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Leadership in a Crisis: A Social Network Perspective on Leader Brokerage Strategy, Intra-Organizational Communication Patterns, and Business Recovery

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Catastrophic events can significantly disrupt businesses and, as a result, understanding how organizations adapt to a crisis is critical. Undeniably, leaders often play a crucial role in times of great uncertainty. Yet, it is unclear exactly how leaders can effectively guide organizations

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through a crisis. Extending theories of network brokerage and organizational adaptation research, we posit that compared to leaders creating structural holes in intra-organizational communication networks, those leaders bridging structural holes can build more effective communication networks with greater cohesion and higher efficiency. In turn, greater cohesion and higher efficiency subsequently drive organizational adaptation and business recovery in a multi-unit enterprise during the early outbreak of COVID-19. Our hypotheses are supported using multi-wave network surveys in 111 chain restaurants with over 3,000 employees. We demonstrate that, during a crisis, leaders can serve as a key architect to shape communication patterns to facilitate organizational adaptation to crises and drive business recovery with faster customer growth and continually decreasing personnel costs.

Keywords: *leadership; crisis leadership; leader brokerage; organizational adaptation; communication networks*

In crisis situations, a leader's instinct might be to consolidate decision-making authority and control information, providing it on a strictly need-to-know basis. Doing the opposite will encourage teams to follow suit.

–D'Auria and De Smet (2020), *McKinsey Insights*

Catastrophic events can have devastating consequences for businesses (Powell, 1991). As one example, the COVID-19 global pandemic created significant disruptions for businesses worldwide. Facing heightened uncertainty, organizations, particularly small businesses that lacked critical resources to cope with the crisis, had to adapt to a new reality to ensure continuity of business operations (Bartik, Bertrand, Cullen, Glaeser, Luca, & Stanton, 2020). In particular, the crisis disrupted business operations globally in the restaurant industry. Many restaurants had to mobilize members to rapidly update core business activities (e.g., shifting from dine-in visits to delivery and takeout orders) and expand customer bases (Berger, 2020). Although organizations strive to adapt to disruptions and develop strategies to cope with uncertainty, it remains unclear why some organizations survive and even thrive through catastrophe while others fail (Collins & Hansen, 2011).

When a crisis strikes, people often rely on leaders for guidance and hope they can help organizations navigate through challenging situations (James & Wooten, 2010; Pearson & Clair, 1998). Surprisingly, despite the burgeoning leadership literature, scholars have devoted limited effort to directly examining how leaders help organizations adapt during crisis events and through what mechanisms leaders make a difference (James, Wooten, & Dushek, 2011; Mitroff, 1988). Although leadership researchers have debated whether leadership is inconsequential to performance (e.g., the romance of leadership, Meindl, Ehrlich, & Dukerich, 1985), it has been less controversial to argue that leadership matters in times of crisis (Pearson & Clair, 1998; Waldman, Ramirez, House, & Puranam, 2001), which makes this omission more problematic.

Triggered by the unprecedented crisis, a few recent studies have examined effective leadership in a crisis (Hu, He, & Zhou, 2020; Sergent & Stajkovic, 2020). Specifically, Hu et al. (2020) found that servant leadership can help employees who have state anxiety caused by the pandemic to be more engaged at work. We join these recent efforts to further investigate how leaders can lead whole organizations to adapt during a crisis. Notably, individual adaptation focuses on a single person's independent motivation, effort, and action. However, organizational adaptation, manifested in the innovation of new or modification of existing capacities to cope with change, is considered a product of members' collective responses to disruptive events. It involves shared interpretations of a crisis and interdependent interactions to cope with change (Ford & Baucus, 1987). Such a collective adaptation process is theoretically well aligned with the perspective of organizations as networks of communication between members (Guler & Nerkar, 2012; Katz & Kahn, 1966). As a result, it is theoretically meaningful to examine how leaders actively shape organizational communication patterns, which subsequently drive business adaptation and recovery (Ford & Baucus, 1987).

A key responsibility of leaders is to purposefully shape the way organizational members collaborate and communicate (Cross, Rebele, & Grant, 2016), which is critical for organizational performance (Soltis, Brass, & Lepak, 2018). Social network theories suggest that critical nodes of a network can have profound effects on overall network structures (Valente, 2012; Valente & Fujimoto, 2010). Leaders are arguably the most prominent organizational actors, as they are expected to influence network patterns via their interactions with members. Their role is paramount during a crisis, as they serve as strategic change agents guiding adaptation (Mitroff, 1988). Thus, the way leaders interact with followers during a crisis to navigate uncertainty can shape organizational communication patterns (Watson, 1982).

More specifically, a crisis event will likely create a strong need for organizational members to unite their efforts to closely collaborate and efficiently communicate to collectively cope with uncertainties (LePine, 2003; Maynard, Kennedy, & Sommer, 2015). To this end, effective leaders during a crisis are those who can develop cohesive and efficient communication patterns to facilitate idea exchange, integration, and adaptation. From a network brokerage perspective (Kwon, Rondi, Levin, De Massis, & Brass, 2020), leaders can maintain separation between members by dominating information flow (i.e., known as a "tertius gaudens" strategy), or enable direct exchanges between disconnected members and integrate information (i.e., known as a "tertius iungens" strategy) (Obstfeld, Borgatti, & Davis, 2014). Given the importance of developing cohesive and efficient communication in organizations during a crisis, we posit that compared to leaders creating structural holes in communication networks, those leaders bridging structural holes can build more effective communication patterns. In turn, effective communication patterns subsequently drive organizational adaptation and business recovery. This novel model will help answer a more general question of how organizational leaders best guide members to collectively navigate and adapt through a crisis. In doing so, we make three theoretical contributions to research on leadership during crisis.

First, although there is little debate about the prominent role of leadership in times of organizational crisis, perhaps surprisingly, there remains a lack of a theoretical account and empirical evidence to understand how leaders actually make a difference during a crisis. Thus, we fill this important void by demonstrating that leaders serve as proactive network architects to optimize collective communication patterns, which extends rare scholarly efforts investigating leadership during a crisis using a narrative perspective (e.g., how leaders articulate a mission and vision; James et al., 2011). We highlight that, in addition to what leaders verbalize during crisis, how they act also matters. Importantly, we leverage a rare opportunity from an exogenous event to examine how some leaders, as key originators of internal network configurations, can optimize their business units' internal communication patterns and adapt successfully.

Second, and more specifically, we develop a dynamic view to link different leader brokering strategies with important network mechanisms to underpin how leaders help organizations navigate a crisis. Drawing on network theories, we argue and demonstrate that the reason leaders matter is that they can structure organizational communication patterns, which play a vital role in driving organizational performance (Soltis et al., 2018). Extending prior findings, we further suggest that during a crisis, network patterns featuring greater communication cohesion and information efficiency facilitate knowledge exchange and integration to cope with uncertainties associated with a crisis. Therefore, we integrate network theories with leadership research to clarify how leaders dynamically create and optimize member collaborations to achieve collective goals. This investigation helps gain a better understanding of the role of organizational communication patterns in driving business success during a crisis.

Finally, we further contribute to a better understanding of leader brokerage research. Previous work often considers brokerage as an advantageous structure that carries benefits for brokers themselves, such as accessing diverse knowledge and achieving career success (Kwon et al., 2020). However, during a crisis leader brokerage that intentionally creates structural holes can prevent organizations from developing cohesive and efficient communication networks. Demonstrating the negative externalities of leadership brokerage provides a more nuanced understanding of brokerage research. Moreover, our research not only captures static leader network structures, but also considers how leaders adjust their brokering strategies when a crisis strikes. Thus, we contribute to a dynamic perspective of network research and show that changes in leaders' networks shape network patterns and, subsequently, organizational adaptation.

Theoretical Development and Hypotheses

A Network View of Leader Brokerage Dynamics and Organizational Adaptation

Sarta, Durand, and Vergne (2021: 44) highlight the agency view of business adaptation as "intentional decision making undertaken by organizational members" to cope with disruptions. Organizational leaders are key decision makers in a crisis and most likely to drive collective adaptation processes by shaping how members communicate and interact in a crisis (Cummings & Cross, 2003). Furthermore, collective adaptation highlights interdependent, shared responses to disruption. One of its core features is the way in which organizational members jointly interpret a disruption and communicate to adjust to emergent changes (Baard, Rench, & Kozlowski, 2014; Burke, Stagl, Salas, Pierce, & Kendall, 2006; Christian, Christian, Pearsall, & Long, 2017; Sarta et al., 2021).

Echoing this perspective, a network view of organizations describes them as a web of networks in which members communicate and interact to achieve collective goals (Katz & Kahn, 1966). Informal network structures capture actual communication patterns among members, which oftentimes are more informative than the formal organization of tasks and resources in understanding business actions (Guler & Nerkar, 2012; McEvily, Soda, & Tortoriello, 2014). Therefore, employees' interdependent interaction and communication (i.e., an intra-organizational communication network) is a useful lens to understand how business units adapted to major crises and experienced business recovery.

Considered network architects, leaders often play a prominent role in structuring and restructuring organizational informal networks, such as communication patterns. For example, Zohar and Tenne-Gazit (2008) found that transformational leaders increased the density of group communication networks. In shaping overall network structures, leaders may not only directly communicate with followers, but oftentimes strategically influence the way in which members interact with one another (Pappas & Wooldridge, 2007; Shi, Markoczy, & Dess, 2009). One common strategy is for leaders to "mediate between unconnected actors, divisions, or small business units" because such a brokerage role is an important instrument to influence strategy formulation and implementation (Shi et al., 2009:1455). Specifically, leaders can influence their business units' communication patterns by serving as arbitraging brokers mediating the exchange of information between unconnected parties by controlling information flows (i.e., tertius gaudens). In addition, leaders can exert influences by collaborating with brokers who actively integrate disconnected members in a manner that stimulates communication and collaboration (i.e., tertius iungens) (Obstfeld et al., 2014; Quintane & Carnabuci, 2016; Soda, Tortoriello, & Iorio, 2018).

Which strategy is more effective for leaders during a crisis? As noted, crises often require members to increase communication frequency to enhance the unity of an organization and process information more efficiently to cope with uncertainties. Thus, effective leaders are likely to dynamically adjust their brokering strategies when managing followers during a crisis and actively facilitate communication among otherwise disconnected employees. In doing so, they can build more efficient and cohesive network structures to aid business recovery.

From a network perspective, numerous studies have found that an efficient network often has many shortcuts connecting different clusters and is manifested by short average path length in a network (Funk, 2014; Vespignani, 2018; Watts & Strogatz, 1998). Additionally, a cohesive communication network is often manifested by high network density, which describes overall connectivity among all members in an organization. However, for larger networks, network researchers further argue that it may not be ideal or even possible to expect all members connected to one another to form a cohesive network. Instead, they distinguish between global cohesion (i.e., overall density of the network) and local cohesion (i.e., employees are densely tied to their neighbors and subgroups, Guler & Nerkar, 2012; Watts & Strogatz, 1998). Researchers often use a high clustering coefficient to represent cohesive communication within clusters (e.g., subgroups). Thus, we focus on three key network signatures that leaders' brokering strategies can drive: (a) average path length indicating overall communication efficiency—the average number of intermediaries between each pair of actors in the network; (b) density, representing the global communication cohesion of an entire business unit—which essentially captures the connectedness and togetherness between actors; (c) the clustering coefficient, or local communication cohesion, which represent optimal communication network signatures that set high-performing business units apart from ineffective ones (Bullmore & Sporns, 2012; Fleming, King, & Juda, 2007; Vespignani, 2018).

Effects of Leaders' Bridging Communication Structural Holes on Communication Network Efficiency and Cohesion During a Crisis

During a crisis, leaders as proactive agents can engage in different brokering strategies to cope with uncertainty. For example, some leaders could bridge holes while others might seek to create and maintain communication gaps among followers. When a crisis starts, leaders face a new reality, and thus they reflect on critical questions of how best to lead an organization to get through the crisis. Therefore, it is theoretically relevant to examine *dynamic changes* in leader brokerage positions to infer different brokering strategies (i.e., how brokers actually "broker"). It is reasonable to expect that leaders change communication patterns with followers in response to a crisis, resulting in changes in network brokerage positions. At the same time, members tend to defer to leaders for work arrangements (Stam, van Knippenberg, Wisse, & Nederveen Pieterse, 2018), so leaders are apt to serve as network architects influencing connectivity among members and also initiators who drive network changes.

For example, regarding uncertainty associated with a crisis, a leader may prefer to have greater structural clarity in an organization, such that all members and subgroups directly report to that leader (Soda et al., 2018). In this way, a leader could enforce existing work structures and routines to get things done quickly and use more direct communication styles to relay instructions to disconnected members, resulting in an increase in brokerage. In contrast, another leader could recognize the importance of unity during a crisis. They may intentionally close communication barriers between otherwise disconnected individuals or clusters to encourage direct communication, leading to brokerage decrease.

Leaders' brokerage decreases (or increases) will likely have meaningful impact on intra-organizational communication patterns in terms of communication cohesion and efficiency during a crisis. Before developing specific arguments linking leader brokerage change and organizational network structures, we first clarify that we focus on the influence of leaders' *direct* brokerage rather than that of secondhand brokerage, which consists of leaders' direct *and* indirect ties (Burt, 2007). Specifically, we argue that only direct brokerage is informative to understand leaders' influence during a crisis because a key leader responsibility is to directly communicate with followers rather than relaying information via others. Empirically, Burt (2007: 119) concluded that secondhand brokerage tends to have little or no value, as the influence of brokerage is mainly "concentrated in the immediate network around a person."

We first posit that leader bridging strategies can increase communication efficiency. Network efficiency captures the average steps a member needs to reach all other members (Funk, 2014). In higher (vs. lower) network efficiency, members can easily and quickly reach other members with fewer steps. By bridging connections across boundaries, leaders as network architects can create many shortcuts in a network and decrease the steps needed to reach other members in an organization (Cummings & Cross, 2003). Specifically, in a business unit, there are multiple subgroups performing different tasks. People in these groups are less frequently connected, and they tend to rely on leaders for information exchange. As a result, there will be greater distance between these employees. When leaders encourage direct inter-group/cluster communications, employees will take fewer steps to reach colleagues in other groups, resulting in higher network efficiency (van der Vegt, Essens, Wahlström, & George, 2015). In contrast, when members must go through leaders to get information, it reduces the inquirer's efficiency and increases steps in an information chain (Cummings & Cross, 2003). By encouraging them to be directly connected, members will take only one step to achieve communication goals. As a result, by fostering many cross-cluster ties between members and shortcuts in the network, the whole network can communicate more efficiently.

In addition, during a crisis when a leader bridges structural holes in a network manifested by his or her brokerage decreases, the leader can increase the cohesion of a communication network at both global and local levels. Specifically, density captures the overall intensity of communication frequency among all members in an organization (Guler & Nerkar, 2012). A leader who bridges structural holes often encourages otherwise disconnected members to directly communicate with one another. For example, in organizations, there are clear divisions of labor and existing subgroups that could prevent people in different teams and branches from frequently communicating with others who are not in the same teams or branches. When a leader breaks barriers between these clusters to encourage members to communicate across boundaries, employees from different subgroups will add more communication ties with less connected colleagues (Quintane & Carnabuci, 2016). As a result, the total number of communication ties will increase. On the flip side, when a leader increases his or her brokerage, that leader discourages direct communication among members and requires them to pass information to the leader (Kauppila, Bizzi, & Obstfeld, 2018). Thus, overall connectivity will decrease.

Studies have noted that individuals, especially leaders, can and often do develop specific brokerage styles (Levin, Walter, & Appleyard, 2011; Stam, 2010). The propensity to assume such roles often depends on various factors, such as job opportunities and workplace dynamics (Fang, Zhang, & Shaw, 2021). This is particularly pertinent for leaders who often serve as brokers to coordinate and unite team members (Long, Cunningham, Wiley, Carswell, & Braithwaite, 2013). For example, employees in a store are subdivided into several subgroups (e.g., service staff, chefs, and food preparation). Each subgroup operates in relative informational isolation, while maintaining close interaction between members within each subgroup. Leaders occupying a central "broker" position stand to gain from the wider range of diverse information accessible due to their unique position. This brokerage role can indeed confer a myriad of benefits for leaders, including fostering novel insights, control over non-redundant information, and enhancing cooperation (Burt, 1992, 2004).

The logic supporting how a leader who bridges structural holes promotes local cohesion is similar. Local cohesion describes a connectivity pattern in which individuals are densely connected to their neighbors, but not necessarily linked with the rest of their organization (Guler & Nerkar, 2012). Individuals tend to have high local cohesion when their neighbors are closely connected to one another (i.e., closed triangles, Opsahl, 2013). Leaders who encourage direct communication and bridge gaps in a network will likely increase local cohesion, manifested by a high clustering coefficient. For instance, when leaders try to connect otherwise disconnected followers, connections among these followers will create tightly knit groups in which they can all directly communicate. In contrast, for leaders who increase their brokerage positions during a crisis, followers tend to directly communicate with their leaders for approval and information. Thus, they are less likely to have discussions with their coworkers, even if they work in close clusters and in the same subgroups, resulting in decreases in local communication cohesion.

Hypothesis 1a:/ Leader communication brokerage decreases during a crisis will be positively related to communication network efficiency (i.e., shorter average network path length).

Hypothesis 1b:/ Leader communication brokerage decreases during a crisis will be positively related to communication network global cohesion (i.e., network density).

Hypothesis 1c:/ Leader communication brokerage decreases during a crisis will be positively related to communication network local cohesion (i.e., network clustering coefficient).

Effects of Communication Network Efficiency and Cohesion on Collective Adaptation

Collective adaptation is the process by which members jointly respond to disruptions, uncertainties, and obstacles by modifying existing routines, products, or services and developing new ways that better fit unique demands of a crisis (Sarta et al., 2021). Thus, the success of adaptation lies in the extent to which employees in a business unit can effectively develop new and feasible ideas and actions to fit a new environment. Research in the creativity literature has underscored the social origins of novel and useful ideas, such that creative solutions are often determined by the way in which different information is shared and integrated at various levels (Guler & Nerkar, 2012; Li, Li, Guo, Li, & Harris, 2018; Perry-Smith & Mannucci, 2017; Perry-Smith & Shalley, 2003). Effective communication patterns facilitate idea and knowledge integration in different areas and ensure that diverse information is shared and recombined among members to develop novel solutions (Guler & Nerkar, 2012; Kijkuit & van den Ende, 2007).

Specifically, communication efficiency and cohesion are two key factors promoting information exchange, integration, and creative solutions (Funk, 2014; Guler & Nerkar, 2012; Nijstad, De Dreu, Rietzschel, & Baas, 2010). Therefore, both communication efficiency (i.e., shorter average path length) and communication cohesion (i.e., density and clustering coefficient) will promote unit collective adaptation. Regarding network efficiency, shorter path lengths facilitate integration of knowledge (Fleming et al., 2007; Schilling & Phelps, 2007). For instance, disruptions in a crisis could require members to redraw work boundaries between different groups. For example, a shift from dine-in to take-out changes the workflow that employees use to prepare food, while people in the kitchen may need to use social media to gain new customers. Related, people interacting with customers need to communicate with kitchen personnel to discuss how to modify food preparation to optimize workflow. In essence, ideas located in different areas need to be integrated via various shortcuts, such that people can pool perspectives from diverse areas to generate feasible solutions (van der Vegt et al., 2015). Empirically, across different disciplines, from neuroscience to innovation management, network efficiency indicated by shorter path lengths increases performance in many different types of network systems (e.g., cognitive ability, Bullmore & Sporns, 2012; regional innovation, Fleming et al., 2007). An efficient network will allow its members to adapt to uncertain environments by developing novel and alternative solutions.

In addition to communication efficiency, cohesive networks enable sharing of tacit knowledge essential for exploration (Hansen, 1999; Uzzi, 1997). Research has shown that both global and local cohesion facilitates information integration and adaptation (Ahuja, Soda, & Zaheer, 2012; Guler & Nerkar, 2012). However, a few studies suggest that local and global cohesion yield different effects on innovation, such that "cohesion benefits are local in nature," and "are unlikely to apply to distant parts of the network" (Guler & Nerkar, 2012: 540). For example, a key difference between local and global cohesion is that they can facilitate members frequently exchanging information and ideas to cope with uncertainties, while global network density could carry extra costs to establish and maintain cohesive ties in large networks (Burt, 1992). Such costs can increase exponentially as network size increases (Guler & Nerkar, 2012).

As a result, organizational members can enjoy the benefits of network global cohesion in developing adaptive actions to cope with a crisis. When all members are cohesively connected in a network, they can frequently communicate ideas and solve key problems during a crisis. High density also indicates that employees are not only connected with their neighbors, but also to colleagues in different groups that allow them to integrate ideas beyond their immediate circles.

Local cohesion also likely facilitates organizational adaptation (Fleming et al., 2007; Watts & Strogatz, 1998). Local cohesion signals an optimized division of labor, and members can effectively communicate with others in similar areas. Clustered dense network structures facilitate trust and frequent information exchange without unnecessary costs from an increasing number of connections. Garcia-Pont and Nohria (2002) found that firms benefit from the local cohesion of alliances in their strategic groups. Studies have demonstrated benefits of cohesive networks in creating novel ideas, such that embeddedness in cohesive communities facilitates trust, knowledge sharing, healthy norms, and psychological safety (Burt, 1992; Obstfeld, 2005).

Hypothesis 2a:/ Communication network efficiency (i.e., shorter average network path length) will be positively related to unit collective adaptation during a crisis.

Hypothesis 2b:/ Communication network global cohesion (i.e., network density) will be positively related to unit collective adaptation during a crisis.

Hypothesis 2c:/ Communication network local cohesion (i.e., network clustering coefficient) will be positively related to unit collective adaptation during a crisis.

Effects of Collective Adaptation on Customer Growth and Personnel Cost Trajectories

Organizational adaptation ensures that businesses survive and thrive in volatile situations. The adaptation process highlights modifying existing routines and developing new ideas to fit a change (Sarta et al., 2021). COVID-19 has disrupted units' customer preferences, internal routines, services, and products. For recovery, each unit needs to quickly modify the way it does business and develop new solutions to satisfy novel demands of the crisis. As customers became hesitant to dine inside, employees needed to collaborate with others to quickly implement online ordering and delivery, retain existing but also obtain new customers, and modify food preparation processes. These collective adaptations are key to overcoming obstacles created by the disruption and ensure business recovery.

Instead of subjective perceptions, we focus on two key objective indicators to capture recovery—customer growth and personnel cost trajectories—that the organization used to evaluate unit performance. As customer growth and retention are critical for business success and overcoming challenges in a crisis, we focus on units' customer growth trajectories since the start of the crisis to indicate how fast business recovery occurs. Additionally, during a crisis, businesses need to be cost effective, and thus we track personnel cost trajectories during the crisis. We posit that unit collective adaptation will: (a) increase customer growth trajectories, such that units gain more customers, develop new ways to obtain them, and keep existing customers by providing exceptional service; and (b) decrease personnel cost trajectories by using efficient time management strategies and optimizing work arrangements.

Hypothesis 3a:/ Unit collective adaptation during a crisis will be positively related to customer growth trajectories.

Hypothesis 3b:/ Unit collective adaptation during a crisis will be negatively related to personnel cost trajectories.

A Serial Mediation Model

We have discussed how a unit leader's brokerage decreases (or increases) can alter communication patterns in each unit, which further influence organizational adaptation processes in developing new ways to serve customers during a crisis. Units that can adapt will experience faster business recovery. For example, leaders who attempt to bring their followers together and thereby generate more open dialogue during a crisis can create more effective communication patterns (Soda et al., 2018; Stovel & Shaw, 2012). Those effective communication patterns enable members to develop new ways to cope with changing environments (Christian et al., 2017). Taken together, we propose an integrated serial mediation theoretical model suggesting that leaders will indirectly and distally impact business recovery trajectories via a series of proximal internal mechanisms, including intra-organizational communication network patterns and adaptation processes. Our integrative model shows how leaders can make a difference for organizational outcomes and the underlying mechanisms responsible for these effects.

Hypothesis 4:/ Leader communication brokerage decreases will have a positive indirect effect on unit customer growth trajectories via optimal communication structures (4a) network efficiency, (4b) global cohesion, and (4c) local cohesion and then unit collective adaptation.

Hypothesis 5:/ Leader communication brokerage decreases will have a negative indirect effect on unit personnel cost trajectories via optimal communication structures (5a) network efficiency, (5b) global cohesion, and (5c) local cohesion and then unit collective adaptation.

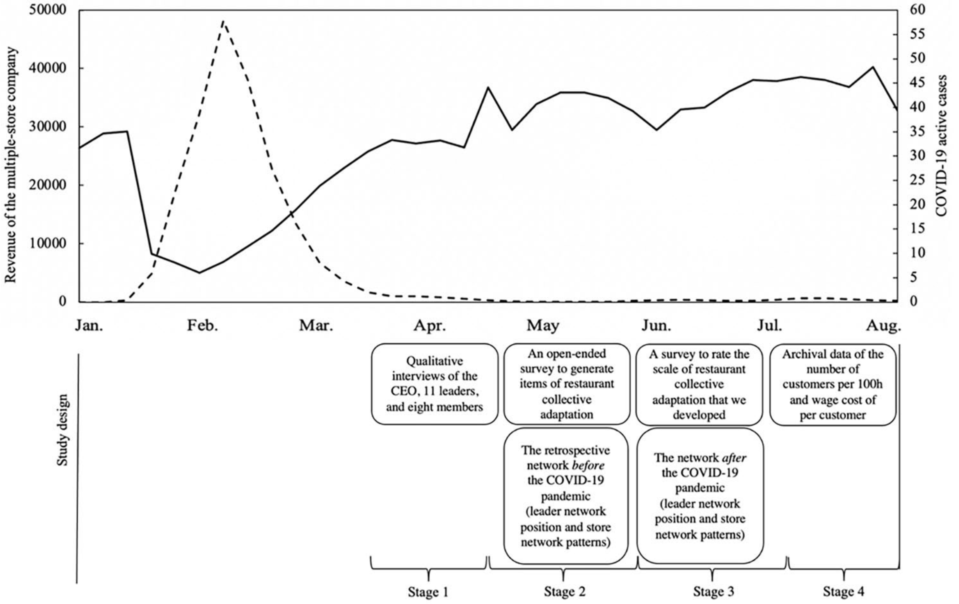
Methods

Study Context

We collected data from a multi-unit enterprise in the restaurant industry in China specializing in Chinese barbecue. By May 2020, the company had 143 restaurants with 5,877 employees in 10 major Chinese cities. The restaurant industry serves as a relevant context to understand how leaders help organizations adapt to a major crisis and recover. The universal impact of COVID-19 on the restaurant industry creates a homogeneous external environment and provides a rare opportunity to examine how leader efforts in relative isolation drive collective adaptation processes during a crisis. As one of the leading brands in the Chinese restaurant industry, however, this company not only survived the crisis but also experienced rapid business growth during the crisis since February 2020, when COVID-19 cases peaked in China.

Although the restaurants we focused on are four to five times larger than typical teams (Shen, Kiger, Davies, Rasch, Simon, & Ones, 2011), they are still relatively small compared to many organizations, particularly larger companies. We thus called each restaurant a "unit" in our study. We emphasized the voluntary nature of participation. Participants had the right to withdraw from the study at any point, which is reflected in the variability in response rates observed. Ensuring privacy and confidentiality, we linked responses only to randomly generated unique IDs. The survey was non-intrusive and did not contain sensitive questions, and

Figure 1
The Research Context and the Research Design



Note. The solid and dashed lines denote revenue of the multiple-unit company and COVID-19 active cases, respectively. We counted in thousands for revenue of the multiple-unit company and counted in thousands for COVID-19 active cases.

there were no right or wrong answers. We accommodated the varying work dynamics, with peaks and downtime, giving participants the flexibility to complete the survey during their downtime. That way, their regular duties were not affected while they were given an opportunity to contribute to a potentially beneficial study.

Study Design and Participants

Figure 1 describes the research context, design, and timeline of data collection. Given the unprecedented impact of COVID-19, we first conducted qualitative interviews for initial guidance about our focus on crisis leadership and restaurant collective adaptation, which emerged as a key driver of business recovery (April 2020, see the the Appendix in the online supplemental materials for details). We then invited 138 restaurants[1] (i.e., 138 leaders and 4,708 members) to participate via an online survey platform in the second stage (May 2020).[2] We adopted an open-ended survey and a network survey to generate items assessing restaurant collective adaptation and to collect retrospective network data before COVID-19, respectively. We provided a roster from the HR department to all colleagues in the same restaurant and asked them to report their communication with others (i.e., members and leaders) before the pandemic.[3] Using the actual roster reduced employees' cognitive load, so that they could more accurately recall their pre-pandemic communication patterns with others.

For the open-ended survey, we obtained 3,290 survey responses (124 leaders with an 89.86% response rate and 3,170 employees with a 67.33% response rate). For the network survey, we received 126 leader questionnaires (a response rate of 91.30%) and 3,221 member questionnaires from 138 restaurants (a response rate of 68.42%).

In the third stage (approximately 1 month after the second stage, June 2020), we administered surveys to quantitatively measure restaurant collective adaptation using the developed scale and collect network data during the COVID-19 pandemic using the updated roster.[4] We calculated the response rates based on the most updated employee roster at different stages to account for natural employee attrition, which is typically high in the restaurant industry, and particularly during the COVID-19 pandemic (Bufquin, Park, Back, De Souza Meira, & Hight, 2021; Self, Gordon, & Ghosh, 2022). Because the conceptual meaning of network indicators is based on employees' interactions at a particular time point, it made the most sense to focus on existing employees to construct network indicators (Li et al., 2018). For restaurant collective adaptation questionnaires, we received 127 leader surveys (a response rate of 92.70%) and 2,897 member questionnaires (a response rate of 78.15%) from 138 restaurants. For the communication network, we collected questionnaires from 125 leaders (a response rate of 91.24%) and 2,876 members (a response rate of 77.58%) from 138 restaurants.

After matching the two-wave data and removing restaurants with lower than 50% response rates in both surveys, the final sample consisted of 111 restaurants,[5] including 111 leaders and 3,014 employees.[6] We also conducted several sensitivity analyses using different response rates as cutoff values to demonstrate the robustness of our findings. In the final sample, 64.80% of employees were male, the average age was 26.94 years (SD = 6.76), the average organizational tenure was 1.34 years, and 15.4% of them had an associate degree or above (SD = .83). For the 111 leaders, 94.60% of them were male, their average age was 28.31 years (SD = 4.01), the average organizational tenure was 5.59 years (SD = 2.02), and 30.63% of them had an associate degree or above (SD = .89). For transparency, we have shared our final dataset, syntax, supplementary analyses, and the online Appendix in an open science platform: (https://osf.io/dw7pu/?view_only=d06b5f21368a49798dabeb77493f5fb7).

The interviews further informed us that there were adequate interactions between restaurant leaders and employees in these restaurants because all restaurants in our sample conducted daily meetings. During these gatherings, leaders would communicate the day's projected customer count, business objectives, material preparation, and other significant matters based on the previous day's events and the anticipated tasks for the current day. Employees were expected to participate in these meetings depending on their shifts. Despite the restaurants operating both day and night shifts, leaders were typically present during key operational hours, especially during peak periods (i.e., noon and evening). It is during these hours that leaders would interact directly with employees to ensure effective business operations.

Measures

Retrospective reporting is increasingly supported as a viable methodology (e.g., de Vaus, 2001; Featherman, 1980). We also conducted a series of analyses to validate our retrospective network measure (see Table S1 in the online supplemental materials). In addition, the definitions and measures of all network variables in our study can be found in Table 1.

Table 1

Conceptualizations of the Network Variables and Measures

Concept	Definition	Measure
Leader Brokerage Change	Brokerage is defined as "behavior by which an actor influences, manages, or facilitates interactions between other actors" (Obstfeld, 2017: 29). Brokerage change, refers to "the opening and closing of brokerage positions over time" (Sasovova, Mehra, Borgatti, & Schippers, 2010: 641). Sasovova et al. (2010: 646) pointed out that "the formation of new brokerage positions and the retention of existing ones are consistent with the tertius gaudens ('the third who enjoys') strategy at the heart of structural hole theory (Burt, 1992, 2005). . . . The closing of structural holes, is more consistent with the contrasting tertius iungens ('the third who connects') strategy (Obstfeld, 2005)."	We calculated managers' scores on efficiency of structural holes to capture leader brokerage position in each restaurant (Quintane & Carnabuci, 2016; Soda, Tortoriello, & Iorio, 2018). A leader in a brokerage position means that their fraction of nodes in an ego network are not redundant (Burt, 1992) and is calculated as effective network size divided by number of nodes in each ego network. After calculating leader brokerage scores at Time 1 and Time 2, we used latent change score modeling (LCSM; McArdle, 2009) to capture the brokerage structural position change over two time points.
Leader Indegree Centrality Change	Indegree centrality captures how frequently a leader interacts with followers (Wasserman & Faust, 2003). It measures the centrality of an actor in the network with others (Fang, Landis, Zhang, Anderson, Shaw, & Kilduff, 2015; Mossholder, Settoon, & Henagan, 2005). Indegree centrality change refers to the alteration in the centrality of a node within a network with respect to the number of incoming connections (in-degrees) it has.	We calculated leader centrality in the communication network using a normalized indegree centrality score (i.e., divided by network size). Similarly, we estimated leader centrality change using LCSM.
Network (In)efficiency (Average Path Length)	Network (in)efficiency has been equated with average path length in previous work (Fang, Lee, & Schilling, 2010; Lazer & Friedman, 2007) and refers to the effectiveness and productivity of a network in terms of its ability to transmit information or resources efficiently. A lower (vs. higher) average path length indicates a more efficient network, as it implies that information or resources can be transmitted quickly and directly between nodes (Ahuja, Soda, & Zaheer, 2012).	We measured network (in)efficiency with the average path length in each restaurant's communication network.
Network Global Cohesion (Network Density)	Network global cohesion refers to the overall interconnectedness and interdependence among individuals or entities in a network on a global scale (Guler & Nerkar, 2012). It measures the extent to which the entire network is tightly knit and integrated, with strong connections and interactions between all network members.	Density is the ratio of the sum of the link values versus the maximum possible total sum for the network (Scott, 2001; Wasserman & Faust, 2003), capturing degree of global cohesion among all nodes of a given network.
Network Local Cohesion (Average Cluster Coefficient)	Network local cohesion refers to the interconnectedness and interdependence among individuals or entities within specific local clusters or subgroups within the network (Guler & Nerkar, 2012). It focuses on the cohesion within smaller subsets of the network, such as cliques or communities, rather than the entire network as a whole. Local cohesion examines the density of connections and interactions within these smaller groups, measuring the strength of ties and relationships within specific clusters.	Following previous research (Guler & Nerkar, 2012), we measured local cohesion in a communication network with the average cluster coefficient, which is the "average of the densities of the neighborhoods of all of the nodes" (Hanneman & Riddle, 2005: 95), and calculated using binary ties.

Intra-organizational communication network. In the first survey, we provided all participants (including leaders and members) with a roster of all their coworkers in the same restaurant and asked them to select coworkers (including leaders) with whom they had interactions or communicated with before the COVID-19 pandemic (i.e., before January 20, 2020). To safeguard potential recall bias, our discussion with several employees revealed that the sudden outbreak of the pandemic was a memorable disruptive event that fundamentally changed the way members interacted. As a result, employees readily recalled their communication patterns with coworkers before the pandemic. In addition, the online survey system automatically screened out unselected coworkers, and employees only rated selected colleagues on the following question (cf. Zhao, Li, Harris, Rosen, & Zhang, 2021): "How frequently had you communicated with [name] before the COVID-19 pandemic?" (Yuan, Fulk, Monge, & Contractor, 2010) using a 5-point scale (1 = *never*, 5 = *always*). In the second survey, we followed these two steps but changed the stem to "after the outbreak of COVID-19 pandemic (i.e., after January 2020)." In supplementary analyses, we also collected additional network data to validate the retrospective measure of social networks (see below).

Leader network brokerage change. We calculated managers' scores on efficiency of structural holes to capture leader brokerage position in each restaurant (Quintane & Carnabuci, 2016; Soda et al., 2018). A leader in a brokerage position means that their fraction of nodes in an ego network are not redundant (Burt, 1992) and is calculated as effective network size divided by number of nodes in each ego network. We employ this measure, rather than betweenness centrality, because it uses direct ties with leaders (Borgatti, Everett, & Freeman, 2002) in line with our focus on leader-follower direct interactions. In contrast, betweenness centrality captures both direct and indirect ties to reflect the extent to which a leader is a broker of indirect connections among all others in a network (Freeman, 1978). We also used an alternative measure of network brokerage to examine the robustness of our results (see supplementary analyses).

After calculating leader brokerage scores at Time 1 and Time 2, we used latent change score modeling (LCSM; McArdle, 2009) to capture the brokerage structural position change over two time points. Using a structural equation modeling framework, LCSM estimates a latent change score through specification of a set of unitary constraints on these scores, which overcomes some limitations of basic difference scores (Li et al., 2018; McArdle, 2009). Because each restaurant only had one manager, there was one latent change score for each restaurant.

Leader network indegree centrality change. Indegree centrality is the most common leader network feature, capturing how frequently a leader interacts with followers (Wasserman & Faust, 2003). We focus on leader indegree, rather than outdegree, centrality because indegree centrality was calculated based on followers reporting when they interacted with their leader. As a result, it can accurately capture leaders' influence in an organization. In contrast, outdegree centrality captures leaders' perceptions of their interaction patterns, which are less objective.[7] Therefore, it is theoretically relevant to consider the potential influence of leader network centrality change when examining the effect of leader brokerage change to separate the effect between pattern (i.e., brokerage) and frequency (i.e., centrality). We thus calculated leader centrality in the communication network using a normalized indegree centrality score (i.e., divided by network size). Similarly, we estimated leader centrality change using LCSM.

Organizational communication network patterns were calculated as efficiency (i.e., shorter average path length) and cohesion (i.e., with density as global cohesion and average cluster coefficient as local cohesion). Given our theoretical focus on members' intra-organizational communication patterns, which are partially driven by leader actions, we removed leaders from restaurant networks when calculating organizational network indicators and, by doing so, we can precisely capture communication among employees. We measured network (in)efficiency with the average path length in each restaurant's communication network. Shorter average path length reflects efficiency in each network, such that a network with a longer path length has more intermediaries separating each node, and thus information spreads more slowly and less accurately as path length increases.

We measured global cohesion with communication network density. Density is the ratio of the sum of the link values versus the maximum possible total sum for the network (Scott, 2001; Wasserman & Faust, 2003), capturing degree of global cohesion among all nodes of a given network. Following previous research (Guler & Nerkar, 2012), we measured local cohesion in a communication network with the average cluster coefficient, which is the "average of the densities of the neighborhoods of all of the nodes" (Hanneman & Riddle, 2005: 95), and calculated using binary ties. Thus, based on arguments of strong and weak ties (Granovetter, 1973; Marsden, 1990) and following previous studies (e.g., Zhao et al., 2021), we dichotomized the network by setting responses of 1 (never), 2 (rarely), and 3 (sometimes) as zero, and the responses of 4 (often) and 5 (always) as one.[8] We computed all network values using ORA software (Carley, Reminga, Storrick, & Columbus, 2010).

Unit collective adaptation. Given the unprecedented nature of the COVID-19 pandemic, employees often displayed unique adaptation behaviors that are not captured by previous adaptation measures. We used an open-ended survey to develop the collective adaptation scale (see the Appendix in the online supplemental material for the scale development and validation details). The scale development yielded a three-dimensional measure, including gaining new customers (three items), retaining existing customers (three items), and learning and skill development (three items, see Table A3 in the online Appendix for details). Members rated collective adaptation (Cronbach's alpha = .92) using our 9-item measure (1 = *strongly disagree* to 5 = *strongly agree*). To support aggregation, the mean and median r_{wg} values are .91 and .92 for restaurant collective adaptation, respectively. A one-way ANOVA test showed significant differences across restaurants ($F = 2.15$, $p < .001$). ICC(1) and ICC(2) for collective adaptation were .05 and .53. In our research context, a lower value of ICC(1) reflects low between-group variance, which means that restaurants had relatively similar levels of collective adaptation. This is reasonable because all restaurants are part of one company. As a result, management systems, human resource management practices, company policies, the CEO, and so forth, are all the same for each restaurant. Despite the modest ICC values, they are comparable to the values reported in similar settings (Liao & Chuang, 2004; Schneider, White, & Paul, 1998); in particular, the ICC(1) is within the acceptable range that Bliese (2000) specified as typical for applied field research, and it should not prevent aggregation when aggregation is justified by theory and supported by high r_{wg}(j) and significant between-groups variance (Chen & Bliese, 2002; James, Demaree, & Wolf, 1984; Kozlowski & Hattrup, 1992).

Customer growth and personnel cost trajectories. We obtained archival performance data from each restaurant. Because different restaurants varied in size and location, which can significantly impact financial performance such as revenue, we used normalized indicators that are less influenced by these attributes. Specifically, we focused on two key indicators, including number of customers served per 100 working hours and personnel cost per customer. We calculated customer growth and personnel cost trajectories, respectively, which are two key performance indicators company headquarters use to evaluate each restaurant. According to company records, most restaurants were severely harmed and had the lowest performance in February, and the recovery process started then. We focused on trajectories of customer growth and personnel cost from February to August. We followed the approach of Chen, Ployhart, Thomas, Anderson, and Bliese (2011) and Joshi and Knight (2015) to describe temporal change as a slope calculated across the 7 months (see Figures S1 and S2 in the supplementary materials as illustrations).

We selected these dependent variables because they are two objective indicators reflecting inputs and outputs of restaurants, respectively. Customer growth is one core source of income and performance, and it indirectly reflects the level of customer satisfaction, preferences, and retention (Babakus, Bienstock, & Van Scotter, 2004; Keiningham, Cooil, Aksoy, Andreassen, & Weiner, 2007). It is a normalized measure of employee work inputs in a restaurant and less influenced by the cost of living or other unobserved factors in different locations. Personnel cost is a key source of cash outlay and reflects the degree to which restaurants operate efficiently (Mathe, 2012; Walczak & Reuter, 2004). These two objective indicators were those that the organization used to evaluate restaurant performance and that all leaders were motivated to improve.

Controls. To examine how leaders drove optimal communication patterns during the pandemic, we included pre-pandemic network patterns as primary controls (i.e., restaurant average path length, density, and average cluster coefficient). As a result, we could examine the incremental influence of leaders on the restaurant network patterns during the COVID-19 pandemic and strengthen causal inferences. In addition to these important network structures, we also controlled for internal factors—including restaurant size (i.e., number of employees), turnover rate during the pandemic, and demographic composition (i.e., diversity in gender, age, education, and organizational tenure)—and one environmental factor: the severity of COVID-19 (i.e., the cumulative cases in each city before August 31, 2020). Specifically, restaurant size could reflect internal resources. Turnover rate often influences business performance (for a review, see Shaw, 2011). Team research has also found that team demographic composition can impact collective processes and performance (Joshi & Roh, 2009). Finally, the severity of COVID-19 could influence restaurant operations. Nevertheless, we note that, with or without these controls, we reached consistent conclusions (see Tables S18 and S19 in the online supplemental materials).

Results

Preliminary Analyses

Table 2 presents descriptive statistics. Before testing hypotheses, we conducted a latent mean structure analysis using Mplus (Version 8.0; Muthén & Muthén, 1998–2017) to determine whether there was significant variance in leader network position changes. Regarding leader brokerage, results showed that there was a marginally significant change (M = .02, p = .052;

Table 2
Descriptive Statistics and Correlations Among Study Variables

	M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Unit size	34.81	7.91																			
2. Turnover rate	0.21	0.09	.12																		
3. Gender diversity	0.48	0.10	.15	–.01																	
4. Age diversity	6.65	1.62	.01	–.26**	–.05																
5. Education diversity	0.82	0.12	.01	.16	.12	–.26**															
6. Organizational tenure diversity	1.25	0.36	.06	–.15	–.14	.42***	–.26**														
7. COVID-19 accumulative cases in the city	637.02	213.15	.07	.22	–.02	.21	–.16	.07													
8. Leader brokerage, Time 1	0.64	0.10	.23*	–.18	–.05	.15	–.25**	.05	.21*												
9. Leader brokerage, Time 2	0.66	0.13	.12	–.12	–.04	.02	–.10	–.06	.12	.61***											
10. Leader centrality, Time 1	0.40	0.12	–.23*	–.14	–.06	.15	–.19*	.06	.17	–.03	.05										
11. Leader centrality, Time 2	0.43	0.14	–.15	.14	–.06	.12	–.09	.08	.32***	–.09	–.10	.68***									
12. Unit average path length, Time 1	4.16	0.90	.25**	.06	–.06	.03	–.01	–.02	.15	.47***	.36***	–.40***	–.22*								
13. Unit average path length, Time 2	3.73	1.01	.30**	–.16	.02	–.01	–.01	.02	.07	.46***	.53***	–.26**	–.34***	.46***							
14. Unit density, Time 1	0.18	0.07	–.34***	–.17	.00	.04	.03	.07	–.13	–.59***	–.38***	.63***	.42***	–.72***	–.51***						
15. Unit density, Time 2	0.19	0.10	–.27**	.19	–.06	.04	.08	.07	.08	–.57***	–.71***	.31***	.51***	–.46***	–.65***	.64***					
16. Unit cluster coefficient, Time 1	0.45	0.19	–.12	–.10	.17	–.04	.09	.06	–.21*	–.41***	–.26**	.40***	.33***	–.72***	–.33***	.60***	.35***				
17. Unit cluster coefficient, Time 2	0.45	0.17	–.05	–.03	–.07	–.00	–.03	.02	–.00	–.39***	–.62***	.26**	.34***	–.47***	–.64***	.45***	.65***	.44***			
18. Unit collective adaptation	4.35	0.19	–.27**	–.10	–.05	.18	–.08	.14	–.02	–.36***	–.40***	.29**	.27**	–.35***	–.49***	.40***	.48***	.28**	.38***		
19. Customer growth trajectory	15.27	4.39	–.25**	–.02	–.09	.14	–.04	–.04	.01	–.18	–.01	–.01	–.08	.04	–.17	.07	.04	–.14	.00	.28**	
20. Personnel cost trajectory	–0.70	0.47	.15	–.03	.07	–.11	–.08	–.04	–.17	.24*	.15	.09	.05	–.09	.07	–.03	–.09	.12	–.04	–.30**	–.75***

Note. N = 111 units. Time 1 and Time 2 represent before and after the COVID-19 pandemic, respectively; COVID-19 accumulative cases in the city were the numbers of accumulative COVID-19 cases by August 31, 2020 in the city in which the unit was located. Data were from the National Health Commission of the People's Republic of China, health commissions and governments in each provinces and cities (https://i.snssdk.com/ugc/hotboard_fe/hot_list/template/hot_list/forum_tab.html); gender: 0 = female, 1 = male; education: 1 = primary school, 2 = junior high school, 3 = high school, 4 = associate degree, 5 = bachelor's degree, 6 = master's degree; organizational tenure was measured by years; turnover rate was calculated by the comparison between the initial sample in the first survey and the sample in the second survey.

*p < .05 (two-tailed). **p < .01 (two-tailed). ***p < .001 (two-tailed).

variance = .01, $p < .001$) in the mean value of T1 ($M = .64$) and T2 ($M = .66$), indicating that there was no significant unified trend of change in leader brokerage. However, this did not necessarily imply that there was not much change before and after the pandemic because changes could be either positive or negative, and the .01 significant variance did show that the value of leader brokerage change varied significantly in different stores. Thus, we calculated the quartiles of leader brokerage change. The first quartile was −.06, indicating that 25% of the changes were lower than −.06. The third quartile was .09, suggesting that 25% of the changes were higher than .09. These results suggested that, in different stores, there were some moderate leader brokerage changes in different directions, without constituting a significant unified change trend. Regarding other network metrics, we found a significant increase ($M = .03$, $p = .005$; variance = .01, $p < .001$) in leader indegree centrality and a significant decrease ($M = -.43$, $p < .001$; variance = .98, $p < .001$) in average path length. The changes in these two metrics indicated that during the pandemic, leaders had become more centralized in the organizational network, with employees increasingly reliant on communication with leaders, while the communication paths within the network had become shorter and more efficient. Additionally, there were no significant changes in the mean values of unit density ($M = .01$, $p = .420$; variance = .01, $p = .001$) and average cluster coefficient ($M = -.00$, $p = .943$; variance = .04, $p < .001$), suggesting that before and after the pandemic there was no significant unified trend of change in overall communication density among employees or in the extent of forming close connections within small employee groups.

Following Murphy's (2021) approach, we assessed whether the mediation hypotheses are plausible based on the examination of descriptive statistics. As shown in Table 2, leader brokerage is detrimental for network efficiency, global cohesion, and local cohesion during the crisis. Specifically, it is positively correlated with unit average path length ($r = .47$ in Time 1, $r = .53$ in Time 2) and negatively correlated with unit density ($r = -.59$ in Time 1, $r = -.71$ in Time 2) and unit cluster coefficient ($r = -.41$ in Time 1, $r = -.62$ in Time 2). Thus, these relationships are consistent with what we predicted in Hypotheses 1a, 1b, and 1c.

Similarly, our results indicated that unit collective adaptation is negatively correlated with unit average path length ($r = -.35$ in Time 1, $r = -.49$ in Time 2), positively correlated with unit density ($r = .40$ in Time 1, $r = .48$ in Time 2) and unit cluster coefficient ($r = .28$ in Time 1, $r = .38$ in Time 2). These results imply that unit collective adaptation is significantly positively correlated with network efficiency, global cohesion, and local cohesion during the crisis, which is consistent with what we predicted in Hypotheses 2a, 2b, and 2c. Unit collective adaptation is positively correlated with customer growth trajectory ($r = .28$) and negatively correlated with personnel cost trajectory ($r = -.30$). These results reflect that unit collective adaptation is beneficial for overall unit performance, which is consistent with what we predicted in Hypotheses 3a and 3b. Based on these results, we conclude that the mediation hypotheses are plausible.

Model Comparisons

We used a path model analysis to test our hypotheses, which examined multiple relationships simultaneously. We entered latent change scores for leader brokerage and indegree centrality into the path models using Mplus (Version 8.0). We compared our hypothesized model (full mediation) with several alternative partial mediation models (see Table 3). Our hypothesized full mediation model[9] provided an acceptable fit to the data: $\chi^2(33) = 78.54$,

Table 3
Model Comparisons Among Full and Partial Mediation Path Models

Models	χ^2	*df*	$\Delta\chi^2$	RMSEA	SRMR	CFI
A full mediation model	78.54	33		.11	.07	.93
Alternative model 1	76.41	31	2.13	.12	.07	.93
Alternative model 2	65.26	25	13.28	.12	.06	.93
Alternative model 3	58.88	21	19.66	.13	.06	.94

Note. N = 111 units. χ^2 = chi-square; *df* = degrees of freedom; RMSEA = root mean square error of approximation; CFI = comparative fit index; SRMR = standardized root mean square residual at the individual level. $\Delta\chi^2$ was the values of chi-square compared with a full mediation model. Alternative model 1: The direct effects from leader network changes to unit collective adaptation were added; Alternative model 2: The direct effects from leader network changes to unit collective adaptation and unit network values to the dependent variables were added; Alternative model 3: The direct effects from leader network changes to unit collective adaptation and the dependent variables, and unit network values to the dependent variables were added.

RMSEA = .11, SRMR = .07, CFI = .93.[10] Alternative models did not provide better model fit, despite increased model complexity. Added relationships in all alternative models were also not significant. Following the parsimony principle (Williams, Vandenberg, & Edwards, 2009), we used our hypothesized model in the following analyses and conducted a robustness check for those alternative partial mediation models (see online supplementary Tables S20a, S20b, and S20c).

Hypotheses Testing

Direct effects. Hypothesis 1a predicted that leader brokerage decreases can enhance network efficiency (i.e., shorter average path length). In support of H1a, we found a significant positive relationship between leader brokerage change and network average path length (b = .21, SE = .07, p = .002), indicating that a leader brokerage score increase is associated with a longer network path length (Table 4 and Figure 2). Likewise, significant negative relationships between leader brokerage change and both the network density (b = –.34, SE = .06, $p < .001$) and cluster coefficient (b = –.41, SE = .07, $p < .001$) also confirmed Hypotheses 1b and 1c, which predicted that leader brokerage decreases enhance network cohesion at both the global and local levels.

H2a was supported by the negative significant relationship between unit average path length and unit collective adaptation (b = –.32, SE = .12, p = .006). Regarding H2b and H2c, the hypothesized positive relationship between unit density was positively and significantly related to collective adaptation (b = .28, SE = .12, p = .023), while unit cluster coefficient and unit collective adaptation were not significant (b = –.01, SE = .12, p = .914). Hence, Hypothesis 2b was supported, but Hypothesis 2c was not. The above results indicated that network efficiency and global cohesion during the crisis can significantly help increase unit collective adaptation.

Hypothesis 3a was supported by the significant positive relationship between unit collective adaptation and customer growth trajectory (b = .28, SE = .09, p = .001). Hypothesis 3b was also supported by the significant negative relationship between unit collective adaptation and personnel cost trajectory (b = −.30, SE = .07, $p < .001$). The results verified that unit collective adaptation is beneficial for unit overall performance.

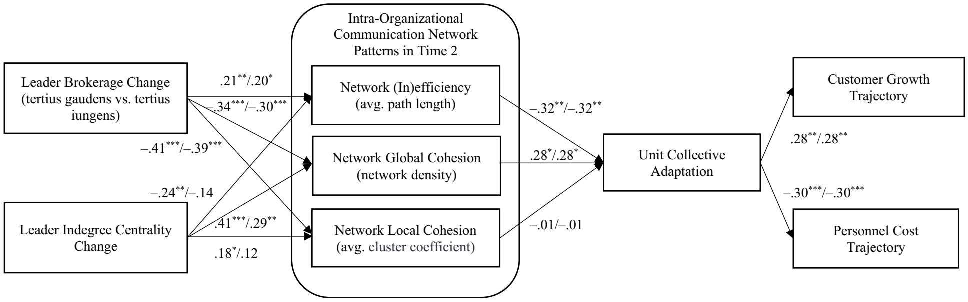
Table 4
Results of Path Analyses

Variables	Coefficients	Standard Errors
Unit average path length, Time 2		
Leader brokerage change	.21**	.07
Leader centrality change	–.24**	.08
Unit average path length, Time 1	.27	.14
Unit density, Time 1	–.43***	.11
Unit cluster coefficient, Time1	.10	.12
Unit density, Time 2		
Leader brokerage change	–.34***	.06
Leader centrality change	.41***	.06
Unit average path length, Time 1	–.08	.09
Unit density, Time 1	.75***	.08
Unit cluster coefficient, Time 1	–.14	.09
Unit cluster coefficient, Time 2		
Leader brokerage change	–.41***	.07
Leader centrality change	.18*	.08
Unit average path length, Time 1	–.16	.11
Unit density, Time 1	.29**	.10
Unit cluster coefficient, Time1	.18	.10
Unit collective adaptation		
Unit average path length, Time 2	–.32**	.12
Unit density, Time 2	.28*	.12
Unit cluster coefficient, Time 2	–.01	.12
Customer growth trajectory		
Unit collective adaptation	.28**	.09
Personnel cost trajectory		
Unit collective adaptation	–.30***	.07

Note. $N = 111$ units. Standardized coefficients were reported.
*$p < .05$ (two-tailed). **$p < .01$ (two-tailed). ***$p < .001$ (two-tailed).

Indirect effects. We used a Monte Carlo simulation with 20,000 replications to build 95% confidence intervals (CIs) around the estimated indirect effects (Preacher & Selig, 2012; Preacher, Zyphur, & Zhang, 2010). Supporting Hypotheses 4a and 5a (Table 5), the indirect effects of leader brokerage change on customer growth (estimate = −.019, 95% CI [−.049, −.003]) and personnel cost (estimate = .021, 95% CI [.003, .051]) trajectories via unit network efficiency (i.e., shorter path length) and unit collective adaptation were significant, respectively. Supporting Hypotheses 4b and 5b, the indirect effects of leader brokerage change on customer growth (estimate = −.026, 95% CI [−.060, −.003]) and personnel cost (estimate = .028, 95% CI [.005, .064]) trajectories via unit density and unit collective adaptation were significant. These results mean that leader brokerage change can influence unit path length and density and unit collective adaptation, and, ultimately, unit performance. Failing to support Hypotheses 4c and 5c, leader brokerage change did not significantly influence customer growth (estimate = .001, 95% CI [−.027, .031]) or personnel cost (estimate = −.002, 95% CI [−.033, .029]) trajectories via unit cluster coefficient and unit collective adaptation (see Table 5). These results reflect that the mediating role of

Figure 2
Results of the Path Model



Note. $N=111$ units. Standardized coefficients were reported. Communication network patterns in Time 1 were added as controls for communication network pattern in Time 2. Fit for model: $\chi^2(33)=78.54$, RMSEA = .11, SRMR = .07, CFI = .93. The model allows for covarying the variables of leader brokerage change and indegree centrality change, three indicators of communication network patterns in Time 1, three indicators of communication network patterns in Time 2, and customer growth trajectory and cost increase trajectory, respectively. Values to the left of the slash are coefficients with primary controls and values to the right are coefficients without primary controls.
$^*p < .05$ (two-tailed). $^{**}p < .01$ (two-tailed). $^{***}p < .001$ (two-tailed).

unit cluster coefficient and unit collective adaptation is minimal in transmitting the effect of leader brokerage change on unit outcomes.

We also estimated values of pseudo-R^2 (Snijders & Bosker, 1999) to assess the amount of variance in the dependent variables explained by our model. The model explained 7.80% of the variance in customer growth trajectory and 9.20% of the variance in personnel cost trajectory.

Robustness Check and Supplementary Analyses

To check the robustness of our results and conclusions, we conducted supplementary analyses (see online supplementary materials).

The impact of missing value evaluation. To maximize statistical power, we included units with greater than a 50% response rate to test all our hypotheses. The response rates for the brokerage calculation are important, particularly for the broker's responses. Fortunately, among those 111 final stores, 110 leaders finished the network measure in the second stage (response rate = 99.10%), and 107 leaders finished the network measure in the third stage (response rate = 96.40%). We also compared the brokerage score distribution between high versus low response stores. Except for kurtosis, the mean, variance, and skewness of these two distributions are very close (see Table S2 and Figure S3). To evaluate the impact of missing network data on the reliability of our results, we used an advanced statistical model (see Figures S4 and S5), the Exponential-Family Random Graph Model (ERGM, Krivitsky, 2012), to impute the missing data in the network analysis. The filled data allowed us to reach consistent conclusions (see Table S3).

Given the potential influence of network response rates on the accuracy of network measures, we tested our hypotheses using subsamples, including only units with higher response

Table 5
Serial Indirect Effects

Customer Growth Trajectory (DV1)	Estimate	95% CI	Personnel Cost Trajectory (DV2)	Estimate	95% CI
Unit average path length (M1)	–.019	[–.049, –.003]	Unit average path length (M1)	.021	[.003, .051]
Unit density (M2)	–.026	[–.060, –.003]	Unit density (M2)	.028	[.005, .064]
Unit cluster coefficient (M3)	.001	[–.027, .031]	Unit cluster coefficient (M3)	–.002	[–.033, .029]

Note. $N = 111$ units.

rates (i.e., 60% and 70% cutoffs), and found consistent results, except for the non-significant relationship between density and adaptation (Tables S4 and S5). We further tested whether missing responses were random by comparing the demographics among the final sample (111 units) and the missing sample (27 units). We found no significant differences in the variables of size ($t[136] = -1.72$, *n.s.*), turnover ($t[136] = -.87$, *n.s.*), leader gender ($t[136] = 1.70$, *n.s.*), leader age ($t[136] = .32$, *n.s.*), leader education ($t[136] = -.33$, *n.s.*), leader organizational tenure ($t[136] = -1.97$, *n.s.*), unit member age diversity ($t[136] = .41$, *n.s.*), unit member education diversity ($t[136] = -.04$, *n.s.*), or personnel cost in August ($t[132] = 1.33$, *n.s.*). The only significant difference between them was on the number of customers served per 100 working hours in August ($t[132] = -2.33$, $p = .022$). To further explore how random missing values could influence our conclusions, we conducted additional analysis by only including high response-rate units (response rates $\geq$ 70%) and then randomly deleting responses from 684 members in T1 and 628 in T2 to reach approximately a 50% response rate in each unit so that the data are more comparable to the results of our final sample. Results showed that we reached consistent conclusions (see Table S6).

Using original rosters as the benchmark. Given that we calculated response rates using the most updated employee rosters at each time point, it is also possible to use original rosters at the first stage to calculate overall response rates. If we use the overall response rate of 50% as a cutoff value, the sample size is 100. The results showed that we reached consistent conclusions, except for the nonsignificant positive relationship between unit density and unit collective adaptation (see Table S7).

Model specification. We conducted a series of additional analyses to test the robustness of our findings. First, we removed leader indegree centrality change from the model because it was considered a control variable, and the results were unchanged (see Table S8). Second, following Preacher and Hayes (2008), we constrained the covariance among predictors, mediators, and dependent variables to test our hypotheses. We further relaxed these constraints to examine whether there are any unexpected relationships among variables that were not hypothesized. The results showed that all the conclusions were unchanged (see Table S9). Third, we excluded leaders when we calculated organizational communication network to examine the unique influences of leader brokerage changes on the communication patterns of followers. However, to test the robustness of our findings, we reanalyzed the data including leaders and reached consistent conclusions (see Table S10). Finally, we tested the mediating role of unit adaptation dimensions (see Tables S11a, S11b, and S11c), and the independent mediating role of each network indicator (i.e., unit average path length, unit cluster coefficient, and unit density), finding that leader brokerage change significantly predicted each network indicator, which all significantly predicted collective adaptation (see Figure S6 and Table S12).

Alternative measures. We used structural hole efficiency to capture a leader's brokerage position, which allowed us to use value ties that we do not need to dichotomize the network. However, research has also used a reversed measure of network constraint to capture network brokerage (Burt, 1992), which is calculated based on dichotomized networks (Altman, Carley, & Reminga, 2020). We tested all hypotheses with this alternative measure of brokerage and found consistent results (see Table S13). Relatedly, and in line with our conceptualization, we argue that only direct brokerage, instead of second-hand brokerage consisting of leaders' direct and indirect ties, is informative to understand leaders' influence during a crisis. Thus, we used betweenness centrality as an alternative measure of brokerage change and found that it did not significantly influence communication patterns (see Table S14). In addition, we considered alternative operationalizations of business recovery outcomes. We created two types of ratio measures to indicate business recovery (i.e., a ratio of August/January performance to capture business recovery compared to before pandemic performance, and another ratio of August/February performance to indicate business recovery compared to the lowest point) and noted identical findings (see Tables S15 and S16).

Discussion

Business longevity is never a given. In fact, one study showed that the typical company only survives about 10 years (Daepp, Hamilton, West, & Bettencourt, 2015). Through business lifecycles, leaders often play a vital role in guiding organizations through a crisis (James & Wooten, 2010). We developed a novel model to examine how organizational leaders can motivate their followers' collective efforts to overcome challenges of a major crisis. Specifically, we demonstrated that the adaptation process is driven by the way leaders interact with their members to form effective intra-organizational communication patterns, which subsequently support collective adaptation to the crisis and, ultimately, business recovery. Our research has several implications for theory and practice.

Theoretical Implications

We first contribute to a better understanding of the process of leadership during crisis. Despite the critical role that leaders play in a crisis, perhaps due to the difficulty of assessing leader dynamics during severe disruption, there is a lack of theory and empirical research detailing the various mechanisms through which leaders help businesses overcome challenges when facing crises. Crises once considered rare and unusual (e.g., severe weather events) have been increasingly disrupting business operations worldwide. These events bring disorder to business activities (Maitlis & Sonenshein, 2010). Leaders are expected to lead in extraordinary ways to move beyond routine problem-solving strategies by helping organizations to adapt.

Specifically, our approach takes a more agency-centric view of business adaptation from a crisis leadership perspective. That is, in many cases, business environments and resource endowments are relatively fixed and out of the control of company leaders. During times of business crisis, internal resources, such as leaders and members, are the main levers that can be leveraged to adapt and recover. In a comprehensive review, James et al. (2011) reviewed crisis management from a leadership perspective and concluded that research on leadership during crisis is rare and predominantly focused on how leaders use different verbal strategies, such as creating a compelling vision, justifying their actions, and interpreting situations. As a result, despite the significant role of leaders during crisis, we know little about how they actually contribute to business recovery, which has impeded theory building on crisis leadership.

In response, we creatively consider leaders not only as communicators, but also as proactive agents that shape overall organizational network patterns supporting companies in adapting to uncertainties. In doing so, our research demonstrates that when facing a relatively similar challenge like a global pandemic, businesses can rely on their leaders' guidance and members' collective efforts to cope with adversity by optimizing internal communication patterns via leaders developing effective brokering strategies as network architects to support business recovery. Thus, we have helped to answer the key question of why some businesses survive and even thrive (i.e., by achieving post-traumatic recovery) during a crisis while others fail with the same resources and similar challenges.

Second, and more specifically, we demonstrate novel mechanisms business leaders use to support collective organizational adaptation through their influencing intra-organizational communication patterns. We thus connect leadership with a view that considers organizations as a web of networks in which members collaborate to achieve collective goals (Katz & Kahn, 1966; McEvily et al., 2014) to enrich our understanding of how leaders can make a difference during crisis. It is well established that informal structures, such as communication patterns, play a vital role in determining organizational success (Pentland, 2012). We further underpin the origins of organizational informal structures and demonstrate that when crises strike, effective leaders can optimize communication patterns by helping organizations to build cohesive and efficient networks that support business adaptation.

We found that leaders enhance network efficiency (i.e., shorter average path length) and both global (i.e., network density) and local (i.e., network cluster coefficient) cohesion when they facilitate communication among otherwise disconnected members. Essentially, leaders enhance organizational communication patterns by bridging structural holes in their networks to make member communication more effective. In doing so, we enrich both leadership and social network research by moving beyond the structure view of brokerage, which uses a static perspective to examine the fixed structural position of brokers, to incorporate the dynamic change of leader brokerage in organizations during a major crisis (i.e., the behavioral view; Quintane & Carnabuci, 2016; Soda et al., 2018). To this end, we can better understand how leaders' different brokering strategies influence business adaptation and outcomes and gain a better understanding of the role of brokerage during crisis.

Finally, our research sheds important insights on understanding the nuanced effects of leader brokerage in organizations. Importantly, research often considers brokerage as an advantageous structure that carries benefits for brokers themselves (Kwon et al., 2020). However, its effects on others are unclear, with research showing both positive and negative spillover effects (e.g., Bizzi, 2013; Clement, Shipilov, & Galunic, 2018; Cummings & Cross, 2003; Galunic, Ertug, & Gargiulo, 2012). We thus extend prior research by showing that leader brokerage can significantly and adversely affect business outcomes. In doing so, we challenge an untested assertion that "the brokerage roles of middle managers may benefit organizations as a whole and not just the managers themselves (Shi et al., 2009: 1458)," and demonstrate that the claimed benefits associated with brokerage may not apply to leaders during crisis, whose primary role is promoting unity and facilitating collaboration in organizations to achieve higher collective performance. Leader brokerage, emphasizing information control, could conflict with this primary role and is thus detrimental by creating suboptimal communication patterns. This echoes Burt's (2004) speculation that although structural holes can result in good ideas, no evidence has indicated that those good ideas ensure implementation efforts, let alone implementation success.

From a methodological perspective, our research has suggested that our findings represent the social structure by conducting these additional analyses despite the lower than desired response rate, thereby bolstering confidence in our conclusions. By employing some statistical approaches (e.g., ERGMs) to impute missing data, our study offers empirical evidence for future researchers grappling with similar challenges about lower than desired response rates in social network research. As obtaining network data often proves difficult, and missing data are common, we believe our study provides useful strategies for addressing these issues.

Practical Implications

Given the inevitability of companies encountering various crises, our research offers valuable insights into how leaders can effectively leverage their internal resources to navigate through these challenging times. For example, early in the COVID-19 outbreak, a rapid shift from dine-in to take-out required swift role changes, such that servers needed to work with kitchen personnel to prepare food. In addition, everyone was mobilized to brainstorm ideas to obtain new customers and engage in marketing activities to promote their business via social media. As our opening quote suggested, in times of crisis, there is a tendency for leaders to consolidate their decision-making authority and control information. Our findings demonstrate that this would be a highly counterproductive move and result in harmful business outcomes. Instead, we demonstrated that leaders need to shift from directly communicating to each group (as they typically did before the pandemic when tasks were more straightforward) to serving as a facilitators and collaborators breaking down barriers among different groups and allowing diverse information to be shared.

Regarding specific leadership behaviors, leaders should bridge structural holes, rather than create communication gaps, in their units. Organizations can benefit from direct interaction between leaders and members. For example, leader network centrality increases also promote network efficiency and density (see Figure 2). However, it could be impractical for leaders to engage with everyone in their organization to increase their indegree centrality due to an upper limit on frequent communication (Oldroyd & Morris, 2012). Therefore, rather than directly connecting to more people, leaders could try to encourage communication among disconnected members and groups by role modeling such behavior themselves.

Our research also speaks to the important discussion on organizational resilience, such that organizations can constantly build resilience and adaptive capability through a series of crises. Our findings suggest one way to achieve such post-traumatic growth is to create more efficient network patterns prompted by crises. Regarding specific strategies, organizations can also develop adaptation capability and resilience by adopting both pre- and post-traumatic coping strategies (Alliger, Cerasoli, Tannenbaum, & Vessey, 2015; Stoverink, Kirkman, Mistry, & Rosen, 2020). That is, organizations can proactively expose employees to simulated crises and uncertainties and develop different training scenarios in which employees can improve their communication processes with other colleagues and enhance adaptive behaviors. After a particular crisis, organizations can encourage employees to reflect upon their adaptive strategies during a crisis and optimize their existing routines based on lessons learned from it. In doing so, organizations can continuously build their adaptation capabilities for future uncertainties.

Finally, given the important role of organizational network structures, companies can intentionally improve their ongoing intra-organizational communication patterns by tracking and mapping network structures. For instance, they could use digital information technology to constantly track real-time, anonymized information flows among members to understand internal communication patterns (e.g., email exchanges, calendars). Leaders also can strategically intervene to optimize network structures (Leonardi & Contractor, 2018; Valente, 2012).

Limitations and Future Research

As with all research, our study is not without limitations. Despite the challenge of obtaining many intra-organizational networks to examine the association between network structures and business unit outcomes, to the best of our knowledge we are the first to use a survey-based approach to examine relationships between organizational networks and business unit outcomes. One limitation of this approach is the potential influence of lower than desired within-network responses rates. We collected two waves of network surveys from over 100 business units and used 50% as a cutoff point, which could influence the accurate representation of network structures. We thus evaluated its potential influence by using stricter cutoff values (i.e., 60%, 70%) and found highly consistent results. We acknowledge this potential limitation in our study and encourage future research to use more non-obtrusive ways to tap internal organizational data (Knight, 2018; Leonardi & Contractor, 2018).

We also measured units' communication networks before COVID-19 retrospectively, which raises questions as to whether employees can accurately recall their interaction patterns before the pandemic. We acknowledge that because respondents are asked to recall a social network rather than a network in which they are currently embedded, the results may be limited by retrospective bias. We addressed this issue in two ways. One, our interviews with company employees reinforced to us that the sudden outbreak of COVID-19 was highly memorable and disruptive to their daily routines. As a result, employees were able to accurately recall their activities before the pandemic. Two, our additional MAPE analyses suggested that retrospective bias was not a major issue in our study. Despite these analyses, we acknowledge that the retrospective approach is limited by potential recall biases, which tend to increase over time. Thus, we acknowledge that there are inherent limitations to the retrospective approach due to potential recall biases, which tend to increase over time. We hope future research can shorten recall time and capture real-time experiences or behaviors.

Our study's sample could be limited because we used front-line workers in a multi-unit enterprise in the restaurant industry in China, raising generalizability issues. It is unclear whether our findings are applicable to other types of jobs, industries, or countries. For instance, Western cultures are lower in power distance (i.e., "the extent to which a society accepts the fact that power in institutions and organizations is distributed unequally"; Hofstede, 1980: 45), whereas non-Western cultures are typically higher. As a result, the driving role of leaders could be attenuated in lower power distance contexts. Additionally, anecdotal interviews revealed that both leaders and employees actively experimented with various strategies to cope with the crisis. Although prior research, such as that by Levin et al. (2011) and Stam (2010), has highlighted that individuals, notably leaders, can and often do cultivate specific brokerage styles, and that occupying the brokerage position can yield a multitude of benefits (Burt, 1992, 2004), our study does not capture this intentionality explicitly. Consequently, we are unable to confirm whether other potential factors may also influence this process. This leaves room for future research to further explore the subject of intent within the context of collective adaptation.

Furthermore, the results supported the indirect effect for global cohesion (network density) but not for local cohesion (clustering coefficient). One possible reason is that because local cohesion of a unit communication network depicts the extent to which intra-unit communication elements link to their immediate neighborhood (Guler & Nerkar, 2012), it may be limited in facilitating collaboration in the whole unit, compared with global cohesion that portrays the structural feature of overall connectedness of intra-unit communication elements (Guler & Nerkar, 2012). In addition, although Hypotheses 4a, 4b, 5a, and 5b were supported, some confidence intervals barely excluded zero.

Our results indicated that bridging structural holes is an effective way to facilitate collaboration and communication among employees during a crisis. However, it would be interesting to know whether such a strategy is effective in more general situations. From a theoretical perspective, the rationale supporting the beneficial effect of bridging structural holes appears to be universal and is well aligned with teams research (Cummings & Cross, 2003). Thus, our conclusions should have broad implications beyond crisis and change contexts and suggest a potentially universal beneficial effect of connecting, rather than creating, structural holes in organizations. It is important that such a conclusion be confirmed in other settings, for both direction and magnitude of the influence.

Conclusion

Adopting and extending theories of network brokerage and organizational adaptation research, we develop and test a theoretical model to explain how leader brokerage and intra-organizational communication patterns drive organizational adaptation and business recovery in a multi-unit enterprise during the crisis. We found that leaders' bridging structural holes is beneficial for more effective communication networks and further facilitates collective adaptation to the crisis driving business recovery. We hope that our research illuminates these important issues in the context of major crises and sets the stage for future research on the network perspective of leadership during crisis.

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Notes

1. The company had 143 restaurants in total in May 2020. We excluded five restaurants from the surveys because three of them had not yet opened at that time and were in the preparatory stage. Two managers were responsible for managing two restaurants each, so we selected only the two restaurants in which the leaders had primary responsibilities to maintain data independence.
2. This is an online survey system that assigns each participant a unique ID number and password to fully ensure participants' anonymity. After participants logged in, they could access each question and only see colleagues from the same restaurant to answer network questions.
3. Notably, as some employees who worked in the restaurant before the COVID-19 pandemic left the company by the time we administered our first survey, their names did not appear on the roster. Despite this, it is appropriate for us to use the roster because the vast majority had remained (M=71.65%, SD=7.12, ranging from to 54.76% to 92.68%).
4. One leader and 1,001 members left the company after the second stage of the survey.
5. Although 116 restaurants had 50% or above response rates, we deleted five restaurants in the analyses due to missing data. Examples include restaurant members not rating their leaders in the surveys, or a leader leaving the restaurant during the second survey.
6. We determined the final sample by deleting those who did not fill out any questionnaires to use all of the valid information from respondents. For example, if a member completed a T1 network survey but not a T2 network survey, they still contributed useful information to calculate T1 network indicators and thus are included in the analysis.
7. We reached a consistent conclusion when we used outdegree centrality in our analyses.
8. When we set the responses of 1 and 2 as zero, and the responses of 3, 4, and 5 as 1, we still arrived at consistent conclusions. The results can be seen in the online supplemental materials (Table S17).
9. In addition to the hypothesized relationships, the model is configured as the covariances among leader network variables, restaurant network control variables, restaurant network mediators, and outcomes, respectively. For more detail, please refer to the Robustness Check and Additional Analyses section.
10. Given the comparative strengths and weaknesses of each indicator (Rigdon, 1996), we needed to include them as a whole. Despite a relatively higher RMSEA, which is positively biased when the sample size is small (Kenny, Kaniskan, & McCoach, 2015), the CFI and SRMR are acceptable in our study because previous work indicates that CFI values no smaller than .90 and SRMR values no higher than .10 are considered good fit (Browne & Cudeck, 1993; Hu & Bentler, 1999).

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