

RESEARCH ARTICLE

Breaking out of the pandemic: How can firms match internal competence with external resources to shape operational resilience?

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Funding information

National Natural Science Foundation of China, Grant/Award Numbers: 71421002, 71902116, 71902145

Handling Editors: Hau L. Lee, Xiang Li, Chris Voss, Xiande Zhao

Abstract

This study explores how firms sought to effectively match their internal competence with external resources from the supply chain network to improve operational resilience (OR) during the COVID-19 pandemic. Drawing upon matching theory, this study provides an internal–external matching perspective based on flexibility–stability features of OR to explain the operational mechanisms underlying the different matchings between internal flexibility (i.e., product diversity)/stability (i.e., operational efficiency) and external flexibility (i.e., structural holes)/stability (i.e., network centrality). We find that more heterogeneous matchings between internal (external) flexibility and external (internal) stability have a complementary effect that enhances OR, whereas more homogeneous matchings between internal flexibility (or stability) and external flexibility (or stability) have a substitutive effect that reduces OR. This study provides valuable contributions to research focusing on the supply chain, organizational resilience, and operations management.

KEYWORDS

COVID-19 pandemic, operational efficiency, operational resilience, product diversity, supply chain network

Highlights

- Firms need to match their internal competence with supply chain network resources in the correct way to improve their operational resilience in the COVID-19 pandemic.
- Matchings between internal flexibility and external stability, and between internal stability and external flexibility can enhance firms' operational resilience in the COVID-19 pandemic.
- Firms with high product diversity and occupying the central position in the supply chain network, and with high operational efficiency and more structural holes in the supply chain network can better resist the shock of the COVID-19 pandemic.

All the authors contributed equally to this article.

1 | INTRODUCTION

Operational resilience (OR) is attracting attention from scholars in operations management and strategic management, who have recognized that it helps firms maintain stable growth in the face of external shocks, such as the COVID-19 pandemic (DesJardine et al., 2019; Essuman et al., 2020; van der Vegt et al., 2015). OR, as the most basic and important part of organizational resilience, comprises the latent ability of a firm's operations to maintain their existing structure/function and recover from supply chain disruptions (Essuman et al., 2020; Williams et al., 2017). The extant research suggests that OR depends on achieving an effective balance between stability and flexibility in the firm's operations (DesJardine et al., 2019). Operational stability reflects the firm's capabilities in maintaining the structure, function, and efficiency of operations, while operational flexibility represents the firm's capabilities in developing alternative operational solutions to resist and mitigate external shocks and disasters (Kortmann et al., 2014).

What influences the stability and flexibility of OR? The internal perspective focuses on the effects of product diversity (PD), which reflects the firm's internal operational flexibility and lays the foundation for the firm's adjustment to external shocks (Reinmoeller & van Baardwijk, 2005), and the effects of operational efficiency (OE), which is defined as the ratio of outputs to inputs in the value creation process and reflects the firm's internal operational stability (Kortmann et al., 2014). In contrast, the external perspective focuses on the effects of centrality and structural holes (SH), which reflect the stability and flexibility of external network resources,

respectively (Phelps, 2010). Specifically, centrality supports network relational stability through the use of network power (Polidoro et al., 2011), while SH can strengthen flexibility through acquired heterogeneous knowledge (Gargiulo & Benassi, 2000).

In the past, these two perspectives have seldom engaged in dialogue with each other. This omission creates a major concern in the literature, because the matching of internal and external factors may generate either complementary or substitutive effects for OR (Mindruta et al., 2016). Specifically, external network structures may either enable or constrain the functioning of the firm's internal competence, while the firm's differential positional advantages in the supply chain network may become useless if they are not supported by internal competence (Williams et al., 2017). In addition, this concern has become particularly salient during the COVID-19 pandemic, given the unique impacts of COVID-19 on supply chains. The pandemic simultaneously hurt some industries (e.g., offline products) but boosted others (e.g., online products); its scope was worldwide and encompassed multiple industries, rather than simply having a local influence in one country and a single industry. Moreover, its long-term nature may have permanently changed the behaviors of supply chain partners (e.g., customers' preferences for online transactions) (Poelman et al., 2021). Such structural, global, and long-lasting impacts on their supply chains have required firms to simultaneously match their internal adjustments with external cooperation from their supply chain partners via their network structures to enhance OR (van der Vegt et al., 2015). Unfortunately, the existing internal and external perspectives have been developed in parallel ways, so as yet we have limited

Internal flexibility (i.e., product diversity)	Cell 1	Cell 2
	<ol style="list-style-type: none"> 1. Internal flexibility provides the foundation for firm adjustment to the pandemic 2. External stability wins over supply chain partners that support firm adjustment 	<ol style="list-style-type: none"> 1. Internal flexibility provides the foundation for firm adjustment to the pandemic 2. External flexibility creates distrust and agency among supply chain partners that hinders firm adjustment
Internal stability (i.e., operational efficiency)	Cell 3	Cell 4
	<ol style="list-style-type: none"> 1. External stability provides redundant information to blind innovation plans 2. Internal stability is conducive to the implementation of any innovation plans 	<ol style="list-style-type: none"> 1. External flexibility provides heterogeneous information to identify innovation plans 2. Internal stability is conducive to the implementation of any innovation plans
	External stability (i.e., network centrality)	External flexibility (i.e., structural holes)

FIGURE 1 Matching modes for operational resilience

understanding about how different matchings between firm internal competence and external network structures affected OR during the COVID-19 pandemic.

To address these issues, we extend the matching perspective to the COVID-19 pandemic setting to argue that the internal and external perspectives should be integrated. Specifically, we formulate a new research model (shown in Figure 1) based on the internal and external flexibility and stability features of OR. This model explores the mechanisms for four different matchings between internal competence (e.g., OE and PD) and external network resources (e.g., centrality and SH) in the supply chain. Further, drawing upon matching theory, we propose that either the matching between internal stability and external flexibility, or the matching between internal flexibility and external stability, can achieve a better matching effect and thereby enhance OR (Mindruta et al., 2016). Using data from Chinese public firms and their supply chain networks, this study examines the effects of the four matching modes on OR, finding that the results support our propositions.

This study makes the following important contributions. First, we enrich the resilience literature by theoretically proposing and empirically examining how the matchings between internal stability and flexibility (e.g., OE and PD) and external stability and flexibility (e.g., network centrality [NC] and SH) influence OR in the context of the COVID-19 pandemic. This study extends the scope of the matching perspective from between-entities matching to within-entity matching. Second, this study advances supply chain management research by exploring how centrality and SH in the supply chain network affect the impact of internal competence on OR in the COVID-19 context. Third, we deepen the extant flexibility research in operations management by explaining the effects of the interactions between OE/PD and network structures on OR.

2 | THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

2.1 | Operational resilience

OR is the latent ability of a firm's operations system to withstand external adversity that negatively affects the supply chain and to recover and maintain its existing structure (Essuman et al., 2020; Williams et al., 2017). OR is based on the stability and flexibility of a firm's operations system (DesJardine et al., 2019; Essuman et al., 2020). Two basic perspectives explain how firms enhance OR through balancing operational stability and flexibility facing external shocks.

First, the internal perspective focuses on leveraging internal factors as a means of resisting the impact of external shocks. It suggests that leveraging internal competence is the basic safeguard for maintaining the flexibility and stability of the operations system. When facing external shocks, firms with internal flexibility can allocate internal resources in a flexible way to capitalize on new market opportunities and recover their production (Hendricks et al., 2009). Specifically, diversification is a resisting-risk strategy that aims to introduce new products or product lines, launch new services, or enter new markets (Reinmoeller & van Baardwijk, 2005). The resulting PD can ensure flexibility in market choice by enabling the firm to develop alternative operational solutions geared toward resisting external adversity (Malhotra & Mackelprang, 2012). Further, a firm with internal stability can effectively maintain the structure and normal functioning of its operations, which is conducive to implementing recovery projects efficiently. OE can ensure operational stability (Kortmann et al., 2014). For example, Manz and Stewart (1997) suggested that the mechanistic efficiency of total quality management might create stability within the work system. As great OE cultivates a routinized operational process, it naturally increases operational stability.

Second, the external perspective suggests that firms can gain access to external resources via their social networks so as to enhance their OR when facing external uncertainty (Dimitriadis, 2021; Pal et al., 2014). NC and SH are two of the most important structural attributes that reflect the stability and flexibility of the network (Afuah, 2013; Gargiulo & Benassi, 2000; Polidoro et al., 2011). NC indicates the firm's proximity to the center of the network (Bellamy et al., 2014; Lan et al., 2020). It characterizes a firm's power and status among its partners in the network (Liu et al., 2021; Wang et al., 2015)—a factor that not only aligns and coordinates the network members' actions (Borgatti & Halgin, 2011), but also reflects the firm's capability in maintaining network stability. When facing external uncertainty, firms with high centrality have a stronger motivation to maintain the stability of their central positions by wielding their network power (Hu et al., 2021; Wang et al., 2019). However, central firms are more likely to receive redundant information from their partners than are noncentral firms (Afuah, 2013), so they are less sensitive to new market changes (Kim et al., 2006) and may lose opportunities to identify external changes and capture novel innovations (Wang et al., 2015).

SH indicate network positions where the focal firm is the only link between two contacts in the social network (Afuah, 2013; Phelps, 2010). They can help firms acquire more heterogeneous resources and diverse information, thereby increasing their potential for knowledge recombination and new-solution generation (Lan et al., 2020; Li et al., 2018). Thus, if the supply chain is disrupted, a firm with more SH in its supply chain network will be more

likely to come up with alternative solutions that increase its operational flexibility (Hu et al., 2021). At the same time, in a network full of SH, the possibility of opportunistic actions increases drastically (Rowley et al., 2000), because SH may be viewed as irresponsible or as double-dealing, especially in China (Wang et al., 2019). In turn, the presence of SH may incur distrust from the firm's partners and weaken their commitment to cooperation (Podolny & Baron, 1997).

In the past, these two perspectives have seldom had a conversation with each other. However, effective matchings between internal and external factors are more likely to generate synergistic effects on OR than are matchings between multiple internal or external antecedents (Mindruta et al., 2016). Thus, it is necessary to explore the mechanisms by which matchings between internal and external determinants influence OR when firms face external shocks.

2.2 | Internal–external matching mechanisms: An internal–external integration perspective

The fundamental tenet of matching theory is to simultaneously address all parties' preferences, opportunities, and constraints in terms of the characteristics or resources that each partner values in the others (Logan, 1996; Mitsunashi & Greve, 2009). In previous work, this principle has been applied in investigations of employer–employee matching (Logan, 1996) and alliance formation (Mitsunashi & Greve, 2009). However, the matching perspective seldom considers how firms match their internal competence with their external network positions to influence OR under conditions of external adversity.

This question becomes more important when one considers the unique impacts of the COVID-19 pandemic on the supply chain. First, the pandemic has had a structural impact on production in a variety of industries. For instance, demand for in-person restaurant dining and off-line education has withered, whereas demand for take-away foods, online education, and cargo delivery has greatly increased. Under this condition, firms need to have available a broad array of choices, couched in terms of either PD or cooperation with more partners in the supply chain, so that they can choose different products and services to grasp new pandemic-related opportunities quickly (van der Vegt et al., 2015; Williams et al., 2017). Second, unlike the traditional disruptions in the supply chain (e.g., natural disasters and terrorist attacks), the COVID-19 pandemic has had global impacts on the supply chain due to the travel restrictions and lockdowns implemented worldwide (Nikolopoulos et al., 2021). This

factor has made it more difficult for firms to gain the support of their supply chain partners compared to a disruption with only local impacts, in which firms can seek support from non-local supply chain partners to mitigate these stresses. In turn, the ability to efficiently acquire the support of supply partners has emerged as a key advantage of firms seeking to improve their OR. Third, the COVID-19 pandemic has lasted longer than most traditional disruptions (e.g., natural disasters). The extended duration of this external shock has been sufficient to permanently alter the behaviors of supply chain partners (e.g., customers' preferences, suppliers' ways of delivering materials) (Poelman et al., 2021), which requires firms to demonstrate an innovative bent when dealing with these pandemic-driven changes (Helfat, 1997).

Given these unique impacts of the COVID-19 pandemic, we argue that the possession of internal competence alone is necessary but not sufficient to help firms recover from this external adversity, because their social networks may either enable or constrain the functioning of their resources and competence (Williams et al., 2017). For instance, PD may help firms address the COVID-19 pandemic's structural impacts, but making such internal adjustments usually requires the cooperation of their external partners (Swafford et al., 2006; Zhao et al., 2008). Similarly, their network positions may help firms observe external changes stemming from the COVID-19 pandemic (e.g., changes in customers' preferences) (Dimitriadis, 2021; Pal et al., 2014). However, without the appropriate internal competence, firms may not be capable of implementing innovative projects to adapt to such external changes and enhance their OR in this context (Williams et al., 2017).

This study extends the matching perspective to the COVID-19 pandemic context to argue that firms' internal competence and external network positions need to be matched together in the correct way to enhance their OR. Based on stability–flexibility features of firms' resilience (DesJardine et al., 2019), we rely on both internal and external indicators of stability and flexibility to build a two-by-two matrix (shown in Figure 1). Since both internal competence and external network positions need to be present simultaneously to influence OR in the COVID-19 pandemic, our theoretical model is a multiplicative model that views internal competence and external network positions in interactive manner (Kim et al., 2015). Based on a specific set of matching criteria—namely, that matched heterogeneous factors generate a complementary effect (e.g., they match internal flexibility with external stability), whereas matched homogeneous factors generate a substitutive effect (e.g., they match internal flexibility with external flexibility) (Mindruta et al., 2016; Mitsunashi & Greve, 2009)—we develop relevant hypotheses to explain how different matchings between internal

competence with external network positions may generate either a complementary or a substitutive effect on OR under the conditions of the COVID-19 pandemic.

2.3 | The effects of matching between product diversity and network structures

As the structural impacts of the COVID-19 pandemic have triggered the waxing and waning of different product markets, PD enables firms to have more choices in how they address product markets, which in turn allows those firms to overcome the negative impacts and exploit the positive opportunities associated with the pandemic (Duchek et al., 2020; Li & Tallman, 2011). However, PD alone cannot guarantee OR, because firms' internal adjustments of their diversified production lines often require the cooperation of their external partners (Swafford et al., 2006; Zhao et al., 2008). For example, even though diversified firms might be able to readily reallocate internal resources (e.g., labor, equipment) among different product lines, they need their suppliers to continuously provide the corresponding raw materials and their customers to purchase those new products (Flynn et al., 2010; Hopp & Spearman, 2021). We argue that only when firms match their PD with high centrality in the supply chain network can they harvest the complementary effect to enhance their OR. High centrality enables the focal firm to obtain and maintain the trust and support of its partners in the supply chain network, which then facilitates the implementation of internal adjustments among different diversified production lines. Firms with high centrality have more direct ties with their partners and more easily connect to others in the networks (Wang et al., 2015), which then enables them to effectively influence others through their advantageous network positions-enabled power advantages (Borgatti & Halgin, 2011; Wang et al., 2019). Thus, centrally positioned firms are more likely to persuade their supply chain partners to cooperate in the desired direction than are peripherally located firms in the supply chain network (Borgatti & Halgin, 2011); this cooperation then supports these firms' internal adjustments among their diversified production lines, enables them to seek and exploit new market opportunities, and, in turn, enhances their OR. This pathway fits our proposed matching criteria, which state that matched heterogeneous factors (i.e., matching of internal flexibility with external stability) generate a complementary effect (see Cell 1 in Figure 1).

In contrast, when firms match their PD with more SH in the supply chain network, the outcome may be a substitutive effect that hinders OR. More SH in the supply chain network may engender loose connections among firms that thwart the

development of shared norms and trust between them, which could undermine cooperation between the firms and their partners (Podolny & Baron, 1997). Existing research has noted that SH impede the flow of communication and coordination, increase the difficulties of achieving cooperation among partners (Inkpen & Tsang, 2005), and reduce the likelihood of cooperation that might otherwise enable firms to grasp market opportunities quickly (Podolny & Baron, 1997). Further, though SH can bring an information advantage to firms (Burt, 1992), the matching between both internal and external flexibility may deplete a firm's resources (e.g., attention), leaving it with insufficient resources to effectively coordinate the diverse products and external heterogeneous information flowing from SH. Thus, the matching between PD and a greater number of SH in the supply chain network may produce a substitutive effect on OR. This pathway fits our proposed matching criteria, which state that matched homogeneous factors (i.e., matching internal flexibility with external flexibility) generate a substitutive effect (see Cell 2 in Figure 1). Therefore, we suggest:

Hypothesis 1. *The matched interaction between product diversity and centrality in the supply chain positively affects operational resilience during the COVID-19 pandemic.*

Hypothesis 2. *The matched interaction between product diversity and structural holes in the supply chain negatively influences operational resilience during the COVID-19 pandemic.*

2.4 | The effects of matching between operational efficiency and network structures

The COVID-19 pandemic has had a deeper impact on OR by permanently changing some behaviors of members of the supply chain, such as consumers' habits in regard to working and eating at home and suppliers' ways of delivering materials (e.g., noncontact delivery) (Poelman et al., 2021). To handle such impacts on their product markets, firms need to engage in innovation (e.g., adopting a technological innovation or business model) so that they can capture the new market opportunities derived from such external changes (Helfat, 1997). Although OE is conducive to implementing any innovative plans efficiently (Essuman et al., 2020), it alone cannot guarantee OR. Instead, firms must first understand and identify their supply chain partners' behavior change, as a precondition to generating an executable innovation that increases OR (Zhang et al., 2015). For instance, if firms do not recognize consumers' increasing need for

working remotely, they may not design innovative products or services to grasp opportunities stemming from this change, regardless of how high their OE level is. Thus, we argue that firms need to match their OE with their network positions (i.e., centrality and SH) to enhance their OR, because different network positions may either facilitate or hinder firms' understanding and identification of new opportunities generated by external change.

Specifically, when firms match their OE with high centrality in the supply chain network, that may generate a substitutive effect that hinders OR. High centrality in this network may decrease their chances of generating innovative ideas; such ideas are expected to then serve as the input for OE that enhances firms' OR. Although high centrality enables firms to mobilize cooperation from their supply chain partners, this matching emphasizes scanning for heterogeneous information and innovation opportunities from supply chain partners rather than seeking their cooperation. However, NC usually increases firms' access to more redundant—rather than novel—information and knowledge (Afuah, 2013). High centrality in the supply chain network is not conducive to observing technological and market changes due to the COVID-19 pandemic (Kim et al., 2006; Wang et al., 2015), and therefore decreases firms' likelihood of generating relevant innovation (Polidoro et al., 2011). Without such innovative input, OE may lose ground, which definitely hurts OR. This pathway fits our proposed matching criteria, which state that matched homogeneous factors (i.e., matching internal stability with external stability) generate a substitutive effect (see Cell 3 in Figure 1).

In contrast, when firms match their OE with more SH in the supply chain network, that may generate a complementary effect that enhances OR. More SH in the supply chain network increase firms' access to more novel and innovative ideas (Burt, 1992), which then feed into OE to enhance the firms' OR. Even though SH may engender a cooperation disadvantage (Podolny & Baron, 1997), seeking heterogeneous information and innovation opportunities rather than cooperation from supply chain partners is more important in this matching context. SH in the supply chain network can provide more heterogeneous information and facilitate understanding of the external changes wrought by the COVID-19 pandemic (Lan et al., 2020; Zaheer & Bell, 2005). Firms with high-OE can quickly exploit this diverse information to launch new products and meet customers' new needs in a timely manner—a key benefit to OR. This pathway fits our proposed matching criteria, which state that matched heterogeneous factors (i.e., matching internal stability with external flexibility) generate a complementary effect (see Cell 4 in Figure 1). Therefore, we suggest:

Hypothesis 3. *The matched interaction between operational efficiency and centrality in the supply chain negatively influences operational resilience during the COVID-19 pandemic.*

Hypothesis 4. *The matched interaction between operational efficiency and structural holes in the supply chain positively affects operational resilience during the COVID-19 pandemic.*

3 | METHOD

3.1 | Data sources

Our sample consists of Chinese public firms listed on the Shanghai or Shenzhen Stock Exchange. We collected key data from the China Stock Market and Accounting Research Database and the TianYanCha website. We obtained a private application programming interface (API) through a data access agreement with tianyancha.com and then collected data on supplier firms and customer firms from its website. We further validated our data for suppliers and customers by leveraging other third-party data sources (e.g., the Wind database, the Chinese Research Data Services Platform) to construct the supply chain network.

On the TianYanCha website, data on suppliers and customers are published for every firm, including suppliers' and customers' names, suppliers' purchase amounts and proportions, customers' sale amounts and proportions, and dates. For each year, using the binary relationships between the focal firm and its corresponding suppliers and customers, we built a one-to-one matrix. In this matrix, even if two firms are not directly linked, they may be linked together through third-party firms to which both firms are linked independently. In other words, two firms are indirectly connected when they share at least one supplier or customer. This indirect connection is vital to the construction of the supply chain network.

Following prior studies, we used a three-year moving window approach to construct the supply chain network for each year in the period from 2016 to 2019 (Chi et al., 2010). This approach can capture the lagged effect of network structure on firms' future performance. We created two snapshots (2016–2018 and 2017–2019) using R software. Each network snapshot was constructed as a directed, weighted (by suppliers' purchase proportions and customers' sale proportions) supply chain network and used to calculate NC and SH for each firm-year observation. NC and SH were programmed via the IGraph package in R.

The COVID-19 environment in China was well suited to testing our hypotheses. The business activities of most industries nationwide were seriously disrupted by the pandemic, though the magnitude of this effect varied across industries (Nikolopoulos et al., 2021). Leveraging the differentiated impacts of the COVID-19 pandemic on the industries, we used a generalized difference-in-difference (DID) approach to test our hypotheses (Alonso & Andrews, 2019; Dimitriadis, 2021). We selected data for 1 year before the pandemic struck to maintain symmetry between the before and after COVID-19 periods, because only 1 year of data (i.e., 2020) after the pandemic hit was available. After removing missing data and merging various data sources, our final sample consisted of 2994 unique firms (1463 treatment firms and 1531 control firms) and 5293 observations.

3.2 | Variables and measures

3.2.1 | Operational resilience

Prior research suggests that financial performance loss is a fundamental indicator for resilience studies (e.g., DesJardine et al., 2019; Tan et al., 2020). The performance loss is the magnitude of the decline that a firm suffers from a shock. In a given period, the smaller a firm's performance loss, the greater the firm's resilience is. Since COVID-19 has impacted both the demand side and the supply side of firms' supply chains (Nikolopoulos et al., 2021), we combined sales from the demand side with operational costs from the supply side in the supply chain to measure OR, defining it as the change in operating revenue per unit production cost (ORPPC) before and after the external crisis (Tan et al., 2020).

In China, the COVID-19 pandemic broke out in January 2020 and was brought under control by April 2020 (World Health Organization, 2020). By the end of 2020, business activities had recovered as a whole. Therefore, data for the entire year of 2020 were used to measure firms' OR loss. To represent the performance loss, we first calculated the average ORPPC for 2017–2019 to obtain a benchmark. Then, we measured OR loss as the ratio of the 2020 ORPPC to the average ORPPC for 2017–2019 (see Table A in the appendix). For OR in 2019, we used the average of ORPPC for 2016 to 2018 as the benchmark. A higher ratio indicates less loss—that is, greater OR.

3.2.2 | Product diversity

Following Hashai (2015), we adopted a count measure for the firm's number of unique product types in each year. We retrieved information on product type from the

Wind database and operationalized PD as the number of unique product types in a given year.

3.2.3 | Operational efficiency

Existing research suggests that two techniques are widely used to measure OE: data envelopment analysis (DEA) and the stochastic frontier approach (SFA) (Li et al., 2021). DEA is more sensitive to sampling errors and outliers. In contrast, SFA incorporates the error term into the formula, avoiding the bias caused by random factors. Further, SFA can capture the relative efficiency of a firm, with respect to other firms in its industry, in transforming inputs into outputs (Dutta et al., 2005), thus making the results comparable across industries. Lastly, compared to any single indicator, SFA is better able to capture the nature of OE by offering a more comprehensive calculation. Thus, following Li et al. (2021), we used SFA to measure OE, and formulated a stochastic production function to model the transformation of operational inputs (i.e., capital expenditure [CE], labor [LAB], and inventory [INV]) into operational outputs (i.e., operating income [OI]) (see Table A in the appendix).

3.2.4 | Network centrality

Research has suggested that eigenvector centrality is an effective indicator of an actor's power and influence (e.g., Bonacich, 2007; Kim & Zhu, 2018; Koka & Prescott, 2008), which suits our analysis. Eigenvector centrality takes both direct and indirect ties and tie strength into account, which is essential for the supply chain network (Lan et al., 2020). This measure is computed as the proportion to the sum of the centralities of a firm's alters and captures the extent to which a firm is linked to the central alters (Kim & Zhu, 2018), which is an integral aspect of a central position (Koka & Prescott, 2008) (see Table A in the appendix).

3.2.5 | Structural holes

We used Burt's (1992) p. 54 network constraint variable, which has been widely used in prior studies to represent SH (e.g., Ahuja, 2000; Bellamy et al., 2014; Lan et al., 2020). We calculated the lack of access to SH using Burt's (1992: 54) network constraint (see Table A in the appendix). We followed Zaheer and Bell (2005) by calculating SH as 1 minus the constraints score. This variable ranges from 0 to 1, where 0 indicates high-link redundancy and 1 indicates that every link is non-redundant. Thus, a higher value indicates that a firm occupies more SH.

3.2.6 | Control variables

Based on prior relevant studies (e.g., Buyl et al., 2019; DesJardine et al., 2019; Dimitriadis, 2021), we controlled for firm level, supply chain network-level, industry-level, and province-level characteristics to rule out alternative sources of OR. We controlled for *firm age*, measured as the number of years that the firm has been in operation (Bellamy et al., 2014), and *firm size*, measured as the natural log of the firm's total assets (DesJardine et al., 2019). Older firms may experience various shocks over their lifespan and, therefore, are well prepared to deal with such shocks. Larger firms may have more resources, but might be less flexible in the face of a shock compared to smaller ones (Ambulkar et al., 2015).

To control for the effect of prior financial performance, we included *return on investment* (ROI) as a control variable. Firms with better financial performance are likely to have more slack resources to deploy when responding to shocks (DesJardine et al., 2019). To capture the effect of ownership structure, we controlled for *ownership concentration*, which we operationalized as the percentage of the firm's shares owned by its largest three shareholders. Mitton (2002) found that ownership concentration significantly influences firm performance during a crisis. Dimitriadis (2021) suggested that organizational slack acts as an important source of resilience. Thus, *organizational slack*, measured as the ratio of loans to total assets, was included as a control variable. Multi-national firms may be more flexible because their suppliers and customers are likely to be more diverse. Thus, we included *international business*, computed as the ratio of international revenue to total revenue, as a control variable.

Innovation creates a competitive advantage, but does not necessarily help firms reduce their losses during a shock (Paunov, 2012). Also, R&D activities are cost-consuming and not likely to create financial benefits in the short run (Dong et al., 2020), so they affect the utilization of production costs. Thus, we controlled for firm innovation by adding R&D spending (log-transformed, +1) and R&D employees, calculated as the ratio of R&D employees to total number of employees. Sajko et al. (2021) found that firms investing in corporate social responsibility (CSR) initiatives tend to be more resilient in the face of external shocks. We controlled for CSR by including CSR ratings published by Rankins CSR Ratings.¹

Buyl et al. (2019), Dimitriadis (2021), and Sajko et al. (2021) suggested managerial characteristics can affect a firm's ability to adapt and survive in stressful times. Based on their ideas, we controlled for top management team (TMT) size, average TMT age, TMT ownership, chief executive officer (CEO) age, CEO duality, and CEO education. TMT size was defined as the number of all top managers, *average TMT age* was operationalized as the average age of

all top managers, and TMT ownership was calculated as the log-transformed total number of shares held by all top managers. Firms with sizable and older TMTs are likelier to develop better managerial practices, enhancing their adaptability during disruptions (Dimitriadis, 2021). TMT ownership can incentivize managers to pursue more value-enhancing strategies, which helps firms to survive shocks (Kashmiri & Brower, 2016). *CEO age* was computed as the number of years since the CEO's birth date. *CEO duality*, as an indicator of CEO power, was coded as 1 if the CEO also served as the chair of the board, and 0 otherwise (Sajko et al., 2021). *CEO education* was coded as 1 if the CEO held a postgraduate degree, and 0 otherwise. CEO age is related to the riskiness of corporate policies, which in turn affects organizational resilience (Buyl et al., 2019). When facing an external shock, more-powerful CEOs can coordinate firm behaviors and resources quickly (Torres & Augusto, 2021). More-educated CEOs may have more knowledge about how to respond to shocks (Andreou et al., 2017).

Apart from network structure and position, other network characteristics may affect OR. In this vein, we controlled for supply chain network size, supply chain stability, supplier concentration, and customer concentration. *Supply chain network size* reflects the total number of partners and was computed as the total number of suppliers and customers (Dong et al., 2020). We computed *supply chain network stability* as the ratio of the total number of years that a firm cooperated with all of its partners to the number of its partners over 5 years before the sample period (Han & Pollock, 2021). We used the percentage of the supply quantity delivered by the largest five suppliers and the percentage of sales purchased by the largest five customers to measure *supplier concentration* and *customer concentration*, respectively. A sizable supply chain network entails a greater amount and diversity of suppliers and customers, which increases partnering flexibility and thus builds resilience. Conversely, more-concentrated suppliers and customers signal that the firm has a smaller number of suppliers and customers (Tang & Rai, 2012), reducing its partnering flexibility. Network stability cultivates relational closeness and relational embeddedness over time, which enables the development of synergies among partners required to respond to and recover from a shock while reducing its impact (Scholten & Schilder, 2015). However, high levels of relational embeddedness may constrain a firm's flexibility because of high-mutual commitments and interdependencies, posing a potentially serious obstacle to quicker recovery from a shock (Sharma et al., 2019).

Finally, to control for provincial and industrial effects, we included *provincial gross domestic product (GDP) growth rate*, measured as the ratio of the GDP difference between year t and year $t - 1$ to GDP in year $t - 1$; *industry concentration*, measured as the ratio of the sales of the

largest three firms to the total sales of all firms in the same three-digit SIC industry; and *province and industry fixed effects* (Dimitriadis, 2021; Sajko et al., 2021).

3.3 | Estimation

The analysis is based on a generalized DID design (Alonso & Andrews, 2019). The outbreak of COVID-19 in January 2020 created a pre-treatment period in 2019 and a post-treatment period in 2020. This bifurcation allowed us to create a *post-COVID-19 dummy*, equal to 1 when the year was 2020 (after the COVID-19 pandemic), and 0 when the year was 2019 (before the pandemic). Since the severity of the pandemic's effects on industries varied, we used differences in severity across industries to create our *treatment dummy*. We used the industry sales growth rates (ISGRs) in 2020 to identify which industries were severely hurt by the COVID-19 shock. The ISGRs in 2020 were computed as the ratio of the sum of the sales growth rate of all firms to the total number of firms in the same industry. To remove prior differences across industries, we subtracted the ISGRs in 2019 from the ISGRs in 2020 (hereafter "DISGRs") and calculated the median value of the DISGRs. The treatment dummy was equal to 1 for treated firms operating in more severely affected industries whose DISGRs were below the median value, and 0 for control firms operating in less severely affected industries whose DISGRs were above the median value.

Because the dependent variable was continuous, we ran OLS regression to test our hypotheses. To account for the underlying industrial heterogeneity, we clustered the robust standard errors for industry sectors. We identified industry sectors based on the Standard Industry Classification enacted in 2012 by the China Securities Regulatory Commission. To test our hypotheses in the COVID-19 context in China, we estimated the following models:

$$\begin{aligned}
 OR_{i,t} = & \beta_0 + \beta_1 D \times PD_{i,t-1} \times NC_{i,t-1} + \beta_2 D \times PD_{i,t-1} \\
 & \times SH_{i,t-1} + \beta_3 D \times OE_{i,t-1} \times NC_{i,t-1} + \beta_4 D \times OE_{i,t-1} \\
 & \times SH_{i,t-1} + \beta_5 D \times \beta_6 D \times PD_{i,t-1} + \beta_7 D \times OE_{i,t-1} \\
 & + \beta_8 D \times SH_{i,t-1} + \beta_9 D \times NC_{i,t-1} + \beta_{10} PD_{i,t-1} \\
 & \times NC_{i,t-1} + \beta_{11} PD_{i,t-1} \times SH_{i,t-1} + \beta_{12} OE_{i,t-1} \\
 & \times NC_{i,t-1} + \beta_{13} OE_{i,t-1} \times SH_{i,t-1} + \beta_{14} PD_{i,t-1} \\
 & + \beta_{15} OE_{i,t-1} + \beta_{16} NC_{i,t-1} + \beta_{17} SH_{i,t-1} + \beta_i X_{i,t-1} \\
 & + \varepsilon_{i,t},
 \end{aligned} \tag{1}$$

where i denotes firm, t denotes time, $X_{i,t-1}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Since generalized DID focuses on the interaction between the *treatment dummy* and the *post-COVID-19 dummy* (Alonso & Andrews, 2019), we created a variable, D (= treatment

dummy \times post-COVID-19 dummy), which indicates the effect of the COVID-19 pandemic on OR. The three-way interactions among D , PD/OE, and NC/SH in our model test our hypotheses. To reduce the possibility of simultaneity and endogeneity issues, all independent and control variables were measured 1 year prior to the dependent variable, unless noted otherwise.

3.4 | Empirical results

The descriptive statistics and correlations of the variables are presented in Table 1. The variance inflation factor (VIF) procedure was used to test for multicollinearity problems. All of the VIF values were below the rule-of-thumb threshold of 5 and had a maximum value of 3.90, confirming that multicollinearity was not an issue.

Table 2 presents the results of the OLS regression. Model 1 includes all explanatory variables, Model 2 tests H1, Model 3 tests H2, Model 4 tests H3, Model 5 tests H4, and Model 6 is the full model with all explanatory variables and interactions. In the following discussion, we use the results from Model 6 to test our hypothesized relationships.

H1 predicts that the interaction between PD and a firm's NC will positively influence OR during the COVID-19 pandemic. The results from Model 6 showed that the interaction between D , PD, and NC positively affected OR ($\beta = 0.131$, $p < .01$), supporting H1.

In H2, we predicted that the interaction between PD and the firm's SH would negatively influence OR during the COVID-19 pandemic. As shown in Model 6, the interaction between D , PD, and SH was negatively and significantly related to OR ($\beta = -0.258$, $p < .01$), supporting H2.

H3 predicts that the interaction between OE and the firm's NC will negatively influence OR during the COVID-19 pandemic. The results from Model 6 showed that the interaction between D , OE, and NC was significant and negative ($\beta = -0.133$, $p < .05$), supporting H3.

H4 states that the interaction between OE and SH will positively influence OR during the COVID-19 pandemic. In Model 6, the effect of the interaction between D , OE, and SH on OR was significantly positive ($\beta = 0.248$, $p < .01$), lending support to H4.

Regarding the control variables, the results from Model 1 showed that ROI, ownership concentration, international business, CSR ratings, supply chain network size, average TMT age, and CEO education significantly enhanced OR, whereas firm size, firm innovation, supply chain network stability, and CEO age significantly and negatively affected OR. When we ran a model including only D , we found that the effect of D on OR was significantly negative

TABLE 1 (Continued)

Variables	13	14	15	16	17	18	19	20	21	22	23	24	25
17. Supplier concentration	0.082*	0.024	0.232*	0.171*	1								
18. Customer concentration	0.021	0.007	0.132*	0.125*	0.378*	1							
19. TMT size	0.045*	0.093*	0.130*	-0.012	0.255*	0.249*	1						
20. Average TMT age	0.091*	0.104*	0.034*	-0.020	0.000	-0.011	0.040*	1					
21. TMT ownership	-0.105*	0.023	0.023	0.007	-0.004	-0.050*	0.048*	-0.196*	1				
22. CEO age	0.056*	0.068*	0.015	-0.010	0.004	0.020	0.082*	0.512*	0.011	1			
23. CEO duality	-0.070*	-0.006	-0.058*	-0.006	-0.001	-0.003	0.021	-0.081*	0.297*	0.171*	1		
24. CEO education	0.062*	-0.006	0.060*	-0.014	0.045*	0.032*	0.048*	-0.002	0.076*	-0.011	0.069*	1	
25. GDP growth rate	-0.022	0.027*	0.011	0.036*	-0.016	-0.017	-0.007	-0.019	0.003	-0.019	-0.018	0.010	1
26. Industrial concentration	-0.060*	-0.026	0.001	0.051*	0.038*	0.039*	0.002	0.077*	-0.149*	-0.016	-0.077*	-0.062*	-0.037*

Note: * $p < .05$; $N = 5243$.

Abbreviations: CSR, corporate social responsibility; ROI, return on investment.

($\beta = -0.409, p < .05$). We conducted post hoc tests to check the robustness of our results; the results are reported in the appendix.²

3.5 | Causal inference

Although we controlled for multiple relevant variables in our models, unobservable factors might potentially bias our results. We endeavored to reduce potential bias in several ways, and the results are reported in Table B1 in the appendix. First, we included firm fixed effects in all models to control for unobserved, time-invariant variation between firms. When we did so, our results remained the same (see Model 1).

Second, to further account for unobserved firm heterogeneity, we included a presample dependent variable and reran our models (Blundell et al., 1995). Specifically, we controlled for the dependent variable in the 3 years prior to the sample period. The results, reported in Model 2, showed that all hypotheses were supported.

Third, an imbalance between the treated firms and the control firms might potentially bias our results. To address this concern, we leveraged the coarsened exact matching (CEM) algorithm (Iacus et al., 2012) to match the treated firms to the control group based on firm-level characteristics. Of the remaining candidates, we selected the nearest neighbor based on six firm-level characteristics: firm age, firm size, ROI, TMT size, ownership concentration, and firm region. CEM produced a dataset of 1206 observations with 746 firms and the sample imbalance decreased from 0.97 to 0.73. With the same model specification, we used the CEM sample to test our hypotheses, and found support for all our hypotheses (see Model 3).

Finally, we ran instrumental variable regression using the heteroskedasticity-based instrument (IVHI) proposed by Lewbel (2012), which has been widely adopted by scholars (Dong et al., 2020). Generated instruments that were correlated with our endogenous variables were created by the heteroskedasticity in the error process. The results from the IVHI regression, reported in Model 4, supported all our hypotheses. Additionally, the generated instruments passed the under-identification and weak-identification tests, suggesting they were valid.

3.6 | Other robustness checks

We conducted several additional robustness checks, whose results are reported in Table B2 in the appendix. First, to further account for the heterogeneity across industries, we measured OR as the industry-adjusted ORPPC and found the results to be consistent (see Model 1).³

TABLE 2 OLS regression analysis results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$D \times$ product diversity \times network centrality (Hypothesis 1)		0.107** (0.047)				0.131*** (0.042)
$D \times$ product diversity \times structural holes (Hypothesis 2)			-0.230*** (0.078)			-0.258*** (0.084)
$D \times$ operational efficiency \times network centrality (Hypothesis 3)				-0.105* (0.059)		-0.133** (0.052)
$D \times$ operational efficiency \times structural holes (Hypothesis 4)					0.224*** (0.064)	0.248*** (0.059)
Product diversity \times network centrality		-0.082* (0.047)				-0.098* (0.049)
Product diversity \times structural holes			0.091*** (0.029)			0.105** (0.036)
Operational efficiency \times network centrality				0.008 (0.031)		0.024 (0.030)
Operational efficiency \times structural holes					-0.005 (0.051)	-0.017 (0.053)
$D \times$ product diversity		-0.053 (0.080)	-0.033 (0.085)			-0.047 (0.083)
$D \times$ operational efficiency				0.227* (0.116)	0.208 (0.126)	0.230* (0.113)
$D \times$ network centrality		-0.068 (0.052)		-0.060 (0.046)		-0.038 (0.053)
$D \times$ structural holes			-0.038 (0.098)		-0.073 (0.101)	-0.056 (0.107)
D	-0.194 (0.155)	-0.297 (0.233)	-0.297 (0.226)	-0.331 (0.246)	-0.344 (0.232)	-0.341 (0.236)
Product diversity	0.010 (0.056)	0.007 (0.040)	-0.013 (0.036)	-0.001 (0.049)	-0.003 (0.049)	-0.018 (0.033)
Operational efficiency	0.486*** (0.094)	0.468*** (0.091)	0.469*** (0.091)	0.404*** (0.103)	0.405*** (0.103)	0.406*** (0.099)
Network centrality	0.070** (0.030)	0.104*** (0.030)	0.078*** (0.022)	0.116*** (0.036)	0.078*** (0.022)	0.097** (0.040)
Structural holes	0.031 (0.052)	0.008 (0.049)	0.024 (0.064)	0.008 (0.049)	0.030 (0.068)	0.024 (0.067)
Firm age	0.014 (0.010)	0.009 (0.010)	0.009 (0.010)	0.009 (0.010)	0.009 (0.010)	0.009 (0.011)
Firm size	-0.260*** (0.057)	-0.274*** (0.050)	-0.273*** (0.050)	-0.274*** (0.051)	-0.272*** (0.051)	-0.275*** (0.051)
ROI	0.066*** (0.004)	0.047*** (0.005)	0.046*** (0.006)	0.047*** (0.005)	0.046*** (0.005)	0.047*** (0.006)
Ownership concentration	0.586* (0.311)	0.559* (0.278)	0.551* (0.277)	0.555* (0.283)	0.543* (0.282)	0.544* (0.284)
Organizational slack	-0.081*** (0.026)	-0.100*** (0.027)	-0.100*** (0.027)	-0.100*** (0.026)	-0.100*** (0.027)	-0.100*** (0.027)
International business	0.829*** (0.149)	0.909*** (0.267)	0.916*** (0.268)	0.931*** (0.273)	0.924*** (0.273)	0.937*** (0.270)
R&D employees	-1.109*** (0.042)	-1.093*** (0.045)	-1.092*** (0.046)	-1.095*** (0.045)	-1.092*** (0.045)	-1.096*** (0.044)

TABLE 2 (Continued)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
R&D spending	−0.058*** (0.014)	−0.052*** (0.012)	−0.052*** (0.012)	−0.051*** (0.012)	−0.051*** (0.012)	−0.052*** (0.012)
CSR ratings	0.031*** (0.005)	0.031*** (0.005)	0.031*** (0.005)	0.031*** (0.005)	0.030*** (0.005)	0.030*** (0.005)
Supply chain network size	0.003** (0.001)	0.003* (0.002)	0.003* (0.001)	0.003* (0.002)	0.003 (0.002)	0.003 (0.002)
Supply chain network stability	−0.122** (0.044)	−0.115** (0.049)	−0.113** (0.047)	−0.116** (0.048)	−0.117** (0.047)	−0.117** (0.048)
Supplier concentration	0.031 (0.056)	0.027 (0.052)	0.031 (0.050)	0.029 (0.052)	0.032 (0.050)	0.033 (0.050)
Customer concentration	0.201 (0.121)	0.206* (0.115)	0.200* (0.111)	0.212* (0.114)	0.213* (0.114)	0.206* (0.115)
TMT size	0.005 (0.026)	0.005 (0.024)	0.006 (0.024)	0.005 (0.024)	0.005 (0.024)	0.006 (0.023)
Average TMT age	0.053*** (0.018)	0.053** (0.021)	0.053** (0.021)	0.053** (0.021)	0.053** (0.021)	0.053** (0.021)
TMT ownership	−0.016 (0.018)	−0.014 (0.015)	−0.014 (0.015)	−0.014 (0.015)	−0.014 (0.016)	−0.014 (0.016)
CEO age	−0.019*** (0.005)	−0.021*** (0.006)	−0.021*** (0.006)	−0.022*** (0.006)	−0.022*** (0.005)	−0.022*** (0.006)
CEO duality	−0.016 (0.179)	−0.019 (0.194)	−0.019 (0.193)	−0.024 (0.193)	−0.017 (0.193)	−0.020 (0.190)
CEO education	0.165** (0.062)	0.178*** (0.054)	0.178*** (0.053)	0.180*** (0.053)	0.172*** (0.054)	0.175*** (0.054)
GDP growth rate	−1.383 (4.393)	−3.922 (4.708)	−3.987 (4.695)	−3.929 (4.726)	−4.320 (4.729)	−4.261 (4.684)
Industrial concentration	−0.225 (0.277)	1.212 (1.285)	1.002 (1.238)	1.253 (1.334)	1.155 (1.272)	1.269 (1.304)
Constant	4.437*** (1.242)	2.609** (1.183)	2.700** (1.205)	2.615** (1.160)	2.641** (1.159)	2.627** (1.216)
Industry/province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5243	5243	5243	5243	5243	5243
R-squared	0.043	0.061	0.061	0.061	0.062	0.063

Note: Robust SE in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$. We standardized independent variables to avoid multicollinearity before hypothesis testing.

D = treatment dummy \times post-COVID-19 dummy.

Abbreviations: CSR, corporate social responsibility; ROI, return on investment.

Second, we used the average value of DISGRs, rather than their median value, to identify treated firms; we found that all our hypotheses were supported (see Model 2). Furthermore, since the extent to which a firm suffered from the COVID-19 pandemic varied across provinces, we used provincial severity rather than industry severity to identify treated firms. Our sample covered Chinese 31 provinces, and we assumed that if a province suffered more from the COVID-19 pandemic, firms located in this province were also likely to have suffered more. In turn, we used the provincial GDP growth rate in 2020 as a proxy to measure the provincial severity of the pandemic. We adopted the same

strategy used for the DISGRs to compute the median value of provincial severity, and found that the results were largely unchanged (see Model 3).

Third, recognizing that diverse products reflect different technological specifications (Katila & Ahuja, 2002), we used technological diversity instead of PD in the model.⁴ The results were largely unchanged (see Model 4).

Fourth, we used degree centrality rather than eigenvector centrality to measure NC. The results were unchanged (see Model 5).

Finally, instead of a three-year window, we used a one-year moving window to calculate a firm's SH and

eigenvector centrality; we found that the results were largely consistent with the original findings (see Model 6). Furthermore, we split our supply chain network into two subnetworks—one including only suppliers, and one including only customers. Using these two subnetworks, we tested our hypotheses and found that the results were largely consistent (see Model 7 for the supplier subnetwork and Model 8 for the customer subnetwork).

4 | DISCUSSION AND CONCLUSION

The purpose of this study is to explore how firms were able to effectively match internal competence and external network positions to improve their OR in the COVID-19 pandemic. By building a framework matching internal and external stability and flexibility, we can explain the mechanisms by which four internal–external matchings affected OR during the COVID-19 pandemic. We found that both the matching between internal flexibility (i.e., PD) and external stability (i.e., NC), and the matching between internal stability (i.e., OE) and external flexibility (i.e., SH), have complementarity and thus enhance OR. In contrast, the matching between PD and SH, and the matching between OE and centrality, have substitutive effects on OR.

4.1 | Theoretical contributions

This study makes three important theoretical contributions. First, it advances resilience research by providing a new theoretical framework to explain the effects of the different matchings between internal and external stability and flexibility on OR in the context of the COVID-19 pandemic. The structural, global, and long-lasting impacts of the pandemic on firms and their supply chain partners requires firms to deftly match internal competence and external resources to mitigate the detrimental impacts of this external event—a new revelation beyond previous research, which has generally explored the effects of either internal competence or external resources on the firm's resilience in traditional crisis contexts such as natural disasters (Dimitriadis, 2021; Reinmoeller & van Baardwijk, 2005). Specifically, the matchings between internal flexibility (or stability) and external stability (or flexibility) can produce complementarity to improve OR—a finding that provides new insights into why and how firms can pursue flexibility–stability balance from their internal and external spaces simultaneously.

In doing so, this study also advances matching theory by emphasizing the roles of matching between an entity's

internal competence and its external network positions in enhancing the firm's OR. Different from previous studies that focused on the matching between two entities such as employers and employees (Logan, 1996), and between alliance partners (Mitsubishi & Greve, 2009), this study indicates that when facing structural, global and long-term impacts of the COVID-19 pandemic, a firm must match its internal competence with its external network positions in the correct way to enhance OR. It suggests that matching can happen within an entity, as well as between two different entities.

Second, this study advances supply chain management research by exploring how firms were able to leverage their structural positions in the supply chain network to improve their OR in the COVID-19 context. Prior studies have usually examined the effects of structural attributes such as centrality and SH on the firm's innovation or decisions in non-crisis contexts (e.g., Wang et al., 2019; Zaheer & Bell, 2005); less attention has been paid to whether the same mechanisms might still work in a crisis context. Extending the extant research, our findings indicate that when matched with the firm's internal competence (e.g., PD, OE), NC and SH in the supply chain network have dual effects on OR in the COVID-19 context. Specifically, centrality (rather SH) can strengthen the stability of external relationships, while SH (rather than centrality) can enable the firm to acquire more heterogeneous external information. These results not only expand the theoretical width and depth of supply chain network research, but also provide new insights into how firms can exploit their supply chains to improve the effects of internal competence on OR.

Third, this study deepens our understanding of flexibility as it affects operations management. Extending previous studies that emphasized the role of the firm's internal flexibility (Swafford et al., 2006), as well as its integrations with other internal competence (e.g., resource structuring) (Li et al., 2017), our research focuses on the effects of the matching between internal flexibility and external flexibility/stability on OR. Specifically, we found that the matching between product flexibility (internal flexibility) and centrality (external stability) can strength OR, while the matching between product flexibility (internal flexibility) and SH (external flexibility) reduces OR in the COVID-19 context. These new insights suggest how different types of flexibility can be utilized efficiently for operations management.

4.2 | Managerial implications

This study also has important implications for managers. First, our results indicating that PD and NC have

complementarity, while PD and SH have a substitutive relationship in regard to the impacts of the COVID-19 pandemic, suggest that the firm with strong PD should exploit its centrality in the supply chain network rather than its SH to facilitate OR. Second, our results indicating that OE and SH have complementarity, while OE and centrality have a substitutive relationship, suggest that the firm with high OE should leverage its SH in the supply chain network rather than its centrality to improve its OR in the COVID-19 context. In other words, the choice of utilizing external NC or SH should be matched with the specific internal competence to effectively manage the impacts of the COVID-19 pandemic.




4.3 | Limitations and future research directions

Despite its valuable contributions, this study has some limitations. First, we did not explore the effects of the firm's supply chain partners on the firm's OR. Because different motivations and behaviors of network alters may differentially affect the firm's performance and strategy (Clement et al., 2018), the behaviors of the partners could influence the firm's OR. Hence, future research needs to focus on how supply chain partners affect the firm's OR.

Second, the COVID-19 pandemic may influence the firm's network structure over time, but this study modeled the firm's network structure in a relatively static way due to data constraints. Since the COVID-19 outbreak started only in January 2020 in China, we have just one year of data available after this outbreak began. This limitation creates difficulties in modeling dynamic social networks, and also limits our ability to examine the long-term effects of COVID-19 on the supply chain. When more data become available in the future, we strongly encourage scholars to resolve this limitation by examining the effects of the pandemic on firms' network positions over time, thereby determining the long-term effects.

Lastly, OR could be measured by more granular firm-level data related to the pandemic, such as production recovery time or labor losses. Due to data constraints, we measured OR as the change in ORPPC in this study. We encourage scholars to collect more granular firm-level data related to the COVID-19 pandemic to explore OR from other dimensions in the future.

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ENDNOTES

- ¹ These ratings, which adapted the MSCI KLD 400 Social Index framework and the standards of the Global Reporting Initiative to create a rating system for firms' CSR reports, have been used widely by prior studies (e.g., Li & Lu, 2020).
- ² In the appendix, we present only the brief results for the full model. All comprehensive results are available on request. In all robustness analyses, unless otherwise indicated, all models included the same control variables shown in Table 2.
- ³ The industry-adjusted operating revenue per unit production cost (ORPPC) was computed as the ORPPC of the focal firm divided by the average ORPPC of all firms in the same industry with the focal firm.
- ⁴ Technological diversity was measured as the ratio of the number of unique International Patent Classification (IPC) held by the focal firm to the total number of unique IPCs held by all firms in the same industry.

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How to cite this article: Li, Y., Wang, X., Gong, T., & Wang, H. (2022). Breaking out of the pandemic: How can firms match internal competence with external resources to shape operational resilience? *Journal of Operations Management*, 1–20. <https://doi.org/10.1002/joom.1176>

APPENDIX A

TABLE A Formulas for key variables

Variables	Formula	Comments
Operational resilience (OR)	$OR_i = \frac{ORPPC_i}{\sum_{i=3}^{i-1} ORPRC/3}$	ORPRC denotes operating revenue per unit production cost. $i = 2019, 2020$
Operational efficiency (OE)	$\ln(OI)_{ijt} = \beta_0 + \beta_1 \ln(CE)_{ijt} + \beta_2 \ln(LAB)_{ijt} + \beta_3 \ln(INV)_{ijt} + \varepsilon_{ijt} - \lambda_{ijt}. (1)$ $OE_{ijt} = 1 - \hat{\lambda}_{ijt}. (2)$	<p>Where ε_{ijt} denotes the stochastic random error and λ_{ijt} is the technical inefficiency of firm i in industry j (three-digit SIC codes) in year t. λ_{ijt} ranges from 0 to 1, with 0 indicating that the firm is technically efficient. Thus, λ_{ijt} captures the relative efficiency of a firm with respect to its competitors in the same industry</p> <p>To reduce the bias caused by the small sample size, we followed Li et al. (2021) and removed industries with fewer than 10 firms. We computed the OE of firm i in industry j in year t as Formula (2)</p>
Network centrality (NC)	$x_{it} = \frac{1}{\lambda} \sum_{j=1}^n a_{ijt} x_{jt}, i = 1, \dots, N$	Based on Bonacich (2007), we computed eigenvector centrality. Where x_{ijt} denotes the eigenvector centrality of firm i in year t , λ indicates the largest eigenvalue of the adjacency matrix A , N represents the number of firms, a_{ijt} is equal to 1 if firm i and firm j are linked by an edge in year t and equal to 0 otherwise, and x_{jt} denotes the eigenvector centrality of cooperator j in year t
Structural holes (SH)	$Constraint_i = p_{ij} + \sum p_{iq} p_{jq}, q \neq i, j$ $SH_i = 1 - Constraint_i$	Where p_{ij} is equal to the strength of direct ties from firm i to firm j , and $\sum p_{iq} p_{jq}$ is the sum of strength of the indirect ties from firm i to firm j via firm q . We followed Zaheer and Bell (2005) and calculated structural holes as 1 minus the constraints score. Following Ahuja (2000), we set this variable to 0 for firms without any partners

TABLE B1 Results for endogeneity test

Variables	Model 1 Firm fixed effect	Model 2 Presample test	Model 3 CEM	Model 4 IVHI
$D \times$ product diversity \times network centrality (Hypothesis 1)	0.130*** (0.042)	0.142*** (0.041)	0.207*** (0.044)	0.109** (0.054)
$D \times$ product diversity \times structural holes (Hypothesis 2)	-0.256*** (0.084)	-0.290** (0.107)	-0.467*** (0.095)	-0.273*** (0.052)
$D \times$ operational efficiency \times network centrality (Hypothesis 3)	-0.131** (0.052)	-0.179** (0.061)	-0.722*** (0.130)	-0.123** (0.054)
$D \times$ operational efficiency \times structural holes (Hypothesis 4)	0.244*** (0.060)	0.318*** (0.071)	0.824*** (0.101)	0.330*** (0.080)
Product diversity \times network centrality	-0.097*	-0.107*	0.059*	-0.080

TABLE B1 (Continued)

Variables	Model 1 Firm fixed effect	Model 2 Presample test	Model 3 CEM	Model 4 IVHI
	(0.049)	(0.054)	(0.029)	(0.055)
Product diversity × structural holes	0.104** (0.036)	0.133*** (0.034)	0.225** (0.082)	0.098** (0.040)
Operational efficiency × network centrality	0.023 (0.030)	0.042 (0.040)	0.167** (0.078)	0.005 (0.025)
Operational efficiency × structural holes	−0.015 (0.052)	−0.051 (0.071)	0.011 (0.098)	−0.111*** (0.031)
<i>D</i> × product diversity	−0.044 (0.082)	−0.060 (0.083)	−0.378** (0.157)	−0.091 (0.074)
<i>D</i> × operational efficiency	0.229* (0.113)	0.265* (0.136)	0.250* (0.133)	0.274* (0.154)
<i>D</i> × network centrality	−0.038 (0.053)	−0.009 (0.063)	−0.045 (0.086)	−0.009 (0.070)
<i>D</i> × structural holes	−0.053 (0.108)	−0.050 (0.139)	0.169 (0.125)	−0.041 (0.084)
<i>D</i>	−0.341 (0.236)	−0.413* (0.235)	0.072 (0.094)	−0.158 (0.141)
Product diversity	−0.018 (0.033)	−0.023 (0.041)	−0.124* (0.063)	−0.004 (0.015)
Operational efficiency	0.406*** (0.099)	0.425*** (0.130)	0.544** (0.186)	2.522*** (0.607)
Network centrality	0.097** (0.040)	0.083 (0.049)	−0.230*** (0.041)	1.278** (0.603)
Structural holes	0.026 (0.066)	0.034 (0.081)	0.015 (0.044)	0.184 (0.164)

Note: Robust SE in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$. *D* = treatment dummy × post-COVID-19 dummy.

TABLE B2 Results for other robustness checks

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
<i>D</i> × product diversity × network centrality (Hypothesis 1)	0.340*** (0.113)	0.171*** (0.025)	0.579*** (0.121)	0.150*** (0.049)	0.714*** (0.240)	0.330*** (0.044)	0.918*** (0.144)	0.133** (0.062)
<i>D</i> × product diversity × structural holes (Hypothesis 2)	−1.284*** (0.416)	−0.265*** (0.056)	−0.549** (0.210)	−0.257*** (0.072)	−0.106* (0.061)	−0.097 (0.129)	−0.114 (0.097)	−0.234*** (0.073)
<i>D</i> × operational efficiency × network centrality (Hypothesis 3)	−1.279** (0.585)	−0.237*** (0.063)	−0.344** (0.145)	−0.188** (0.065)	−0.383** (0.171)	−0.323*** (0.071)	−1.371*** (0.216)	−0.185** (0.075)
<i>D</i> × operational efficiency × structural holes (Hypothesis 4)	1.073** (0.441)	0.343*** (0.073)	0.347 (0.841)	0.353*** (0.069)	0.497** (0.220)	0.367** (0.166)	0.729*** (0.216)	0.206 (0.187)
Product diversity × network centrality	−0.157 (0.102)	−0.134*** (0.023)	−0.029* (0.015)	−0.057* (0.029)	−0.094*** (0.016)	−0.109** (0.040)	−0.350*** (0.062)	−0.075 (0.046)
Product diversity × structural holes	0.161 (0.211)	0.168*** (0.048)	0.039 (0.035)	0.097*** (0.033)	0.051 (0.058)	0.081 (0.047)	0.104*** (0.026)	0.099** (0.037)
Operational efficiency × network centrality	0.604** (0.257)	0.115*** (0.032)	−0.050 (0.030)	−0.004 (0.029)	0.034* (0.019)	−0.073* (0.041)	−0.022*** (0.007)	0.054* (0.027)
Operational efficiency × structural holes	−0.361*** (0.106)	−0.226*** (0.039)	−0.038 (0.029)	−0.125*** (0.039)	0.014 (0.097)	−0.065 (0.060)	−0.213*** (0.041)	−0.006 (0.068)

(Continues)

TABLE B2 (Continued)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
$D \times$ product diversity	0.123 (0.283)	-0.109* (0.058)	0.157 (0.255)	-0.156** (0.057)	-0.003 (0.113)	-0.018 (0.072)	-0.103* (0.050)	-0.097* (0.053)
$D \times$ operational efficiency	3.864** (1.479)	0.290 (0.184)	0.551 (0.505)	0.200 (0.126)	0.233 (0.283)	0.042 (0.090)	0.271 (0.182)	0.245 (0.152)
$D \times$ network centrality	1.611*** (0.540)	0.009 (0.059)	0.345** (0.125)	0.048 (0.088)	0.178 (0.122)	-0.166 (0.101)	0.324** (0.138)	0.029 (0.045)
$D \times$ structural holes	-2.570*** (0.868)	-0.229** (0.093)	-0.398 (0.535)	-0.070 (0.098)	-0.370 (0.253)	-0.072 (0.066)	-0.292** (0.125)	-0.178 (0.138)
D	-10.061** (4.086)	0.165 (0.198)	-0.682 (0.559)	-0.217 (0.161)	-0.670*** (0.124)	-0.199 (0.203)	-0.323* (0.171)	-0.132 (0.168)
Product diversity	-0.192 (0.139)	-0.005 (0.042)	0.005 (0.046)	0.031 (0.051)	0.042 (0.083)	-0.037 (0.048)	0.030 (0.046)	-0.002 (0.039)
Operational efficiency	-0.737* (0.392)	0.338* (0.162)	0.577*** (0.098)	0.536*** (0.098)	0.553*** (0.067)	0.461*** (0.090)	0.509*** (0.102)	0.480*** (0.119)
Network centrality	-0.702*** (0.144)	0.072** (0.034)	0.082*** (0.018)	0.122 (0.098)	0.034 (0.023)	0.109*** (0.017)	-0.146*** (0.026)	0.047* (0.025)
Structural holes	0.701*** (0.176)	0.237*** (0.063)	0.088* (0.047)	0.091 (0.069)	-0.025 (0.045)	0.052 (0.032)	0.122** (0.050)	0.046 (0.057)

Note: Robust SE in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$. D = treatment dummy \times post-COVID-19 dummy.