action" (Lipshitz & Strauss, 1997, p. 158). As Galbraith (1974, p. 28) stated "the greater the task uncertainty, the greater amount of information that must be processed among decision makers during task execution in order to achieve a given level of performance." Hence, information processing helps build confidence in decisions made as part of a response process, which was set into motion by an immediate and unexpected uncertainty (e.g., a supply chain disruption), as well as the effect of those decisions on the desired recovery outcome.

A large body of research has used information processing as a theoretical lens to understand decision-making processes at the organizational level that occur in response to an exogenous event. The model by Daft and Weick (1984) explains organizational responses or decisions as a result of three sequential stages—scanning, interpretation, and action—which collectively function as a decision-making mechanism between an exogenous event (e.g., a disruption) and the elicited response. In a similar vein, Mintzberg, Raisinghani, and Théorêt (1976) lays out a general process model of strategic decision-making with three high-level stages: identification, development, and selection. A year earlier, Ansoff (1975) discussed similar elements in the context of responses to strategic surprise. Several of the elements in these studies overlap, namely: recognition, diagnosis, planning, and implementation. Dutton et al. (1983, p. 308) cited Mintzberg et al. (1976) when honing in on "recognition, formulation, evaluation, and implementation." Cowan (1986) chose to focus on recognition and diagnosis as keys to the process descriptors of problem formulation, again, citing Mintzberg et al. (1976). Finally, Hale, Hale, and Dulek (2006) transitioned a simplified version of the process model by Mintzberg et al. (1976) to a crisis response context, which would be similar to a disruption management response. Research of the various factors showed that only the steps of recognition (identification of the problem), search (for information), and evaluation/choice were reported as being clear steps in all fifteen crisis-recovery processes discussed by Hale et al. (2006).

In summary, common stages of the decision process from these examples are *recognition* of the problem, *diagnosis* and gathering of information of the problem, *development* of a response, and *implementation* of the chosen response. In the following, we focus on these four stages as the elements of a firm's recovery response formation process.

Total Response Speed

"The important thing is to act and act fast," stated Galbraith (1973, p. 143) in the context of organizational operations seeking relevant information for decision-making. Using the information processing lens, we know that highly connected networks (termed "organismic" in Tushman & Nadler, 1978) may take longer to process information. A supply chain is a type of interconnected network with a number of connected organizational entities. This seems to imply that longer information processing times should delay disruption recovery processes. However, during a disruption, firms tend to look to a single manager for recovery leadership (Dubrovski, 2004), which would theoretically speed up the decision-making in a suddenly hierarchical ("mechanistic") network (Tushman & Nadler, 1978).

We know that working through decisions quickly is also a measure of confidence in the information that is available. As an example, detecting an unknown object on the side of the road while driving at night will often cause a driver to slow down, check their mirrors, and focus in on the object with the goal of determining what the object is. Once the object is confirmed as being a signpost or other inanimate object (meaning, not an animal about to try crossing the road) the driver will resume normal driving operations. Clear information facilitates decision-making and allows the risks to be minimized.

The literature has anecdotally focused on the notion that increased decision speed lowers the impact of disruptions on firms. The anecdotal evidence provided has consisted of examples such as delayed decisions in California regarding insect control (Sodhi & Tang, 2009), quick decisions after 9/11 by Chrysler (Sodhi &

Tang, 2009), and a speedy collaborative relationship between Toyota and one of their suppliers (Hopp et al., 2012). It has been proposed that "an unplanned event that disrupts a supply chain with the capability to [. . .] respond quickly and effectively [. . .] is less likely to be severe" (Craighead et al., 2007, p. 146). Similarly, it is expected that a disruption's impact can be reduced when the response and recovery lead times can be reduced (Sodhi & Tang, 2009). Likewise, it has been argued that speed is crucial for success in making decisions and articulate the proposition that "crisis management efforts will be more successful if information is disseminated quickly, accurately, directly, and candidly" (Pearson & Clair, 1998, p. 73). Accordingly, we propose:

H1: Faster total response speed will reduce the disruption impact on a firm.

Speed of the Individual Response Stages

While total decision time is likely important, so too is the time required by an organization to work through each of the four stages individually. The first stage, *recognition*, deals with the scanning and discovery of signals. Recognition was included by Melnyk, Zobel, Macdonald, and Griffis (2014) as part of their simulation model on detecting disruption outliers and reducing firm impact. Their results showed that early warning reduced the total time of recovery. From an information processing perspective, Daft and Weick (1984) distinguished between active and passive firms. Active firms frequently monitor and assess their environment, thereby increasing the likelihood to notice early warning signals and to have a faster (lower) recognition time. Passive firms are less vigilant towards their environment and wait until they notice a deviation from an expected or a desired performance level. If such a deviation is perceived as significant (i.e., exceeds some level defined as acceptable), it serves as an impetus for the firm to initiate a focused information-search process. This argument is supported by the behavioral theory of the firm (Cyert & March, 1963), which suggests that information-search processes are triggered by performance exceptions. In this regard, it is important to note that a firm experiences a supply chain disruption only if it is perceived as such (Hermann, 1963; Billings, Milburn, & Schaalman, 1980; Merton, 1995). Hence, it is both the objective information as well as the decision-makers' subjective perception that shape the organizational response (Mintzberg et al., 1976; Dutton, 1986).

Though recognition has likely been the most documented of the four stages (it happens first), the other three stages can similarly be seen in the literature. *Diagnosis* was cited by Dubrovski (2004) as being important because firms need to understand whether and to what extent previous information (i.e., information gathered prior to the disruptive event) can be applied to the situation. Being able to quickly gather and interpret relevant additional information should lower the impact on a firm. In addition to gathering, it is important for the information to be visible to the decision makers. Increased visibility of information should lead to enhanced task performance, according to information processing theory (Galbraith, 1977). The speed of the *development* stage was cited by Tang (2006) when Continental airlines introduced their new *CrewSolver* decision support system after the 9/11 terrorist attacks and attributed this development to reducing the impact that 9/11 had. Similarly affected by the 9/11 attacks, Hopp et al. (2012) cited quick *implementation*, the final stage, as making the difference between Chrysler recovering well and Ford being forced to shut down five manufacturing plants due to a parts shortage (the same parts that Chrysler needed).

With each of these stages being referenced either anecdotally or in empirical results as having an individual influence on reducing the impact of disruptions on firms, we hypothesize the following:

H2a: Faster recognition of a supply chain disruption (stage 1) reduces disruption impact.
H2b: Faster diagnosis of a supply chain disruption (stage 2) reduces disruption impact.
H2c: Faster development of a response (stage 3) reduces disruption impact.
H2d: Faster implementation of a response (stage 4) reduces disruption impact.

Response Stages as Constraining Factors

In recent conversations with supply chain directors, three were individually asked which of the stages they felt was the most important stage to impacting recovery performance. One answered that *recognition* was most important, another that *implementation* was vital, and still another that *development* was of primary significance. While anecdotal, these conversations raise the question of whether any of the four stages act as a constraining stage, or factor, to the other stages. In other words, if a stage acting as a constraining factor (the slowest of the group) were improved, would the entire recovery process also be improved? Do any of the stages act as a bottleneck? If so, this would mean that trying to reduce the impact of the disruption by merely improving the other three stages without improving the constraining factor would have no effect.

While the concept of an operational bottleneck is well established (think "The Goal" by Goldratt 1984), few authors have applied this concept to the question of whether variables of interest act as a constrained factor in a data model. Two recent examples stand out. In their study of factors impacting the likelihood of knowledge sharing, Siemsen, Roth, and Balasubramanian (2008) tested a model that included motivation to share knowledge, time to share knowledge, and ability to share knowledge in a constrained factor model. They were interested in whether any of these factors acted as a bottleneck to knowledge sharing, which some did. Narasimhan, Narayanan, and Srinivasan (2013) looked at whether the dimensions of procedural, distributive, and interactional justice could act as a constraining factor when impacting supply chain relationships. Their results revealed that all three justice dimensions can act as constraining factors, and that strengthening perceptions of justice on two dimensions does not positively impact the relationship unless the third factor is also improved. In this research, a constraining factor is defined as an independent variable that is complementary to other independent variables and limits the ability of the other independent variables to increase the impact on a shared dependent variable.

All four stages must be worked through for any given disruption, but there are managerial implications to thinking of them as possible constraining factors. For example, if a firm recognizes the occurrence of a disruption only very late (slow stage 1) it may not be possible to make up this liability in the later stages to effectively mitigate the impact of the disruption. This is nicely illustrated by the "Albuquerque fire" supply chain disruption, mentioned in the introduction: In 2000, a fire destroyed the entire production capacity of a semiconductor plant of Philips Electronics in Albuquerque, New Mexico (USA), a subsupplier to both the Scandinavian telecommunication equipment manufacturers Nokia and Ericsson, for several weeks. While Ericsson was severely hit and incurred a loss of about US$400 million, Nokia was able to manage the disruption and to mitigate the detrimental consequences by swift recognition and diagnosis (Sheffi, 2005). Once Ericsson realized the magnitude of the disruption, they had already lost too much time to effectively mitigate the consequences. Despite the apparently vital role of recognition in this example, efforts to improve the firm's recovery performance will not be successful by speeding up the remaining three stages if recognition is a constraining factor. In order to determine whether any of the stages act as a bottleneck, we therefore hypothesize that:

H3a: When recognition (stage 1) is the constraining factor in the response stages, the disruption impact will be reduced by focusing on recognition over the other stages.

H3b: When diagnosis (stage 2) is the constraining factor in the response stages, the disruption impact will be reduced by focusing on diagnosis over the other stages.

H3c: When development (stage 3) is the constraining factor in the response stages, the disruption impact will be reduced by focusing on development over the other stages.

H3d: When implementation (stage 4) is the constraining factor in the response stages, the disruption impact will be reduced by focusing on implementation over the other stages.

Response Stages as Mediators of Disruption Antecedents

Thus far, we have hypothesized that the stages in the recovery process affect the impact of disruptions as a complete response decision process and as individual response stages, with and without possible complementarity. Risk and disruption management researchers have also worked to determine other antecedent factors to the ultimate impact of disruptive events. However, in the temporal process, the response occurs between these antecedents and the performance impact and hence may have a mediating effect between them—particularly, when the antecedents affect the information processing needs associated with the four response stages. Three important antecedents to the impact of disruptive events and the response formation are now considered: readiness, supplier dependence, and supply chain complexity.

Internal antecedent: Readiness

From an information processing perspective, Galbraith (1974) argued that information processing can be accelerated if firms preplan task routines or decisions prior to the need for their execution. When well-defined task processes exist, managers will face less uncertainty and less information processing needs than when they have to figure out ways to perform a task in an ad-hoc fashion (Daft & Macintosh, 1981).

In the supply chain risk context, this aspect is widely considered vital to disruption recovery and to reduce disruption impact. Many authors (e.g., Mitroff & Alpaslan, 2003; Norrman & Jansson, 2004) advocate proactive reflection of the potential risks that could befall a given supply chain and their associated levels of probability and impact. The concept of *readiness* has been suggested to be one of the critical elements of supply chain resilience in the face of disruptions (Ponomarov & Holcomb, 2009), to be a core competency in dealing with disruptions (Van Wassenhove, 2006), and to be a key to disruption recovery efforts that are well-managed (Macdonald & Corsi, 2013). In congruence with this literature, we define readiness as the culmination of a process of self-assessment and preparation for supply chain risks resulting in the ability to decisively react to risks as they manifest. In the management literature, the related concept of mindfulness was suggested as a state of permanent alertness and lively awareness that helps an organization to quickly detect and effectively handle errors (Langer, 1989). The application of readiness varies for each firm, and is referred to in the literature in the context of risk plans (Mitroff & Alpaslan, 2003), training and rehearsing for crises (Sniezek, Wilkins, Wadlington, & Baumann, 2002), choosing strategies for mitigation (Tang, 2006), and implementation of those plans (Zsidisin & Smith, 2005).

As mentioned previously, the response stages exist in a time series between readiness and the ultimate performance impact of the disruptive event. As the information processing perspective suggests that readiness affects information processing needs during the response stages and as the supply chain risk management literature suggests that readiness affects disruption impact, it is hypothesized that:

H4a: Response decision stages mediate the relationship between readiness and disruption impact.

Relationship antecedent: Supplier dependence

Being dependent on a supplier is a critical concern to supply chain managers (Zsidisin & Ellram, 2003; Tang, 2006). Manuj & Mentzer (2008) quoted a manager they interviewed as fearing the loss of leverage with a supplier if they are dependent on that supplier. That leverage was important to reduce the risk of a supplier acting opportunistically, which could either create the supply disruption or otherwise negatively increase the impact of another type of disruptive event. In fact, research by Tang (2006) thoroughly outlined many strategies to avoid a firm being put in the scenario in which a supplier issue directly affects the impact of a disruption.

Dependence can also act as a constraint put upon the persons tasked with the recovery effort. The information processing perspective suggests that the more information needed the greater the levels of interdependence (Srinivasan & Swink, 2015). High dependence on an exchange partner implies that it is more difficult to find, design, and implement a recovery solution. This additional need for information will likely slow down the response stages.

In response to the challenge of dependence, firms have developed multiple strategies. One of them is better supplier integration (Manuj, 2013). Integration can come in the form of sharing information and collaboration, but often also includes working together to recover from supply chain disruptions. For example, General Motors worked hand-in-hand with suppliers in Japan after the earthquake in 2011 triggered a tsunami that left automotive suppliers with severe disruptions (Samilton, 2011). This example reveals that the disruption response stages likely contain a link between supplier dependence and the final event impact. It is therefore hypothesized that:

H4b: Response decision stages mediate the relationship between supplier dependence and disruption impact.

Supply chain antecedent: Supply chain complexity

Complexity in the interconnected flows of materials, funds, and information between firms is widely considered to be one of the most critical problems in modern supply chains and a key impediment to performance (Choi & Krause, 2006; Bozarth, Warsing, Flynn, & Flynn, 2009; Bode & Wagner, 2015). Hendricks et al. (2009) reported that negative stock market reactions to supply chain disruptions are more severe for firms that are more geographically diversified and have a higher level of outsourcing. This is in line with normal accident theory (Perrow, 1984), which purports that socioeconomic systems (i.e., systems in which there is a close interrelationship between technical infrastructures and human individuals) become more challenging to manage and control with increasing complexity. Perrow's (1984) observation was that, in the presence of a high degree of complexity, small, independent failures can interact in unplanned ways and produce unfamiliar, unexpected events that are not immediately comprehensible. From an information processing perspective, the more equivocal the information to process, the more information processing and communication cycles it requires to reduce ambiguity to an acceptable level. Against this background, one would expect not only that the severity of a disruption increases with the degree of supply chain complexity, but also the response decision times (Christopher & Lee, 2004).

Though not addressing a supply chain network directly, the capacity to process information can mitigate against decision complexity (Tushman & Nadler, 1978), thereby providing impetus for managers to design supply chain structures that provide the necessary information. Hence, we hypothesize:

H4c: Response decision stages mediate the relationship between supply chain complexity and disruption impact.

METHOD

Data and Procedure

To test the hypotheses empirically, we used data gathered by means of a self-administered Internet-based survey of 3,945 firms in Europe. The empirical context was the manufacturing sector and firms that experienced at least one supply chain disruption in the year preceding the survey. Contact addresses for the survey

Table 1: Sample supply chain disruptions from survey.

Description	Purchased Item	Location of Triggering Event	Disruption Impact[a]
"Supplier was bought by a larger company and is no longer able to provide previous products to us."	Unit, module, or component	USA	3.00
"Subsupplier terminated a critical series of raw materials that are unique to certain equipment."	Raw material	Germany	2.33
"Allocation of raw material prevented supplier from receiving usual monthly allotment."	Raw material	Canada	3.50
"Transition of a key supplier's manufacturing from one plant to another caused several shortages and unexpected increases in lead-time."	Unit, module, or component	USA	3.00
"Delay in clearing of customs of a sea container carrying important production parts."	Unit, module, or component	Czech Republic	4.67

[a]Formative six-item index.

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). As key informants, we contacted senior managers with responsibilities for purchasing or supply management who were likely to have an overarching, boundary-spanning view of their firms' supply chains and supplier activities. Respondents were asked to base their answers on a specific supply chain disruption entailing a significant (perceived) performance deviation that had occurred during the 12 months preceding data collection and in which a specific supplier was involved. Table 1 provides some examples of the reported disruptions.

In exchange for participation, respondents were offered a summary of the results and a practitioner-oriented book about purchasing. Three follow-up e-mails and reminder phone calls resulted in 462 questionnaires (an overall response rate of 11.71%) with few missing values. However, due to those missing values, particularly in the single items for the four response stages, the number of cases usable for testing our hypotheses reduced to 438.

The data collection yielded a heterogeneous sample covering a broad range of manufacturing industry sectors and firm sizes, and revealed no indication of systematic bias. The total annual revenues of the respondents' firms ranged from less than US\$ 1 million to US\$ 114.8 billion (M = US\$ 1.16 billion, SD = US\$ 7.79 billion) and the number of employees ranged from fewer than 100 to 475,000 (M = 4,739, SD = 35,875). Most respondents were senior managers in purchasing who had been in their current positions for an average of 6.73 years ($SD = 5.73$) and with their firms for 11.24 years ($SD = 9.18$). Their work experience involved purchasing, logistics, or supply chain operations for 14.33 years ($SD = 8.30$).

Two strategies were used to assess whether nonresponse bias was present in the sample. First, differences were inspected between early (initial invitation) and late respondents (second and third reminder) on all survey items in our model by means of a multivariate analysis of variance. No significant mean differences were found ($p < .05$), either at the multivariate or univariate level. Second, the sample was compared with a sample of 100 nonresponding firms randomly drawn from the initial sampling frame ($N = 3{,}945$) on the basis of firm size (number of employees) and firm age. *T*-tests for these variables indicated no statistically significant differences between the two groups ($p < .05$). In sum, the performed analyses do not suggest that nonresponse bias poses a significant threat to the validity of the results.

For all cases in the survey data set, objective secondary data was gathered for the two variables firm size and firm age from two commercial databases (Bloomberg Professional Service and AMADEUS from BvDEP). As these variables were also included in the survey instrument, we were able to perform a comparison check on the data quality. In both cases, the variables are highly correlated ($r > .80$), suggesting that the primary data is of good quality.

Survey Instrument and Measures

Considerable attention was paid to the design of the survey instrument, especially its ease of use, the burden on the respondent, and the maintaining of the respondent's interest until the survey was completed. In addition, several procedural measures were implemented to minimize the introduction of common method variance into our data (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). The survey instrument provided only general information about the study's objectives, but no clues about the actual relationships under investigation. We offered anonymity (on the level of the respondent) and confidentiality to reduce the chance of responses that were socially desirable or consistent with how respondents believe researchers wanted them to respond. Following Doty and Glick (1998), the design of the survey instrument emphasized the concreteness of constructs by anchoring responses in a particular situation (a specific supply chain disruption).

For half of our variables, we were able to draw on scales that had been previously developed and validated in the pertinent literature. However, in order to fit the original scales to the specific context, it was necessary to amend or modify several items. For all remaining constructs, it was necessary to develop new measures for which standard scale development techniques were followed (DeVellis, 2003). This process included several preliminary qualitative interviews with purchasing managers, an extensive review of the extant academic and practitioner literature, in-person pretesting, as well as a pretest study. Translations of the final measurement items, after their refinement with data from the survey, appear in Appendix A. Descriptive statistics for the employed measures and correlations appear in Table 2. All items were presented on five-point scales. *Disruption impact* was conceptualized in a formative index, whereas all other variables were conceived of as reflective or single item measures.

Table 2: Bivariate correlations and descriptive statistics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Disruption impact	–	*.01*	*.00*	*.01*	*.01*	*.00*	*.02*	*.02*	*.04*	*.02*	*.02*	*.02*	*.03*
(2) Firm size[a]	–.08	–	*.00*	*.01*	*.00*	*.00*	*.00*	*.00*	*.00*	*.00*	*.00*	*.00*	*.00*
(3) Competitive intensity	.03	.01	***.45***	*.04*	*.00*	*.00*	*.00*	*.00*	*.01*	*.01*	*.01*	*.01*	*.00*
(4) Prod. complexity	.09	.11*	–.19***	***.70***	*.08*	*.00*	*.05*	*.03*	*.00*	*.00*	*.01*	*.00*	*.01*
(5) Prod. importance	.10*	–.07	.05	.28***	***.53***	*.01*	*.08*	*.01*	*.01*	*.00*	*.03*	*.01*	*.00*
(6) Readiness	–.01	.04	.07	.02	.12*	***.55***	*.00*	*.01*	*.04*	*.02*	*.04*	*.02*	*.01*
(7) Supplier dependence	.15**	.03	.03	.22***	.29***	.03	***.69***	*.02*	*.01*	*.00*	*.00*	*.01*	*.03*
(8) Supply chain complexity	.15*	.02	.04	.18***	.08	.12*	.14**	***.42***	*.01*	*.01*	*.01*	*.00*	*.00*
(9) Total resp. speed	–.20***	–.05	.12*	.01	.10*	.21***	–.09	–.08	–	*.44*	*.62*	*.61*	*.48*
(10) Stage 1	–.14*	–.04	.11*	.05	.06	.14**	.01	–.10*	.66***	–	*.28*	*.06*	*.02*
(11) Stage 2	–.13*	–.01	.11*	.09	.17***	.21***	.03	–.10*	.79***	.53***	–	*.26*	*.08*
(12) Stage 3	–.14*	–.07	.12*	.01	.12*	.13**	–.10*	–.01	.78***	.24***	.51***	–	*.28*
(13) Stage 4	–.18***	–.02	.02	–.10*	–.03	.12*	–.18***	–.02	.69***	.15**	.28***	.53***	–
M	2.96	6.03	3.30	2.99	4.05	2.92	3.74	2.32	3.57	3.66	3.75	3.62	3.25
SD	.79	1.59	.76	1.01	.78	.86	.99	.77	.63	.88	.82	.84	.90

Note. Pearson product–moment correlation coefficients are shown below the diagonal; diagonal values represent average variances extracted (where appropriate), squared correlations (shared variance) are shown above the diagonal in italics ($n = 438$).
$^{*}p < .05$ (equals $|r| > .09$), $^{**}p < .01$ (equals $|r| > .12$), $^{***}p < .001$ (equals $|r| > .16$) (two-tailed).
[a]Transformed using the natural logarithm.

Disruption impact

Disruption impact ($M = 2.96$, $SD = .79$) measures the extent to which the supply chain disruption had (direct or indirect) negative effects on the focal buying firm (Bode et al., 2011). To entirely capture the multifaceted nature of supply chain disruptions, we used a six-item scale, which captures negative effects to the resource provision (procurement costs), production process (efficiency of operations, quality of final products), customers (responsiveness, delivery reliability), and financial performance (return on sales).

Response stages

Prior research suggests using single-item scales for constructs that are doubly concrete, meaning that they are unidimensional in both their content and their attributes (Bergkvist & Rossiter, 2007). As the response stages are factual and uniformly imagined, the use of multi-item psychometric scales was avoided and single-item, five-point rating scales were used instead. Following previous research in the field of crisis response (Hermann, 1963; Billings et al., 1980), decision processes (Mintzberg et al., 1976; Cowan, 1986), and supply chain disruption recovery research (Blackhurst et al., 2005; Macdonald & Corsi, 2013), we conceptualized the disruption response as consisting of four distinct stages: *recognition* ($M = 3.66$, $SD = .88$), *diagnosis* ($M = 3.75$, $SD = .82$), *development* ($M = 3.62$, $SD = .84$), and *implementation* ($M = 3.25$, $SD = .90$). Respondents were asked to indicate the speed by which their firm was able to accomplish each of the four stages (1: very slow to 5: very fast). The items were coded so that higher numbers reflect increases in the underlying items. For the remainder of the article, the aggregated score of these variables will be called *total response speed* ($M = 3.57$, $SD = .63$).

Antecedents

Readiness ($M = 2.92$, $SD = .86$, $\alpha = .82$) refers to the buying firm's proactive investment in disruption response capabilities prior to the disruption (Macdonald & Corsi, 2013). The four-item measurement scale assesses internal awareness for supply disruptions, existence of contingency plans, and proactive supply chain risk management activities. *Supplier dependence* ($M = 3.74$, $SD = .99$, $\alpha = .90$) was measured by a scale proposed by Jap and Ganesan (2000). This four-item scale assesses the firm's inability to replace the exchange partner and to achieve its goals in the event that the relationship is terminated. For *supply chain complexity* ($M = 2.32$, $SD = .77$, $\alpha = .77$), a four-item scale was developed that captures the extent to which the buying firm's upstream supply chain (in which the disruption materialized) was complex. Following works on the complexity of sociotechnical systems (Simon, 1962; Perrow, 1984), items were developed to measure the extent to which it is difficult to explain, understand, or analyze the supply chain.

Control variables

Five variables—firm size, competitive intensity, product complexity, product importance, and reaction category—were used as control variables in the models. *Firm size* ($M = 6.03$, $SD = 1.59$), measured as the number of employees of the buying firm and transformed using the natural logarithm, may affect organizational actions and inertia (Kelly & Amburgey, 1991; Zajac & Kraatz, 1993). *Competitive intensity* ($M = 3.30$, $SD = .76$, $\alpha = .75$), the extent to which the firm perceives its competition to be intense, is included as it may affect the interpretation of adverse environmental events (Barr, 1998). This construct is measured with a four-item scale adopted from Jaworski and Kohli (1993), asking respondents to elaborate on the intensity of rivalry among firms in their industry. We also controlled for *product complexity* ($M = 4.05$, $SD = .78$, $\alpha = .90$) and *product importance* ($M = 2.30$, $SD = 1.01$, $\alpha = .72$), both measured using the five-point semantic differential scales suggested by Cannon and Perreault (1999) and Cannon and Homburg (2001), to capture key characteristics of the purchased item that may affect the response formation process. Finally, the response process and the final disruption impact could be affected by a firm's preexisting decision-making routines (Bode et al., 2011; Tenhiälä & Salvador, 2014). For this reason, a categorical control variable, *reaction category*, was included. Following Billings et al. (1980), the respondents were asked to characterize their disruption response according to three different reaction types: "inaction," "routine response," or "original/nonroutine response." Seven cases were deleted because the respondent indicated "inaction." For the resulting binary variable, two dummy variables were created using "routine response" as the baseline category, which was coded as "0."

Measure Assessment

The psychometric properties of the six reflective scales (readiness, supplier dependence, supply chain complexity, competitive intensity, product complexity, and product importance) were assessed by means of a covariance-based confirmatory factor analysis (CFA). Given that some indications of the presence of multivariate nonnormality were found (Mardia's multivariate kurtosis = 59.62, $p < .001$), we applied maximum-likelihood estimation with robust standard errors using the MLR estimator in the statistical software package Lavaan (.5–20) in *R* (3.3.1) (Rosseel, 2012). The measurement model reveals an acceptable fit to the data (Hair, Black, Babin, & Anderson, 2009):[i] Satorra–Bentler-scaled χ^2/df = 2.29 (SB-scaled $\chi^2_{(237)} = 543.82$, $p < .001$), CFI = .93, TLI = .92, SRMR = .061, and RMSEA = .054 (90% confidence interval CI = [.048, .060]).

Without exception, each item loaded on its hypothesized factor with a large and significant loading (all λ significant at $p < .001$). Composite reliabilities and average variances extracted met or exceeded the common cut-off values of .70 and .50 (Hair et al., 2009), respectively. Only for *competitive intensity* (.45) and *supply chain complexity* (.42), the received average variance extracted were slightly below the common cut-off. Discriminant validity was assessed on the basis of the criterion suggested by Fornell and Larcker (1981). As shown in Table 2, each construct extracts variance that is larger than the highest variance it shares with other constructs, thus providing support for discriminant validity. Having established the validity and reliability of the reflective scales, we used scale averages as latent variable scores for the final estimation.

[i] The Satorra–Bentler-scaled χ^2 value incorporates a scaling correction based on the degree of multivariate nonnormality. CFI refers to comparative fit index; TLI refers to Tucker–Lewis index; SRMR refers to standardized root mean square residual; RMSEA refers to root mean square error of approximation.

Formative measurement raises the issues of indicator multicollinearity (Petter, Straub, & Rai, 2007). For this reason, ordinary least squares (OLS) regressions were run to check for redundant items in the formative index for *disruption impact*. Multicollinearity was not found to pose a problem as all variance inflation factors (VIF) were low (VIF < 3) and the bivariate correlations between the indicators were within an acceptable range ($r < .80$) (Diamantopoulos & Siguaw, 2006).

ANALYSIS AND RESULTS

This section presents three different analyses conducted to investigate the proposed hypotheses. All analyses are based on linear models that were estimated using OLS regression. For each model analyzed, the assumptions underlying OLS estimation were verified and met. Neither the scrutinized influence diagnostics nor Bonferroni-adjusted outlier tests raised specific concerns over outliers. Indications were not found for problematic levels of multicollinearity: for all models, zero-order correlations were within acceptable ranges and the variance inflation factors and the condition numbers were substantially below conservative thresholds (Cohen, Cohen, West, & Aiken, 2003). In conclusion, no reasons were found that the chosen estimation approaches are inappropriate.

Direct Effects

The first two sets of hypotheses (H1 and H2a–d) pertain to the direct effects of response speed on disruption impact. To test these effects, the following linear models were specified and estimated in hierarchical order[ii]:

$$IMP = a_0 + a_1 SZE + a_2 CMP + a_3 PCX + a_4 PIP + a_5 RCT + \varepsilon, \qquad (1)$$

$$\begin{aligned} IMP = a_0 + a_1 SZE + a_2 CMP + a_3 PCX + a_4 PIP + a_5 RCT \\ + a^T SPD^T + \varepsilon, \end{aligned} \qquad (2)$$

$$\begin{aligned} IMP = a_0 + a_1 SZE + a_2 CMP + a_3 PCX + a_4 PIP + a_5 RCT \\ = + a^{S1} SPD^{S1} + a^{S2} SPD^{S2} + a^{S3} SPD^{S3} + a^{S4} SPD^{S4} + \varepsilon. \end{aligned} \qquad (3)$$

Model 1 includes only the control variables and serves as the baseline. *Model 2* captures the direct effect of total response speed whereas *model 3* captures the direct effects of the four individual response stages. The results appear in Table 3.

We hypothesized, first, that total response speed has a direct effect on disruption impact. The results indicate that the impact of a supply chain disruption

[ii] The variable identifiers are as follows: *IMP* = disruption impact, *SZE* = firm size, *CMP* = competitive intensity, *PCX* = product complexity, *PIP* = product importance, *RCT* = reaction category (baseline: "routine response"), SPD^T = total response speed, SPD^{S1} = speed in stage 1 (recognition), SPD^{S2} = speed in stage 2 (diagnosis), SPD^{S3} = speed in stage 3 (development), SPD^{S4} = speed in stage 4 (implementation).

Table 3: Regression analysis of the direct effects on disruption impact.

		Model 1: Control Variables		Model 2: Direct Effect of Response Speed		Model 3: Direct Effects of Individual Response Stages		Model 4: Constraining Factors[a]		
Variables	Hyp.	Est	*SE*	Est	*SE*	Est	*SE*	Est	*SE*	Net eff.[a]
Constant		2.78***	(.06)	2.79***	(.06)	2.79***	(.06)	3.03***	(.17)	
Firm size		–.06	(.04)	–.07†	(.04)	–.07†	(.04)	–.06	(.04)	
Competitive intensity		.05	(.04)	.07†	(.04)	.06†	(.04)	.08*	(.04)	
Product complexity		.06†	(.04)	.07†	(.04)	.07†	(.04)	.08*	(.04)	
Product importance		.04	(.04)	.06†	(.04)	.05	(.04)	.04	(.04)	
Reaction category[b]		.31***	(.08)	.29***	(.07)	.29***	(.07)	.26***	(.08)	
Total response speed	H1			–.17***	(.04)	–	–	–	–	
Stage 1: Recognition	H2a					–.09*	(.04)	–	–	
Stage 2: Diagnosis	H2b					–.03	(.05)	–	–	
Stage 3: Development	H2c					–.04	(.05)	–	–	
Stage 4: Implementation	H2d					–.09*	(.04)	–	–	
Stage 1 is constraining factor										
Stage 1	H3a							.06	(.13)	–
Stage 2								.03	(.15)	–
Stage 3								–.24†	(.13)	–
Stage 4								–.11	(.12)	–
Stage 2 is constraining factor										
θ_{cf2}								–.72***	(.21)	
θ_{cf2} × Stage 1								–.11	(.16)	–.05
θ_{cf2} × Stage 2	H3b							–.56**	(.20)	–.53***
θ_{cf2} × Stage 3								.46**	(.16)	.21*
θ_{cf2} × Stage 4								.36*	(.16)	.25*

Continued

Table 3: Continued

		Model 1: Control Variables		Model 2: Direct Effect of Response Speed		Model 3: Direct Effects of Individual Response Stages		Model 4: Constraining Factors[a]		
Variables	Hyp.	Est	*SE*	Est	*SE*	Est	*SE*	Est	*SE*	Net eff.[a]
Stage 3 is constraining factor										
θ_{cf3}								–.55	(.35)	
θ_{cf3} × Stage 1								–.15	(.21)	–.08
θ_{cf3} × Stage 2								.16	(.32)	.19
θ_{cf3} × Stage 3	H3c							–.04	(.30)	–.28
θ_{cf3} × Stage 4								.03	(.18)	–.08
Stage 4 is constraining factor										
θ_{cf4}								–.24	(.22)	
θ_{cf4} × Stage 1								–.04	(.18)	.03
θ_{cf4} × Stage 2								.00	(.18)	.03
θ_{cf4} × Stage 3								.08	(.17)	–.17
θ_{cf4} × Stage 4	H3d							–.03	(.17)	–.14
R^2		.06		.11		.11		.18		
F		5.51***		8.52***		5.78***		3.77***		

Note. Dependent variable is *disruption impact*. OLS regression with robust standard errors was used ($n = 438$). Except for the categorical control variable *reaction category*, reported estimates refer to standardized regression coefficients. θ_{cf2}, θ_{cf3}, and θ_{cf4} are binary dummy variables that are coded "1" if the corresponding response stage (2, 3, or 4) is the minimum (slowest) of the four stages; Stage 1 serves as the baseline.

†$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$ (two-tailed).

[a]For the net effect, standard errors and p-values were calculated using the LINCOM command in Stata (14.1).

[b]"Routine response" served as the baseline category.

is, in fact, significantly reduced by a faster response ($a^T = -.17$, $p < .001$). This provides support for H1.

Second, total response speed was unpacked into the four individual response stages and analyzed for their effects on disruption impact. The results suggest that the speed by which a firm is able to accomplish each of the four response stages mitigates the disruption impact, but that the effect sizes differ. We find that the speedy accomplishments of stage 1 (recognition) ($a^{S1} = -.09$, $p = .04$) and stage 4 (implementation) ($a^{S4} = -.09$, $p = .04$) have strong and significant mitigating effects on disruption impact. These results provide support for H2a and H2d. In contrast, the coefficients for stage 2 (diagnosis) ($a^{S2} = -.03$, $p = .56$) and stage 3 (development) ($a^{S3} = -.04$, $p = .39$), albeit in the predicted direction, are small and not significantly different from zero, which rejects H2b and H2c. These results also align with the direction predicted by information processing theory.

Constraining Factors

For the third set of hypotheses (H3a–d), in order to better understand how the four individual response stages work in concert, a constraining factor model (*model 4*) was constructed. This model assumes that a low speed in one of the four stages *cannot* be compensated for by swift decisions in the other three stages. Such a constraining factor situation represents an extreme form of complementarity (Siemsen et al., 2008; Narasimhan et al., 2013).[iii] The corresponding regression approach allows for an intercept and linear effects of the four response stages, but it also allows both the intercept and the linear effects to change, depending upon which variable of the four is the lowest. To this end, three binary dummy variables are used—θ_{cf2}, θ_{cf3}, and θ_{cf4}—which take the value "1" if the corresponding stage was the lowest of all four stages (based on standardized values). Stage 1 serves as the baseline: If stage 1 is the slowest of all stages, all three dummy variables are coded as "0." The constraining factor model is then specified as follows (Siemsen et al., 2008; Narasimhan et al., 2013):

$$\begin{aligned} IMP = {} & b_1 SZE + b_2 CMP + b_3 PCX + b_4 PIP + b_5 RCT \\ & + \left(b_{cf1} + b_{cf1}^{S1} SPD^{S1} + b_{cf1}^{S2} SPD^{S2} + b_{cf1}^{S3} SPD^{S3} + b_{cf1}^{S4} SPD^{S4}\right) \\ & + \theta_{cf2}\left(b_{cf2} + b_{cf2}^{S1} SPD^{S1} + b_{cf2}^{S2} SPD^{S2} + b_{cf2}^{S3} SPD^{S3} + b_{cf2}^{S4} SPD^{S4}\right) \\ & + \theta_{cf3}\left(b_{cf3} + b_{cf3}^{S1} SPD^{S1} + b_{cf3}^{S2} SPD^{S2} + b_{cf3}^{S3} SPD^{S3} + b_{cf3}^{S4} SPD^{S4}\right) \\ & + \theta_{cf4}\left(b_{cf4} + b_{cf4}^{S1} SPD^{S1} + b_{cf4}^{S2} SPD^{S2} + b_{cf4}^{S3} SPD^{S3} + b_{cf4}^{S4} SPD^{S4}\right) \\ & + \varepsilon. \end{aligned} \tag{4}$$

[iii]We also investigated a possible multiplicative influence (moderate complementarity) of the response stages on disruption impact and estimated corresponding regression models with interaction effects. Eventually, this approach led to six two-way, four three-way, and one four-way interaction terms. The results are shown in Appendix B. Of the 11 interaction terms, only three are significant ($p < .10$), which rejects the notion of moderate complementarity among the four response stages.

Results for *model 4* appear in the last column of Table 3. The net effects (slopes) of each individual stage variable on disruption impact (when a certain stage is the constraining factor) are the linear combinations of their direct effects and their interaction effects with the corresponding constraining factor dummy variable. For example, the net effect of response stage 3 on disruption impact when stage 2 is the constraining factor (.21, $p = .03$) is the sum of its base effect ($b_{cf1}^{S3} = -.24$) and the interaction effect with the constraining factor dummy variable of stage 2 ($\theta_{cf2} \times b_{cf2}^{S3} = .46$). Standard errors and p-values for the net effects were calculated using the LINCOM command in Stata (14.1).

The received results are mixed. Only when stage 2 (diagnosis) is the constraining factor do the results suggest that relaxing this bottleneck has a strong and significant mitigating effect on disruption impact ($b_{cf1}^{S2} + \theta_{cf2} \times b_{cf2}^{S2} = -.53$, $p < .001$), thus providing support for H3b. For the other stages, the results do not support the notion of constraining factors: When stage 1 is the constraining factor, the net effect of increasing the speed of stage 1 is not significantly different from zero (.06, $p = .68$). The same applies to stage 3 (–.28, $p = .22$) and stage 4 (–.14, $p = .33$). These three results reject hypotheses H3a, H3c, and H3d.

Mediation of Antecedents

Finally, we analyzed the effects of the three hypothesized antecedent variables—readiness, supplier dependence, and supply chain complexity—on the response behavior and on disruption impact. To this end, we conducted two mediation analyses, one with total response speed being the single mediator (*model 5* and *model 6*) and one where the four response stages act separately as meditators (*models 7a–d* and *model 8*).[iv] The results are reported in Table 4.

Given that the distributions of indirect effects are typically not normal (Hayes, 2013), we assessed the indirect effects by means of a bootstrapping approach (bias-corrected and accelerated) with 100,000 replications. We consider an indirect effect to be "significant" when the bootstrapped 95% CI does not contain zero (Hayes, 2013).

First, to test H4a–c with regard to total response speed, the following equations were estimated:[v]

$$\begin{aligned} SPD^{A} = {} & c_0 + c_1 SZE + c_2 CMP + c_3 PCX + c_4 PIP + c_5 RCT \\ & + c_6 RDY + c_7 DPD + c_8 SCX + \varepsilon, \end{aligned} \tag{5}$$

$$\begin{aligned} IMP = {} & d_0 + d_1 SZE + d_2 CMP + d_3 PCX + d_4 PIP + d_5 RCT \\ & + d_6 RDY + d_7 DPD + d_8 SCX + d^{T} SPD^{T} + \varepsilon. \end{aligned} \tag{6}$$

[iv]The effects were also tested using structural equation modeling using maximum likelihood estimation. The obtained results are substantively equivalent to the reported OLS results.

[v]In addition to the variable identifiers used in Equations (1)–(3), the following are used: RDY = readiness, DPD = supplier dependence, and SCX = supply chain complexity.

Table 4: Results of mediation analysis.

Variables	Hyp.	Model 5 (*Antecedents→Speed*)	Model 6 (*Speed→Impact*)	Indirect Effects (*Antecedents→ Speed→Impact*)	Models 7a–d (*Antecedents→Speed*)				Model 8 (*Speed→Impact*)	Indirect Effects (*Antecedents→ Speed→Impact*)
		Tot. resp. s.	Impact		Stage 1	Stage 2	Stage 3	Stage 4	Impact	
Constant		.02	2.80***		–.01	.02	.02	.03	2.80***	
Firm size		–.05	–.07[†]		–.05	–.02	–.07	–.01	–.07[†]	
Competitive intensity		.12*	.06		.12*	.12*	.12*	.01	.05	
Product complexity		.10[†]	.04		.10[†]	.11*	.04*	–.06	.04	
Product importance		.06	.05		.01	.12	.12*	.02	.04	
Reaction category[a]		–.03	.27***		.02	–.03	–.03	–.06	.27***	
Readiness	H4a	.20***	.02		.15**	.21***	.12*	.12*	.02	
Indirect effect thru Total resp. speed				–.03 **[–.06, –.01]**						
Indirect effect thru Stage 1										–.01 **[–.03, –.00]**
Indirect effect thru Stage 2										.00 [–.03, .01]
Indirect effect thru Stage 3										.00 [–.02, .01]
Indirect effect thru Stage 4										–.01 **[–.03, –.00]**
Supplier dependence	H4b	–.12*	.06		–.01	–.02	–.14*	–.18**	.05	
Indirect effect thru Total resp. speed				.02 **[.00, .04]**						
Indirect effect thru Stage 1										.00 [–.01, .01]
Indirect effect thru Stage 2										.00 [–.00, .01]
Indirect effect thru Stage 3										.01 [–.01, .02]
Indirect effect thru Stage 4										.01 **[.00, .04]**

(*Continued*)

Table 4: Contnued

Variables	Hyp.	Model 5 (*Antecedents→Speed*)	Model 6 (*Speed→Impact*)	Indirect Effects (*Antecedents→ Speed→Impact*)	Models 7a–d (*Antecedents→Speed*)				Model 8 (*Speed→Impact*)	Indirect Effects (*Antecedents→ Speed→Impact*)
		Tot. resp. s.	Impact		Stage 1	Stage 2	Stage 3	Stage 4	Impact	
Supply chain complexity	H4c	–.11*	.07*		–.14**	–.16***	–.03	–.00	.07*	
Indirect effect thru Total resp. speed				.02 **[.00, .04]**						
Indirect effect thru Stage 1										.01 **[.00, .03]**
Indirect effect thru Stage 2										.00 [–.01, .02]
Indirect effect thru Stage 3										.00 [–.00, .01]
Indirect effect thru Stage 4										.00 [–.01, .01]
Total response speed			–.16***							
Stage 1									–.08*	
Stage 2									–.02	
Stage 3									–.04	
Stage 4									–.08†	
R^2		.09	.12		.06	.10	.06	.05	.12	
F		6.09***	7.75***		2.96**	7.17***	3.46***	2.98**	5.83***	

Note: For the indirect effects, bootstrapped 95% confidence intervals (100,000 samples, BCa), shown in brackets, were calculated using the MEDIATE macro by Hayes and Preacher (2014) in SPSS (22) ($n = 438$). Confidence intervals that do not contain zero are highlighted in bold font.
†$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$ (two-tailed, based on robust standard errors).
[a]"Routine response" served as the baseline category.

As shown in Table 4, the results for *model 5* indicate that readiness has a strong and significant positive effect on total response speed ($c_6 = .20$, $p < .001$), while supplier dependence ($c_7 = –.12$, $p = .02$) and supply chain complexity ($c_8 = –.11$, $p = .02$) have a significant negative effect on response speed. Hence, the higher the level of readiness, the quicker the disruption response is; the greater the supplier dependence and the greater the supply chain complexity, meanwhile, the slower the disruption response is. To understand whether there is mediation as suggested in H4a–c, these variables' indirect effects have to be scrutinized (i.e., the product of the coefficients c_6, c_7, c_8 in *model 5* with d^T in *model 6*). For readiness, we find a significant indirect effect through total response speed ($c_6 \times d^T = .20 \times –.16 = –.03$, $CI = [-0.06, -0.01]$), which provides support for H4a. The corresponding total effect of readiness on disruption impact is negative but relatively small ($d_6 + c_6 \times d^T = –.02$). The results also suggest a significant indirect effect of supplier dependence on disruption impact through total response speed ($c_7 \times d^T = .02$, $CI = [0.00, 0.04]$), which provides support for H4b. The total effect on disruption impact is positive ($d_7 + c_7 \times d^T = .08$), which suggests that increasing supplier dependence has a negative effect on disruption impact that stems (partially) from hampering response speed. A very similar result is found for supply chain complexity: the indirect effect of supply chain complexity on disruption impact ($c_8 \times d^T = .02$, $CI = [.00, .04]$) provides empirical support for hypothesis H4c, with the corresponding total effect on response speed being positive ($d_8 + c_8 \times d^T = .09$).

Second, to analyze H4a–c with the response stages as separate mediators, the following models were estimated:

$$\begin{aligned} SPD^{S1} = {} & e_0^{S1} + e_1^{S1} SZE + e_2^{S1} CMP + e_3^{S1} PCX + e_4^{S1} PIP + e_5^{S1} RCT \\ & + e_6^{S1} RDY + e_7^{S1} DPT + e_8^{S1} SCX + \varepsilon, \end{aligned} \tag{7a}$$

$$\begin{aligned} SPD^{S2} = {} & e_0^{S2} + e_1^{S2} SZE + e_2^{S2} CMP + e_3^{S2} PCX + e_4^{S2} PIP + e_5^{S2} RCT \\ & + e_6^{S2} RDY + e_7^{S2} DPT + e_8^{S2} SCX + \varepsilon, \end{aligned} \tag{7b}$$

$$\begin{aligned} SPD^{S3} = {} & e_0^{S3} + e_1^{S3} SZE + e_2^{S3} CMP + e_3^{S3} PCX + e_4^{S3} PIP + e_5^{S3} RCT \\ & + e_6^{S3} RDY + e_7^{S3} DPT + e_8^{S3} SCX + \varepsilon, \end{aligned} \tag{7c}$$

$$\begin{aligned} SPD^{S4} = {} & e_0^{S4} + e_1^{S4} SZE + e_2^{S4} CMP + e_3^{S4} PCX + e_4^{S4} PIP + e_5^{S4} RCT \\ & + e_6^{S4} RDY + e_7^{S4} DPT + e_8^{S4} SCX + \varepsilon, \end{aligned} \tag{7d}$$

$$\begin{aligned} IMP = {} & f_0 + f_1 SIZE + f_2 COMP + f_3 PRCX + f_4 PRIP + f_5 RCT + f_6 RDY + f_7 DPT \\ & + f_8 SCX + f^{S1} SPD^{S1} + f^{S2} SPD^{S2} + f^{S3} SPD^{S3} + f^{S4} SPD^{S4} + \varepsilon. \end{aligned} \tag{8}$$

As shown in Table 4, a key result of *models 7a–d* is that readiness seems to serve as an important factor for each of the four individual response stages. Readiness significantly accelerates response stage 1 ($e_6^{S1} = .12, p = .02$), response stage 2 ($e_6^{S2} = .21, p < .001$), response stage 3 ($e_6^{S3} = .15, p = .003$), and response stage 4 ($e_6^{S4} = .12, p = .01$). Supplier dependence shows significant effects on the response stages, but only on the later stages, namely stage 3 ($e_7^{S3} = -.14, p = .01$) and stage 4 ($e_7^{S4} = -.18$, $p < .001$). This suggests that dependence particularly hampers the speed of the development and the implementation stages, but not the recognition or diagnosis stages. On the other hand, supply chain complexity shows only statistically negative effects on the earlier stages, namely stage 1 ($e_8^{S1} = -.14$, $p = .009$) and stage 2 (diagnosis) ($e_8^{S2} = -.16$, $p < .001$). Thus, in contrast to dependence, supply chain complexity slows down the recognition and diagnosis stages, but has no discernable effects on the stages of response development and implementation.

With regard to the 12 indirect effects, the results are mixed. For readiness (H4a), we find two indirect effects that are negative and statistically different from zero, namely the ones through stage 1 ($e_6^{S1} \times f^{S1} = -.01$, $CI = [-0.03, -0.00]$) and stage 4 ($e_6^{S4} \times f^{S4} = -.01$, $CI = [-0.03, -0.00]$). All indirect effects of supplier dependence (H4b) on disruption impact through the individual response stages are positive (as expected), but only the effect through response stage 4 seems to be different from zero ($e_7^{S4} \times f^{S4} = .01$, $CI = [0.00, 0.04]$). Finally, the results suggest that there is an indirect effect of supply chain complexity on disruption impact (H4c) through response stage 1 ($e_8^{S1} \times f^{S1} = .01$, $CI = [0.00, 0.03]$). In summary, for all three antecedents, the results indicate that some of the four response stages act as mediators, providing only partial support for H4a–d.

DISCUSSION

The results of this study provide insights and direction to researchers and managers working through the key response stages of recognition, diagnosis, development, and implementation. These stages are confirmed as forming the building blocks of disruption management, and help answer the research questions posed earlier. Decision-making speed and the ability to process information quickly make a difference in reducing the impact of the disruption. There is some evidence of the importance of some decision stages over others, with these stages playing a mediating role to the effect the three antecedents have.

Implications for Research

There are several important contributions from these results. One contribution has been to further refine our understanding of the response stages in the process of disruption management, and how the ability of decision makers to process information affects these stages. A second contribution has been to take previously correlated concepts and provide a more detailed analysis of the underlying causal mechanisms. Specifically, we find this between the antecedents and disruption impact. Firmly establishing this link now allows researchers to refine the variations that may exist within antecedents and the effect this has on the impact of the disruption. A third contribution has been to begin to show how the antecedents affect the amount and clarity of information being provided to decision makers. Confidence in the signals facilitates moving more quickly through the disruption response.

Direct effects

When aggregated together as *total response speed*, working through the four stages at a faster speed reduces the impact of the disruption. This is consistent with our predictions built from information processing theory, and supports the idea that managers' efforts at investments and decision processes to facilitate these stages yield a benefit. Unpacking total response speed and taking the analysis to the individual level, the strongest (and most significant) mitigating effects of disruption impact are the stages of recognition (stage 1) and implementation (stage 4). This indicates that adding resources to the supply chain functions that help detect disruptions as soon as they have occurred will reduce the impact of those disruptions. Similarly, though it may take some time to decide on an implementation plan, the ability to implement the chosen plan quickly and accurately substantially reduces the disruption impact. This is not to say that the middle stages of diagnosis and development are unimportant, but that focusing primarily on them yielded inconsistent results. Faster recognition and implementation more consistently reduce the impact of the disruption, while diagnosis and development sometimes do and sometimes do not.

Constraining factors

One of the stages acting as a constrained factor would mean that, when it is the lowest scoring (slowest) stage, it acts as a bottleneck and limits the ability of the other stages to have a significant effect on reducing the impact of the disruption. Three conversations with managers were mentioned earlier in the article showing that each believed a different stage to be of primary importance. Analytical results show that only one stage, diagnosis, acts as a constraining factor.

Diagnosis is described earlier as the knowledge acquisition stage in the disruption management process. The implication of this stage acting as a constraining factor is that slow diagnosis limits the ability of quick recognition or fast implementation to reduce the impact of the disruption. Increasing the speed of diagnosis does not directly affect the impact of the disruption, but instead allows the recognition or implementation stages to be more effective. This result, taken by itself, can be easily understood. A manager might discover a supply chain disruption quickly, but if the diagnosis stage takes too long because there is low confidence in the information being provided, the possible help that a quick discovery may have offered is rendered null. Similarly, if the diagnosis takes too long, a quick implementation later on cannot make up the lost time.

It is surprising that none of the other three stages act in a similar way to be a constraining factor. This means that if, for example, recognition (the first stage) is slow, working through the other stages quickly is able to make up the difference and reduce the impact of the disruption. The stages cannot make up the difference if diagnosis is slow. Reasons for this are speculative, but could include that the amount of time involved in this stage to gather the desired information (as a real measure of time) is long in comparison to the other stages. Another reason could be the carryover effects of improper or incorrect information gathering. Incorrect information could be gathered in a stressful or ambiguous disruption situation with the managers making a quick, but incorrect, decision for implementation. After a period of time, as more information is gathered, managers would realize the mistake and change course. In summary, this result ultimately suggests that if a manager has sparse resources, putting them toward improved information gathering allows the other stages to have a greater impact.

Mediation of antecedents

We looked at three latent system properties that exist prior to (and therefore are antecedents to) the disruption and resulting response process. All three affect information confidence and information processing ability in different ways. Significantly, the response process at least partially mediates all three antecedents of readiness, dependence, and complexity as they are effectively activated once the disruption event occurs and the response process begins. Only then does their effect fully engage with the supply chain. Readiness holds little value until a disruption occurs, and supplier dependence and complexity is not of concern when a supply chain is running smoothly. For example, many people are familiar with the result of a liquid "geyser" when certain candies are dropped into a 2-L bottle of soda. By itself, the soda bottle will not react. Instead, the triggering event of dropping the candy into the soda initiates the reaction of the latent soda bottle. Similarly, the disruption recovery process initiates, and mediates, the effect that readiness, dependence, and complexity are found to have on disruption impact. A final comment should be added regarding the fact that complexity is both mediated by the stages (with a negative, decreasing effect on disruption impact) and has a direct positive (increasing) effect on disruption impact. This competitive mediation situation (Zhao, Lynch, & Chen, 2010) indicates that there are additional variables (unknown to this research) that are likely mediating the relationship between complexity and the response stages.

Readiness, our internally oriented measure, is the only antecedent that directly affects the total response speed measure as well as each individual stage. This is a clear indication that readiness is valuable in reducing the time needed to work through each response stage. However, as mentioned, readiness does not directly decrease the impact of the disruption. Instead, readiness must work through the stages, which indicates a strong mediating effect of the total response stages. Prior studies that discuss readiness, mentioned in the hypothesis section, have correlated readiness and disruption impact. However, this study advances our understanding by showing causality and describing how readiness actually engages and works through the recovery process. Viewing readiness from an information processing perspective, readiness is a way to anticipate some of the processing that will be required when the disruption event occurs. For example, our survey items asked the respondents to indicate their levels of creating internal awareness, assessing the probability and impact of disruptions, improving supply disruption prevention, and engaging in contingency planning. Hence, these items measure a level of preprocessing with regards to disruptive events. This preprocessing directly speeds up the response stages, but only indirectly (through the stages) is able to reduce the impact of the disruption. With this preprocessing, readiness also provides more information confidence during the disruption recovery process, allowing for quicker decisions.

Dependence on a supplier is relationally oriented, and the first variable that has a significant worsening effect on decision-making after a disruption. Greater supplier dependence slows down response speed, and directly worsens the impact of the disruption. At the individual level, dependence specifically affects the latter two response stages by slowing down the development and implementation of the recovery decisions. It does not significantly affect the recognition or diagnosis stages. Similar to readiness, dependence has its effect on disruption impact only through the disruption stages (mediation), and not directly. We noted in the hypothesis section that connected networks take longer to process information, but that a single decision maker often surfaces during critical recoveries. However, dependence on an affected supplier forces decision makers from both firms to maintain greater levels of communication and information processing, reducing the likelihood of streamlining the latter stages of the decision-making process. Dependence also means less confidence in switching to an alternative supplier, reducing the range of alternatives available during the development and implementation stages, and providing less flexibility, a key aspect of disruption recovery. This is a serious result, and indicates that managers need to find opportunities to mitigate against this effect, whether through reduced supplier dependence or perhaps through added resources to the final stages of response when in a dependent supplier situation.

The final antecedent has a broader supply chain orientation and measures complexity. The results indicate that supply chain complexity has no effect on total response speed. However, as complexity increases, there is a significant slowdown effect on the first two stages of recognition and diagnosis. When the supply chain network is complex, there is a lot of noise and ambiguity in the information being processed. It becomes difficult for the managers to discern what is happening in the supply chain with the disruption, resulting in the slowdown of the early response stages. Similar to the driving example mentioned in the hypothesis section, managers have less confidence in the information available and "slow down." Once the signal becomes clear, the latter two stages of development and implementation are not impacted by complexity. The effect of noise or lack of information confidence is so strong that the initial recognition stage even mediates between complexity and the impact of the disruption.

These results support, and offer deeper insight, to organizational information processing. Earlier in this research, Tushman and Nadler (1978) were cited in reference to organismic and mechanistic supply chain structures. The results seem to support that complexity (which is similar to an organismic structure) has a stronger effect than the mechanistic structure that we proposed in balance. Even more specifically, this article offers insights into what parts of the recovery process are affected by this organismic structure and the resulting slowdown of information processing.

Implications for Practice

These insights offer suggestions to guide supply chain managers with their strategic decisions, with certain research study boundaries. This study explores the impact of a disruption, not total economic efficiency. Hence, it is important to carefully analyze the trade-off between costs and benefits in order to determine the true advantage of quick disruption response provided for any given supply chains. That said, at the highest level, being able to process information and recover quickly reduces the impact of disruptions. Specifically, investing in programs that aid managers' confidence in gathered information will increase the speed of moving through the decision stages and reduce the disruption impact. While the exact type of disruption is not in the control of the manager, building programs to provide timely and accurate information is.

Similarly, the antecedents looked at in this study are strategic decisions made by the managers. They can choose how dependent to allow themselves to be on suppliers, and how complex to arrange the supply chain. This study showed that the diagnosis stage can act as a bottleneck. Operating in a complex environment versus a dependent environment, makes it more likely that diagnosis could become the bottleneck by being the slowest stage, and that working quickly in the other stages will not allow the recovery to actually "catch up." Depending on the cost of disruptions for a given firm, a manager may choose instead to work toward a less complex, more dependent, supply environment to reduce the impact of disruptions. An example of this may be the chemical industry. For this industry, the cost of a failure (such as a chemical spill) is high, and may guide the manager toward less complex supply networks being preferred in order to avoid slow recognition or diagnosis of any problem.

Programs that train or aid quick implementation of decisions, especially in supply chains with greater dependence on key suppliers, will also reduce disruption impact. This result was affirmed by a senior supply chain manager from a Fortune 50 company (who was interviewed as part of this research project), which is dependent on a few key suppliers. First, this manager confirmed that moving faster reduced their disruption impact, which is why his company had documented processes and trained individuals at the constant ready. Second, with regards to supplier dependence and a supplier perspective, the manager elucidated that suppliers have no inherent means with which to understand the broader ramifications of their decisions to the operations of the customer. Suppliers, whether impacted or not, needed direction and understanding of the plans the buyer will employ. Communication of this type of information was key to mitigate some of the negative effects supplier dependence can have.

There are two additional nuanced implications for managers that the results reveal. First, for a given response team, if it is determined that the team is weak in collecting information and diagnosing the disruption, making investments to speed that response stage will allow capabilities in the other stages to have an even greater impact. This is the result seen from the constrained factor model. Second, many managers believe, either consciously or subconsciously, that preparation, training, and readiness is vital. The results confirm that in each stage, readiness speeds up the response stage and should be invested in. However, readiness does not directly change the impact of the disruption, but instead works through these individual response stages. Managers should not look for resources allocated to lessening the impact of disruptions to do so directly, but to instead see the speed of the stages as making the discernable difference.

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 relatively low response rate, (2) our inability to draw on objective data for the dependent variable in our model (speed of the response stages and disruption impact), and (3) our inability to provide strong evidence for causality, given our cross-sectional design and estimation strategy. In addition, the used response stage variables assess only response speed, which can be viewed as a proxy for confidence, but does not cover other important aspects of the response (e.g., response quality).

Besides these limitations, there are several additional directions for future research. As managers are biased information processors who differ in their modes of interpretation (i.e., the manner in which they process information in decision-making) (Ford & Baucus, 1987), it would be interesting to study response styles of firms. Referring to the analogy of shooting behavior by a marksman, some firms may prefer a "ready → aim → fire" process (bias for planning or "wait-and-see" attitude until information becomes clearer) while others prefer "ready → fire → aim" (bias for action). Additionally, there are further antecedents that could be explored that may vary the speed of the response stages and their ultimate effect on the impact that disruptions have on firms. As the disruption management process is composed of decisions made at each response stage, it would be interesting to know what decision-maker characteristics likely play a role in affecting response speed and impact. Finally, some of the results can be combined with other research. For example, this article finds that supply chain complexity leads to slower recognition and diagnosis. However, other research has looked at the effect of trust and honesty in supply chain relationships. Trust and honesty may interact with complexity to reduce its negative effect on response speed.

CONCLUSION

As managers cannot anticipate every risk scenario and not all risks can be prevented (Zsidisin, Melnyk, & Ragatz, 2005), it is important for firms to possess proper reactive disruption management and response capabilities. This research is an attempt to unravel organizational decision-making processes after a disruption occurred. The goal is to aid researchers and managers in identifying the key stages of disruption response and prioritizing the stages that will reduce the impact of disruptions.

The results from this article represent a specific call to action for supply chain managers: develop the capabilities to accurately problem-solve and assess the supply chain during times of disruptive uncertainty and limited information. Using the lens of information processing theory, we show that it is vital to invest resources in processing information and recovering quickly from disruptions as this is revealed to reduce disruption impact. Specifically, results show that within the response process, accelerated recognition and implementation reduce disruption impact, but can be rendered less effective if the information gathered and processed as part of the diagnosis stage becomes a constraining factor and is not worked through quickly. Efforts to improve risk management often result in greater readiness, which also accelerates each stage of the recovery process. These are some of the key areas on which a manager can focus.

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APPENDIX A: MEASUREMENT ITEMS AND SCALES

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.

1. *Disruption impact* (Bode et al., 2011) (formative measurement)

How did the disruption negatively affect (directly or indirectly) your business unit on the following dimensions in the short-run? (1: not at all to 5: to a very large extent)

Item 1 Procurement costs/Prices for the purchased item
Item 2 Overall efficiency of our operations
Item 3 Product quality of our final product(s)
Item 4 Responsiveness to customer demands
Item 5 Delivery reliability (on-time delivery, order accuracy)
Item 6 Sales

2. *Response speed* (single items)

During the period from the occurrence of the disruption until your business unit fully recovered, please indicate the speed with which your business unit accomplished the following sequential stages: (1: very slow to 5: very fast)

Stage 1 *Recognition*: Time to completely recognize that there is a threatening situation.
Stage 2 *Diagnosis*: Time for information gathering and interpretation of cues to gauge the magnitude, location, and causes of the disruption.
Stage 3 *Development*: Time for identification, formulation, and evaluation of a set of possible responses.
Stage 4 *Implementation*: Time for the implementation of a response and restoration of the standard or desirable state.

3. *Readiness* (reflective measurement)

Before the disruption, to what extent did your business unit pursue the following supply chain risk management activities with this supplier?

Item 1 We created internal awareness for supply disruptions and made attempts to drive this awareness to this supplier.
Item 2 We analyzed and assessed both probability and impact of potential supply disruptions.
Item 3 We improved our supply disruption prevention capabilities.
Item 4 We engaged in contingency planning to prepare for potential supply disruptions.

4. *Supplier dependence* (Jap & Ganesan, 2000) (reflective measurement)

Please indicate your opinion on the following statements referring to the relationship with this supplier:

Item 1 If our relationship with this supplier had been discontinued, we would have had difficulty achieving our goals.
Item 2 It would have been difficult for us to replace this supplier.
Item 3 We were quite dependent on this supplier.
Item 4 We did not have a good alternative to this supplier.

5. *Supply chain complexity* (reflective measurement)

Please indicate your opinion on the following statements referring to the supply chain (material, information, and financial flows) for the purchased item.

Item 1 This supply chain was very complex.
Item 2 This supply chain involved a lot of players (e.g., suppliers, logistics service providers) and/or a lot of logistics/transportation transactions.
Item 3 This supply chain was a quite intricate network.
Item 4 It was difficult to quickly get a general idea of this supply chain.

6. *Firm size* (single item)

Total number of employees in [the most recent year]?

7. *Competitive intensity* (Jaworski & Kohli, 1993) (reflective measurement)

Please indicate your opinion on the following statements concerning the market for the given product line (1: not at all to 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.

8. *Product complexity* (Cannon & Perreault, 1999; Cannon & Homburg, 2001) (reflective measurement)

Please characterize the purchased item on the following dimensions:

Item 1 Simple–Complex
Item 2 Easy to understand–Difficult to understand
Item 3 Uncomplicated–Complicated
Item 4 Unsophisticated–Sophisticated

9. *Product importance* (Cannon & Perreault, 1999; Cannon & Homburg, 2001) (reflective measurement)

Please characterize the purchased item on the following dimensions:

Item 1 Low profit impact–High profit impact
Item 2 Uncritical to our operations–Critical to our operations
Item 3 Unimportant for us–Important for us
Item 4 Low priority for us–High priority for us

10. *Reaction category* (single item)

How would you describe your business unit's response to the disruption?

Cat. 1 *Inaction*: We did not take any specific action to respond to the disruption.
Cat. 2 *Routine response*: The disruption was covered by our routine response repertoire.
Cat. 3 *Original/Nonroutine response*: We developed a new response particularly for this disruption.

APPENDIX B: INTERACTION EFFECT (MULTIPLICATIVE) MODELS

	Direct Effect Model		Interaction Effect Models: Two-way		Three-way		Four-way	
	Est	*SE*	Est	*SE*	Est	*SE*	Est	*SE*
Constant	2.79***	(.06)	2.80***	(.06)	2.81***	(.06)	2.81***	(.06)
Firm size	–.07†	(.04)	–.06	(.04)	–.06†	(.04)	–.06†	(.04)
Competitive intensity	.06†	(.04)	.08*	(.04)	.07†	(.04)	.07†	(.04)
Product complexity	.05	(.04)	.05	(.04)	.06†	(.04)	.06†	(.04)
Product importance	.07†	(.04)	.08*	(.04)	.07†	(.04)	.07†	(.04)
Reaction category[a]	.29***	(.07)	.28***	(.07)	.27***	(.08)	.27***	(.08)
Direct effects								
Stage 1: Recognition	–.09*	(.04)	–.08†	(.04)	–.12*	(.05)	–.12*	(.05)
Stage 2: Diagnosis	–.03	(.05)	–.05	(.05)	–.02	(.05)	–.02	(.05)
Stage 3: Development	–.04	(.05)	–.04	(.05)	–.04	(.05)	–.05	(.05)
Stage 4: Implementation	–.09*	(.04)	–.08†	(.04)	–.04	(.05)	–.05	(.05)
Two-way interaction effects								
Stage 1 × Stage 2			.06	(.04)	.06	(.04)	.06	(.04)
Stage 1 × Stage 3			–.01	(.05)	.01	(.06)	.01	(.06)
Stage 1 × Stage 4			.00	(.05)	.02	(.05)	.02	(.06)
Stage 2 × Stage 3			–.06	(.05)	–.08†	(.05)	–.08†	(.05)
Stage 2 × Stage 4			–.06	(.05)	–.07	(.05)	–.07	(.05)
Stage 3 × Stage 4			.03	(.04)	.02	(.04)	.01	(.04)
Three-way interaction effects								
Stage 1 × Stage 2 × Stage 3					.00	(.03)	.01	(.03)
Stage 1 × Stage 2 × Stage 4					–.03	(.04)	–.03	(.04)
Stage 1 × Stage 3 × Stage 4					.11*	(.05)	.12*	(.05)
Stage 2 × Stage 3 × Stage 4					–.07*	(.03)	–.07*	(.03)
Four-way interaction effect								
Stage 1 × Stage 2 × Stage 3 × Stage 4							.01	(.03)
R^2	.11		.13		.14		.14	
F	5.78***		4.03***		3.58***		3.39***	
ΔR^2	–		.02		.01		.00	
F of ΔR^2	–		1.35		1.77		.08	

Note. Dependent variable is *disruption impact*. OLS regression with robust standard errors was used ($n = 438$). The largest VIF in the four reported models is 3.02. Except for the categorical control variable *reaction category*, reported estimates refer to standardized regression coefficients.
†$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$ (two-tailed).
[a]"Routine response" served as the baseline category.

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