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On supplier resilience: How supplier performance, disruption frequency, and disruption duration are interrelated

Davide Burkhart *, Christoph Bode

University of Mannheim, Business School, Schloss Schneckenhof Ost, 68131, Mannheim, Germany

A R T I C L E I N F O

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A B S T R A C T

Supply chain disruptions have a well-documented detrimental impact on firm performance, and recent crises have reaffirmed this effect. While the relationship between a supplier's overall performance and the frequency and duration of supply chain disruptions is often suggested, it lacks substantial empirical evidence. We conducted three comprehensive empirical analyses using panel data involving 352 suppliers to investigate the relationship between supplier performance and supply chain disruptions. Our findings indicate a negative correlation between supplier performance and the frequency and duration of disruptions, that is, poorly performing suppliers are associated with more frequent and longer disruptions. Furthermore, disruption intensity (*disruption frequency* × *disruption duration*) exacerbates the negative impact on performance. We find that disruptions have a milder negative performance effect when they emanate from suppliers that have a history as "good performers" compared to "poor performers." A supplementary analysis shows that disruptions notably affect supplier quality. This study bears significance for practitioners and contributes to the literature on supplier resilience. Our analyses highlight that supplier performance is not only an important predictor for the occurrence of supply chain disruptions but also mitigates (i.e., moderates) the negative effects in case they occur.

1. Introduction

"*When disasters occur, major business disruptions follow*" (Tang, 2006, p. 33).

Disasters can have a long-lasting influence on firms operational strategy (Durach et al., 2023) and current geopolitical tensions are adding to the pressure on strained supply chains, many of which are still struggling to recover from the negative effects of the COVID-19 pandemic or Russia's invasion of the Ukraine. Supply chain risk management strategies are pushed beyond the limit by variabilities in supply and demand (Dohmen et al., 2023).

Supply chain disruptions are known to have a negative effect on the firms' financial performance and shareholder wealth (Hendricks and Singhal, 2003, 2005a, 2005b; Papadakis, 2006). While some supply chain disruptions might be unavoidable (Craighead et al., 2007), firms can try to limit their risk of occurrence or severity. In reaction to this, the operations management literature has dealt with mitigation strategies, such as increasing stock levels and flexible sourcing strategies (e.g., Craighead et al., 2007; Sheffi and Rice, 2005; Tang, 2006; Tomlin, 2006). Preventive approaches, addressing the antecedents of supply chain disruptions, such as complexity and the risk management approach (e.g., Bode and Wagner, 2015; Revilla and Sáenz, 2017; Wissuwa et al., 2022), or research considering both antecedents and mitigation strategies (Brandon-Jones et al., 2014), received less academic attention.

Antecedents and outcomes of disruptions at the level of the individual supplier remain largely unexplored, although academics have acknowledged that it is "useful to analyze the risk for each supplier" (Blackhurst et al., 2008, p. 153). While the concept *supplier resilience* currently receives more attention in research, most studies traditionally considered the buying firm as unit of analysis. In that regard, supplier resilience refers to the supplier's ability to detect and withstand disruptive events, and, if affected, to return quickly to normal operations (Choksy et al., 2022; Rice and Caniato, 2003; Verghese et al., 2022). Supplier resilience is contributing to the buyer's financial resilience (Durach et al., 2020) and to better buyer-relationships (Choksy et al., 2022). However, while the concept supplier resilience is being studied, it is difficult to measure, analogously to supply risks (Schoenherr et al., 2023).

To the best of our knowledge, the impact of supply chain disruptions

* Corresponding author.
E-mail addresses: burkhart@uni-mannheim.de (D. Burkhart), bode@uni-mannheim.de (C. Bode).

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on the individual buyer-experienced supplier performance has not been scrutinized empirically. In addition, and in terms of antecedents, the relationship between supplier performance and disruption frequency and durations also remained largely unexplored. Hence, considering the supplier as unit of analysis, our study aims to shed light on the interrelation of buyer-experienced supplier performance and disruptions, addressing the research question: *"How are buyer-experienced supplier performance, disruption frequency, and disruption duration interrelated?"*

After reviewing the extant empirical literature on supply chain disruptions and delineating the research gap, we develop 4 hypotheses revolving around supplier performance, disruption frequency, duration, and intensity. Based on three empirical analyses of panel data of 352 suppliers, our results suggest that supplier resilience is related to supplier performance in multiple ways. That is, prior supplier performance is negatively associated with disruption frequency and disruption duration (i.e., "bad performers" were the source of more and longer disruptions). The higher the disruption intensity (*disruption frequency* × *disruption duration*), the higher the negative impact on performance. For most of our sample, disruptions have a weaker negative performance impact on prior "good performers" than on prior "bad performers." On a more detailed level, our results also indicate that disruptions have a negative effect on supplier quality performance. Thus, our study makes a variety of contributions to the literature on supplier resilience by investigating supply chain disruptions on a supplier level and considering the impact of varying degrees of disruption frequency and duration. Our results extend the well-known disruption profile (Sheffi and Rice, 2005) by including multiple disruptions and by investigating the interrelations among performance, disruptions, and time.

2. Literature review

In the last two decades, supply chain disruptions have received ample attention by academics and practitioners. In supply chain risk management, disruption risks are distinguished from the normal supply-demand coordination risks, and relate to operational risks such as equipment malfunctions, unforeseen supply interruptions and human problems ranging from strikes to fraud, as well as risks arising from natural disasters, terrorism, and political instability (Kleindorfer and Saad, 2005; Wagner and Bode, 2006). Thus, "supply chain disruptions are unplanned and unanticipated events that disrupt the normal flow of goods and materials within a supply chain" (Craighead et al., 2007, p. 132). Given that supply-side disruption risk factors are associated with greater impact on normal business performance than customer-side factors (Bode and Wagner, 2015; Habermann et al., 2015), we focus here on risks that occur in the upstream supply chain. Those "supply disruptions" are unintended and unexpected events triggered in the network of suppliers, the inbound logistics network, or the sourcing environment and a consequential situation (e.g., supplier quality problems, delivery failures, supplier defaults, and plant fires), that significantly threatens or impairs the normal course of business operations of the focal firm (Bode and Wagner, 2015; Bode et al., 2011).

Global competition has created complex and tightly coupled interfirm networks in which disruptions to material and information flows have become normal and unavoidable (Bode et al., 2011; Craighead et al., 2007). One way for firms to address supply side factors is by simplifying their supply chains (Bode and Wagner, 2015). Besides reducing the number of suppliers in the supply base, this includes striving for a less globally distributed supply chain. Sourcing from suppliers that are more distant from the firm leads to increased uncertainty (Zsidisin and Wagner, 2010), and longer lead times on the supplier side are significantly associated with more supply chain disruption risk factors (Habermann et al., 2015). Moreover, firms can decrease the occurrence of disruptions through building reliability into their supply chains by focusing on efficient processes, the elimination of failures, and by collaborating with their suppliers (Revilla and Sáenz, 2017).

Initially, the supply chain disruption literature addressed mitigation strategies – reducing the impact of disruptions – such as increasing stock levels and flexible sourcing strategies (e.g., Craighead et al., 2007; Sheffi and Rice, 2005; Tang, 2006; Tomlin, 2006). More recently, academics focused on recovery efforts and relational outcomes of supply chain disruptions (e.g., Cheng et al., 2020; Polyviou et al., 2022; Wang et al., 2022). Focusing more on the individual supplier, recently literature also covered the concept of supplier resilience, which refers to the supplier's ability to withstand disruptive events and to return quickly to normal operations (Choksy et al., 2022; Rice and Caniato, 2003; Verghese et al., 2022). Lastly, events such as the COVID-19 pandemic or Russia's invasion of the Ukraine and its resulting disruptions gave rise to studies investigating various phenomena in that contexts, in particular associated with resilient supply chains (e.g., Dube et al., 2022; Kähkönen and Patrucco, 2022; Schoenherr et al., 2023).

While the literature on supply chain disruptions grew significantly, there remain some relevant shortcomings which require more attention. Reviewing the empirical literature reveals that many studies follow a rather qualitative approach of considering disruptions by considering "supply risks" or "disruption risks" instead of investigating concrete disruptions (e.g., Habermann et al., 2015; Parast and Subramanian, 2021; Wagner and Bode, 2008). As displayed in Table 1, the literature considers more often the buying firm than the supplier as unit of analysis, in particular when studying antecedents of supply disruptions. As mentioned before, studies are increasingly revolving around recovery efforts and relational outcomes, as well as supplier resilience. While these studies consider the supplier as unit of analysis, the (short/-long-term) impact on individual supplier performance remains unexplored. Further, empirical studies on supply chain disruptions are predominantly cross-sectional and focus either on antecedents or the impact of disruptions, as illustrated in Table 1. Finally, while the frequency of disruptions is often considered in literature, implications of the disruption duration is rarely empirically investigated, although its value for the buying firm is acknowledged (Mehrotra and Schmidt, 2021; Sheffi and Rice, 2005). Due to our unique supplier panel data, we believe we are able to address some of the highlighted important gaps in literature and, adopting the supplier as unit of analysis, shed light on the interrelation of supplier performance and concrete supply disruptions, in particular disruption frequency and disruption duration.

3. Hypotheses development

3.1. Supplier performance and supply disruptions

In general, disruptions tend to follow a specific profile in terms of their effect on a firm's performance, whether measured by sales, production rate, profit, or another relevant metric (Sheffi and Rice, 2005). Considering supply disruptions which involve an individual supplier, after a triggering event, the buyer-experienced supplier performance will drop significantly until, during the recovery process, it converges to a steady level below, above, or similar to the pre-disruption performance, as displayed in Fig. 1 (Sheffi and Rice, 2005). In this regard, buyer-experienced supplier performance is usually measured in various dimensions, such as costs, quality, delivery, innovation, or flexibility (Schoenherr and Swink, 2012), which is mostly in line with the competitive priorities framework in operations management (e.g., Krause et al., 2001; Ward et al., 1998). For the sake of our study, we focus on a performance index for supplier performance, consisting of costs, quality, and delivery. All four hypotheses of our study are displayed in Fig. 2 and revolve around the presumption of supplier performance as a proxy for supplier resilience, which is further explained below.

In practice, predicting supply disruptions poses great challenges (Blackhurst et al., 2008). Disruptions can occur out of many different reasons and some disruptions, such as those triggered by earthquakes are almost impossible to predict, and the likelihood of accidents, supply shortages, or human-centered issues such as labor strikes is also hard to

Table 1
Selected empirical literature on antecedents and impacts of supply disruptions.

Disruption stage (based on Sheffi and Rice, 2005)	Unit of analysis	Dependent variable(s)	Key variable(s)	Selected literature
Preparation/antecedents	Buyer	Disruption frequency	Supply chain complexity, compliance, interorganizational orientation, supply risk perceptions	Bode and Wagner (2015); Marley et al. (2014); Park et al. (2016); Revilla and Sáenz (2014, 2017); Zsidisin and Wagner (2010)
		Disruption frequency, disruption duration	Supplier and customer co-location, lead time	Habermann et al. (2015)
	Supplier	Disruption frequency	Supplier complexity	Wissuwa et al. (2022)
Recovery/mitigation	Buyer	Operating and financial performance	Supply chain disruptions, disruption attributes, recovery stages	Bode and Macdonald (2017); Hendricks and Singhal (2003); Macdonald and Corsi (2013); Papadakis (2006)
	Supplier	Retention/Switching intentions	Severity, alternatives, attribution, frequency, anger, justice	Bode et al. (2011); Cheng et al. (2020); Polyviou et al. (2018); Primo et al. (2007); Wang et al. (2022); Wang et al. (2014)
		Recovery performance	Governance mechanisms, power	Lee et al. (2023)
Long-term impact	Buyer	Stock price	Supply chain disruptions, equity risks	Hendricks and Singhal (2005b)
		Inventory and flexibility levels	Risk attitude, previous inventory level	Durach et al. (2023)
Interrelation of stages/ multiple stages	Buyer	Plant performance, disruption frequency	Slack resources, visibility, complexity, disruption frequency	Brandon-Jones et al. (2014)
	Supplier	(Posterior) supplier performance, disruption frequency, disruption duration	(Prior) supplier performance, disruption intensity	*This study*

Note: Although both – the buying and supplying firms – are potential units of analysis, the supply chain disruption literature primarily focuses on the buying firm's perspective.

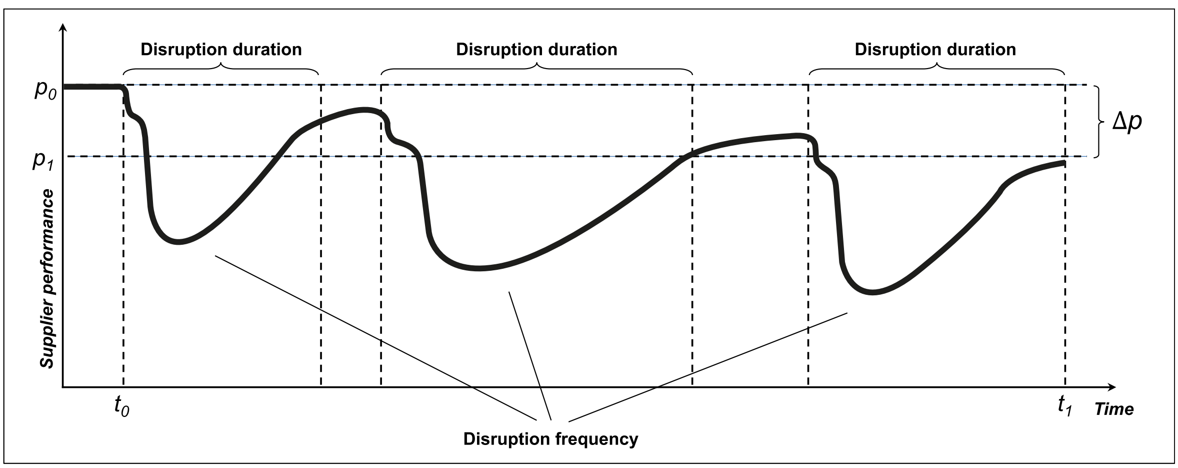

Fig. 1. Multiple disruption profiles and supplier performance.

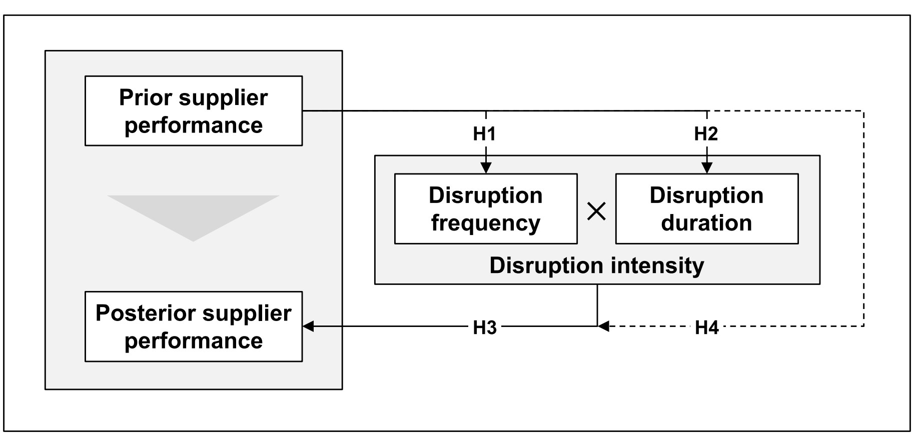

Fig. 2. Conceptual framework.

determine (Sheffi and Rice, 2005). Although arguably "[p]rior to their actual occurrence, all crises send out a repeated train of early warning signals" (Mitroff, 2000, p. 102), those signals can be hard to interpret. For example, a buyer will not experience every disruption in the upstream supply chain, and consequently at the supplier. In that regard, while the concept supplier resilience is being studied, it is difficult to measure, analogously to supply risks (Schoenherr et al., 2023).

A good performing supplier might therefore already resolve some upstream supply disruptions and serve as a buffer for buyer-experienced disruptions. In this vein, practitioners report that when disruptions are well managed, customers never know that they have occurred (Macdonald and Corsi, 2013). Further, a recent study revealed that a firm's alertness for disruptions and the learning experience from disruptions is positively related to the firm's performance (Stekelorum et al., 2023). Consequently, suppliers that perform well, will have better preconditions, by, for example, incorporating the latest technological advances in their operations and adhering to specified quality standards, which eventually result in a decreased likelihood of supply risk (Zsidisin and Ellram, 2003) through an improved ability to detect and respond to disruptions (Ambulkar et al., 2015). In turn, suppliers with incoming product problems, inherent complexity, ineffective (labor) management and financial instability, will perform worse, and thus, represent significant supply risk sources with a higher frequency of disruptions (Wagner and Neshat, 2012; Wissuwa et al., 2022; Zsidisin and Wagner, 2010). We will therefore argue that buyer-experienced (good) prior supplier performance can act as a proxy for supplier resilience. Taken together, these arguments lead to the following hypothesis:

Hypothesis 1. Supplier performance experienced by the buyer is negatively related to disruption frequency.

In addition to their frequency, the duration of disruptions is a critical determinant of system reliability (Habermann et al., 2015) and consequently the reaction of buying firms (Mehrotra and Schmidt, 2021). As displayed in Fig. 1, the buyer-experienced duration of a disruption refers to the time between the initial disruption in the usual supply (by the supplier) and the resumption of supply at a steady level of performance, regardless of being below, above or similar to the pre-disruption performance (Sheffi and Rice, 2005). Again, prior (bad) performance might act as an early warning signal (i.e., Mitroff, 2000) for longer supply disruptions. In the same vein, longer lead times on the supplier side are related to more supply disruption risk factors, such as longer disruptions (Habermann et al., 2015).

Suppliers that adopt professional supply chain management strategies not only demonstrate increased supply chain performance, but also better management of supply risks (Wagner and Neshat, 2012; Zsidisin and Ellram, 2003). These strategies include business continuity plans, which refer to defined plans for various scenarios which impair operations, such as disruptions. Business continuity planning is positively related to a firm's performance (Azadegan et al., 2020) and, as mentioned above, a firm's alertness for disruptions is also positively related to the firm's performance (Stekelorum et al., 2023). We will therefore argue that suppliers with a good prior performance, will quicker resolve a potential disruption, resulting in less severe (Craighead et al., 2007), and eventually shorter buyer-experienced supply disruptions. Taken together, these arguments lead to the following hypothesis:

Hypothesis 2. Supplier performance experienced by the buyer is negatively related to disruption duration.

3.2. Supply disruption impact

Besides identifying risks and vulnerabilities, the assessment of risks is an integral part of supply risk management, and serves to reveal the potential harm to the firm from supply disruptions (Kleindorfer and Saad, 2005). Supply disruptions can impact firms financially, through the costs incurred as a result of the disruption, and in terms of services, as suppliers cannot devote as much attention to meeting customer demand as they would in a normal operating environment (Macdonald and Corsi, 2013). Thus it comes as no surprise that, a firm's dissatisfaction with a supplier increases with the impact of a disruption (Primo et al., 2007) which then affects the buying firm's reaction (Bode et al., 2011). Therefore, the impact of a disruption is an important information that a firm interprets (Primo et al., 2007). In that regard, the disruption impact is usually measured (indirectly) as negative performance effects, such as the impact on delivery performance, quality, costs, cycle times, or efficiency (e.g., Bode and Macdonald, 2017; Bode et al., 2011; Brandon-Jones et al., 2014).

As shown in Fig. 1, we will argue that both the duration and the frequency of a disruption are detrimental to performance. Frequent supply disruptions are related to a negative impact on the buying firm's plant operating performance (Brandon-Jones et al., 2014). Multiple supply disruptions, even short ones, might pile up (Fig. 1), harming the supplier's internal and external processes, and lead to lasting problems with supplier quality, poor delivery performance, or fluctuations in capacity. In that sense, those consequences could be comparable to those caused by a single severe disruption. Therefore, we characterize *disruption intensity* as a measure of disruption severity over a period of time, which takes into account both the duration and the frequency of a disruption.

As mentioned before, disruptions are known to have a negative impact on a firm's operational performance (Brandon-Jones et al., 2014; Hendricks and Singhal, 2005a), and negative effects increase with the severity of the impact (i.e., intensity), such as dissatisfaction (Bode et al., 2011; Primo et al., 2007). Consequently, disruption intensity will have negative effects on buyer-experienced supplier performance. Taken together, these arguments lead to the following hypothesis:

Hypothesis 3. Disruption intensity experienced by the buyer is negatively related to supplier performance.

Buyer-experienced (good) prior supplier performance is potentially related to less supply disruptions, as argued before. Yet, some supply disruptions are unavoidable (Craighead et al., 2007). The preconditions of higher performing (resilient) suppliers, that hasten the detection of disruptions and the initiation of countermeasures, might also result in less severe disruptions (Ambulkar et al., 2015; Craighead et al., 2007; Durach et al., 2020). Not only faster detection, but also predefined strategies (e.g., business continuity plans) for handling those disruptions are more likely to be associated with recovery efforts that lead to a positive perception of performance (Macdonald and Corsi, 2013). In that regard, firms which analyze thoroughly past supply disruptions and how they could have been avoided, are associated to have a higher (economic and environmental) performance (Stekelorum et al., 2023). Thus, even when higher performing suppliers are disrupted, the negative impact on performance will be weaker (e.g., due to better recognition and recovery processes) than with lower-performing suppliers facing similar severe disruptions. Therefore, as illustrated in our conceptual framework shown in Fig. 2, we argue that buyer-experienced (good) prior supplier performance both prevents disruptions (i.e., reduces their probability), and mitigates (i.e., moderates) the impact of those disruptions. Taken together, these arguments suggest the following hypothesis:

Hypothesis 4. The negative impact of disruption intensity on posterior supplier performance experienced by the buyer is negatively moderated by prior supplier performance; the better the prior supplier performance, the less the impact.

4. Data and measures

4.1. Data collection

To examine the hypothesized relationships between supplier performance, disruption duration, and disruption frequency, we compiled a unique supplier panel dataset. The data stem from a heterogenous set of 352 suppliers, distributed worldwide and from various industries (Table 2), all of which supply to the same focal buying firm. The 352 suppliers are the firm's top suppliers, which collectively capture 80% of the direct spend, and thus are subject to annual performance

Table 2
Sample characteristics.

Material group	n	%	Country	n	%
Machined/Unmachined parts	65	18.47%	Germany	166	47.16%
Weldments/Springs/Knifes	63	17.90%	France	48	13.64%
Hydraulics	38	10.80%	Italy	30	8.52%
Power train/Drivelines	33	9.38%	Hungary	16	4.55%
Electrics/Electronics	33	9.38%	India	11	3.13%
Tires/Rims/Bearings	25	7.10%	USA	9	2.56%
Power Pac	24	6.82%	Netherlands	9	2.56%
Production materials/Filters/Belts	21	5.97%	Poland	8	2.27%
Coatings/Paintings/Plastics	21	5.97%	Czechia	7	1.99%
Cabins	15	4.26%	Slovakia	6	1.70%
Steel	14	3.98%	Russia	6	1.70%
			Belgium	6	1.70%
			United Kingdom	5	1.42%
			Türkiye	5	1.42%
			Other	20	5.68%
∑	352	100%	∑	352	100%

evaluations. The buying firm is a German manufacturing (large industrial machinery) business-to-business company with subsidiaries in Europe, Asia and America, a total turnover of over 4 billion Euro, and more than 10,000 employees worldwide. Due to the large industrial machines the firm produces, the volumes procured at suppliers are relatively low and mostly single-sourced. As a consequence, any supply disruption might have a high impact on the firm's operations and eventually its financial results, providing a suitable context to study individual supply disruptions and their characteristics (i.e., impact, frequency, and duration). Further, by focusing on the supplier base of one firm, we reduce the range of extraneous variations that might influence the variables of interest and ensure that factors such as market position, corporate culture, or supplier management policy are held constant over the entire sample, which should improve the internal validity of our findings (Chen et al., 2016; Subramani and Venkatraman, 2003). Relevant variables of the dataset include the supplier's location, material group, strategic importance, and the performance evaluation (from the perspective of focal buying firm) on costs, quality, and delivery over a two-year horizon (i.e., two data-points per supplier).

This panel data was complemented with data collected from analyzing protocols of weekly supply situation calls with the heads of the logistics and purchasing departments of the focal buying firm, and the statements of lead buyers. Between March 2020 and January 2021, 69 of the 352 suppliers were associated with a total of 109 disruptions varying in duration, which hit the focal buying firm. As previously defined, a disruption in the dataset refers to an unexpected event at the individual supplier and a subsequent deviation of a magnitude severe enough to be discussed in the weekly supply situation calls. Although the reason of all of these supply disruptions could not be identified, Table 3 shows the frequency of selected recorded reasons from the supply situation calls, including sub-supplier issues, quarantined personnel, and missing steel with varying mean disruption durations.

Table 3
Selected reasons mentioned for supply disruptions.

Reason	n	%	Disruption duration (weeks)	
			M	SD
Sub-supplier issues	14	36.84%	3.79	2.96
Quarantined staff	9	23.68%	7.07	5.60
Production capacity issues	6	15.79%	7.60	13.15
Lockdown/shutdown	4	10.53%	5.50	3.51
Transport issues	2	5.26%	9.25	10.25
Steel missing	2	5.26%	2.50	0.71
∑	37	100.00%		

4.2. Measures

4.2.1. Dependent variables

The dependent variables of our empirical analyses are disruption frequency, disruption duration, and posterior supplier performance. *Disruption duration* (DD) is the amount of time (in weeks per supplier) a disruption took. *Disruption frequency* (DF) refers to the count of disruptions per supplier in the 11-month time window from March 2020 to January 2021. For disruptions to be considered separate events, there had to be an interval of at least two weeks of normal business operations between them to ensure that they are not directly related to the other. To measure *posterior supplier performance* (P_1), we use "supplier overall performance," a yearly index calculated as the arithmetic mean (unweighted average) of three supplier performance dimensions: costs, quality, and delivery, which also form the main part of the competitive priorities framework in operations management (e.g., Krause et al., 2001; Ward et al., 1998). The cost performance index reflects, cost savings and development cost plans. Quality performance is also an index measure and includes product quality in parts per million, supply quality, disturbance rates, and quality management systems. The delivery performance index considers delivery time and quantity accuracy, and delivery disturbance rates. More details on the calculation basis for the performance indicators can be found in the supplementary materials. The performance indicators are used in practice by the focal company and are based on reports from the ERP system which are compiled annually into the respective performance indices. All three supplier performance variables, and consequently overall supplier performance, are measured on a 0 to 100 scale, with 100 being the best score. For posterior supplier performance, we use the 2021 value of this index.

4.2.2. Independent variables

The independent variables of our empirical analyses are prior supplier performance and disruption intensity. For *prior supplier performance* (P_0) we use the 2019 value of the supplier overall performance index described above (i.e., the arithmetic mean of the dimensions costs, quality, and delivery). Finally, *disruption intensity* (DI) measures the disruption severity over a period of time for the supplier and was calculated as the product of disruption frequency and mean disruption duration (i.e., measured in weeks).

4.2.3. Control variables

We use several control variables for our empirical analyses: Strategic importance, material group, and national lockdown. *Strategic importance* (SI) refers to the importance of the individual supplier to the focal firm, measured on a 4-point rating scale ranging from 1 = "supplier with no potential" to 4 = "strategic supplier." We included this variable as a control variable because strategic suppliers might allocate more resources and attention to the focal firm which might influence the frequency and duration of a disruption. In turn, when strategic suppliers are facing severe disruptions, the impact on performance might be stronger and more critical to the buying firm (Craighead et al., 2007).

The *national lockdown* (NL) variable aims at considering the effects of governmental decisions such as production shutdowns (Choksy et al., 2022). While production facilities in many countries in our sample, like the UK, the US, and Germany stayed open, other countries closed their non-essential shops, factories and other businesses for multiple weeks (e.g., 8 weeks in France and 3 weeks in India; Ahmed, 2020; Salaün and Lough, 2020) to slow the spread of COVID-19. With regard to disruption duration, the national lockdown variable is also measured in weeks, so we assigned the number of production shutdown weeks based on the country for each supplier. Countries where there was no production shutdown (e.g., UK, Germany) were assigned the value 0 for the national

Table 4
Descriptive statistics and correlations.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Strategic importance	–						
(2) National lockdown	−0.10	–					
(3) Disruption frequency	−0.01	0.10	–				
(4) Disruption duration	0.01	0.03	0.45***	–			
(5) Disruption intensity	0.00	0.02	0.59***	0.93***	–		
(6) Prior supplier performance	0.19***	−0.22***	−0.19***	−0.13*	−0.12*	–	
(7) Posterior supplier performance	0.13*	−0.13*	−0.28***	−0.20***	−0.22***	0.56***	–
Minimum (*Min*)	1.00	0.00	0.00	0.00	0.00	40.72	39.12
Maximum (*Max*)	4.00	8.00	4.00	31.00	32.00	98.91	100.00
Mean (*M*)	3.37	1.96	0.31	0.78	1.07	80.42	79.87
Standard deviation (*SD*)	0.78	3.25	0.71	2.68	3.53	9.91	9.76

Note: Pearson product-moment correlation coefficients are shown below the diagonal ($n = 352$); $*p < 0.05$, $**p < 0.01$, $***p < 0.001$ (equals $|r| > 0.10$, 0.14, and 0.17, respectively).

shutdown variable.

Finally, we included the *supplier's material group* (MG) at the focal firm as a control variable to consider, for example, industry effects and varying category strategies, which could influence the supplier's performance, and the frequency and duration of the disruption.

5. Analyses and results

Given that the hypotheses address three dependent variables (Fig. 2), we report our results in three analyses: Analysis 1 investigates the effects of prior supplier performance on disruption frequency (Hypothesis 1); Analysis 2 scrutinizes the effects of prior supplier performance on disruption duration (Hypothesis 2); and Analysis 3 focuses on the impact of disruptions on the supplier's performance (Hypothesis 3) and the moderating effect of prior supplier performance (Hypothesis 4). As is common with longitudinal data, we faced minor issues with missing data. Although the focal buying firm meticulously measures supplier performance, for posterior supplier performance (P_1), 20 of the 352 suppliers were rated on their quality and delivery performance only, but not on their costs performance. Following methodological recommendations, we neither imputed the missing values, nor list-wise deleted the data of the 20 suppliers, but calculated the overall performance based on two posterior supplier performance items (Newman, 2014). Table 3 presents the descriptive statistics and bivariate correlations for all dependent, independent, and control variables. Robustness analyses (e.g., regarding other approaches handling the missing data) are discussed at the end of this section.

5.1. Analysis 1 – prior supplier performance and disruption frequency

Considering that the dependent variable at hand (*disruption frequency*, DF) takes on only non-negative discrete values, the first hypothesis is best investigated using count regression. The common starting point of a count regression is the Poisson regression, yet actual data usually has too much variability (i.e., overdispersion) to be represented by standard Poisson regression (Coxe et al., 2009). In our case, the mean value of our dependent variable is lower than its variance ($M_{DF}/\sigma_{DF} = 0.61$) and a subsequent likelihood ratio test (Cameron and Trivedi, 1986; Hilbe, 2011) revealed a statistically significant ($p < 0.001$) overdispersion in the data. To account for the overdispersion, we followed prior studies (e.g., Bellamy et al., 2014; Bode and Wagner, 2015) and adopted a negative binomial model, which assumes that there will be unexplained variability among individuals who have the same predicted value (Coxe et al., 2009). Further, a comparison of the predicted and actual probabilities indicated that the negative binomial model fits the probability mass better than the standard Poisson model, a zero-inflated Poisson model, or a zero-inflated negative binomial model (Long and Freese, 2006). Therefore, we estimated the following two models:

$$lnE(DF_i|\bullet) = b_0 + b_1SI_i + b_2NL_i + \sum_{k=1}^{10} b_{3,k}\, MG_{k,i} + \varepsilon_i \tag{1}$$

$$lnE(DF_i|\bullet) = b_0 + b_1SI_i + b_2NL_i + \sum_{k=1}^{10} b_{3,k}\, MG_{k,i} + b_4P_{0,i} + \varepsilon_i \tag{2}$$

Following a hierarchical approach, we entered our control variables as a block in model 1, followed by the main effect variables in model 2. Based on likelihood ratio tests, the model fit increased and model 2 was statistically significant ($p < 0.05$). No indications for multicollinearity were found, zero-order correlations among the variables were relatively low, and variance inflation factors ($VIF_{max} = 1.77$) were below the commonly suggested thresholds for all models (Cohen et al., 2003). Our results are reported in Table 5.

The results of model 1 indicate that various material groups have a statistically significant influence on disruption frequency. Including our independent variable prior supplier performance in the full model 2, suppliers of the material group "machined/unmachined parts" were still statistically significant less often disrupted than the other material groups ($b_{3,4} = -1.04$, $p < 0.05$). Further, buyer-experienced prior supplier performance has a statistically significant negative effect on the frequency of disruptions ($b_4 = -0.04$, $p < 0.01$). That means, that better performing suppliers in our sample are less often disrupted, and poorly performing suppliers are more often disrupted. Fig. 3 shows the corresponding plot and indicates that the relationship between supplier performance and disruption frequency is not constant over the observed value range. A performance increase could be especially beneficial at poorly performing suppliers as the frequency of disruptions increases not linearly with decreasing supplier performance.

Given that our regression results in Table 5 cannot be interpreted directly as marginal effects (Hoetker, 2007), we additionally computed the marginal effects of prior supplier performance on disruption frequency using the delta method. In this regard, the marginal effect of a predictor is the expected rate of change in the dependent variable as a function of the change in the specified predictor, maintaining the values of the other predictors (i.e., control and independent variables) at some constant value (Hilbe, 2011). As shown in Table 6, the (unstandardized) marginal effect of prior supplier performance on disruption frequency is −0.013. While this might not seem much on an individual supplier basis, each percent difference in performance of the whole 352 supplier sample relates to an average of 4.58 disruptions in the 11-month time frame. Taken together, the results of our first analysis provide empirical support for Hypothesis 1.

5.2. Analysis 2 – prior supplier performance and disruption duration

In our second analysis, the dependent variable is *disruption duration* (DD), and we investigated whether prior bad performing suppliers are

Table 5
Results of negative binomial regression.

Variables	Model 1: Control variables			Model 2: Main effect		
	b	SE	CI	b	SE	CI
Constant	−0.36	0.67	[−1.64; 0.93]	2.56*	1.11	[0.29, 4.93]
Controls						
Strategic importance	−0.06	0.16	[−0.37; 0.26]	0.03	0.16	[−0.29, 0.35]
National lockdown	0.06	0.04	[−0.02; 0.13]	0.04	0.04	[−0.04, 0.12]
Material group						
Electrics/ Electronics	−0.32	0.50	[−1.30; 0.65]	−0.21	0.48	[−1.17, 0.75]
Cabins	−0.55	0.66	[−1.88; 0.74]	−0.67	0.66	[−1.99, 0.62]
Weldments/ Springs/Knifes	−1.00*	0.47	[−1.93; −0.10]	−0.83†	0.47	[−1.76, 0.07]
Machined/ Unmachined parts	−1.02*	0.46	[−1.94; −0.13]	−1.04*	0.46	[−1.95, −0.15]
Production materials/ Filters/Belts	−1.42†	0.74	[−3.05; −0.04]	−1.16	0.75	[−2.79, 0.22]
Steel	−1.41	0.88	[−3.42; 0.20]	−1.30	0.85	[−3.31, 0.29]
Hydraulics	−0.75	0.51	[−1.78; 0.25]	−0.65	0.51	[−1.68, 0.34]
Power Pac	−0.87	0.60	[−2.09; 0.29]	−0.92	0.60	[−2.13, 0.23]
Coatings/ Paintings/ Plastics	−1.38†	0.70	[−2.84; −0.07]	−1.12	0.72	[−2.59, 0.20]
Tires/Rims/ Bearings	−0.82	0.59	[−2.01; 0.32]	−0.68	0.58	[−1.87, 0.46]
Main effect						
Prior supplier performance				−0.04**	0.01	[−0.07, −0.01]
–Log Likelihood	240.48			235.86		
Likelihood ratio (χ^2)	13.27			22.51*		
$\Delta\chi^2$	–			9.24**		
McFadden's Pseudo R^2	0.03			0.05		
Cragg–Uhler (Nagelkerke) Pseudo R^2	0.05			0.08		

Note: Negative binomial regression was used ($n = 352$). Dependent variable is *disruption frequency* (count of disruptions during a 11-month period). "Power train/Drivelines" served as the baseline material group. Table shows regression estimates (*b*), standard errors (*SE*) and bootstrapped (1000 reps) 95%-confidence intervals (*CI*). †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

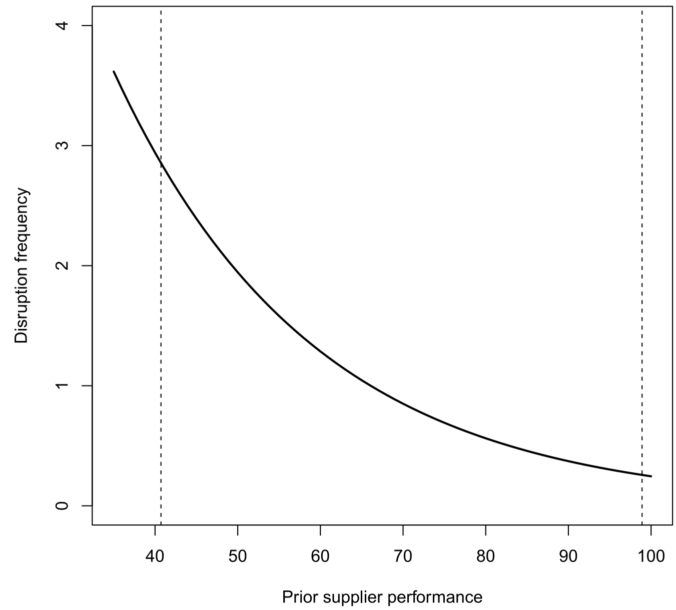

Fig. 3. Direct effect of prior supplier performance on disruption frequency
Note: Dashed lines indicate minimum and maximum values of the observed independent variable. "Power Train/Drivelines" served as the baseline material group; all other control variables were kept at their mean.

Table 6
Marginal effect of prior supplier performance on disruption frequency.

Variable		Unstandardized (change per 1 unit)		
		δy/δx	SE	CI
Prior supplier performance	Marginal effect at mean	−0.011 **	0.004	[−0.018, −0.004]
	Average marginal effect	−0.013 *	0.005	[−0.023, −0.003]

Note: Table shows marginal effects (based on estimates of Model 2) calculated using the delta method, standard errors (SE), and bootstrapped (1000 reps) 95%-confidence intervals (CI). *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

linked to longer disruptions. Considering the continuous correlated multilevel data – as some suppliers in our sample were source of more disruptions (Table 4) with various durations – we opted for a linear mixed-effects regression. Mixed-effects regressions incorporate both random and fixed effects in a linear expression with which the conditional mean of the response can be assessed (Luke, 2017). This approach allows us to model the independent variable and the control variables as fixed effects in addition to the supplier as a random effect to account for the within-subject variance. Thus, we estimated (each) disruption duration with the following model (indices: j = disruption; i = supplier):

$$DD_{j,i} = \gamma_0 + \gamma_1 SI_i + \gamma_2 NL_i + \sum_{k=1}^{10} \gamma_{3,k} MG_{k,i} + \gamma_4 P_{0,i} + u_i + \varepsilon_{j,i} \quad (3)$$

Consistent with methodological recommendations (Luke, 2017), we fitted the model using a restricted maximum likelihood (REML) estimator and derived p-values using the Satterthwaite approximation. The results are presented in Table 7.

Overall, the mixed-effects model explains 16% of the variance in each disruption duration. While the results do not suggest statistically significant influences of the supplier's strategic importance or material group, there is a statistically significant effect of prior supplier performance on our dependent variable. In this regard, every additional percent in prior supplier performance decreases each disruption duration and thus supports Hypothesis 2 ($\gamma_4 = -0.04, p < 0.05$). That means on average a 25% difference in individual buyer-experienced supplier performance relates to one week of disruption duration for every disruption. Finally, the effect of the duration of the national lockdowns (i.e., production shutdowns) on disruption duration was not statistically different from zero, maybe due to pre-existing inventory for the relevant weeks of the shutdown or a possible delivery from a different location.

5.3. Analysis 3 – disruption intensity and posterior supplier performance

Now, we investigate the relationship between disruption intensity and posterior supplier performance (P_1) and ask whether prior supplier performance (P_0) moderates this relationship. As our panel data only includes two observations per supplier for the focal firm, we applied a pooled ordinary least squares (OLS) regression with our supplier panel data to test our predictions (Hypotheses 3 and 4) (Baltagi, 2005; Baltagi and Griffin, 1997). There are discussions whether including a lagged dependent variable as an independent variable is appropriate in an OLS regression, as they can suppress the explanatory power of other independent variables (Achen, 2000). In turn, other studies encourage

Table 7
Results of mixed effects regression.

Variables	Model 3		
	γ	*SE*	*CI*
Constant	3.35*	1.49	[0.51, 6.37]
Controls			
Strategic importance	0.13	0.21	[−0.29, 0.55]
National lockdown	0.00	0.05	[−0.10, 0.10]
Material group			
Electrics/Electronics	0.15	0.70	[−1.20, 1.49]
Cabins	−0.22	0.91	[−2.05, 1.60]
Weldments/Springs/Knifes	0.83	0.62	[−0.37, 2.04]
Machined/Unmachined parts	0.02	0.61	[−1.19, 1.28]
Production materials/Filters/Belts	0.24	0.85	[−1.47, 2.00]
Steel	−0.57	0.97	[−2.47, 1.40]
Hydraulics	0.36	0.70	[−1.04, 1.81]
Power Pac	0.26	0.79	[−1.33, 1.78]
Coatings/Paintings/Plastics	−0.23	0.83	[−1.93, 1.35]
Tires/Rims/Bearings	1.25	0.78	[−0.21, 2.82]
Main effect			
Prior supplier performance	−0.04*	0.02	[−0.07, −0.01]
Conditional R^2	0.16		
Marginal R^2	0.03		

Note: Restricted maximum likelihood (REML) estimator was used (*observations* = 392, *groups* = 352). Dependent variable is *disruption duration* (duration of a single disruption). "Power Train/Drivelines" served as the baseline material group. Table shows regression estimates (*γ*), standard errors (*SE*) and bootstrapped (1000 reps) 95%-confidence intervals (*CI*). R^2 were calculated following Nakagawa and Schielzeth (2013). †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

including lagged dependent variables in OLS regressions to address residual serial correlation, which is common in time series data (Keele and Kelly, 2006). In case the relationships analyzed are to some extent dynamic, OLS with a lagged dependent variable provides estimates that are superior to other models or estimators (i.e., general least squares) even in the presence of minor residual auto correlation (Keele and Kelly, 2006). Eventually, we estimated the following models with an OLS estimator in hierarchical order:

$$P_{1,i} = \beta_0 + \beta_1 SI_i + \beta_2 NL_i + \sum_{k=1}^{10} \beta_{3,k} MG_{k,i} + \varepsilon_i \tag{4}$$

$$P_{1,i} = \beta_0 + \beta_1 SI_i + \beta_2 NL_i + \sum_{k=1}^{10} \beta_{3,k} MG_{k,i} + \beta_4 P_{0,i} + \beta_5 DI_i + \varepsilon_i \tag{5}$$

$$P_{1,i} = \beta_0 + \beta_1 SI_i + \beta_2 NL_i + \sum_{k=1}^{10} \beta_{3,k} MG_{k,i} + \beta_4 P_{0,i} + \beta_5 DI_i + \beta_6 P0_i \times DI_i + \varepsilon_i \tag{6}$$

As shown in Table 8, control variables were entered as a block in model 4, followed by the main effect variables in model 5, and the interaction effect in model 6. While the control variables in model 4 already explained about 13% of the variance of the dependent variable, including the independent variables in model 5 significantly increased the explained variance by 29% ($p < 0.001$) and enhanced the model fit. However, including the interaction term in model 6 did not improve the explained variance compared to model 5 in a statistically significant way ($p > 0.05$). We found no indications of multicollinearity as zero-order correlations and variance inflation factors of the included variables were low ($VIF_{max} = 1.27$), and thus, below the commonly suggested thresholds (Cohen et al., 2003).

In model 5, we investigate the direct effect of disruption intensity on posterior supplier performance. Our results reveal that disruption intensity has a negative impact on posterior supplier performance. The longer and more often a supplier is associated with a disruption, the larger the impact on its buyer-experienced posterior performance, supporting Hypothesis 3 ($\beta_5 = -0.47, p < 0.001$). Unsurprisingly, prior supplier performance – as a lagged dependent variable – has a statistically significant influence on posterior supplier performance ($\beta_4 = 0.52$, $p < 0.001$). Further, the supplier performance of various material groups, including "Power Pac," "Coatings/Paintings/Plastics," and "Tires/Rims/Bearings" deteriorated in the two-year time frame with the

Table 8
Ordinary least squares regression results.

Variables	Model 4: Control variables			Model 5: Main effects			Model 6: Interaction effect		
	β	SE	CI	β	SE	CI	β	SE	CI
Constant	76.02***	2.80	[70.5, 81.53]	38.78***	3.92	[31.06, 46.5]	39.52***	4.04	[31.57, 47.47]
Controls									
Strategic importance	1.48*	0.64	[0.22, 2.75]	0.34	0.54	[−0.72, 1.39]	0.36	0.54	[−0.70, 1.41]
National lockdown	−0.30†	0.16	[−0.6, 0.01]	0.03	0.13	[−0.23, 0.29]	0.03	0.13	[−0.23, 0.29]
Material group									
Electrics/Electronics	1.25	2.29	[−3.25, 5.74]	0.79	1.87	[−2.88, 4.46]	0.69	1.87	[−2.99, 4.37]
Cabins	−3.53	2.90	[−9.23, 2.17]	−3.46	2.37	[−8.12, 1.19]	−3.49	2.37	[−8.15, 1.17]
Weldments/Springs/Knifes	1.41	2.00	[−2.52, 5.33]	−0.66	1.64	[−3.89, 2.57]	−0.65	1.64	[−3.89, 2.58]
Machined/Unmachined parts	−2.17	1.99	[−6.08, 1.74]	−3.05†	1.62	[−6.24, 0.15]	−3.04†	1.63	[−6.24, 0.16]
Production materials/Filters/Belts	4.05	2.59	[−1.05, 9.15]	0.65	2.13	[−3.55, 4.84]	0.64	2.13	[−3.56, 4.83]
Steel	−7.71**	2.96	[−13.54, −1.87]	−8.10***	2.42	[−12.87, −3.34]	−8.16***	2.42	[−12.93, −3.40]
Hydraulics	3.74†	2.21	[−0.61, 8.09]	2.30	1.81	[−1.26, 5.86]	2.27	1.81	[−1.29, 5.83]
Power Pac	−4.49†	2.50	[−9.41, 0.42]	−4.16*	2.04	[−8.18, −0.15]	−4.12*	2.04	[−8.14, −0.10]
Coatings/Paintings/Plastics	−1.64	2.59	[−6.74, 3.47]	−6.39**	2.15	[−10.62, −2.17]	−6.36**	2.15	[−10.59, −2.13]
Tires/Rims/Bearings	−4.50†	2.46	[−9.34, 0.33]	−5.05*	2.01	[−9.00, −1.09]	−5.24*	2.03	[−9.22, −1.25]
Main effects									
Prior supplier performance				0.52***	0.04	[0.44, 0.61]	0.52***	0.05	[0.42, 0.61]
Disruption intensity				−0.47***	0.12	[−0.70, −0.24]	−1.39	1.20	[−3.75, 0.98]
Interaction effect									
Prior supplier performance × Disruption intensity							0.01	0.02	[−0.02, 0.04]
F	4.15***			17.62***			16.47***		
R^2	0.13			0.42			0.42		
ΔR^2	–			0.29			0.00		
F of ΔR^2	–			86.02***			0.59		

Note: OLS regression was used ($n = 352$). Dependent variable is *posterior supplier performance*; "Power Train/Drivelines" served as the baseline material group, reported estimates (*β*) and standard errors (*SE*) refer to unstandardized regression coefficients. *CI* refers to bootstrapped (1000 reps) 95%-confidence intervals. †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

largest negative impact for steel suppliers ($\beta_{3,6} = -8.10, p < 0.001$).

As mentioned above, the inclusion of the interaction effect did not improve the explained variance in a statistically significant fashion. While the direct effect of prior supplier performance on the dependent variable remains statistically significant different from zero, the results in Table 8 indicate that the direct effect of disruption intensity and the interaction effect are not statistically significant ($p > 0.05$). Yet, this does not necessarily mean that there is no interaction effect present; the interaction effect (and the resulting slopes) might only be statistically significant at certain values of prior supplier performance (Brambor et al., 2006). A following floodlight analysis (Spiller et al., 2013) illuminating the entire range of prior supplier performance in Fig. 4 reveals that there is in fact a conditional relationship: When prior supplier performance is inside the interval [54.09; 86.38] (covering 68% of the sample), the slope of disruption intensity is statistically significant different from zero ($p < 0.05$). The results even indicate that high performing suppliers (*Performance* > 86%) might not be affected at all by disruptions in their relevant performance metrics at the focal firm. The plotted regression surface of model 6 in Fig. 5 supports this relationship, the slope of prior low performing suppliers facing severe disruptions is much steeper than the slope of high performing suppliers. Taken together, for 98.9% of the sample ($P0 \in [54.09; 98.91]$), prior supplier performance moderates the influence of disruption intensity on posterior supplier performance up to statistically insignificance of the interaction with disruption intensity, resulting in partial support for Hypothesis 4.

5.4. Post-hoc analyses and robustness checks

As mentioned at the beginning of this section, we performed additional analyses to ensure the robustness of our results by testing (1) a sub-sample, (2) different measures for our dependent variables, (3) alternative estimation approaches, and (4) alternative dependent variables.

First, following methodological recommendations (Newman, 2014), we neither imputed the missing values, nor list-wise deleted the data of the 20 suppliers with missing posterior cost performance values. Yet, for our robustness check, we list-wise deleted those suppliers (leading to a sample of $n = 332$) and performed the three analyses of this section. Besides slightly differing coefficient values and model fits, we obtained qualitatively similar results.

Second, regarding the count of disruptions, we earlier stipulated that

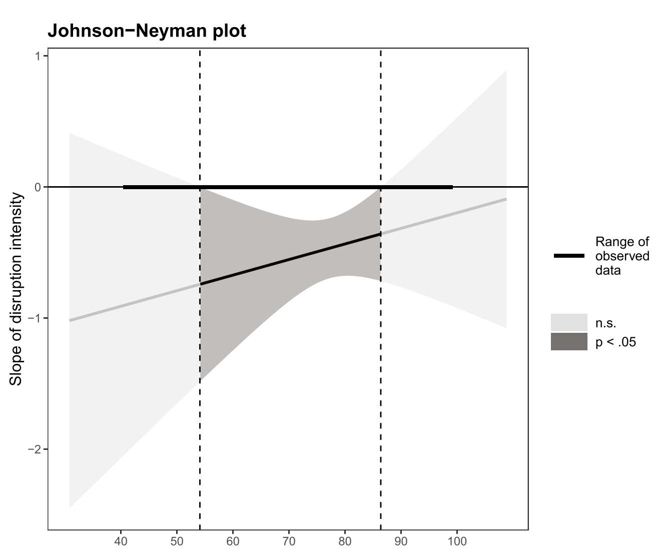

Fig. 4. Johnson-Neyman plot of prior supplier performance and disruption intensity.

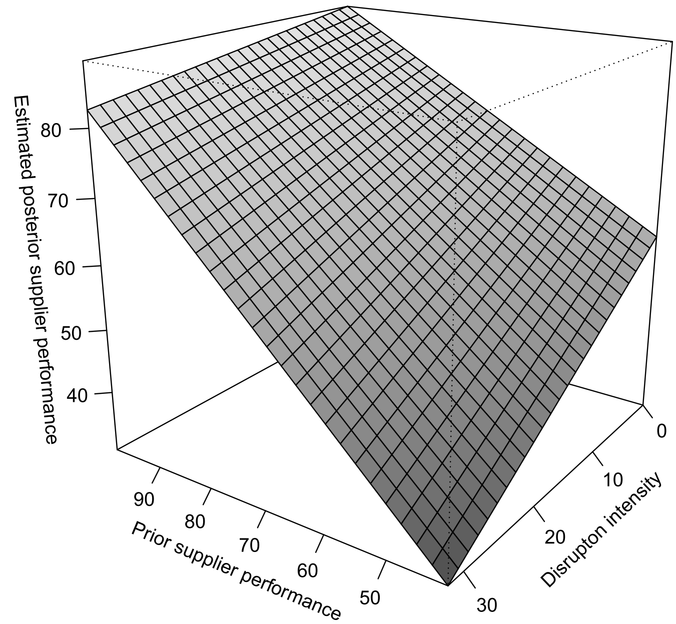

Fig. 5. Moderating effect of prior supplier performance on disruption intensity.

there had to be at least two weeks of regular performance between disruptions for those disruptions to be considered separate events. In further analyses, we required either one or three weeks of regular supplier performance between disruptions. The results for our three analyses are consistent with our original results.

Third, supplementary OLS regressions for the first two analyses (negative binomial count regression and mixed-effects regression) produce consistent results in terms of the coefficients' signs and statistical significance. The computed alternative models 1_{alt}, 2_{alt}, and 3_{alt} were all statistically significant ($p < 0.05$) and explained 5%, 13%, and 7% of the variance in the respective dependent variable (disruption frequency and disruption duration).

Finally, in additional analyses, we investigated the relationships of supplier performance and disruptions on a more granular level. Following the same procedure as in analysis 3 and focusing on prior and posterior supplier quality and supplier delivery performance, the results presented in Table 9 and Table 10 reveal that disruption intensity has a statistically significant negative effect on supplier quality performance (model 5a and model 5b, $p < 0.01$). Again, prior performance moderates this relationship for most of the sample, especially suppliers with a prior good quality performance (>80%; Fig. 6) seem to be barely affected by disruptions in their quality performance (Fig. 7), while the impact on prior bad performer is detrimental. Compared to the other performance dimensions in the dataset (i.e., cost and delivery), the negative effect of disruptions was the largest for supplier quality performance. Additional analyses on cost, quality, and delivery performance level can be found in the supplementary materials appendix.

6. Discussion

This study contributes to a better understanding of supplier resilience by investigating the interrelation of supply disruptions and supplier performance, as experienced by the buyer. In essence, intuition holds that disruptions hurt supplier performance, yet prior supplier performance plays a significant role in this relationship, even before the disruption occurs. The results of our three empirical analyses support our predictions and have several important theoretical and managerial implications.

Table 9
Ordinary least squares regression results of supplier quality performance.

Variables	Model 4a: Control variables			Model 5a: Main effects			Model 6a: Interaction effect		
	β	SE	CI	β	SE	CI	β	SE	CI
Constant	81.19***	4.93	[71.49, 90.88]	48.51***	5.58	[37.54, 59.48]	50.03***	5.67	[38.88, 61.17]
Controls									
Strategic importance	0.37	1.13	[−1.86, 2.60]	−0.28	1.00	[−2.24, 1.67]	−0.30	0.99	[−2.26, 1.65]
National lockdown	−0.24	0.28	[−0.78, 0.30]	0.21	0.25	[−0.27, 0.70]	0.21	0.25	[−0.27, 0.69]
Material group									
Electrics/Electronics	1.00	4.02	[−6.91, 8.90]	1.96	3.52	[−4.97, 8.88]	1.95	3.51	[−4.96, 8.86]
Cabins	−8.26	5.10	[−18.28, 1.76]	−7.91†	4.46	[−16.68, 0.87]	−7.85†	4.45	[−16.61, 0.91]
Weldments/Springs/Knifes	−1.98	3.51	[−8.89, 4.93]	−1.74	3.07	[−7.78, 4.31]	−1.41	3.08	[−7.46, 4.65]
Machined/Unmachined parts	−6.47†	3.50	[−13.34, 0.41]	−5.57†	3.06	[−11.59, 0.46]	−5.30†	3.06	[−11.33, 0.72]
Production materials/Filters/Belts	6.49	4.56	[−2.48, 15.45]	1.19	4.03	[−6.73, 9.11]	1.48	4.02	[−6.44, 9.40]
Steel	−9.84†	5.21	[−20.09, 0.41]	−11.66*	4.57	[−20.65, −2.68]	−11.46*	4.56	[−20.44, −2.49]
Hydraulics	4.30	3.89	[−3.35, 11.95]	3.65	3.40	[−3.04, 10.35]	3.55	3.40	[−3.13, 10.24]
Power Pac	−9.68*	4.40	[−18.33, −1.03]	−7.19†	3.86	[−14.78, 0.40]	−6.46†	3.88	[−14.10, 1.18]
Coatings/Paintings/Plastics	−11.90**	4.56	[−20.87, −2.93]	−14.89***	4.00	[−22.77, −7.01]	−14.52***	4.01	[−22.40, −6.64]
Tires/Rims/Bearings	−4.86	4.32	[−13.36, 3.65]	−6.04	3.79	[−13.50, 1.43]	−6.41	3.80	[−13.88, 1.06]
Main effects									
Prior quality performance				0.45***	0.05	[0.35, 0.54]	0.42***	0.05	[0.33, 0.52]
Disruption intensity				−0.70**	0.22	[−1.13, −0.27]	−2.77†	1.45	[−5.63, 0.08]
Interaction effect									
Prior quality performance × Disruption intensity							0.03	0.02	[−0.01, 0.07]
F	3.16***			11.08***			10.51***		
R^2	0.10			0.32			0.32		
ΔR^2	–			0.21			0.00		
F of ΔR^2	–			52.78***			2.08		

Note: OLS regression was used ($n = 352$). Dependent variable is *posterior supplier quality performance*; "Power Train/Drivelines" served as the baseline material group, reported estimates (β) and standard errors (*SE*) refer to unstandardized regression coefficients. *CI* refers to bootstrapped (1000 reps) 95%-confidence intervals. †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 10
Ordinary least squares regression results of supplier delivery performance.

Variables	Model 4b: Control variables			Model 5b: Main effects			Model 6b: Interaction effect		
	β	SE	CI	β	SE	CI	β	SE	CI
Constant	81.97***	3.18	[75.71, 88.23]	37.23***	4.48	[28.41, 46.04]	37.37***	4.57	[28.38, 46.37]
Controls									
Strategic importance	0.71	0.73	[−0.73, 2.15]	0.14	0.59	[−1.03, 1.31]	0.15	0.60	[−1.03, 1.32]
National lockdown	−0.20	0.18	[−0.55, 0.15]	−0.08	0.14	[−0.36, 0.21]	−0.07	0.14	[−0.36, 0.21]
Material group									
Electrics/Electronics	−1.13	2.59	[−6.23, 3.98]	−0.65	2.10	[−4.77, 3.47]	−0.65	2.10	[−4.78, 3.48]
Cabins	−3.15	3.29	[−9.62, 3.31]	−3.31	2.66	[−8.54, 1.92]	−3.31	2.66	[−8.54, 1.93]
Weldments/Springs/Knifes	−0.66	2.27	[−5.13, 3.81]	−0.97	1.84	[−4.59, 2.64]	−0.95	1.84	[−4.58, 2.67]
Machined/Unmachined parts	−3.05	2.26	[−7.49, 1.39]	−1.91	1.83	[−5.50, 1.68]	−1.90	1.83	[−5.50, 1.70]
Production materials/Filters/Belts	−2.76	2.94	[−8.54, 3.03]	−1.64	2.38	[−6.33, 3.04]	−1.64	2.38	[−6.33, 3.05]
Steel	−11.99***	3.36	[−18.61, −5.38]	−8.02**	2.75	[−13.42, −2.61]	−8.02**	2.75	[−13.43, −2.61]
Hydraulics	−0.91	2.51	[−5.85, 4.02]	−1.07	2.03	[−5.06, 2.92]	−1.06	2.03	[−5.06, 2.93]
Power Pac	1.67	2.84	[−3.91, 7.25]	1.29	2.29	[−3.22, 5.80]	1.30	2.30	[−3.22, 5.81]
Coatings/Paintings/Plastics	5.56†	2.94	[−0.23, 11.35]	2.11	2.39	[−2.59, 6.82]	2.13	2.40	[−2.59, 6.84]
Tires/Rims/Bearings	−5.73*	2.79	[−11.21, −0.24]	−4.76*	2.26	[−9.2, −0.32]	−4.78*	2.26	[−9.23, −0.32]
Main effects									
Prior delivery performance				0.55***	0.04	[−0.72, −0.20]	0.55***	0.05	[0.46, 0.64]
Disruption intensity				−0.46***	0.13	[−0.01, 0.07]	−0.58	0.71	[−1.98, 0.82]
Interaction effect									
Prior delivery performance × Disruption intensity							0.00	0.01	[−0.02, 0.02]
F	2.79**			16.63***			15.48***		
R^2	0.09			0.41			0.41		
ΔR^2	–			0.32			0.00		
F of ΔR^2	–			90.80***			2.05		

Note: OLS regression was used ($n = 352$). Dependent variable is *posterior supplier delivery performance*; "Power Train/Drivelines" served as the baseline material group, reported estimates (β) and standard errors (*SE*) refer to unstandardized regression coefficients. *CI* refers to bootstrapped (1000 reps) 95%-confidence intervals. †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

6.1. Theoretical implications

By adopting the research question *"How are buyer-experienced supplier performance, disruption frequency, and disruption duration interrelated?"*, our analyses extend the literature in terms of antecedents of buyer-experienced supply disruption frequency and duration, as well as empirically examining the impact of supply disruptions with the individual supplier as unit of analysis. In line with the literature review (cf. Table 1), our contributions are organized according to relevant stages of the disruption profile (Sheffi and Rice, 2005). This structure allows us to provide a comprehensive analysis and align with the pertinent literature.

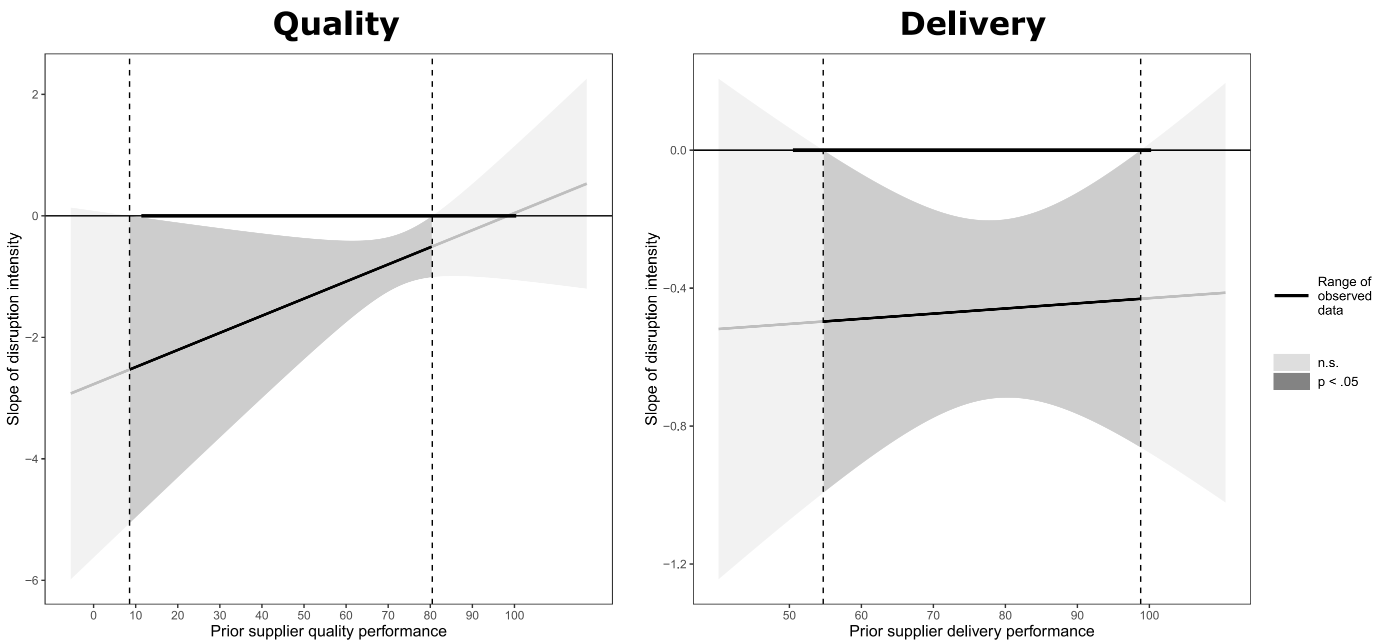

Fig. 6. Johnson-Neyman plots of prior supplier quality and delivery performance, and disruption intensity.

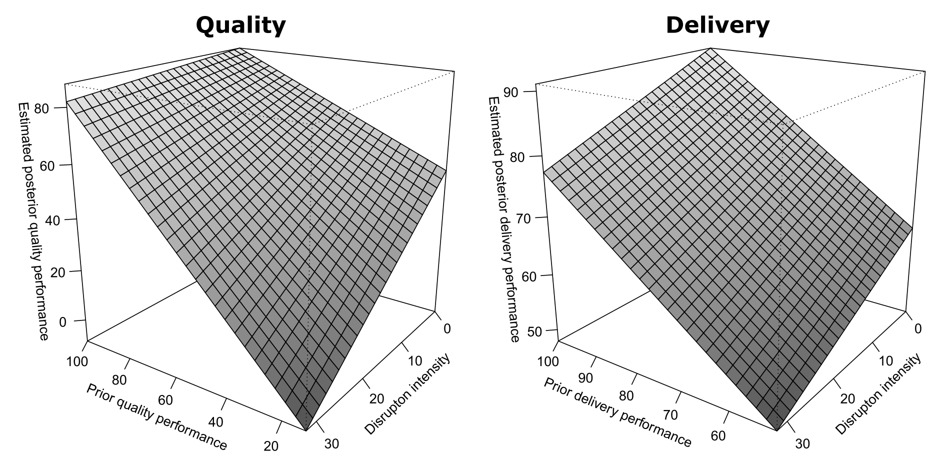

Fig. 7. Moderating effects of prior supplier quality and delivery performance on disruption intensity.

6.1.1. *Preparation for supply chain disruptions*

While supply chain disruptions are seen as unavoidable, firms can try to limit the risk of experiencing disruptions, such as reducing supply chain complexity (Bode and Wagner, 2015) and promoting a high interorganizational orientation (Revilla and Sáenz, 2017). Taking the individual supplier as the unit of analysis, the results of our first analysis reveal that prior supplier performance has a statistically significant effect on disruption frequency; the better the supplier's performance, the less prone it is to disruptions. As supply risks are difficult to measure (Schoenherr et al., 2023), our results suggest that buyer-experienced supplier performance could act as a simple proxy for supplier resilience (Choksy et al., 2022; Durach et al., 2020; Verghese et al., 2022). Thus, our results suggest that buyer-experienced (bad) prior supplier performance acts as an early warning signal (Mitroff, 2000) for disruptions.

In addition, the results extend the literature addressing antecedents of supply chain disruption duration. While the value of disruption duration was discussed (Mehrotra and Schmidt, 2021), almost no empirical study considers disruption duration. The results of our second analysis suggest a statistically significant influence of prior supplier performance on disruption length; the higher the prior supplier performance, the less the disruption duration. On average a 25% difference in individual supplier performance is associated with one week of disruption duration for every disruption. While it is a great challenge for firms to predict supply disruptions and their course prior to their occurrence (Blackhurst et al., 2008), our results indicates that buyer-experienced supplier performance is related to the supplier's ability to recover from a disruption.

6.1.2. *Recovery and mitigation of supply chain disruptions*

While the negative effect of supply chain disruptions on a firm's financial performance is well known (Hendricks and Singhal, 2003, 2005a, 2005b), our paper provides quantitative empirical evidence for the negative impact of disruptions on the individual buyer-experienced supplier performance. To account for disruption severity, we introduce disruption intensity considering both disruption frequency and disruption duration. The assumption is that not only the disruption duration and frequency is detrimental to performance (Brandon-Jones et al., 2014; Sheffi and Rice, 2005). Multiple supply disruptions – even short ones – can pile up, negatively influence the supplier's internal and external processes, and eventually hurting the supplier's performance registered at the buying firm (e.g., supplier quality issues, poor supplier delivery performance, or capacity fluctuations). The results of our third analysis reveal that disruption intensity does have a negative influence on posterior supplier performance; the longer and more often a supplier is disrupted, the larger the impact on its performance. Additional analyses reveal that this relationship persists on a more granular level; disruptions significantly hurt the supplier's posterior (i.e., future) quality performance. Our results are particularly relevant, as it is difficult for practitioners to quantify the costs of supply disruptions (Macdonald and Corsi, 2013). Further, our study extends the literature on disruption impacts, as we adopt the supplier as unit of analysis and examine buyer-experienced performance impacts, while most studies focus on the performance impacts with the buying firm as unit of analysis (e.g., Bode and Macdonald, 2017; Hendricks and Singhal, 2005a, 2005b; Macdonald and Corsi, 2013; Papadakis, 2006).

For most of our sample, our results also suggest that the negative influence of disruptions on buyer-experienced posterior supplier performance is moderated by prior supplier performance. Disruption intensity has a weaker negative performance impact on prior good performing suppliers than on suppliers with a prior poor performance. This relationship also persists on a more granular level; suppliers with a history of good quality performance (>80%) seem unaffected by disruptions in their quality performance, while the impact on prior bad performers is detrimental.

6.1.3. Interrelation of disruption stages

Finally, our paper extends the disruption profile (Sheffi and Rice, 2005) and the literature on supplier resilience by analyzing multiple disruptions of various durations and their impact on performance. Besides investigating the effect of supplier resilience on the buyer's financial resilience (Choksy et al., 2022), the literature on supplier resilience rather focused on influencing supplier resilience through several customer management styles including benevolence and leadership (Verghese et al., 2019; Verghese et al., 2022). As our study considers antecedents and the impact of disruptions – compared to most studies only focusing on either antecedents or impacts, we are able to reveal some relevant interrelations. In that regard, the results of our three analyses suggest that the key variables of the disruption profile – prior performance, disruption (recovery) duration, and posterior performance – are not independent from each other. Rather, there is a path dependency determined by prior performance. Thus, in summary, our analyses reveal that in terms of supplier resilience, good supplier performance does not only reduce the likelihood of disruptions but also mitigates the impact of supply disruption on supplier performance.

6.2. Managerial implications

Our study sends four important messages for practitioners regarding the management of their suppliers. First, our findings help supply chain managers to prioritize their supply risk management efforts. Risk management of buyers tends to focus on strategically important suppliers, but our results indicate that managers should not overlook underperforming suppliers. This is in particular relevant, as an approach on how to best measure supply risks in their broad is still lacking (Schoenherr et al., 2023). Not only do poor performing suppliers cause challenges for the buying firm, but they are also more susceptible to experiencing frequent and prolonged disruptions. Our results suggest that this relationship is not linear, so practitioners should consider phasing out the poorest performing suppliers. Where eliminating or switching the supplier is not possible, practitioners should either try to develop those suppliers to elevate their performance, or rely on redundancies, perhaps by building up safety stocks, or adopting a multi sourcing approach (e.g., Sheffi and Rice, 2005; Tomlin, 2006).

Second, buyer-experienced disruptions are detrimental to supplier performance; the longer and more often a supplier is disrupted, the larger the impact, especially on its quality performance. While this negative effect is less pronounced for resilient, good performing suppliers (performance >80%), disruptions worsen the posterior performance of suppliers that are already underperforming. Practitioners should be aware of this relationship and consider supporting a supplier in its disruption recovery efforts to limit the duration of a disruption, and thus the negative impact on the supplier's future performance.

Third, our results indicate that supplier programs addressing an improvement of the overall performance of the supply base can be also beneficial regarding supply chain disruptions. As our first analysis suggests, while the marginal effect of a 1% difference in performance for a single supplier does not have a huge impact on the individual disruption frequency, considering the full supplier sample, the average marginal effect of 1% difference in the performance of the supply base makes a significant difference in the occurrence of supply disruptions at the focal firm in the observed time frame. Thus, practitioners should consider implementing programs to enhance the performance of the whole supply base.

Finally, our study highlights the importance of supplier performance measurement systems in disruptive times, such as the COVID-19 pandemic, the Russia-Ukraine war, or the attacks in the Red Sea affecting the Suez Canal route. Without measuring performance at the supplier level, managers cannot track performance before and after the disruption to estimate the impact on relevant performance metrics (i.e., cost, quality, and delivery), and initiate appropriate countermeasures. As our results suggest, buyer-experienced supplier performance is related to disruption duration, frequency, and impact, and thus could serve as a simple proxy for the individuals supplier resilience in practice.

6.3. Limitations and future research

The reported results are based on a panel dataset of obtained from the supplier base of a single buying firm. As highlighted above, by focusing on a supplier base of one focal buying firm, we reduce the influence of some not included variables by keeping market position, corporate culture or supplier management policy constant over the entire sample (Subramani and Venkatraman, 2003). This leads to a high internal validity of our findings, but our results might vary, for example when investigating a company with a different market position or approach to supplier management.

Due to the timeframe of our sample, some long-lasting performance impacts of the recorded supply chain disruptions may not have fully manifested and experienced by the buyer, which potentially could lead to an underestimation of the disruption impact. In addition, and also due to the time frame of the panel data set, we focus on supply disruptions, which are at least to some extent connected to the COVID-19 pandemic. Although supply chain management during a crisis has been studied extensively in the operations management literature, crises of this magnitude have not occurred recently (Shen and Sun, 2023), which might play a role in interpreting the results of our analyses.

In summary, we acknowledge some limits of our dataset, yet, it is difficult to obtain (extensive) datasets in supply chain risk research (Sodhi et al., 2012), especially containing sensitive information such as the individual supplier performance on costs, quality, and delivery dimensions. Future studies should – if possible – extend this initial study to provide more generalizable findings. Further, the interrelations of supplier performance programs and disruptions (i.e., frequency and duration) should be examined in more detail, as our first analysis suggests that every 1% increase in the whole supply base performance could make a significant difference. Additional research opportunities include investigating prevention and mitigation strategies for supply disruptions at the supplier level, such as the specific influence of a supplier's disruption orientation (e.g., Stekelorum et al., 2023), or its business continuity tactics (e.g., Dohmen et al., 2023), influencing the (negative) performance impact of disruptions.

CRediT authorship contribution statement

Davide Burkhart: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Christoph Bode:** Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pursup.2024.100921.

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