Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

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Predicting the effects of supply chain resilience and robustness on COVID-19 impacts and performance: Empirical investigation through resources orchestration perspective

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ABSTRACT

This study investigates the effects of supply chain (SCRE) and robustness (SCRO) on COVID-19 super disruption impacts and firm's financial performance by mobilizing the resources orchestration theory (ROT) as the main theoretical framework. We adopt structural equation modeling analysis of data collected from 289 French companies.

The findings reveal the significantly positive influence of resources orchestration on SCRE and SCRO and the role of the latter in mitigating the pandemic disruption impacts. Notwithstanding, depending on whether the measures are objective or subjective, the effects of SCRE and SCRO on financial performance vary. Overall, this paper presents empirical evidence of the influence of both of SCRE and SCRO on pandemic disruption impacts and financial performance. Furthermore, this research provides insights to guide practitioners and decision makers regarding resources orchestration and the deployment of SCRE and SCRO.

1. Introduction

The COVID-19 outbreak has generated an influx of studies in the Supply Chain Management (SCM) field seeking to investigate the disruptive effects of the pandemic. Supply chain (SC) disruption is a phenomenon that impedes the continuity of flows (merchandises, services and information) and degrades firms' financial performance (Ambulkar et al., 2015). In this respect, the COVID-19 outbreak can be considered as 'super-disruption' (Ivanov, 2020b, 2021; Moosavi & Hosseini, 2021; Ruel, El Baz, Ivanov, & Das, 2021) because it has created unprecedented effects in the SCs on a global scale. Indeed, the pandemic has generated supply difficulties with shortages of materials (such as steel), components (such as electronic chips), unavailability of containers in several geographical areas coupled with extreme volatility of demand and significant increase in the price of energy, etc. Thus, some authors consider the COVID-19 pandemic crisis to be a disaster of an unprecedented nature for SCs (Govindan et al., 2020; Ruel and Elbaz, 2023) due to its effects on the economic and social levels.

A review of SCM studies on COVID-19 reveals the presence of several viewpoint/conceptual papers and literature reviews (see Table 1). Regarding empirical research, only a minority of studies has investigated the effects of supply chain resilience and robustness on performance. Table 1 presents a synthesis of the SCM studies on COVID-19 in relevant journals according to the association of business schools (ABS) ranking (Harvey et al., 2010).

The need for further research on the SC impacts of the pandemic has prompted several scholars (e.g., Van Hoek, 2020; Sarkis et al., 2020) to call for additional empirical, event-based investigation to reduce the gap between theory and practice. The new challenges brought about the pandemic have put SC resilience (SCRE) at the forefronts of firms' priorities which can be shown through their communications with their stakeholders regarding COVID-19 crisis management (Sharma et al., 2020). SCRE can be viewed as the SC ability to recover performance following the occurrence of a disruption (Hosseini et al., 2019; Mirzoudot, 2020). Contrastingly, supply chain robustness (SCRO) is conceptualized as the capability of a SC to maintain its planned performance in spite of disruptive events (Simchi-Levi et al., 2018).

Based on resource orchestration theory (ROT), bundling and structuring, firm's resources can generate a positive impact on competitive advantages; enhance value creation and influence SCRE (Chunsheng

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Table 1
Synthesis of SCM research in the context of COVID-19.

Method	Scope	References	ABS ranking	Citations	Main highlights
Conceptual/ Simulation/ Literature review	SCRE (n = 11)	Ivanov (2020a)	ABS3	596	SCRE is a part of SC viability.
		Ivanov and Das (2020)	ABS1	310	SCRE requires more than proactive redundancies, situational responses to real-time changes are needed.
		Ivanov and Dolgui (2020)	ABS3	881	SCRE is not enough to analyze intertwined supply networks.
		Burgos and Ivanov (2021)	ABS3	103	SCRE should be based on: evaluating the impact of the disruption, responding to the immediate challenges, and seizing opportunities.
		Golan et al. (2021)	ABS2	23	SCRE analytics will support SC managers to better quantify SCRE tradeoffs.
		Hobbs (2021)	ABS2	67	Investments in adaptability and flexibility can enhance SCRE.
		Moosavi and Hosseini (2021)	ABS2	29	Extra inventory leads to a higher SCRE than a backup supplier.
		Qrunfleh et al. (2022)	ABS1	1	There is no framework on how mitigation strategies relate to SCRE.
		Spieske and Birkel (2021)	ABS2	81	Big data analytics is suitable for improving SCRE.
		Sytch et al. (2022)	ABS3	2	Organizations necessitate investing in SCRE.
		Zamani et al. (2022)	ABS3	0	SCRE follows four phases: readiness, response, recovery and adaptability. Artificial intelligence and Big data analytics support SCRE.
	SCRO (n = 3)	Ivanov (2020a)	ABS3	596	SCRO is a part of SC viability.
		Ivanov and Dolgui (2020)	ABS3	881	SCRO is not enough to analyze intertwined supply networks.
		Sytch et al. (2022)	ABS3	2	Organizations necessitate investing in SCRO.
Empirical	SCRE (n = 13)	Van Hoek (2020)	ABS4	459	Qualitative round tables — Improving supplier relationship management will improve SCRE.
		Belhadi et al. (2021)	ABS3	383	Quantitative survey — The paper offers and integrated decision-making framework for SCRE.
		El Baz and Ruel (2021)	ABS3	303	Quantitative survey — SCRE is not negatively influenced by disruptions impacts. SCRE is influenced positively by SC risk management practices.
		Kähkönen et al. (2023)	ABS3	21	Quantitative survey — A firm's capability to seize and reconfigure influences SCRE.
		Paul et al. (2021)	ABS1	27	Qualitative survey — Building SCRE is the most important strategy to survive COVID-19
		Queiroz et al. (2021)	ABS1	20	Quantitative survey — SC agility does not have a positive effect on SCRE during a highly disruptive crisis. SC disruption orientation has a positive effect on SCRE during a highly disruptive crisis. Resource reconfiguration has a positive effect on SCRE during a highly disruptive crisis.
		Ruel and El Baz (2023)	ABS3	13	Quantitative survey — SCRE is positively influenced by SC disaster readiness. A firm's financial performance is not positively influenced by SCRE.
		Shen and Sun (2023)	ABS4*	34	Secondary data — There is a need to set up performance metric to measure SCRE.
		Cherrafi et al. (2022)	ABS1	0	Qualitative interviews — The use of smart technologies and automation can lead to better SCRE.
		Modgil et al. (2022)	ABS1	61	Qualitative interviews — Artificial Intelligence can enhance SCRE.
		Nikookar and Yanadori (2022)	ABS4	13	Quantitative survey — SC managers' firm-specific SCM skills are positively associated with SCRE and SC managers' SC disruption perception is positively associated with SCRE.
		Queiroz et al. (2022)	ABS3	16	Quantitative survey — Supply chain alertness positively affects supply SCRE. Resource reconfiguration has a positive effect on SCRE. Supply chain efficiency does not positively affect SCRE.
		Sharma et al. (2022)	ABS1	150	Qualitative survey — SCRE increases operational efficiency and SC sustainability.
	SCRO (n = 6)	El Baz and Ruel (2021)	ABS3	303	Quantitative survey — SCRO is negatively influenced by disruptions impacts. SCRO is influenced positively by SC risk management practices i.e. Risk identification Risk control, but not by risk assessment and risk mitigation.
		Queiroz et al. (2021)	ABS1	20	Quantitative survey — SCRO does not have a positive effect on SCRE during a highly disruptive crisis.
		Ruel and El Baz (2023)	ABS3	13	Quantitative survey — SCRO is positively influenced by SC disaster readiness. A firm's financial performance is positively influenced by SCRO.
		Cherrafi et al. (2022)	ABS1	0	Qualitative interviews — The use of smart technologies and automation can lead to better SCRO.
		Juan et al. (2021)	ABS1	8	Quantitative survey — SC collaboration positively affects SCRO. SC visibility positively affects SCRO. SCRO does not negatively affect SC performance under disruption in the short term.
		Sharma et al. (2022)	ABS1	150	Qualitative survey — SCRO increases operational efficiency and SC sustainability.

et al., 2020; Sirmon et al., 2007, 2011). The way organizational resources are orchestrated can explain how the coordination of internal functions and collaboration with partners help firms manage SC processes, deal with undesirable events and regain their performance after being impacted by disruptions (Queiroz et al., 2022; Wong et al., 2018).

According to Miroudot (2020), building SCRO and SCRE requires different strategies based on the type of products (e.g., face masks, ventilators, etc.). In SCM research on COVID-19, SCRO was less frequently investigated in comparison with SCRE (Table 1). Therefore, it is necessary to assess whether and how both of SCRE and SCRO can help mitigate the effects of COVID-19 'super-disruption' while maintaining the firms' financial performance. The interactions of both of SCRO and SCRE with financial performance have not been examined sufficiently in prior research and the context of COVID-19 constitutes an appropriate opportunity to do so. In this optic, addressing such topic is relevant because prior studies have struggled to delineate the different contributions of robustness and resilience to SCM (Spiegler et al., 2012). On the whole, this paper is an attempt to contribute to extant literature by investigating the following research questions:

RQ1. Does resources orchestration affect significantly and positively SCRO and SCRE following the circumstances of COVID-19 pandemic outbreak?

RQ2. Can resources orchestration have a significant impact on how SCRE and SCRO affect the financial performance of firms and disruptions damage of the COVID-19?

To answer the research questions, an empirical study is undertaken based on survey-based questionnaire and data analysis mobilized partial least square structural equation modelling (PLS-SEM).

The contributions of this research can be summarized as following. First, this study attempts to explore research opportunities related to COVID-19 impacts that several scholars have outlined (Ivanov, 2020b; Van Hoek, 2020). In addition, this study is an answer to the call of scholars for new theoretical frameworks to study SC disruptions, resilience and robustness (Tukamuhabwa et al., 2015). In this respect, mobilizing ROT (Sirmon, Hitt, & Ireland, 2007; 2011) in this study helps explain how firms bundle their resources to achieve SCRE and SCRO in a turbulent COVID-19 disruption. Moreover, the results shed light on the interrelationships between SC disruption impacts, firm's financial performance, and both of SCRE and SCRO. The findings underscore the need for firms to first build SCRO in order to limit the short-term impacts of SC disruptions, and then rely on SCRE in order to maintain financial performance in an uncertain environment. Such results provide helpful insights to practitioners and academics on the temporal characteristics of SCRE and SCRO which can clarify the peculiarities of the concepts and how they can affect financial performance and super-disruptions' damage.

Following this introduction, the paper consists of three other sections and a conclusion. In Section 2, we present the theoretical framework based on ROT together with the hypotheses and the research model. Next, we describe the methodology (Section 3) and data analysis. Following this, we depict the findings (Section 4) and present a discussion of the results in Section 5. The paper concludes by synthesizing the implications, limitations and potential research avenues.

2. Theoretical background

2.1. Resource orchestration theory

The framework of this study is drawing on ROT which was introduced to overcome some of the limitations of dynamic capabilities view and resource-based view theory (Burin et al., 2020), namely, their lack of operational perspective and static approach to firms and processes (Lewis et al., 2010; Priem and Butler, 2001a, 2001b). Indeed, accumulating resources and capabilities for firms is not sufficient to achieve competitive advantage as stipulated by the resource-based view (RBV) theory unless such capabilities are managed efficiently (Ketchen et al., 2014). ROT provides an alternative to the operationalization gap by developing a comprehensive view of how resources can be bundled and mobilized. Thus, in ROT the emphasis is first on the formal way of structuring a resource portfolio (similar to RBV perspective of Wernerfelt (1984) and Barney et al. (2011)), then on bundling the resources to generate synergistic effects (Hitt et al., 2016; Sirmon, Hitt, & Ireland, 2007) and finally on leveraging configurations to seize market opportunities and thus improve the firm's financial performance (Barney et al., 2011; Hughes et al., 2018; Sirmon & Hitt, 2009; Sirmon et al., 2011).

ROT was introduced by Sirmon et al. (2007) and Sirmon et al. (2011) and is useful both at the firm and at the SC levels (Ellram et al., 2013; Wowak et al., 2016), especially in turbulent environment (Cui & Pan, 2015). ROT has become increasingly deployed in SCM research, for example in studies on e-commerce (Cui & Pan, 2015), reverse logistics (Ketchen et al., 2014), SC integration (Liu et al., 2016) and environmental management in SCs (Wong et al., 2018). ROT also helps clarify resource deployments and capabilities through SCRE and SCRO (Chunsheng et al., 2020; Tukamuhabwa et al., 2015), information orchestration following the outbreak of the pandemic (Pan & Zhang, 2020; Pan et al., 2020) and the design of organizational capability processes in the post-pandemic "new normal" era (Hitt et al., 2021). Nevertheless, the applicability of ROT to a 'super-disruption' context has been seldom tested despite the growing literature on the pandemic. To our knowledge, the recent study of Queiroz et al. (2022) constitutes the only example of research mobilizing ROT to investigate SCRE.

2.2. Hypotheses development

2.2.1. The contribution of resources orchestration to supply chain robustness and resilience

According to Sirmon et al. (2011), managing resources is pivotal for a firm in order to deal with threats or recover their performance. Bundling resources through internal and external integration generates fluid coordination, effective information exchange and collaboration. Drawing on ROT, it can be surmised that a firm coordinating efficiently its resources can deal more efficiently with the challenges of a volatile environment. With the involvement of their SC members, firms can achieve SCRE and SCRO through exchanging strategic information and coordinating processes which ultimately helps them reduce the level of uncertainties and mitigate the effects of SC risks (Wong et al., 2018, 2020). SCRO is the "*ability of a SC to maintain its function despite internal or external disruptions*" (Brandon-Jones et al., 2014, p.56) and resist the immediate disruption's impacts (Li & Zobel, 2020). On the other hand, SCRE stands for the capability to anticipate and overcome disruption effects (Pettit et al., 2013). SCRE is defined as *"the ability of a SC to return to normal operating performance, within an acceptable period of time, after being disturbed"* (Brandon-Jones et al., 2014, p. 55–56). If thoroughly implemented, the collaboration that ROT calls for, can generate effective communication among firms' functions and their partners which improves the level of preparedness in the SC and provides better responses to disruptive events. Therefore, although the effects of resource orchestration on SCRE and SCRO seem logically positive in an uncertain environment, it is necessary to study them in a "super-disruptive" context. Based on prior arguments, the following hypotheses are proposed:

H1. Resources orchestration influences significantly and positively SCRE in the context of a 'super-disruption'.

H2. Resources orchestration influences significantly and positively SCRO in the context of a 'super-disruption'.

2.2.2. Supply chain robustness, resilience and disruption impacts

The volatile environment of SCs (Christopher & Holweg, 2017) may generate SC disruptions that cause significant challenges to organizations (Hendricks & Singhal, 2003). The COVID-19 outbreak has created an unprecedented SC disruption (Nikolopoulos et al., 2021) due to its

long duration, unpredictable effects and the scale of volatility (Hobbs, 2021; Ivanov, 2020b). Previous studies have conceptualized both of SCRE and SCRO as a set of dynamic capabilities aiming to anticipate, mitigate and recover from a SC disruption (e.g., Bode et al., 2011; Chowdhury & Quaddus, 2017; Pettit et al., 2010, 2013).

SCRE was often examined in a fragmented manner without highlighting its outcome on organizations (Shishodia et al., 2022). Therefore, Miroudot (2020) calls for research investigating both SCRE and SCRO in the aftermath of COVID-19 that challenges prevalent knowledge about those concepts (Nikolopoulos et al., 2021). Based on previous premises, we propose the following hypotheses:

H3. SCRE can reduce significantly the super disruptions impacts of the COVID-19 pandemic.

H4. SCRO can lessen significantly the super disruptions impacts of the COVID-19 pandemic.

2.2.3. Supply chain resilience, robustness and firm's financial performance

This paper intends to investigate the 'super-disruptions' impacts of the pandemic on the firm's financial performance. To our knowledge, few studies have investigated the potential link between SCRE and the firm's financial performance –some scholars have obtained contradictory results (Li et al., 2017; Liu et al., 2018; Abeysekara et al., 2019; Yu et al., 2019; Wong et al., 2020) and a minority of studies has examined the influence of SCRO on financial performance (Madzimure, 2020; Srimarut & Mekhum, 2020). All the aforementioned studies were conducted prior to the COVID-19 'super-disruption'; whereas several scholars have highlighted how this pandemic has challenged many of the "certainties" of the past (Sarkis et al., 2020; Van Hoek, 2020). Given the temporal differences between the concepts, i.e. SCRO aiming to resist immediate impacts, SCRE aiming to return to normal, we put forward the following hypotheses:

H5. The effects of SCRE on financial performance in the context of a 'super-disruption' would take time to materialize.

H6. The effects of SCRO on financial performance in the context of a 'super-disruption' would quickly manifest in the short run.

Fig. 1 depicts the research model.

3. Research method

3.1. Research design

To gather data, a questionnaire was designed by the authors. To clarify and validate the items in the questionnaire, we conducted a pilot survey of 9 SC managers and 10 academics. After integrating amendments and revisions to the questionnaire, we sent it via e-mail to a random sample of 2112 executives and managers of French companies in March 2020. After two reminders sent, we collected 289 completed questionnaires amounting to 13.68 % response rate which can be considered as acceptable according to Dillman (2000).

3.2. Construct and items

3.2.1. Items measurements

The measures of constructs were adapted from validated instruments in prior studies. Five constructs are deployed in the research model, namely: *Resources orchestration, SCRO, SCRE, Disruption Impacts* and *Financial performance.*

Resources orchestration was measured based on seven items following several studies (Chunsheng et al., 2020; Rodrigues et al., 2004; Stank et al., 2001). The respondents were asked to rate their internal (intra-firm) and external integration with their SC partners (suppliers and customers) and how they share operational information, risk and rewards with their partners.

Four items are suggested as measures for SCRE based on prior studies (Ambulkar et al., 2015; Chunsheng et al., 2020; Wieland & Wallenburg, 2012). Thus, the respondents were asked to rank the capability of their SCs to cope with changes, the adaptability to disruptive events, the quickness of response and alertness.

To provide measurements for SCRO, we draw on several studies (Ambulkar et al., 2015; Bode et al., 2011; Chowdhury & Quaddus, 2017). Four items are used to operationalize SCRO. Thus, respondents had to rank the ability of their SCs to: (i) retain stability, (ii) develop an efficient reaction to disasters, (iii) maintain performance without adaption, and (iv) attain its objectives in spite of disruptive events.

Disruption impacts items were adapted from the instruments proposed by Ambulkar et al. (2015) and DuHadway et al. (2019). Thus, three items are mobilized to measure SC disruption impacts on the efficiency of operations, the procurement costs and the reliability of delivery.

Financial performance was measured using both of subjective (perceptual) instruments and objective data (e.g. Azadegan et al., 2020; Chunsheng et al., 2020). Objective data were extracted from Cap Financials database that provides current information about French firm's financial indicators taken from Official Journals and INSEE[1] databases. Cap Financials evaluates firms' activities through a notation that takes into account several ratios such as return on equity, return on investment and return on assets[2]. Objective data figures relate to the period of 2020 which allows us to have an insight about the financial performance of investigated firms two years after the pandemic.

Perceptual financial performance is operationalized based on several instruments established in previous studies (e.g., Azadegan et al., 2020; Kroes & Ghosh, 2010). Accordingly, the respondents were asked to rank their profit margin, return on sales, return on assets and sales over assets in comparison with their competitors.

3.2.2. Control variables

In this paper, size and age of firms are the main control variables for SCRE and SCRO. Annual sales constitute the main measurement of size (Azadegan et al., 2020) with the underlying assumption that size accounts for resources that organizations might allocate to risk practices (Kumar et al., 2018) which might lead to more developed SCRE and SCRO. Second, we controlled for the firm age given the fact that experienced organizations acquire skills to better deal with disasters (Ambulkar et al., 2015; Bode et al., 2011) which allows them to develop advanced SCRE and SCRO.

Appendix 1 presents a complete list of the items used in this study.

3.3. Sample size adequacy, non-response and common method biases tests

Based on the guidelines of Cohen (1988), the adequacy of the sample size was assessed using the G*Power tool (Faul et al., 2009). The "a priori" analysis reveals that the adequate sample size is 129 for minimum values of the coefficient of determination (R2 = 0.1), 80 % statistical power and four predictors (Resources orchestration, SCRO, SCRE and Disruption impact). The post-hoc analysis in G*Power with the survey sample (289) reveals a statistical power of 0.99 which exceeds the minimum of Cohen (1988) and confirms the sample size's adequacy.

We have also checked for the sample selection bias through the Heckman procedure (Thomaz & Swaminathan, 2015; Zaefarian et al., 2017). Thus, in a probit model we included a dummy variable (1, 0) for response as a dependent variable whereas age, size and sales represent the independent variables. Based on the estimates obtained via Stata software, the inverse Mills Ratio was calculated. The results reveal values of Sigma = 0.004, Rho = 0.005 and the Lambda parameter =

[1] INSEE: The National Institute of Statistics and Economic Studies collects, analyses and disseminates information on the French economy and society.

[2] See: https://capfinancials.com/ (accessed October 18, 2022).

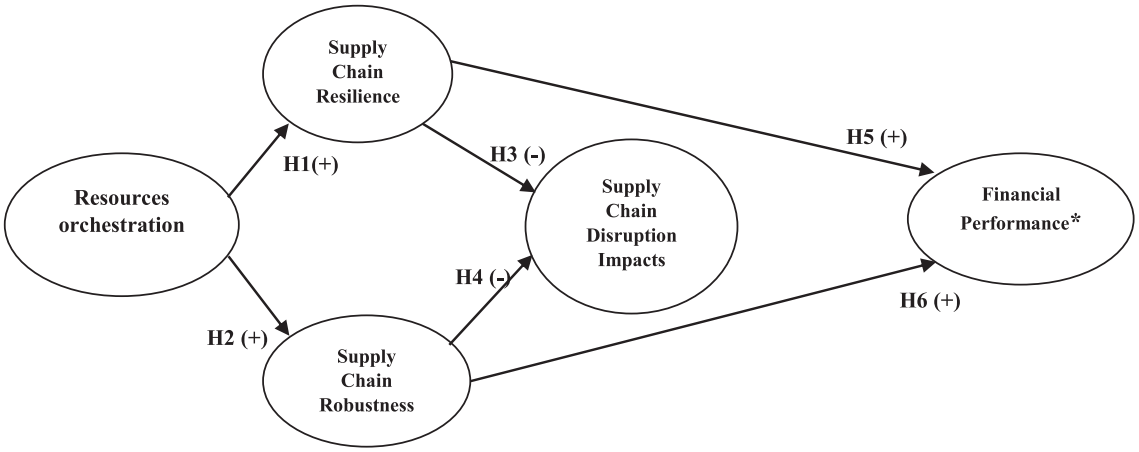

Fig. 1. Research model.

0.011[3] (t = 0.93n.s). Such results indicate that sample bias does not constitute an issue for this study.

Non-response bias was assessed based on the guidelines of numerous scholars (Armstrong & Overton, 1977; Wagner & Kemmerling, 2010; Werner et al., 2007). Thus, we conducted a *t*-test of equality of means to assess the differences between early and late respondents. The results of the *t*-test were not significant regarding sector, annual sales and employee's number ($p > 0.1$). We also tested for non-response by comparing the characteristics of respondents (size, sector and sales) with those of companies that were contacted but with no response from their part. The results of comparison reveal no significant difference between respondents and non-respondents ($p > 0.1$).

We tested for common method bias (CMB) in the dataset based on the recommendations of Podsakoff et al. (2003). Therefore, we complied with ex ante conditions (Podsakoff et al., 2003) by collecting data from key informants, i.e. respondents possessing relevant knowledge of resource orchestration, SCRE and SCRO (SC managers and executives, purchasing managers and executives). In addition, we formulated the questionnaire in a clear manner by separating the dependent and independent constructs and we avoided double-barreled questions to facilitate data gathering. Moreover, perceptual measures and objective data of firm's performance were both collected for this study which addresses the CMB issue (Azadegan et al., 2020). The perceptual metrics are self-reported, whereas objective measures of financial performance were gathered from official databases based on firm's annual reports.

We performed post-hoc analysis of CMB using the marker variable (MV) technique as suggested by several scholars (e.g. Fuller et al., 2016; Ketokivi & Schroeder, 2004). A single item scale of respondents experience served as a MV and we assessed its correlation with the other constructs of the model. The findings have revealed weak and insignificant correlations between the MV and the other constructs and no difference in the correlations between the model's constructs. Based on the combination of all the previous results, the effects of CMB can be considered as non-substantial for this study.

Table 2 presents a summary of the respondents' characteristics.

Table 2
Descriptive characteristics of the sample.

Characteristics of respondents (n = 289)	Count	%
Job		
SC Manager	217	42.5
SC Management Director	141	27.6
Purchasing/SCM team member	60	11.7
Vice President (SCM, Operations, Purchasing)	39	7.6
Operations Director	32	6.3
Purchasing Manager	14	2.7
Purchasing Director	8	1.6
Sector		
Manufacturing	234	45.8
Retail	115	22.5
Chemicals, pharmaceuticals	77	15.1
Services	39	7.6
Transport	23	4.5
Annual sales (in millions €)		
<50	97	19
[50–249]	112	21.9
[250–499]	50	9.8
[500–999]	47	9.2
≥1000	196	38.4
Employees		
<50	39	7.6
[50–249]	95	18.6
[250–999]	93	16.4
[1000–4999]	93	18.2
≥5000	196	38.4
Experience (in years)		
[0–4]	80	15.7
[5–8]	83	16.2
[9–15]	146	28.6
>5	202	39.5

3.4. Data analysis approach

We adopt the PLS-SEM approach for its adequacy to test the research model. PLS offers a flexible predictive assessment of theoretical frameworks (Hair et al., 2019; Sarstedt et al., 2022) which is the case of our research model. The PLS analysis involves the assessment of the measurement model, the evaluation of the structural model and the hypotheses tests. We considered the latest guidelines proposed by Sarstedt et al. (2022) for PLS-SEM approach and employed SmartPLS 3 for data analysis.

[3] Sigma is the estimator of the standard error of the residual in the Heckman regression. Rho is the correlation coefficient of the error terms in the Heckman regression. Lambda is the inverse Mills ratio.

4. Results

4.1. Assessing the measurement model

We assessed the measurement model using reliability, convergent validity and discriminant validity of the constructs.

First, based on the outer loadings values, we eliminated all the items below threshold of 0.7 (Hair et al., 2019). Thus, the items RO1, RO2, RO3, RO5, SCROB1, SCROB2, and DI3 were discarded due to their insufficient loadings. Regarding constructs reliability, we employed the composite reliability, i.e., Dillon-Goldstein's rho, Dijkstra-Henseler's rho_A and Cronbach's α all of which should be above 0.7 (Hair et al., 2017). The results in Table 3 corroborate the constructs' reliability. In addition, the average variance extracted (AVE) measures of all the constructs support the convergent validity of the constructs by having statistics above 0.50 (Table 3).

The discriminant validity was assessed based on Fornell-Larcker Criterion and Hetrotrait-Monotrait ratio (HTMT) test. According to the Fornell-Larcker's criterion, the discriminant validity of a construct is determined when the square root of its AVE is greater than its correlation with all the other constructs (Fornell & Larcker, 1981) which is the case in our dataset as shown in Table 4. In addition, we explored the (HTMT) ratio, which should not contain values >0.9 for any of the constructs. Table 4 shows that HTMT values range from 0.004 to 0.835 thus supporting discriminant validity of the constructs.

4.2. Structural model assessment

The structural model evaluation consists of assessing collinearity, the explanatory power and the contribution of predictor variables in terms of R^2 (coefficient of determination) and f^2 (effect size), the predictive relevance (Q^2), the exact fit of the standardized root mean square residual (SRMR), and the normed fit index (Table 5).

To assess collinearity, variance inflation factors (VIF) are calculated with values below 3 are recommended for all the predictor constructs (Hair et al., 2017). The coefficient of determination (R^2 or adjusted R^2) provides an assessment of the explanatory power of endogenous variables, i.e. the variance explained by exogenous variables. The findings indicate weak levels of R^2 for disruption impacts (0.07) and performance (0.06), which can be expected for this research model that adopts a predictive PLS-SEM approach rather than an explanatory one (Hair et al., 2017, 2019). The effect sizes f^2 which also measure the explanatory power of predictor variables, range from weak to moderate levels (0.01–0.34) (Cohen, 1988).

Predictive relevance of the model is assessed using Stone-Geisser Q^2 values which have to be larger than zero. The results of all the constructs support the predictive relevance. The cut-off of SRMR exact fit is 0.08 (Hu & Bentler, 1999). The model quality is significant with SRMR = 0.06. Finally, the normed fit index (NFI) indicates a moderate fit of the model with a value of 0.8 (Hair et al., 2019). On the whole, the results in Table 5 show appropriate model fit.

As an additional assessment of the predictive relevance of the research model we performed the PLSpredict technique as suggested by Shmueli et al. (2019). Thus, the results in Table 6 indicate that the values of financial performance (objective and subjective) have a lower prediction error (RMSE and MAE) than the linear model (LM) which constitutes an additional support to the predictive power of the research model.

Table 3
The measurement model's parameters.

Construct/Items	Loading	ρc CR	Alpha (α)	Pa	AVE
Resources orchestration		0.801	0.758	0.799	0.574
RO1	0.6224*				
RO2	0.6662*				
RO3	0.4746*				
RO4	0.8114				
RO5	0.6528*				
RO6	0.7567				
RO7	0.7017				
Supply Chain Resilience		0.89	0.887	0.908	0.684
SCRE1	0.841				
SCRE2	0.846				
SCRE3	0.874				
SCRE 4	0.734				
Supply Chain Robustness		0.837	0.753	0.796	0.565
SCRO1*	0.677				
SCRO2*	0.658				
SCRO3	0.813				
SCRO4	0.712				
Disruptions impact		0.802	0.788	0.829	0.804
DI1	0.923				
DI2	0.704				
DI3*	0.672				
Financial Performance		0.961	0.961	0.961	0.860
Perform1	0.934				
Perform2	0.950				
Perform3	0.913				
Perform4	0.912				

AVE = Average variance extracted; ρc = Composite Reliability; ρA = Dijkstra-Henseler's rho_A.
* Items eliminated for insufficient loadings (<0.7).

4.3. Hypotheses test

We present the hypotheses test in Table 7. The bootstrap resampling method is adopted to calculate the β coefficient estimates at a significance level of 5 % with 5000 subsamples and bias corrected and accelerated (BCa) interval to generate robust results (Hair et al., 2017, 2019).

In the context COVID-19 'super-disruption', positive and significant relationships between resource orchestration and both of SCRE and SCRO are found, thus supporting H1 and H2. Furthermore, there is a significant and negative effect of SCRO on COVID-19 disruption impacts; whereas the impact of SCRE on the latter was not substantial. This means that SCRO constitutes an important capability to mitigate the 'super-disruption' effects. Thus, H3 is rejected and H4 is supported.

The results about the effects of SCRE and SCRO on financial performance vary according to the measures adopted (perceptual or objective). Consequently, with subjective measures of financial performance, we find the influence of SCRE and SCRO to be positive and significant. Conversely, with objective data on financial performance that relates to firms' updated financial situation two years after the pandemic 'super-disruption', the findings show a positive influence of SCRE on performance (H5 supported) and no significant influence of SCRO on performance, therefore we reject H6.

Finally, the results show that there is a difference regarding SCRE in term of firms' size ($\beta = 0.146$, $p < 0.01$), i.e., firms with larger size expect to have better SCRE, whereas firms with small size have less advanced (low level) SCRE. Conversely, age had no effect on SCRE and SCRO.

4.3.1. Results of mediation analysis

We conducted additional tests to check whether there were indirect effects of resources orchestration on disruption damage and financial performance via SCRE and SCRO (Table 8). Based on the categorization of Nitzl et al. (2016) there are three types of mediation relationships. When both of direct and indirect effects have the same sign and are significant, we have a complementary mediation. When both of indirect and direct effects are significant but do not point in the same direction, there is a competitive mediation. Finally, the "indirect only mediation" appears when the only significant effect is the indirect effect.

The mediation test reveals a complementary mediation of SCRO between resources orchestration and COVID-19 'super-disruption' impacts. Once again, there is a discrepancy between the mediation effects

Table 4
Assessment of discriminant validity*.

	RO	SCRE	SCRO	DI	PERF	Size	Age
RO	**0.7576**	0.6044	0.4349	0.1073	0.2393	0.1253	0.1453
SCRE	0.3120	**0.8271**	0.5986	0.2101	0.1945	0.1467	0.0681
SCRO	0.1651	0.2398	**0.7517**	0.3382	0.0802	0.0043	0.0041
DI	0.008	0.303	0.0758	**0.8962**	0.0861	0.0089	0.0144
PERF	0.0547	0.0329	0.0061	0.0058	**0.9273**	0.8359	0.2774
Size	0.0153	0.0184	0.0002	0.0001	0.6988	**1.00**	0.3155
Age	0.0215	0.0043	0.0001	0.0001	0.0770	0.0995	**1.00**

RO: resource orchestration SCRE: Supp chain resilience; SCRO: supply chain robustness; DI: disruption impact; PER: financial performance.
* In the diagonal cells we insert in bold the values of the square root of the average variance of each construct. The correlations between the construct and other variables are presented below the diagonal cells. The score of the HTMT are inserted above the diagonal cells.

Table 5
Assessment of the structural model fit.

Constructs	R^2	Adj. R^2	f^2	Q^2	VIF	SRMR	NFI
Quality						0.065	0.801
RO	–	–	(0.193–0.341)		1.023		
SCRE	0.269	0.261	(0.004–0.009)	0.169	1.285		
SCRO	0.163	0.155	(0.000–0.048)	0.106	1.318		
DI	0.075	0.069	0.0013	0.051	1.082		
PERF	0.067	0.065		0.691			

Table 6
Results of PLSpredict.

	PLS		LM		PLS-LM	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
Perform 1 (subjective)	1.745	1.405	1.756	1.420	−0.011	−0.015
Perform 2 (subjective)	1.653	1.301	1.682	1.348	−0.029	−0.047
Perform 3 (subjective)	1.678	1.293	1.693	1.345	−0.015	−0.052
Perform 4 (subjective)	1.689	1.311	1.707	1.366	−0.018	−0.055
Financial performance (objective)	0.882	0.626	0.883	0.633	−0.001	−0.007

whether financial performance is subjective or objective. Thus, there is a significant complementary mediation of SCRO in the relationship between resources orchestration and subjective financial performance. In contrast, for objective measures of financial performance there is a complementary mediation of SCRE between resources orchestration and financial performance.

4.4. Robustness tests

Additional tests to reinforce the robustness of the results were conducted. We specifically tested for endogeneity and unobserved heterogeneity biases (Sarstedt et al., 2022). Endogeneity bias arises in research models with several hypotheses having the risk of omitting a construct (Ketokivi and McIntosh, 2017; Peel, 2018).

To minimize the impact of endogeneity on the estimates, we adopted the approach suggested by Park and Gupta (2012) based on Gaussian copula test. First, we verified that the variables presenting potential bias of endogeneity are non-normally distributed through the Kolmogorov–Smirnov test with Lilliefors correction. We found that all the all p-value scores are <0.05 and therefore conclude that none of the constructs have a normal distribution (Sarstedt & Mooi, 2014). Then we run the Gaussian copulas regression in the software R to obtain the different combinations of the model (Appendix 2). Since none of the combinations were significant (p-value > 0.05), we can conclude that the threat of endogeneity bias is minimal and confirm the robustness of model (Hult et al., 2018).

Moreover, we test for unobserved heterogeneity using finite mixture PLS (FIMIX-PLS) procedure (Sarstedt et al., 2022). We conducted the analyses based on the minimum sample size requirements with two- and three-segment solutions as recommended by Hair et al. (2017). The findings reveal that unobserved heterogeneity does not constitute an issue for this study (Appendix 3).

Table 7
Hypotheses test.

Hypothesis test	Coeff (β)	Std. deviation	T statistics	p-values	95 % BCa CI	Conclusion
RO → SCRE	0.478	0.051	**9.427**	**0.000**	(0.398–0.563)***	H1 supported
RO → SCRO	0.416	0.057	**7.304**	**0.000**	(0.325–0.513)***	H2 supported
SCRE → DI	−0.066	0.072	0.920	0.179	(−0.183, 0.053) n.s	H3 rejected
SCRO → DI	−0.237	0.064	**3.700**	**0.000**	(−0.351, −0.137)***	H4 supported
SCRE → PER *(subjective)*	0.076	0.075	1.018	0.154	(−0.047, 0.199) n.s	H5 rejected
SCRO → PER *(subjective)*	0.203	0.069	**2.940**	**0.002**	(0.083, 0.312)***	H6 supported
SCRE → PER *(objective)*	0.060	0.033	**1.809**	**0.035**	(0.006,0.113)*	H5 supported
SCRO → PER*(objective)*	0.001	0.035	0.028	0.489	(−0.052,0.056) n.s	H6 rejected
Size → SCRE	0.101	0.055	**1.828**	**0.034**	(0.006, 0.189)*	Supported
Size → SCRO	0.016	0.058	1.130	0.281	(−0.081, 0.189) n.s	Rejected
Age → SCRE	−0.037	0.053	0.705	0.240	(−0.116, 0.067) n.s	Rejected
Age → SCRO	−0.051	0.072	0.706	0.240	(−0.146, 0.118) n.s	Rejected

Note: BCa CI: Bias corrected and accelerated confidence interval, RO: resource orchestration SCRE: SC Resilience; SCRO: SC Robustness; DI: disruption impact; PER: financial performance.
**$p < 0.05$.
*** $p < 0.01$.
* $p < 0.1$. n.s: non significant.

Table 8
Mediation analysis.

Relationships	Coeff (β)	Std. deviation	T statistics	p-values	95 % BCa CI	Conclusion
RO → SCRE → DI	−0.032	0.036	0.887	0.188	(−0.092, 0.025) n.s	No mediation
RO → SCRO → DI	−0.099	0.032	**3.076**	**0.001**	(−0.156, −0.050) ***	Complementary mediation
RO → SCRE → PER *(subjective)*	0.036	0.036	0.998	0.159	(−0.022, 0.096) n.s	No mediation
RO → SCRO → PER *(subjective)*	0.084	0.033	**2.540**	**0.006**	(0.033, 0.141) ***	Complementary mediation
RO → SCRE → PER *(objective)*	0.029	0.017	**1.686**	**0.046**	(0.002, 0.057) *	Complementary mediation
RO → SCRO → PER *(objective)*	0.001	0.014	0.029	0.488	(−0.020, 0.027) n.s	No mediation

Note: BCa CI: Bias corrected and accelerated confidence interval, RO: resource orchestration SCRE: SC Resilience; SCRO: SC Robustness; DI: disruption impact; PER: financial performance.
**p < 0.05.
*** p < 0.01.
* p < 0.1. n.s: non significant.

5. Discussion

Overall, the findings reveal the appropriateness of ROT as a framework to understand the effects of SCRE and SCRO during 'super-disruptions'. In this particularly uncertain context, the results underscore the difference in SCRE and SCRO effects on financial performance.

The findings show that it is mainly SCRO that was found to be effective in mitigating the 'super-disruption' impacts. The perceptual measures of financial performance that were collected shortly after the pandemic outbreak show that SCRE had no effect, whereas SCRO has a significant impact on performance. Conversely, the objective data on financial performance collected several months after the pandemic, reveal that the measures taken to consolidate SCRE have affected positively firms' performance; whereas the influence of SCRO on performance was not significant. In this respect, SCRO has made it possible to limit the short-term impacts of 'super-disruptions' related to the pandemic crisis, but SCRE was objectively the main contributor to the firm's financial performance. Such findings confirm the temporal characteristics of both concepts and underscore how disruption impacts can constitute an opportunity to learn from disasters such as COVID-19 pandemic, which can eventually yield positive effects on firms' financial performance.

The previous premises seem to reinforce the perspective of SCRE and SCRO as two specific capabilities to be mobilized for different purposes depending on the firms' sensitivity to risks and super-disruptions. Extant literature does not clearly distinguish the features or differences between SCRE and SCRO despite the emphasis placed by several scholars on the need to do so (Ivanov, 2020a). SCRE and SCRO necessitate different combination of resources (El Baz & Ruel, 2021). Indeed, SCRO is a capacity anchored in short-term perspective with the aim to maintain operations during a crisis (Brandon-Jones et al., 2014). Contrastingly, SCRE is based on the adaptability to disastrous events which necessitates a long time to accumulate (Ivanov, 2020b), in order to affect performance (Simchi-Levi et al., 2018). The findings of our study imply that there is a need to orchestrate resources as per ROT tenets and that this orchestration effort is applicable even in a 'super-disruption' context.

To recall, ROT is a process based on (1) structuring a resource portfolio, (2) combining/bundling the resources to generate synergistic effects and (3) leveraging configurations to improve the firm's financial performance in uncertain environments (Barney et al., 2011; Hughes et al., 2018; Sirmon et al., 2011). In this respect, the results show the need for a firm to first build SCRO in order to limit the short-term impacts of SC disruptions, and then to rely on SCRE in order to maintain financial performance in a 'super-disruptive' environment.

In this optic, we suggest viewing SCRO as an efficient tool of risk mitigation as it helps address the immediate effects of super disruptions, whereas SCRE can be considered as a capability to maintain firms' performance in the long run.

Since the impacts of this crisis are expected to span over several years (slowdown in international trade, successive lock-downs in many countries around the world[4]); orchestrating SCRE and SCRO would be crucial to face the upcoming challenges and to maintain firms' performance. Therefore, SCRE can constitute a powerful outlet to foster financial performance, which might be useful for companies that have been badly affected from the outset of the crisis.

6. Conclusion

Several theoretical and practical insights can be gained from our research.

6.1. Theoretical implications

This study provides new insights to organizational theory by underlining the applicability of ROT to SC disruption management especially in "super-disruptive" contexts. Specifically, the ROT refers to the managers' decisive responsibility to bundle, structure and leverage firms' resources to gain performance while taking into account the (uncertain) environment (Sirmon et al., 2011). To do so, an effective synchronization is necessary to ensure the orchestration of resources. Thus, the ROT helps outline how orchestration of resources in the context of a 'super-disruptive' pandemic leads to SCRE and SCRO which can affect financial performance (Singh et al., 2021; Yang et al., 2020). Overall, we contribute to ROT with this empirical investigation that links resource orchestration with both of SCRE and SCRO which was not attempted by previous studies that have mainly focused on SCRE (e.g., Chunsheng et al., 2020; Chowdhury et al., 2020; Queiroz et al., 2022). In doing so, we provide insights about the potential effects of resource orchestrations and its relevance to offer additional explanations to disaster management literature.

The positive impact of SCRO on mitigating the SC disruptions impact in a pandemic outbreak era reinforces the findings of previous studies (e.g., Bode et al., 2011, Chowdhury & Quaddus, 2017; Pettit et al., 2013). This research provides additional insights to prior studies by analyzing in the same research model both of SCRE and SCRO as Miroudot (2020) called for. Indeed, both capabilities are recognized as being valuable in SC disruption mitigation (Brandon-Jones et al., 2014; Li & Zobel, 2020; Pettit et al., 2013). However, this study shows the dominance of SCRO (scarcely examined in previous studies) over SCRE when mitigating SC disruptions impacts. Such results encourage scholars to study further the contribution of SCRO in a turbulent environment and to further investigate its peculiar features (Spiegler et al., 2012).

Furthermore, the findings of this study reinforce the results of prior studies on the influence of SCRE on financial performance (Hendricks et al., 2009; Lee & Rha, 2016; Wong et al., 2020; Yu et al., 2019). In particular, our results, anchored in objective data collected after the outbreak of COVID-19 'super-disruption', show that SCRE has an impact

[4] See https://www.supplychaindigital.com/procurement/top-five-2021-key-procurement-and-supply-chain-trends (accessed October 18, 2022).

on the firms' financial performance that was assessed in the long run; whereas on the short run perceptual measures indicate a lack of its impact. This result corroborates the perception of SCRE as a capability that unfolds in the long run (Pettit et al., 2010). This temporal feature that has been overlooked in prior research on SCRE and SCRO has been highlighted by the findings in the previous sections of this paper. Our research therefore allows us to underline the role of SCRO in mitigating the COVID-19 damaging effects in its early stages.

6.2. Practical implications

Along the lines of the ROT, a first implication for managers is for them to understand their key role in orchestrating the resources and capabilities linked to SCRE and SCRO in order to maintain the firm's performance in a 'super-disruption' situation. This orchestration of SCRO may help organizations attenuate the disruptions impacts. This can be achieved by flexibility and redundancy in the SC activities (from procurement to delivery through production). Then, we recommend focusing on SCRE to maintain financial performance. This is possible by improving agility, collaboration and even alertness capabilities along the SC.

Another contribution relates to the investment decisions that organizations have to make in a period where financial resources might be scarce. When SC practitioners request more resources for greater resilience and/or robustness, they often face resistance from top management, who would question the relevance of such investments on the grounds of costs (Parast, 2020; Shou et al., 2018). Not all the firms may have the capabilities and resources to deal with 'super-disruptions' such as the COVID-19 pandemic. Notwithstanding, our findings encourage firms to develop at least SCRO in order to mitigate the impacts of SC disruptions. Concerning firms experiencing a high impact of SC disruptions, investing in SCRE would also be necessary. Thus, SC practitioners should assess the intensity of SC disruption impacts in order to determine whether the investment can be limited to SCRO or whether there is a need to develop a set of resources to improve SCRE.

In several consulting firms' reports and articles in press about the COVID-19 pandemic and SCM, there is a strong emphasis placed on SCRE, whereas SCRO is often overlooked. In contrast, our results indicate that it is beneficial for SC practitioners to develop both of SCRO and SCRE.

6.3. Limitations and further research avenues

It is important to point out that the data were collected in a French context (a country severely affected by the COVID-19 pandemic[5]) and that it would be appropriate to undertake empirical investigation it in other contexts to highlight potential differences and similarities. Moreover, perceptual data were collected at the beginning of the pandemic crisis in Europe, and objective data relate to the year 2020. Thus, the results of this study could change over time, which reinforces the need for a longitudinal study. Such investigation might provide novel insights on the orchestration of resources and the effects of deploying both of SCRE and SCRO on disruptions impacts and other dimensions related to performance. In addition, future research might consider investigating firms based on the level of disruption they experienced as a result of the pandemic. Organizations might be surveyed in groups according to the level or location of the impact: upstream impact (e.g., sourcing, purchase prices), downstream impact (e.g., distribution, sales prices) or operational impact (e.g., shutdown of production lines, storage difficulties). Thus, future research might explore how the level of the disruptions generated by the pandemic might affect SCRE, SCRO and firms' financial performance.

CRediT authorship contribution statement

Jamal El Baz: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Salomée Ruel:** Writing – review & editing, Writing – original draft, Project administration, Investigation, Validation. **Zahra Fozouni Ardekani:** Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1. Construct items

Resources orchestration (RO) (1 = strongly disagree, 7 = strongly agree)
RO1 We share operational information with our partners, i.e. suppliers and customers.
RO2 We develop operational flexibility via collaboration with SC partners.
RO3 We develop SC arrangements with our partners (suppliers and customers) regarding resources deployment.
RO4 We have specific procedures to share information with our suppliers and customers.
RO5 We have an integrated database to facilitate information sharing across internal functions of our firm.
RO6 We ensure that internal functions share operational information.
RO7. Risk management information is shared by internal functions of our firm.
Supply chain resilience (SCRE) (1 = strongly disagree, 7 = strongly agree)
SCRE1. With our supply chain partners we are able to cope with changes resulting from disruptive events.
SCRE2. We can ensure that our supply chain is capable of adapting easily to disruptive events.
SCRE3. We can provide quick response to disruptive events with our supply chain partners.
SCRE4. We maintain alertness and situational awareness in our supply chain.
Supply chain robustness (SCRO) (1 = strongly disagree, 7 = strongly agree)
SCRO1. We can maintain stability for a long time in our supply chain.
SCRO2. We can have sufficient time to consider reactive measures to disruptions in our supply chain.
SCRO3. We have a wide array of scenarios in which our supply chain is capable of maintaining performance without necessary adaptation.
SCRO4. In spite of damages and disruptions, our supply chain can still operate and achieve the various aims set.
Disruption impacts (DI) (1 = no impact at all, 7 = to a large extent)

[5] Daily data including contaminations, hospitalizations and mortality in France is available on https://www.santepubliquefrance.fr/dossiers/coronavirus-covid-19/coronavirus-chiffres-cles-et-evolution-de-la-covid-19-en-france-et-dans-le-monde (accessed October 18, 2022).

Disruption1. The impact of COVID-19 disruption on the efficiency of operations.
Disruption2. The impact of COVID-19 disruption on the delivery reliability.
Disruption3. The impact of COVID-19 disruption on purchasing/procurement costs.
Financial performance (PERF) (1 = worse, 7 = better)
Perform1. Profit margin (%) in comparison with competition.
Perform2. Return on sales in comparison with competition.
Perform3. Return on total assets in comparison with competition.
Perform4. Sales over assets in comparison with competition.

Appendix 2. The endogeneity test results*

Variables	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
RO	0.0338	0.907	0.01486	0.826	0.014	0.832	0.030	0.657	−0.0035	0.990
SCRE	0.0715	0.303	0.23661	0.169	0.069	0.320	0.051	0.460	0.237	0.170
SCRO	0.1997	0.003	0.19536	0.004	0.115	0.561	0.196	0.003	0.195	0.004
DI	0.1365	0.023	0.13287	0.027	0.135	0.024	0.275	0.006	0.018	0.027
Cro	−0.0211	0.940								
Cscre			−0.1540	0.294					−0.018	0.948
Cscro					0.080	0.653			0.018	0.295
Cdi							−0.093	0.088		

Variables	Model 6		Model 7		Model 8		Model 9		Model 10	
	Coeff.	p-value	Coeff.	p-value	Coeffi.	p-value	Coeff.	p-value	Coeff.	p-value
RO	0.048	0.869	0.056	0.845	0.017	0.794	0.031	0.6456	0.036	0.599
SCRE	0.069	0.319	0.052	0.459	0.249	0.151	0.190	0.274	0.045	0.587
SCRO	0.113	0.573	0.196	0.004	0.076	0.703	0.193	0.047	0.035	0.861
DI	0.135	0.024	0.275	0.006	0.131	0.029	0.264	0.009	0.289	0.004
Cro	−0.033	0.905								
Cscre					−0.168	0.257	−0.127	0.384		
Cscro	0.082	0.647	−0.026	0.926	0.112	0.534			0.1535	0.399
Cdi			−0.093	0.088			−0.0883	0.109	−0.104	0.064

Variables	Model 11		Model 12		Model 13	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
RO	0.0132	0.964	0.0246	0.9338	0.0873	0.766
SCRE	0.2495	0.153	0.1905	0.277	0.004	0.515
SCRO	0.0772	0.704	0.1932	0.004	0.0312	0.878
DI	0.1315	0.029	0.2642	0.009	0.2898	0.004
Cro	0.004	0.987	0.0066	0.9812	-0.051	0.857
Cscre	−0.168	0.260	−0.1283	0.388		
Cscro	0.112	0.536			0.157	0.392
Cdi			−0.0088	0.111	−0.104	0.065

*The results present the various models using Gaussian Copula combinations.

Appendix 3. Unobserved heterogeneity test with fit values of the FIMIX approach

For the first run of FIMIX, we set 1 as number of segments, 5,000 iterations, and stop criterion of $1 - 10^{-5}$. To define a range of reasonable segment numbers, we consider one segment as the lower bound and the largest integer when dividing the sample size by the minimum segment sample size as the upper bound. In our case, when analyzing a data set with 289 observations, and the requirement of a minimum segment sample size of 50 it is not reasonable to run FIMIX-PLS with more than three segments (Hair et al., 2016; Mathews et al., 2016).

Num. of segments	1	2	3	4
1	1(289)			
2	0.653(189)	0.347(100)		
3	0.433(125)	0.343(99)	0.224(65)	
4	0.343(99)	0.338(98)	0.26(75)	0.058 (17)

The calculations show that, for a four segment solution, the breakdown of segment sizes is segment 1 with 34.3 per cent (of 289 = 99 observations), segment 2 with 33.8 per cent (of 289 = 98 observations) segment 3 with only 26 per cent (of 289 = 75 observations) and segment 4 with only 5.8 per cent (of 289 = 17 observations). Consequently, with merely 17 observations, segment 4 is too small for a specific PLS-SEM analysis.

Regarding the FIMIX measures, the optimal solution is the number of segments with the lowest value, except in terms of EN, where higher values indicate a better separation of the segments.

Criteria	Segment 1	Segment 2	Segment 3
AIC (Akaike's Information Criterion) >	2804.504	2705.914	**2510.854**
AIC3 (Modified AIC with Factor 3) <	2821.504	2740.914	**2563.854**
AIC4 (Modified AIC with Factor 4) <	2838.504	2775.914	**2616.854**
BIC (Bayesian Information Criteria) <	2866.833	2834.239	**2705.175**
CAIC (Consistent AIC) <	2883.833	2869.239	**2758.175**
HQ (Hannan Quinn Criterion) <	2829.479	2757.333	**2588.717**
MDL5 (Minimum Description Length with Factor 5) <	**3252.15**	3627.538	3906.457
EN (Entropy Statistic (Normed)) <	n/a	0.513	**0.679**

The number of potential segments should be higher than the segment indicated by minimum description length with factor 5 (MDL5) which is owned by segment 1 (Hair et al., 2016). The number of potential segments should be lower than the segment indicated by AIC, AIC4, BIC and CAIC (Hair et al., 2016) which is owned by segment 3. Therefore, the results suggest the two segments solution which reveals an EN value exceeding the threshold of 0.50, suggesting that the two segments are valid and well separated. Overall, the results suggest that there is no substantial level of heterogeneity in the data.

References

Abeysekara, N., Wang, H., & Kuruppuarachchi, D. (2019). Effect of supply-chain resilience on firm performance and competitive advantage. *Business Process Management Journal, 25*(7), 1673–1695.

Ambulkar, S., Blackhurst, J., & Grawe, S. (2015). Firm's resilience to supply chain disruptions: Scale development and empirical examination. *Journal of Operations Management, 33*, 111–122.

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research, 14*(3), 396–402.

Azadegan, A., Mellat Parast, M., Lucianetti, L., Nishant, R., & Blackhurst, J. (2020). Supply chain disruptions and business continuity: An empirical assessment. *Decision Sciences, 51*(1), 38–73.

Barney, J. B., Ketchen, D. J., Jr, & Wright, M. (2011). The future of resource-based theory: Revitalization or decline? *Journal of Management, 37*(5), 1299–1315.

Belhadi, A., Kamble, S., Jabbour, C. J. C., Gunasekaran, A., Ndubisi, N. O., & Venkatesh, M. (2021). Manufacturing and service supply chain resilience to the COVID-19 outbreak: Lessons learned from the automobile and airline industries. *Technological Forecasting and Social Change, 163*, Article 120447.

Bode, C., Wagner, S. M., Petersen, K. J., & Ellram, L. M. (2011). Understanding responses to supply chain disruptions: Insights from information processing and resource dependence perspectives. *Academy of Management Journal, 54*(4), 833–856.

Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A contingent resource-based perspective of supply chain resilience and robustness. *Journal of Supply Chain Management, 50*(3), 55–73.

Burgos, D., & Ivanov, D. (2021). Food retail supply chain resilience and the COVID-19 pandemic: A digital twin-based impact analysis and improvement directions. *Transportation Research Part E: Logistics and Transportation Review, 152*, Article 102412.

Burin, A. R. G., Perez-Arostegui, M. N., & Llorens-Montes, J. (2020). Ambidexterity and IT competence can improve supply chain flexibility? A resource orchestration approach. *Journal of Purchasing and Supply Management, 26*(2), Article 100610.

Cherrafi, A., Chiarini, A., Belhadi, A., El Baz, J., & Benabdellah, A. C. (2022). Digital technologies and circular economy practices: Vital enablers to support sustainable and resilient supply chain management in the post-COVID-19 era. *The TQM Journal, 34*(7), 179–202.

Chowdhury, M. M. H., & Quaddus, M. (2017). Supply chain resilience: Conceptualization and scale development using dynamic capability theory. *International Journal of Production Economics, 188*, 185–204.

Chowdhury, M. T., Sarkar, A., Saha, P. K., & Anik, R. H. (2020). Enhancing supply resilience in the COVID-19 pandemic: A case study on beauty and personal care retailers. *Modern Supply Chain Research and Applications, 2*(3), 143–159.

Christopher, M., & Holweg, M. (2017). Supply chain 2.0 revisited: A framework for managing volatility-induced risk in the supply chain. *International Journal of Physical Distribution & Logistics Management, 47*(1), 2–17.

Chunsheng, L., Wong, C. W., Yang, C. C., Shang, K. C., & Lirn, T. C. (2020). Value of supply chain resilience: Roles of culture, flexibility, and integration. *International Journal of Physical Distribution & Logistics Management, 50*(1), 80–100.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed). Hillsdale, NJ: Lawrence Erlbaum Associates.

Cui, M., & Pan, S. L. (2015). Developing focal capabilities for e-commerce adoption: A resource orchestration perspective. *Information & Management, 52*(2), 200–209.

Dillman, D. A. (2000). *Mail and internet surveys: The tailored design method*. New York: Wiley.

DuHadway, S., Carnovale, S., & Hazen, B. (2019). Understanding risk management for intentional supply chain disruptions: Risk detection, risk mitigation, and risk recovery. *Annals of Operations Research, 283*(1), 179–198.

El Baz, J., & Ruel, S. (2021). Can supply chain risk management practices mitigate the disruption impacts on supply chains' resilience and robustness? Evidence from an empirical survey in a COVID-19 outbreak era. *International Journal of Production Economics, 233*, Article 107972.

Ellram, L. M., Tate, W. L., & Feitzinger, E. G. (2013). Factor-market rivalry and competition for supply chain resources. *Journal of Supply Chain Management, 49*(1), 29–46.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 1149–1160.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50.

Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. *Journal of Business Research, 69*(8), 3192–3198.

Golan, M. S., Trump, B. D., Cegan, J. C., & Linkov, I. (2021). Supply chain resilience for vaccines: Review of modeling approaches in the context of the COVID-19 pandemic. *Industrial Management & Data Systems, 121*(7), 1723–1748.

Govindan, K., Mina, H., & Alavi, B. (2020). A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (COVID-19). *Transportation Research Part E: Logistics and Transportation Review, 138*, Article 101967.

Hair, J.F.H., Hult, G.T.M., Ringle, C.M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)*. 2nd ed. Los Angeles: Sage.

Hair, J. F. H., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24.

Hair, J. F., Sarstedt, M., Matthews, L., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: Part I - method. *European Business Review, 28*(1), 63–76.

Harvey, C., Kelly, A., Morris, H., & Rowlinson, M. (2010). *Academic journal quality guide*. London: The Association of Business Schools.

Hendricks, K. B., & Singhal, V. R. (2003). The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management, 21*(5), 501–522.

Hendricks, K. B., Singhal, V. R., & Zhang, R. (2009). The effect of operational slack, diversification, and vertical relatedness on the stock market reaction to supply chain disruptions. *Journal of Operations Management, 27*(3), 233–246.

Hitt, M. A., Arregle, J. L., & Holmes, R. M., Jr (2021). Strategic management theory in a post-pandemic and non-ergodic world. *Journal of Management Studies, 58*(1), 259–264.

Hitt, M. A., Carnes, C. M., & Xu, K. (2016). A current view of resource based theory in operations management: A response to Bromiley and Rau. *Journal of Operations Management, 41*(10), 107–109.

Hobbs, J. E. (2021). Food supply chains during the COVID-19 pandemic. *Canadian Journal of Agricultural Economics/Revue canadienne d'Agroeconomie, 68*, 171–176.

Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review, 125*, 285–307.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55.

Hughes, P., Hodgkinson, I. R., Elliott, K., & Hughes, M. (2018). Strategy, operations, and profitability: The role of resource orchestration. *International Journal of Operations & Production Management, 38*(4), 1125–1143.

Ivanov, D. (2020a). Viable supply chain model: Integrating agility, resilience and sustainability perspectives-lessons from and thinking beyond the COVID-19 pandemic. *Annals of Operations Research, 1*, 1125–1143.

Hult, G. T. M., Hair, J. F., Jr, Proksch, D., Sarstedt, M., Pinkwart, A., & Ringle, C. M. (2018). Addressing endogeneity in international marketing applications of partial least squares structural equation modeling. *Journal of International Marketing, 26*(3), 1–21.

Ivanov, D. (2020b). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. *Transportation Research Part E: Logistics and Transportation Review, 136*, 101–922.

Ivanov, D. (2021). Exiting the COVID-19 pandemic: After-shock risks and avoidance of disruption tails in supply chains. *Annals of Operations Research, 1–18*. https://doi.org/10.1007/s10479-021-04047-7

Ivanov, D., & Das, A. (2020). Coronavirus (COVID-19/SARS-CoV-2) and supply chain resilience: A research note. *International Journal of Integrated Supply Management, 13*(1), 90–102.

Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. *International Journal of Production Research, 58*(10), 2904–2915.
Juan, S. J., Li, E. Y., & Hung, W. H. (2021). An integrated model of supply chain resilience and its impact on supply chain performance under disruption. *The International Journal of Logistics Management, 33*(1), 339–364.
Kähkönen, A. K., Evangelista, P., Hallikas, J., Immonen, M., & Lintukangas, K. (2023). COVID-19 as a trigger for dynamic capability development and supply chain resilience improvement. *International Journal of Production Research, 61*(8), 2696–2715.
Ketokivi, M., & McIntosh, C. N. (2017). Addressing the endogeneity dilemma in operations management research: Theoretical, empirical, and pragmatic considerations. *Journal of Operations Management, 52*, 1–14.
Ketokivi, M., & Schroeder, R. (2004). Manufacturing practices, strategic fit and performance: a routine-based view. *International Journal of Operations & Production Management, 24*(2), 171–191.
Ketchen, D. J., Jr, Wowak, K. D., & Craighead, C. W. (2014). Resource gaps and resource orchestration shortfalls in supply chain management: The case of product recalls. *Journal of Supply Chain Management, 50*(3), 6–15.
Kroes, J. R., & Ghosh, S. (2010). Outsourcing congruence with competitive priorities: Impact on supply chain and firm performance. *Journal of Operations Management, 28*(2), 124–143.
Kumar, V., Bak, O., Guo, R., Shaw, S. L., Colicchia, C., Garza-Reyes, J. A., & Kumari, A. (2018). An empirical analysis of supply and manufacturing risk and business performance: A Chinese manufacturing supply chain perspective. *Supply Chain Management: An International Journal, 23*(6), 461–479.
Lee, S. M., & Rha, J. S. (2016). Ambidextrous supply chain as a dynamic capability: Building a resilient supply chain. *Management Decision, 54*(1), 2–23.
Lewis, M., Brandon-Jones, A., Slack, N., & Howard, M. (2010). Competing through operations and supply. *International Journal of Operations & Production Management, 30*(10), 1032–1058.
Li, X., Wu, Q., Holsapple, C. W., & Goldsby, T. (2017). An empirical examination of firm financial performance along dimensions of supply chain resilience. *Management Research Review, 40*(3), 254–269.
Li, Y., & Zobel, C. W. (2020). Exploring supply chain network resilience in the presence of the ripple effect. *International Journal of Production Economics, 228*, Article 107693.
Liu, H., Wei, S., Ke, W., Wei, K. K., & Hua, Z. (2016). The configuration between supply chain integration and information technology competency: A resource orchestration perspective. *Journal of Operations Management, 44*, 13–29.
Madzimure, J. (2020). Supply chain robustness, firm competitiveness and performance of South African logistics firms. *Eurasian Journal of Business and Management, 8*(2), 137–149.
Miroudot, S. (2020). Resilience versus robustness in global value chains: Some policy implications. *COVID-19 and trade policy: Why turning inward won't work* (pp. 117–130).
Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience: Learning from Covid-19. *The International Journal of Logistics Management, 33*(4), 1246–1268.
Moosavi, J., & Hosseini, S. (2021). Simulation-based assessment of supply chain resilience with consideration of recovery strategies in the COVID-19 pandemic context. *Computers & Industrial Engineering, 160*, Article 107593.
Nikolopoulos, K., Punia, S., Schäfers, A., Tsinopoulos, C., & Vasilakis, C. (2021). Forecasting and planning during a pandemic: COVID-19 growth rates, supply chain disruptions, and governmental decisions. *European Journal of Operational Research, 290*(1), 99–115.
Nikookar, E., & Yanadori, Y. (2022). Preparing supply chain for the next disruption beyond COVID-19: Managerial antecedents of supply chain resilience. *International Journal of Operations & Production Management, 42*(1), 59–90.
Nitzl, C., Roldan, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management & Data Systems, 116*(9), 1849–1864.
Pan, S. L., Cui, M., & Qian, J. (2020). Information resource orchestration during the COVID-19 pandemic: A study of community lockdowns in China. *International Journal of Information Management, 54*, Article 102143.
Pan, S. L., & Zhang, S. (2020). From fighting COVID-19 pandemic to tackling sustainable development goals: An opportunity for responsible information systems research. *International Journal of Information Management, 55*, Article 102196.
Parast, M. M. (2020). The impact of R&D investment on mitigating supply chain disruptions: Empirical evidence from US firms. *International Journal of Production Economics, 227*, Article 107671.
Park, S., & Gupta, S. (2012). Handling endogenous regressors by joint estimation using copulas. *Marketing Science, 31*(4), 567–586.
Paul, S. K., Moktadir, M. A., & Ahsan, K. (2021). Key supply chain strategies for the post-COVID-19 era: Implications for resilience and sustainability. *The International Journal of Logistics Management*. https://doi.org/10.1108/IJLM-04-2021-0238
Peel, M. J. (2018). Addressing unobserved selection bias in accounting studies: The bias minimization method. *European Accounting Review, 27*(1), 173–183.
Pettit, T. J., Croxton, K. L., & Fiksel, J. (2013). Ensuring supply chain resilience: Development and implementation of an assessment tool. *Journal of Business Logistics, 34*(1), 46–76.
Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring supply chain resilience: Development of a conceptual framework. *Journal of Business Logistics, 31*(1), 1–21.
Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903.
Priem, R. L., & Butler, J. E. (2001a). Is the resource-based "view" a useful perspective for strategic management research? *Academy of Management Review, 26*(1), 22–40.
Priem, R. L., & Butler, J. E. (2001b). Tautology in the resource-based view and the implications of externally determined resource value: Further comments. *Academy of Management Review, 26*(1), 57–66.
Qrunfleh, S., Vivek, S., Merz, R., & Mathivathanan, D. (2022). Mitigation themes in supply chain research during the COVID-19 pandemic: A systematic literature review. *Benchmarking: An International Journal.*. https://doi.org/10.1108/BIJ-11-2021-0692
Queiroz, M. M., Wamba, S. F., & Branski, R. M. (2021). Supply chain resilience during the COVID-19: Empirical evidence from an emerging economy. *Benchmarking: An International Journal, 29*(6), 1999–2018.
Queiroz, M. M., Wamba, S. F., Jabbour, C. J. C., & Machado, M. C. (2022). Supply chain resilience in the UK during the coronavirus pandemic: A resource orchestration perspective. *International Journal of Production Economics, 245*, Article 108405.
Rodrigues, A. M., Stank, T. P., & Lynch, D. F. (2004). Linking strategy, structure, process, and performance in integrated logistics. *Journal of Business Logistics, 25*(2), 65–94.
Ruel, S., & El Baz, J. (2023). Disaster readiness' influence on the impact of supply chain resilience and robustness on firms' financial performance: A COVID-19 empirical investigation. *International Journal of Production Research, 61*(8), 2594–2612.
Ruel, S., El Baz, J., Ivanov, D., & Das, A. (2021). Supply chain viability conceptualization, measurement, and nomological validation. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-03974-9
Sarkis, J., Cohen, M. J., Dewick, P., & Schröder, P. (2020). A brave new world: Lessons from the COVID-19 pandemic for transitioning to sustainable supply and production. *Resources, Conservation, and Recycling, 159*, Article 104894.
Sarstedt, M., Hair, J. F., & Ringle, C. M. (2022). PLS-SEM: Indeed a silver bullet" – retrospective observations and recent advances. *Journal of Marketing Theory and Practice*. https://doi.org/10.1080/10696679.2022.2056488
Sarstedt, M., & Mooi, E. (2014). *A Concise Guide to Market Research* (2nd edition.). Springer Texts in Business and Economics, Springer.
Sharma, A., Adhikary, A., & Borah, S. B. (2020). Covid-19′ s impact on supply chain decisions: Strategic insights from NASDAQ 100 firms using Twitter data. *Journal of Business Research, 117*, 443–449.
Sharma, M., Luthra, S., Joshi, S., & Kumar, A. (2022). Developing a framework for enhancing survivability of sustainable supply chains during and post-COVID-19 pandemic. *International Journal of Logistics Research and Applications, 25*(4–5), 433–453.
Shen, Z. M., & Sun, Y. (2023). Strengthening supply chain resilience during COVID-19: A case study of JD.com. *Journal of Operations Management, 69*(3), 359–383.
Shishodia, A., Verma, P., & Karuna, J. (2022). Supplier resilience assessment in project-driven supply chains. *Production Planning & Control, 33*(9–10), 875–893.
Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing, 53*(11), 2322–2347.
Shou, Y., Hu, W., Kang, M., Li, Y., & Park, Y. W. (2018). Risk management and firm performance: The moderating role of supplier integration. *Industrial Management & Data Systems, 118*(7), 1327–1344.
Simchi-Levi, D., Wang, H., & Wei, Y. (2018). Increasing supply chain robustness through process flexibility and inventory. *Production and Operations Management, 27*(8), 1476–1491.
Singh, S., Kumar, R., Panchal, R., & Tiwari, M. K. (2021). Impact of COVID-19 on logistics systems and disruptions in food supply chain. *International Journal of Production Research, 59*(7), 1993–2008.
Sirmon, D. G., & Hitt, M. A. (2009). Contingencies within dynamic managerial capabilities: Interdependent effects of resource investment and deployment on firm performance. *Strategic Management Journal, 30*(13), 1375–1394.
Sirmon, D. G., Hitt, M. A., & Ireland, R. D. (2007). Managing firm resources in dynamic environments to create value: Looking inside the black box. *Academy of Management Review, 32*(1), 273–292.
Sirmon, D. G., Hitt, M. A., Ireland, R. D., & Gilbert, B. A. (2011). Resource orchestration to create competitive advantage: Breadth, depth, and life cycle effects. *Journal of Management, 37*(5), 1390–1412.
Spiegler, V. L., Naim, M. M., & Wikner, J. (2012). A control engineering approach to the assessment of supply chain resilience. *International Journal of Production Research, 50*(21), 6162–6187.
Spieske, A., & Birkel, H. (2021). Improving supply chain resilience through industry 4.0: A systematic literature review under the impressions of the COVID-19 pandemic. *Computers & Industrial Engineering, 158*, Article 107452.
Srimarut, T., & Mekhum, W. (2020). Enhancing financial performance through supply chain innovation (SCI) with mediating role of robustness and resilience capability in Thailand's manufacturing sector. *International Journal of Supply Chain Management, 9*(1), 175–182.
Stank, T. P., Keller, S. B., & Daugherty, P. J. (2001). Supply chain collaboration and logistical service performance. *Journal of Business Logistics, 22*(1), 29–48.
Sytch, M., Kim, Y., & Page, S. (2022). Supplier-selection practices for robust global supply chain networks: A simulation of the global auto industry. *California Management Review, 64*(2), 119–142.
Thomaz, F., & Swaminathan, V. (2015). What goes around comes around: The impact of marketing alliances on firm risk and the moderating role of network density. *Journal of Marketing, 79*(5), 63–79.
Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2015). Supply chain resilience: Definition, review and theoretical foundations for further study. *International Journal of Production Research, 53*(18), 5592–5623.

Van Hoek, R. (2020). Research opportunities for a more resilient post-COVID-19 supply chain–closing the gap between research findings and industry practice. *International Journal of Operations & Production Management, 40*(4), 341–355.
Wagner, S. M., & Kemmerling, R. (2010). Handling nonresponse in logistics research. *Journal of Business Logistics, 31*(2), 357–381.
Werner, S., Praxedes, M., & Kim, H. G. (2007). The reporting of nonresponse analyses in survey research. *Organizational Research Methods, 10*(2), 287–295.
Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal, 5*(2), 171–180.
Wieland, A., & Wallenburg, C. M. (2012). Dealing with supply chain risks. *International Journal of Physical Distribution & Logistics Management, 42*(10), 887–905.
Wong, C. W., Lirn, T. C., Yang, C. C., & Shang, K. C. (2020). Supply chain and external conditions under which supply chain resilience pays: An organizational information processing theorization. *International Journal of Production Economics, 226*, Article 107610.
Wong, C. W., Wong, C. Y., & Boon-itt, S. (2018). How does sustainable development of supply chains make firms lean, green and profitable? A resource orchestration perspective. *Business Strategy and the Environment, 27*(3), 375–388.
Wowak, K. D., Craighead, C. W., Ketchen, D. J., Jr, & Hult, G. T. M. (2016). Toward a "theoretical toolbox" for the supplier-enabled fuzzy front end of the new product development process. *Journal of Supply Chain Management, 52*(1), 66–81.
Yang, J., Xie, H., Yu, G., & Liu, M. (2020). Antecedents and consequences of supply chain risk management capabilities: An investigation in the post-coronavirus crisis. *International Journal of Production Research*, 1–13.
Yu, W., Jacobs, M. A., Chavez, R., & Yang, J. (2019). Dynamism, disruption orientation, and resilience in the supply chain and the impacts on financial performance: A dynamic capabilities perspective. *International Journal of Production Economics, 218*, 352–362.
Zaefarian, G., Kadile, V., Henneberg, S., & Leischnig, A. (2017). Endogeneity bias in marketing research: Problem, causes and remedies. *Industrial Marketing Management, 65*, 39–46.
Zamani, E. D., Smyth, C., Gupta, S., & Dennehy, D. (2022). Artificial intelligence and big data analytics for supply chain resilience: A systematic literature review. *Annals of Operations Research, 1–28*. https://doi.org/10.1007/s10479-022-04983-y

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