Working from home and firm resilience to the COVID-19 pandemic

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Abstract
The COVID-19 pandemic has disrupted firms’ operations. To cope with the crisis, many firms have allowed their employees to work from home (WFH). We examine whether a firm’s WFH capacity has increased its resilience during the pandemic. We test the hypotheses using a unique data set that combines listed firms’ financial statements, supply chain partners, and job postings on a leading online platform that provides hiring services. We find that imposing COVID-19 anti-contagion policies on firms and their suppliers or customers significantly increases their operating revenue volatility, slows their recovery, and has repercussions on their supply chains. WFH enhances firms’ resistance capacity by reducing the effect of COVID-19 on their operating revenue volatility and disruptions to their supply chain partners; however, it also decreases their recovery capacity by extending the time taken to return to normal. Firm attributes, along with workers’ occupations, education, and experience, have an impact on the effect of WFH on firm resilience. This study enhances our understanding of shock transmission across supply chains and WFH as a source of firm resilience.

Keywords
COVID-19 pandemic, resilience, supply chain, work from home

Highlights
• Measures of Work-from-Home (WFH) capacity are developed for Chinese listed firms based on their online job postings.
• Exploring the variation of policies against COVID-19 across Chinese cities, we find these policies increased listed firms’ operating revenue volatility, slowed their recovery, and generated repercussions on their supply chains.
• WFH acted like a double-edged sword: on the one hand, it enhanced firms’ resistance capacity by reducing the effect of COVID-19 on their operating revenue volatility and disruptions to their supply chain partners; on the other hand, it decreased their recovery capacity by extending the time taken to return to normal.
1 | INTRODUCTION

Since January 2020, the COVID-19 pandemic, also known as the coronavirus pandemic, has caused severe public health crises in many countries. By April 2022, more than 512 million cases and more than 6 million deaths had been reported, making COVID-19 one of the deadliest pandemics in history. The pandemic has also had enormously negative consequences for global economic development. For instance, during the first quarter of 2020, China (the first epicenter) had a year-on-year GDP growth rate of $\approx -6.8\%$; for the entirety of 2020, the World Bank reported a world GDP growth rate of $\approx -3.36\%$, indicating the worst recession since the Great Depression (World Bank, 2021).

From a micro-perspective, the pandemic is posing unprecedented challenges to many firms, such as drastic fluctuations in demand for end-consumer products and services, wide-ranging interruptions in the logistics of materials and flow of people, and frequent restrictions on or even suspensions of firms and other organizations’ operations and production activities. In the interest of public health, governments around the world are enforcing measures such as social distancing, home quarantines, border closures, and even total city lockdowns to contain the spread of the virus. Although such policies have saved millions of lives, they are inevitably causing unprecedented disruptions to supply chains, making resilience one of the most vital capacities for any firm or actor active in those systems to survive (Ivanov, 2021).

Under these circumstances, firm resilience is critical because it determines whether firms can adapt to changes during the pandemic and recover from pandemic-related disruptions. Long before the pandemic, firms have realized the importance of building resilience to mitigate the impact of disruptions in turbulent and uncertain environments (Jüttner & Maklan, 2011) and there has been increasing research on how firms can develop resilience to supply chain disruptions (Ambulkar et al., 2015; Blackhurst et al., 2011; Huang, 2017). However, the COVID-19 pandemic sheds light on an unprecedented context of supply chain disruptions, and as noted by Ivanov (2021), based on a comprehensive analysis of the literature, “the COVID-19 pandemic has laid out a set of novel decision-making situations that have not been previously considered in resilience theory and principally go beyond its scope” (p. 131). It is critical both to determine how to develop resilience in this novel, far-reaching context and to conduct more research on related issues.

One of the most salient characteristics of the pandemic, which distinguishes it from more typical disruptions (e.g., power outages), is that commuting to the office has become less safe and even, when there are local lockdowns, temporarily forbidden. This labor disruption is felt most keenly in supply chains, because the pandemic affects firms’ operations both directly and, through their suppliers and customers, indirectly. To mitigate the effects of these disruptions and maintain business operations, some firms are arranging for their employees, if possible, to work from home (WFH) instead of commuting to their offices. Working from home, as a popular tool for alleviating pandemic-related disruptions, has attracted a new wave of research (Barrero et al., 2021; Dingel & Neiman, 2020; Garrote Sanchez et al., 2021; Saltiel, 2020).

Despite its growing popularity, the impact of WFH on firm resilience remains largely underexplored. Will a firm be more capable of withstanding and recovering from the COVID-19 shock if more of its jobs can be done from home? If so, how does a firm achieve these goals through WFH? We focus on the following key issues: (1) evaluating the economic impact of the COVID-19 pandemic on firms with different levels of exposure and (2) investigating the effect of WFH on firm resilience. Following previous studies (Cardoso & Ramos, 2016; Ivanov, 2021; Melnyk et al., 2014), we divide firm resilience into resistance capacity and recovery capacity. Resistance capacity refers to the capabilities or measures employed to mitigate risk and enhance preparedness for disruptions in the pre-disruption phase, whereas recovery capacity refers to the capabilities employed in the post-disruption phase to restore operations and performance (Ivanov, 2021). By decomposing firm resilience into these two dimensions, we provide a more comprehensive understanding of how WFH can help firms become more resilient in the face of pandemic-related disruptions.

We use epidemiological data, financial data, and online job postings data from China and exploit the shocks induced by COVID-19 to answer these questions. The epidemiological data are mainly from Ding Xiang Yuan (DXY), a leading online platform for Chinese medical professionals. The online job postings data are from a leading Chinese online platform that provides hiring services. We classify the posted jobs into those that can be done from home (WFH jobs) and those that cannot based on their work context and activities (Dingel & Neiman, 2020) and time-use surveys of workers (Koren & Pető, 2020). Based on firms’ pre-pandemic job postings, we use the share of WFH jobs in total posted jobs to measure the WFH ability of their employees during the pandemic. We then match the job postings data with listed firms from the Chinese Research Data Services Platform (CNRDS) and the China Stock Market and Accounting Research Database (CSMAR). The CNRDS provides information on firms’ suppliers and customers, which allows us to construct their supply chains. The CSMAR provides corporate financial statements, which enables us to measure firm performance.
We first measure firms' exposure to COVID-19 shocks based on location, purchases from suppliers and sales to customers, and the spatial and temporal evolution of the pandemic and anti-contagion policies. Next, we exploit a difference-in-differences (DID) strategy to estimate the effect of the COVID-19 shocks on firms with different degrees of WFH capacity. The idea is to see whether firms with different exposure to COVID-19 shocks respond differentially according to their WFH capacity. We find that WFH significantly increases firms' resistance capacity by reducing their operating revenue volatility and the disruption to their supply chain partners during the pandemic. However, contrary to our expectations, we find that WFH capacity does not foster firms' recovery capacity. Indeed, firms with a higher degree of WFH capacity experience a longer period of negative growth. These results indicate that WFH has tradeoffs: it helps firms cope with labor disruptions, but it also prolongs their pain. These baseline results are robust to alternative measures of COVID-19 shocks and WFH.

We also conduct a rich set of heterogeneous treatment effect analyses by extending the baseline to a triple-DID estimation. These analyses reveal that the effect of the COVID-19 shocks and WFH is heterogeneous across firms of different sizes and from different industries. For example, we find that COVID-19 shocks increase the relative (to other firms) operating revenue volatility of manufacturing firms but reduce the relative volatility of service firms. Manufacturing firms recover more rapidly than others, whereas service firms recover more slowly. We also explore how the effect of WFH depends on employees' education and work experience. We find that firms that hire WFH workers with more working experience gain a more significant reduction in their operating revenue volatility, but they also recover more slowly. We also find that firms with more educated and experienced WFH employees have a more stable supply chain than firms with less educated and experienced WFH employees.

We make two main contributions to the literature. First, we identify the WFH capacity as a new (but essential) antecedent of firm resilience during a pandemic in which governments broadly implement anti-contagion policies. The supply chain resilience literature usually assumes an interruption of the normal flow of goods and materials while largely ignoring disruptions to other critical aspects of supply chain operations. Although labor availability is generally not an element of supply chain resilience in regular disruptions, it has played an essential role in sustaining supply chain operations and decision-making during the COVID-19 pandemic. Given that the COVID-19 pandemic is causing tremendous, unprecedented disruptions, our study is among the first to both demonstrate the effect of those disruptions on firm performance and to consider whether WFH is an effective strategy to alleviate them. Second, by explicitly conceptualizing and operationalizing firm resilience into the dimensions of resistance capacity and recovery capacity, we are among the first to explore the role played by WFH in enhancing these two essential capacities. Our analyses also provide an unexpected finding: whereas the WFH capacity increases firms' resistance capacity, it decreases their recovery capacity. The counterintuitive findings related to WFH's negative role in firm resilience requires firms to reflect on their strategic choice to use WFH and on how WFH can be better crafted to enhance multiple dimensions of firm resilience against disruptions caused by anti-contagion policies. Our further exploration of the heterogeneous effect (industry type, firm size, worker characteristics) of WFH on firm resilience also has critical implications that will benefit the operations and supply chain management (OSCM) literature and the use of WFH in practice.

2 | LITERATURE REVIEW

2.1 | Firm resilience to supply chain disruptions

Resilience is defined as a system's capacity to maintain its structure and function when responding to unpredictable changes (Holling, 1973) and can be seen from both multidisciplinary and multidimensional perspectives (Tukamuhabwa et al., 2015). In materials science, the notion represents the ability of a material to recover its original shape following a deformation (Sheffi, 2005). Among the first attempts to introduce resilience into the context of OSCM, Rice and Caniatoo's work (Rice & Caniato, 2003) described it as an organization's ability to react to an unexpected disruption, such as one caused by a terrorist attack or a natural disaster, and restore normal operations (p. 25). Thereafter, it has received increasing attention by OSCM researchers studying how to manage supply chains in a volatile world (Ambulkar et al., 2015; Brandon-Jones et al., 2014; Pettit et al., 2010). Resilience has gradually been distinguished from similar concepts such as stability (Disney & Towill, 2002) and robustness (Simchi-Levi et al., 2018) in OSCM research and widely investigated to understand how to support the continuity of firm operations in the presence of uncertainties and disruption (Ivanov, 2021). Likewise, we are using notions and ideas of resilience derived from OSCM literature to develop and explain our focal resilience in this study.

Because of the complex and dynamic nature of supply chains, the notion of resilience has been defined and analyzed in divergent ways in OSCM literature, leading to
ambiguity in what resilience actually means (Novak et al., 2021) and inconsistency in using the terminologies to develop supply chain resilience through antecedents, attributes, capabilities, elements, and enhancers (Hohenstein et al., 2015). Some studies on supply chain resilience even fail to define and explicitly analyze it at precise levels (Kim et al., 2015). For these reasons, we follow the line of research that examines firm resilience to supply chain disruptions at the firm level (Ambulkar et al., 2015) and define resilience for our purposes as a firm’s capacity to withstand, adapt, and recover from disruptions to meet customer demand, ensure target performance, and maintain operations in vulnerable environments (Hosseini et al., 2019; Ivanov, 2021). Our subsequent analysis and discussion are mainly from the perspective of a firm’s resilience capacity.

Recent studies on developing and operationalizing resilience capacity have provided important insights into its multidimensional and dynamic nature, contributing to a more systematic way of interpreting this capacity. Accordingly, a firm’s resilience should account for proactive and reactive orientations (Iftikhar et al., 2021; Ivanov et al., 2017; Ponomarov & Holcomb, 2009), the dynamic nature of supply chain disruption (Novak et al., 2021; Tukamuhabwa et al., 2015), the disturbance phase (Hohenstein et al., 2015), and the resilience phase (Iftikhar et al., 2021). Although some of these interpretations of firm resilience are not yet a matter of consensus (Conz & Magnani, 2020), the multidimensional nature of firm resilience has been recognized by many studies. Given that a resilient supply chain seeks to maintain desired performance despite disruptions, resilience capacity can be further disassembled into two rudimentary capacities or subdimensions: resistance capacity and recovery capacity (Cardoso & Ramos, 2016; Ivanov, 2021; Melnyk et al., 2014). Following this approach, we split firm resilience into these two categories. Resistance capacity concerns how a firm absorbs disruptions and reduces performance degradation through avoidance and preparedness. In contrast, recovery capacity concerns how a firm restores its operation and performance by stabilizing essential activities and adapting to new circumstances after a disruption. This distinction also provides clues to identify the specific abilities, strategies, and measures that develop a firm’s resilience against disruptions: the former capacity is mainly built on proactive strategies or planning preparedness measures during the pre-disruption phase, whereas the latter is based on reactive strategies or actions to stabilize and adapt during the post-disruption phase (Ivanov, 2021).

Because the primary purpose of a firm’s resilience is to help withstand, adapt, and recover from disruptions, the characteristics and nature of various disruptions have become another major topic of research on supply chain resilience. There are various types of direct causes and manifestations of disruptions, such as natural disasters, human-caused disasters, and financial crises. With respect to risk, the literature on risk management in supply chains suggests that disruptions can be considered high-impact, low-frequency events (Akkermans & Van Wassenhove, 2018), but this explanation is too vague to capture the varied nature and types of disruption.

Varying in their appearance and consequences (Ivanov et al., 2017; Paul et al., 2019), supply chain disruptions can be classified into three categories: random disruptions, hazard disruptions, and deep disruptions (Ivanov, 2021; Klibi et al., 2010). Random disruptions are considered to have known-known uncertainty, that is, both their appearance and their consequences can be anticipated. Hazard disruptions are closely related to known-unknown uncertainty, that is, we may know that they can happen, but we have no idea of when they will happen and what they will affect. Deep disruptions are the most complex, having unknown-unknown uncertainty, that is, both their appearance and consequences are unpredictable. The COVID-19 pandemic is a typical instance of deep disruption (Ivanov, 2021), which has been the topic of relatively little research.

In addition, it is somewhat surprising that in the literature defining and classifying various supply chain disruptions, most studies have assumed that such disruptions consistently interrupt the normal flow of goods and materials, and they have failed to consider other critical aspects of supply chain operations, such as labor availability and power supply. One of only a few exceptions is Parker and Ameen (2018), who investigated firms’ resilience to power supply disruption and called for more papers investigating firm resilience to more types of disruptions. The COVID-19 pandemic provides an unprecedented context for such investigations.

Ivanov and Dolgui (2020) suggested that the COVID-19 pandemic brings new challenges for firm resilience. According to Sodhi and Tang (2021), the supply chain challenges associated with COVID-19 can differ significantly from those associated with a normal supply chain disruption in terms of demand certainty, supply certainty, channel stability, labor availability, supply chain visibility, geopolitical stability, supply chain permanence, and the reliability of financial flows in the supply chain. These challenges distinguish the disruptions caused by the COVID-19 pandemic from disruptions of a more typical nature and are associated with rarely explored research opportunities. First, the COVID-19 pandemic is having an adverse impact worldwide, frequently triggering unpredictable, large-scale, and lasting interruptions to people's ability to move freely because of anti-contagion policies such as border closures and quarantines (Araz et al., 2020; Linton & Vakil, 2020). These types of disruptions severely hinder and even prevent people from commuting and moving around more...
generally, disrupting the operations of many firms and their supply chains. Second, the pandemic has broken out almost everywhere in the world, and its shocks are widely propagated through global supply chains (Fang et al., 2020). This provides the most substantial test of the resilience of supply chains (Ivanov, 2021) and enables the study of rare scenarios that may complement both simulation findings (Ivanov, 2021; Zhao et al., 2019) and mathematical modeling (Hosseini et al., 2019). Third, this disruptive event is evolving dynamically, providing opportunities for a more dynamic multistage investigation and more comprehensive assessments of firm resilience. As Tukamuhabwa et al. (2015) argued in their study exploring the dynamic nature of disruption, more longitudinal research is needed to examine the behavioral patterns of firm resilience in multiple phases. Dynamic resilience is more critical than ever if firms are to survive the pandemic, and there is a need for further investigation (Iftikhar et al., 2021). Fourth, because the powerful disruptions caused by the COVID-19 pandemic are challenging and exposing the vulnerabilities of the entire value chain, there has been increasing discussion among practitioners and researchers about how to create a resilient supply chain that balances personal protection and operational resilience against disruptions through the use of novel measures or unconventional approaches. WFH has emerged as an effective measure that is frequently mentioned in these discussions (Sharma et al., 2020), and it merits further investigation.

### 2.2 Working from home

The second stream of research that is closely related to our work focuses on the important role of WFH as an occupational characteristic and measures whether employees in a given occupation can WFH during the pandemic (Dingel & Neiman, 2020). Interest in WFH as an occupational characteristic is related to research on work arrangements (Mas & Pallais, 2020). This line of research dates to the 1980s, when telecommunications technology emerged as a substitute for physical travel to a central workplace. Some organizations started encouraging their employees to WFH regularly instead of traveling to the physical workplace (Olson & Primpis, 1984). Since then, the literature has assessed the nature, prevalence, trend, determinants, and consequences of WFH as an alternative work arrangement within organizations (Bailey & Kurland, 2002; Haddon & Lewis, 1994; Pinsonneault & Boisvert, 2001). Studies have generally focused on two central issues: (1) the efficacy of WFH as a management practice for organizations, and (2) WFH’s effects on work-life balance for employees (Bloom et al., 2015). On the one hand, WFH has several advantages at both the individual and organizational levels, such as more work autonomy, increased job satisfaction, improved productivity, better work-life balance, improved agility, and in some contexts, financial advantages. On the other hand, the adoption of WFH still involves many challenges and contradictions related to teamwork and collaboration, infrastructure and technology, blurred work-life balance, security, and costs, with these issues affecting organizations, jobs, and individuals (Boell et al., 2013; Pinsonneault & Boisvert, 2001). The significant heterogeneity in the efficacy of WFH as a flexible work arrangement found in this line of research is a key indicator that the feasibility of WFH may vary by occupation.

Inspired by these findings, recent studies have begun to assess WFH as an occupational characteristic and have explored both its potential link with economic performance and its role in the labor market. Country-level WFH measures have received increasing attention during the pandemic with the widespread adoption of “social distancing” and “home segregation” measures to curb the spread of COVID-19. More than ever, employees are encouraged to stay at home and work remotely. The pandemic makes WFH the most preferable and (in some cases) the only viable option, instead of an alternative work arrangement on ordinary days. Research on WFH and COVID-19 is in its early stages and its primary focus is to develop valid measures at the aggregate level (Dingel & Neiman, 2020; Garrote Sanchez et al., 2021; Saltiel, 2020). Evidence shows that WFH is closely related to income and affects the labor market’s vulnerability to widespread shutdowns, mobility restrictions, and social distancing measures. Dingel and Neiman (2020) developed a WFH index in which all occupations were matched with employment data. They found that more than one-third of the jobs in the United States can be performed from home. Following Dingel and Neiman (2020), Saltiel (2020) examined the proportion of WFH jobs in developing countries and associated worker characteristics. He found that the likelihood of WFH is positively correlated with high-paying occupations across countries and that various groups of workers whose jobs are not likely to be done from home are more vulnerable to the negative impact of the pandemic on the labor market. In another study, based on new estimates of the proportion of WFH jobs at the country level by considering the availability of Internet access, Garrote Sanchez et al. (2021) showed that the burden of COVID-19 on the labor market is greater for countries with a smaller proportion of WFH jobs and weaker social protection systems. They also showed that employees who are less likely to be successful at WFH are more vulnerable to pandemic-related labor market shocks. Therefore, whether and the extent
to which jobs can be performed from home in a country is a key determinant of the vulnerability of its labor market to widespread shutdowns, mobility restrictions, and social distancing policies.

All of these efforts are aimed at developing country-specific WFH measures and investigating the differential impact of COVID-19 on the labor market. However, our view is that the importance of WFH is far beyond the scope of the current research. Although the dramatic advance in information and communication technologies, the greater availability of high-speed Internet, and the development of ready-made solutions for remote collaboration and communication make WFH a more feasible option for many jobs than in the past, firms did not widely adopt it before the pandemic (Kossek & Lautsch, 2018). One important reason for this might be that there are costs associated with implementing WFH, and there remain many challenges associated with WFH related to maintaining or improving employee engagement and productivity, such as work-home interference, ineffective communication, procrastination, and loneliness (Wang et al., 2021). However, the unprecedented COVID-19 pandemic has wholly reversed firms’ reticence to adopt WFH, instantly increasing the value of their ability to support a higher proportion of WFH employees. As a result, WFH is now an effective measure that is frequently mentioned by practitioners and researchers in discussion of how to create a resilient supply chain (Sharma et al., 2020). Given that the research on supply chain resilience has not explicitly incorporated the ability to WFH into any framework or identified it as a strategy to obtain resilience capacity, we are eager to explore its role in facilitating supply chain resilience and its efficacy in helping firms cope with pandemic-related disruptions.

3 | RESEARCH HYPOTHESES

3.1 | The COVID-19 pandemic and supply chain disruptions

The COVID-19 pandemic represents a mega-disruption with an epic global impact that “was previously inconceivable” (Flynn et al., 2021, p. 3). Unlike previous supply chain disruption events, COVID-19 has had extreme impacts across industries, led to complex interactions among multiple stakeholders, and caused ripple effects on global supply chains (Craighead et al., 2020). Because of the unpredictability of the outbreak and its consequences on global supply chains (Kilpatrick & Barter, 2020), researchers have tended to regard the supply chain disruption caused by the COVID-19 pandemic as deep destruction with unknown-unknown uncertainty (Ivanov, 2021). As noted above, when a disruption has unknown-unknown uncertainty, we cannot predict either its appearance or its consequence (Ivanov, 2021; Klibi et al., 2010). However, as the pandemic’s impact on supply chains has unfolded and we have accumulated relevant observations in practice and the literature, we have learned some of what was once entirely “unknown.” Now we can identify at least one of its most salient disruptions on the supply chain: the unpredictable but frequent, large-scale, and continuous interruption of employees’ normal movements, which are critical to sustaining supply-chain operations. This disruption differs from a typical disruption characterized by an interruption of the normal flow of goods and materials in a supply chain network, bringing new challenges to supply chain management.

During the COVID-19 pandemic, anti-contagion policies have been implemented to prevent or contain the spread of the virus, including city lockdowns, border closures, and home quarantines. These policies hinder and even suspend movement and commuting, disrupting the operations of many firms and their supply chains. For instance, most of the world’s largest 1000 supply chain facilities are in quarantine areas (Linton & Vakil, 2020); the International Air Transport Association (2020) reported that both international and domestic passenger traffic in 2020 fell drastically compared to the corresponding period of 2019.

For these reasons, we believe that one of the most salient disruptions of supply chains caused by the COVID-19 pandemic is its interruption of worker flow caused by anti-contagion measures. This argument coincides with the findings of recent studies. For instance, in their exploration of the supply chain challenges associated with COVID-19, Sodhi and Tang (2021) argued that although the availability of labor, as part of a firm’s capacity, is usually assumed to be constant in the context of regular supply chain disruptions, the COVID-19 pandemic overturned this assumption and caused unplanned labor unavailability.

The labor disruption caused by anti-contagion policies also affects other aspects of the supply chain. With respect to production and logistics, both anti-contagion measures and the resulting shortage of workers in positions with a relatively high risk of infection exposure (e.g., truck driver, stevedores, and production line workers) sharply decreases the efficiency of production and logistics on a global scale, causing most firms to experience substantial uncertainties related to supply. Logistics service providers bear the brunt of the COVID-19 pandemic because of the dramatic delay, decline, and halting of production and flows worldwide (Choi, 2020; Ivanov & Dolgui, 2020; Paul & Chowdhury, 2020).
On the demand side of supply chains, an unprecedented shift in demand has been observed across existing channels for various products. This shift has triggered volatile and unpredictable demand. For instance, China’s nationwide efforts to contain the COVID-19 pandemic have shaped consumer habits and patterns of consumption, leading to a preference for online channels and increased demand for no-contact options (Nyrop et al., 2020). Consequently, supply chains optimized for demand from different channels prior to the pandemic have become less efficient and effective (Sodhi & Tang, 2021).

For these reasons, we anticipate adverse effects on the operations and transactions of firms in supply chains exposed to pandemic-related anti-contagion policies. If a firm cannot maintain normal operations, its suppliers or customers will be affected. Similarly, shocks to suppliers or customers will also affect the focal firm. Severe interruptions of workers’ normal movements challenge and adversely affect various aspects of firm operations, such as profitability and supplier and customer management, through their disruption of labor availability, supply chain permanence, and demand stability. Although the global crisis caused by COVID-19 is not yet over, and empirical research assessing its disruptions to supply chain operations remains scarce, recent surveys have provided preliminary evidence of the pandemic’s adverse effects. For instance, 94% of Fortune 1000 firms report supply chain disruptions caused by the COVID-19 pandemic (Sherman, 2020). In addition, ~75% of firms have experienced capacity disruptions in their supply chains, and 16% of them have adjusted their revenue targets downward (Zeiger, 2020). Thus, we propose the following hypotheses.

**H1a.** The COVID-19 pandemic disrupts firms’ operations; specifically, the COVID-19 pandemic increases the volatility of firms’ operating revenue and extends the period of negative growth.

**H1b.** The COVID-19 pandemic disrupts firms’ transactions with their supply chain partners; specifically, the COVID-19 pandemic increases the instability of the ranking of firms’ supply chain partners.

### 3.2 The role of WFH in facilitating firm resilience

Because the super-disruptions caused by the COVID-19 pandemic challenge and expose the vulnerabilities of the entire value chain, there has been increasing discussion among practitioners and researchers about how to create a resilient supply chain that frequently mentions WFH as an effective measure (Sharma et al., 2020). Although most models and frameworks that have been proposed in the literature of supply chain resilience cannot directly capture such disruptions, leading to a lack of understanding of how to cope with them, the WFH literature has provided some clues about the potential role of WFH in facilitating supply chain resilience.

As previously noted, a resilient supply chain seeks to maintain desired performance despite disruptions. From this perspective, supply chain resilience itself can be disassembled into two rudimentary capacities: resistance capacity and recovery capacity (Cardoso & Ramos, 2016; Ivanov, 2021; Melnyk et al., 2014). Resistance capacity is closely associated with proactive strategies or preparedness measures during the pre-disruption phase, whereas recovery capacity depends more on reactive strategies or actions to stabilize and adapt during the post-disruption phase (Ivanov, 2021). We speculate that in the face of labor disruptions caused by anti-contagion policies, a firm’s ability to use WFH may play an essential role in enhancing both capacities, thus facilitating firm resilience.

First, WFH capacity developed during the pre-disruption phase of the COVID-19 pandemic may serve as a proactive measure that helps sustain the firm’s essential activities and absorb disruption impacts without performance degradation. For firms to allow WFH, they must take additional measures and devote additional efforts and resources to cope with the challenges of WFH, including training staff for remote working, establishing routines and policies for engagement, providing plentiful communication technology options, and structuring methods of remote social interaction (Larson et al., 2020). Although such measures and investments confer an ability on the firm that other firms may not have, there have been few studies of WFH as a firm capacity, as its efficacy and advantage over conventional working arrangements is still largely in doubt (Boell et al., 2013; Pinsonneault & Boisvert, 2001).

The COVID-19 pandemic has completely changed the old view of WFH. Anti-contagion policies make WFH the optimal or even the only feasible option for working in most affected areas. Under these circumstances, WFH capacity developed prior to the disruptions has been a critical factor in firms’ response to the pandemic. A ready-to-use ability to WFH, serving as a redundant working arrangement, can enable a firm to absorb pandemic-related disruptions with few operational changes through the immediate provision of a feasible way of working. In other words, WFH capacity enables
the firm’s employees to quickly switch to a WFH arrangement, which not only effectively reduce employees’ risk of infection by avoiding physical contacts while commuting and working but also make the firm’s operation to some extent less vulnerable to labor disruption caused by anti-contagion policies.

Recent studies on the efficacy of WFH during the pandemic have provided initial evidence for this speculation. For firms that previously adopted WFH, employee productivity has not been substantially affected by pandemic quarantines (Donnelly & Johns, 2021). In contrast, in developing countries with fewer WFH jobs, the COVID-19 pandemic has had more severe consequences (Garrote Sanchez et al., 2021; Saltiel, 2020). These findings, from the firm level to the country level, consistently imply that the more jobs that can be done from home, the less disruption the pandemic causes to a firm’s operations.

Moreover, this effect is expected to propagate through a supply chain. If a firm has WFH capacity, its suppliers or customers can benefit from its uninterrupted operation and likelihood of being less vulnerable to pandemic-related disruptions. In contrast, without the ready ability to implement WFH, employees cannot work at all if pandemic restrictions require them to stay away from the workplace. Therefore, until pandemic measures are lifted or the firm identifies a feasible way to put its employees back to work, operations, and production are severely disrupted and even interrupted entirely. We therefore make the following hypothesis.

**H2a.** The WFH capacity enhances a firm’s resistance capacity by mitigating pandemic-related disruptions; specifically, with a better WFH capacity, the COVID-19 pandemic causes fewer disruptions to the volatility of a firm’s operating revenue and the stability of its supply chain.

Moreover, the WFH capacity may serve as a solid basis for reactive capabilities during the post-disruption phase (e.g., adaptive capacity and restorative capacity) (Biringer et al., 2013) that help a supply chain stabilize its essential operations, adapt to and recover from the disruption. The wide range, long duration, and repeated deterioration of the COVID-19 pandemic impact both the upstream and the downstream of almost every industry on a large scale and shapes the supply and demand for many products and services. Therefore, in addition to leveraging proactive measures to sustain operations and reduce performance degradation, firms must also develop and utilize reactive capabilities to adapt to these unprecedented challenges and respond to collapsing or surging demand. In this regard, the ability to WFH, whether established passively or actively, may play a subtle role. WFH capacity transcends not only restrictions on personnel mobility but also the constraints of time and space on operations and resources, so it enables firms to quickly adapt with enhanced flexibility, scalability, and visibility. Indeed, WFH is found to increase flexibility in employment and working arrangements (Donnelly & Johns, 2021). This flexibility is closely linked with adaptation (Tang & Tomlin, 2008) and is highly valued by firms seeking to achieve resilience during the COVID-19 pandemic (Dubey et al., 2021). Furthermore, WFH may also lead to better scalability, allowing the firm to cope with volatile demand by more flexibly adjusting employees working hours and timelier recruiting employees on demand.

The ability to WFH is supported by the availability of digital remote working. Advanced digital technologies and infrastructure make it easier for firms to monitor and analyze their operations remotely and provide employees with a better predictive ability to match demand and supply in the highly uncertain environment of the pandemic (Almeida et al., 2020). These technologies also enhance supply-chain visibility (Brandon-Jones et al., 2014), which may serve as another effective capability to manage the impact of the COVID-19 pandemic. In addition, flexible IT infrastructure can help operational coordination in supply-chain integration, resulting in higher operational performance (Liu et al., 2016).

Finally, WFH’s better protection of employees’ health enables a firm adopting WFH to retain a workforce that can restore its operations and production quickly and efficiently after temporary inoperability, that is, the restorative capacity introduced by Biringer et al. (2013). In other words, WFH firms are more likely to return to normal by simply recalling their employees to the workplace after anti-contagion measures are lifted. By synthesizing the arguments above, we propose the following hypothesis.

**H2b.** A firm’s WFH capacity enhances its recovery capacity by accelerating recovery from pandemic-related disruptions; specifically, when a firm has better WFH capacity, the duration of its negative growth decreases.

### 4 | DATA

#### 4.1 | The COVID-19 pandemic

The COVID-19 pandemic first emerged in Wuhan and gradually spread to other Chinese cities. To capture
shocks induced by COVID-19, we collected two sets of data: COVID-19 epidemiological data and data on anti-contagion policies across Chinese cities.

The primary source of our epidemiological data is DXY, a leading online platform for Chinese medical professionals that collects data from Chinese cities in real-time. It is also the primary data source for the interactive dashboard operated by Johns Hopkins University (Dong et al., 2020) and has been used widely in previous studies (Fang et al., 2020; Hsiang et al., 2020). We downloaded the DXY data from an open-source GitHub project (Lin, 2020). Because DXY only started reporting data after the Wuhan lockdown began on January 23, 2020, we used the Harvard Dataverse for earlier dates. Using these sources, we obtained a panel of COVID-19 data covering 365 Chinese cities from January 15, 2020, to December 31, 2020. Figure 1a plots the evolution and key events of the pandemic in China. The pandemic emerged in mid-January and peaked in early February 2020, gradually receding as the epicenter moved to the rest of the world.

We also collected anti-contagion policies implemented by city governments. These policies slowed the spread of the virus (Hsiang et al., 2020; Maier & Brockmann, 2020), but also led to significant economic disruptions (Chetty et al., 2020; Fang et al., 2020). Following Hsiang et al. (2020), we collected a sample of Chinese cities that imposed local travel bans and stay-at-home policies during 2020. Overall, 142 cities implemented stay-at-home policies for workers, and 37 cities halted all local transportation (Figure 1b).

4.2 Firms and supply-chain partners

We constructed the supply chains of Chinese listed firms using data from the CNRDS from 2015 to 2020. Firms in the CNRDS report their top five suppliers and top five customers. The data set also reports purchases from each supplier and sales to each customer. Based on that information, we constructed the supply chains of listed firms. To obtain information on firms’ production and financial status, we retrieved the listed firms’ financial statements from CSMAR for Q1 2015 to Q3 2021. These data allowed us to measure firms’ performance (e.g., operating revenue), along with characteristics such as total employment, leverage ratio, and price-to-book ratio.

4.3 Online job postings and WFH

In addition to financial statements, we measured firms’ WFH capacities by examining their online job postings. The advantage of these data is that they allowed us to capture granular labor demand with a high frequency almost in real-time. An increasing number of studies have used such data to study various labor market issues (Acemoglu et al., 2020; Campello et al., 2020; Deming & Kahn, 2018). We collected job postings data from one of China’s leading online platforms providing hiring services (51job.com) by running a web-scraping algorithm. We obtained pre-pandemic job advertisements posted on the platform from January 1, 2017, to January 24, 2020. We collected the essential job characteristics listed in each advertisement, including the occupation, job location, education and experience requirements, number of vacancies, and date when the advertisement was created.

We also obtained information about the firms that posted these advertisements, including their industry classification and most importantly, their names, which allowed us to match them with CNRDS.

Lockdown and social distancing measures forced many people to WFH, but occupations have varying levels of ability to offer WFH. Dingel and Neiman (2020) classified the feasibility of WFH for all US occupations using survey data from the Occupational Information Network (O*NET). Based on survey questions about work context and activities, occupations were classified as can or cannot be performed at home. For example, if the average respondent in an occupation says they use email less than once per month, the occupation was classified as one in which it is not feasible to WFH. To measure the WFH capacity of Chinese occupations, we first mapped the O*NET occupations to the occupations in our online job posting data. We then assigned the Dingel and Neiman (2020) WFH index to each of the occupations in our data. Based on the index, we measured each firm’s WFH capacity based on the jobs it posted before the pandemic in two ways: the share of the total number of posted ads that were WFH job ads; and the share of posted vacancies that were WFH vacancies. Both measures have benefits and drawbacks. The second measure considers the number of vacancies available in each job ad. However, not all posted job ads indicated the number of vacancies.

Figure 2 plots the average share of WFH jobs for firms within each industry. The measures vary significantly across industries but are highly correlated. Firms in service industries such as education and finance tend to hire more WFH workers. In contrast, firms in the utilities, mining, and manufacturing industries tend to hire fewer WFH workers. Koren and Petó (2020) calculated the share of workers who indicate they can WFH for each occupation using data from the American Time Use Survey. As a robustness check, we use this share to construct an alternative measure of firms’ WFH capacity. As shown in Figure A2 in Appendix A, it is highly correlated with
(a) Development of the COVID-19 pandemic in China

(b) COVID-19 anti-contagion policies across cities

FIGURE 1 The COVID-19 pandemic and anti-contagion policies in China. (a) Development of the COVID-19 pandemic in China, (b) COVID-19 anti-contagion policies across cities
the measure based on Dingel and Neiman (2020), implying that the measures are consistent.

4.4 Summary statistics

Table 1 defines the variables used in our empirical analysis and presents their summary statistics. We assembled three data sets to test our hypotheses. Panel (a) consists of data of listed firms matched with the job posting data from 2015 to 2020. The main variable is VolRev, the annual output volatility of firms measured by the standardized standard deviation of quarterly operating revenue. We also constructed three measures capturing the COVID-19 shocks faced by each firm. The first measure, COVID policy, is the weighted average of COVID policy shocks on the listed firm and its suppliers and customers. The weights are the shares of procurements from the suppliers or the purchases by the customers. A firm is exposed to the COVID-19 policy shock if it was subject to city-level travel bans or stay-at-home policies in 2020 (Figure 1b). For firm \( n \) in city \( i \), we constructed a firm-specific exposure to COVID shocks via supply chains:

\[
\text{Covid policy}_n^i = \left( \text{COVID policy}_i + \sum_j \theta_{jn} \text{COVID policy}_j + \sum_k \mu_{nk} \text{COVID policy}_k \right) / 3,
\]

where \( \theta_{jn} \) is the expenditure share of inputs from suppliers in city \( j \), and \( \mu_{nk} \) is the share of sales to customers in city \( k \). By replacing the policy in each city by the number of cumulative local COVID-19 cases, we arrived at the second measure, COVID cases. In addition, listed firms can have subsidiaries in different cities from their headquarters. Therefore, we constructed a third measure, COVID sub, which adds shocks on subsidiaries in the baseline COVID policy, where the subsidiaries’ shocks are weighted by their working capital. In addition to the measures of WFH capacities, we included listed firms’ total number of employees, working capital, price-to-book ratio, return on assets, and leverage ratio in the year 2019 as control variables.

Panel (b) consists of a panel of supplier-customer data at an annual frequency. The key variable of interest is DeltaRank, a dummy variable which equals one if the rank of the supplier/customer among the listed firms’ suppliers/customers fell and 0 otherwise. The idea was that in the face of a negative shock to the supplier-customer relationship, the top five customers and suppliers are more likely to maintain their current rank if the supply chain is more resilient. Otherwise, their rank falls. Therefore, this variable measures the instability of the supply chains. Similar to Panel (a), there are three measures of COVID-19 shocks on the supply chains. COVID policy is a dummy variable that equals one if the city where either the customer or the supplier located had stay-at-home policies or travel bans in 2020, and 0 otherwise. COVID sub further includes policy shock on the firms’ subsidiaries. Finally, COVID cases is a weighted sum of cumulative COVID-19 cases in local cities of the listed firm and its suppliers or customers.

Panel (c) consists of a two-period panel of listed firms: pre-pandemic and post-2020. The key variable is
Duration of Negative Growth (DNG), the number of quarters with negative quarter-on-quarter revenue growth rates for each firm. We first measured each firm’s average duration of negative growth episodes before COVID-19. The shorter the previous average duration, the sooner a firm can get out of a negative shock. We also measured the firms’ negative growth duration from the time COVID-19 started to Q3 2021. The shorter the previous duration, the faster the firm can recover from COVID-19. The other variables are the same as in Panel (a).

5 | EMPIRICAL STRATEGY AND RESULTS

Our empirical strategy is to adopt the DID approach with differing treatment intensity (Angrist & Pischke, 2008). The idea is to contrast firms with different shares of WFH workers in their performance before and after the COVID-19 shocks, controlling for observable firm-level characteristics, and unobserved time-invariant fixed effects common across cities, industries, and firms, along with time fixed effects. This approach is summarized by the following regression model:

\[
y_{nt} = \alpha \text{Shock}_{mnt} + \beta WFH_{n} + \gamma WFH_{n} \cdot \text{Shock}_{mnt} + \sum_{k} \delta_{k} X_{nk} + C_{n} + I_{n} + T_{t} + F_{n} + \epsilon_{mnt},
\]

where \( y_{nt} \) is the outcome variable of a firm \( n \) at time \( t \), \( \text{Shock}_{mnt} \) is a variable that captures COVID-19 shocks on the listed firm and its customers/suppliers, and \( WFH_{n} \) measures firm \( n \)’s share of WFH workers. We control for firm-level observables \( X_{nk} \), and city \( C_{n} \), industry \( I_{n} \), time \( T_{t} \), and firm \( F_{n} \) fixed effects. \( \epsilon_{mnt} \) is the error term. In the model, \( \gamma \) is the main coefficient of interest that captures how firms with different shares of WFH workers respond to COVID-19 shocks. Given Hypothesis 1a, we expect the estimated \( \alpha \) to be positive when the outcome variable is \( \text{VolRev} \), that is, the COVID-19 pandemic negatively disrupts a firm’s operation by increasing the volatility of its operating revenue. Given Hypothesis 2a, we expect the estimated \( \gamma \) to be negative when the outcome variable is \( \text{VolRev} \), that is, firms with a higher share of WFH workers are less volatile during the COVID-19 pandemic. Given Hypothesis 2b, we expect the estimated \( \gamma \) to be negative when the outcome variable is \( \text{DNG} \), that is, firms with a higher share of WFH workers recover more quickly during the COVID-19 pandemic.

To examine how the supply chains respond to COVID-19 shocks and whether or not WFH affects the stability of firms’ supply chains, we estimate the following model:

\[
\text{DeltaRank}_{mnt} = \alpha \text{Shock}_{mnt} + \beta WFH_{n} + \gamma WFH_{n} \cdot \text{Shock}_{mnt} + \sum_{k} \delta_{k} X_{nk} + \sum_{k} \theta_{k} Z_{nk} + C_{m} + C_{n} + I_{m} + I_{n} + T_{t} + F_{m} + F_{n} + \epsilon_{mnt},
\]

where \( \text{DeltaRank}_{mnt} \) captures changes in firms’ supply chains, a dummy that equals one if the rank of firm \( m \) decreases among firm \( n \)’s suppliers/customers, and \( \text{Shock}_{mnt} \) is a variable that captures the COVID-19 shock on firm \( m \) and \( n \). \( X_{nk} \) and \( Z_{nk} \) are the observables of firm \( m \) and \( n \), respectively. \( C_{m} \) and \( C_{n} \), \( I_{m} \) and \( I_{n} \), \( T_{t} \), and \( F_{m} \) and \( F_{n} \) are city, industry time, and firm fixed effects, respectively. \( \epsilon_{mnt} \) is an error term. Given Hypothesis 1b, we expect \( \alpha \) to be positive, that is, the COVID-19 shock raised the probability that the top suppliers/customers had a lower ranking. Given Hypothesis 2a, we expect \( \gamma \) to be negative, that is, the suppliers or customers of firms with a higher share of WFH workers are more likely to maintain their rank during the COVID-19 pandemic.

5.1 | Baseline results

Table 2 presents the results of running regression Model (1) using data from Panel (a) of Table 1, with \( \text{VolRev} \) as the outcome variable. Our baseline measure of COVID-19 shock is \( \text{COVID policy} \), and firms’ WFH capacity is \( WFH \) ads share. According to column (1), the coefficient of \( \text{COVID policy} \) is positive and significant. Therefore, exposure to COVID-19 shocks, either directly or indirectly through suppliers/customers, increases firms’ operating revenue volatility, conditional on observable firm characteristics such as firm size and working capital, industry, city, and year fixed effects. Column (2) adds the control variables listed in Table 1. The coefficient remains positive and significant. Therefore, Hypothesis 1a is supported. Column (3) presents the results of a DID specification. The coefficient of the interaction term between WFH and the COVID shock is negative and significant. This implies that exposure to COVID-19 policy shocks has a smaller effect on firms with a higher share of WFH workers. Column (4) further includes the firm fixed effect. The results remain robust. Overall, these results are consistent with Hypothesis 2a, that is, WFH increases firms’ resistance capacity to COVID shocks.

Table 3 presents the results of running regression Model (1) using data from Panel (b) of Table 1, with \( \text{DNG} \) as the outcome variable. According to column (1), a
### Variable definitions and summary statistics

#### Panel (a). Firm-year level data

| Variables       | N   | Mean | SD  | Definition                                                                 |
|-----------------|-----|------|-----|-----------------------------------------------------------------------------|
| VolRev          | 2442| 0.86 | 0.51| Output volatility measured by the standardized standard deviation of quarterly operating revenues. |
| COVID policy    | 2442| 0.05 | 0.12| Weighted average of COVID policy shocks on the firm and its suppliers and customers. |
| COVID sub       | 2442| 0.07 | 0.17| Weighted average of COVID policy shocks on the firm, its suppliers and customers, and its subsidiaries. |
| COVID cases     | 2442| 0.93 | 2.14| Natural logarithm of the weighted sum of cumulative COVID cases in a firm’s city and its suppliers and customers. |
| WFH ads share   | 2442| 0.70 | 0.19| Firms’ pre-pandemic WFH job ads over total recruitment ads, with WFH measured by Dingel and Neiman (2020). |
| WFH time-use    | 2442| 0.52 | 0.11| Firms’ pre-pandemic WFH job ads over total recruitment ads, with time-use data from Koren and Pető (2020). |
| WFH vacancy share | 2424| 0.67 | 0.24| Firms’ pre-pandemic WFH vacancies over total vacancies, with WFH measured by Dingel and Neiman (2020). |
| ln (employees)  | 2442| 7.61 | 1.32| Natural logarithm of total employees of firms in 2019.                       |
| Working capital | 2442| 0.88 | 5.61| Working capital over operating revenue in 2019.                              |
| PB              | 2442| 3.61 | 7.57| Price-to-book ratio in 2019.                                                |
| ROA             | 2442| 3.54 | 22.38| Return on assets in 2019.                                                    |
| Leverage ratio  | 2442| 0.43 | 0.23| Long-term liabilities plus current liabilities over total assets in 2019.     |

#### Panel (b). Buyer-customer-supplier-year level data

| Variables       | N   | Mean | SD  | Definition                                                                 |
|-----------------|-----|------|-----|-----------------------------------------------------------------------------|
| DeltaRank       | 26,805| 0.20 | 0.40| Dummy variable equals 1 if the rank of the supplier/customer fell, and 0 otherwise. |
| COVID policy    | 26,805| 0.19 | 0.39| Dummy variable equals 1 if the city where either customer or supplier is located had a stay-at-home order or a travel ban in 2020, and 0 otherwise. |
| COVID sub       | 27,105| 0.20 | 0.39| Weighted average of COVID policy shocks on the listed firm, its suppliers and customers, and its subsidiaries |
| COVID cases     | 26,805| 1.27 | 2.62| Natural logarithm of weighted sum of cumulative COVID cases in the focal firm’s city or the cities of its suppliers or customers. |
| WFH ads share   | 26,805| 0.71 | 0.19| Listed firm’s WFH ads over total recruitment ads before the pandemic.       |
| WFH time-use    | 27,105| 0.52 | 0.11| Firm’s pre-pandemic WFH job ads over total recruitment ads, with WFH measured by Koren and Pető (2020). |
| WFH vacancy share | 26,660| 0.68 | 0.24| Listed firm’s WFH vacancies over total posted vacancies before the pandemic. |
| ln (employees)  | 26,805| 7.51 | 1.27| Natural logarithm of total employees of firms in 2019.                       |
| Working capital | 26,805| 0.70 | 4.22| Working capital over operating revenue in 2019.                              |
| PB              | 26,805| 3.19 | 6.21| Price-to-book ratio in 2019.                                                |
| ROA             | 26,805| 2.79 | 14.78| Return on assets in 2019.                                                    |
| Leverage ratio  | 26,805| 0.43 | 0.24| Long-term liabilities plus current liabilities over total assets in 2019.     |

(Continues)
### Table 1 (Continued)

| Variables | N  | Mean | SD | Definition |
|-----------|----|------|----|------------|
| **Panel (c). Firm pre-pandemic and post-2020 data** | | | | |
| DNG       | 820 | 2.78 | 2.15 | Number of quarters with negative quarter-on-quarter revenue growth rates. |
| COVID policy | 820 | 0.14 | 0.17 | Weighted average of COVID policy shocks on the firm and its suppliers and customers. |
| COVID sub | 820 | 0.21 | 0.23 | Weighted average of COVID policy shocks on the firm, its suppliers and customers, and its subsidiaries. |
| COVID cases | 820 | 2.65 | 2.91 | Natural logarithm of the weighted sum of cumulative COVID cases in local cities of the focal firm and its suppliers and customers. |
| WFH ads share | 820 | 0.70 | 0.20 | Firms’ pre-pandemic WFH ads over total recruitment ads before the pandemic, with WFH measured by Dingel and Neiman (2020). |
| WFH time-use | 820 | 0.52 | 0.11 | Firm’s pre-pandemic WFH job ads over total recruitment ads, with WFH measured by Koren and Pető (2020). |
| WFH vacancy share | 814 | 0.67 | 0.24 | Firm’s pre-pandemic WFH vacancies over total posted vacancies, with WFH measured by Dingel and Neiman (2020). |
| ln (Employees) | 820 | 7.57 | 1.30 | Natural log of total employees of firms in 2019. |
| Working capital | 820 | 0.88 | 5.59 | Working capital over operating revenue in 2019. |
| PB | 820 | 3.60 | 7.59 | Price-to-book ratio in 2019. |
| ROA | 820 | 3.48 | 22.37 | Return on assets in 2019. |
| Leverage ratio | 820 | 0.43 | 0.23 | Long-term liabilities plus current liabilities over total assets in 2019. |

### Table 2 COVID shocks, work from home, and resistance capacity

| Dependent variable | (1) Volatility of operating revenue (VolRev) | (2)  | (3)  | (4)  |
|--------------------|---------------------------------------------|------|------|------|
| COVID policy       | 0.847*** (0.238)                            | 0.850*** (0.237) | 1.576*** (0.464) | 1.637*** (0.516) |
| WFH ads share      | 0.140* (0.078)                              |      |      |      |
| COVID policy · WFH ads share | −1.031* (0.551) | −1.104* (0.610) |      |      |
| Observations       | 2442                                        | 2442 | 2442 | 2442 |
| R-squared          | 0.132                                       | 0.134 | 0.136 | 0.165 |
| Year FE and industry FE and city FE | Yes | Yes | Yes | Yes |
| Controls           | No                                          | Yes | Yes | Yes |
| Firm FE            | No                                          | No  | No  | Yes |

**Note:** This table presents the results of a difference-in-differences OLS estimation of the differential impact of COVID-19 policy shock on operating revenue volatility across firms with varying degrees of WFH capacities. The variable COVID policy is a weighted average of policy shocks on the focal firm and its suppliers and customers. WFH measures the focal firms’ WFH capacity in terms of the total share of job postings for WFH jobs before 2020. The controls include ln(employees), working capital, ROA, leverage ratio, and PB ratio. Robust standard errors are in parentheses. Singletons are dropped during the regressions. The significances are indicated as ***p < .01, **p < .05, and *p < .1.
firm’s exposure to COVID-19 policy shock prolongs the duration of negative growth, consistent with Hypothesis 1a. Column (2) adds controls. The coefficient remains similar. Column (3) includes our WFH variable and its interaction with the COVID-19 policy shock. The interaction term is positive and statistically significant. Column (4) further includes firm fixed effects. The coefficient increases slightly but remains statistically significant. These results are not consistent with Hypothesis 2b, implying that WFH increases the duration of negative growth. In other words, it takes longer for firms with a higher share of WFH workers to return to their normal growth trajectory.

### Table 3: COVID shocks, work from home, and recovery capacity

| Dependent variable | (1) Duration of negative growth (DNG) | (2) | (3) | (4) |
|-------------------|--------------------------------------|-----|-----|-----|
| COVID policy      | 1.009*** (0.152)                     | 1.007*** (0.148) | -2.181*** (0.662) | -2.397*** (0.510) |
| WFH ads share     |                                      | -0.183 (0.173)   |                |                |
| COVID policy - WFH ads share | 1.971** (0.780) | 2.231*** (0.611) |                |                |

Observations: 820 820 820 816
Pseudo $R^2$: .075 .085 .098 .232
Industry FE and city FE: Yes Yes Yes Yes
Controls: No Yes Yes Yes
Time FE: No No Yes Yes
Firm FE: No No No Yes

Note: This table presents the results of a difference-in-differences PPML estimation of the differential impact of COVID-19 policy shock on the duration of negative growth before and during COVID across firms with varying degrees of WFH capacities. The variable COVID policy is a weighted sum of the policy shocks on the focal firm and its suppliers and customers. WFH measures the focal firms’ WFH capacity in terms of the total share of job postings for WFH jobs before 2020. The controls include ln(employees), working capital, ROA, leverage ratio, and PB ratio. Robust standard errors are in parentheses. Singletons are dropped during the regressions. The significances are indicated as ***$p < .01$, **$p < .05$, and *$p < .1$.

### Table 4: COVID shocks, work from home, and supply chain stability

| Dependent variable | (1) Disruption to the supply chains (DeltaRank) | (2) | (3) | (4) |
|-------------------|-----------------------------------------------|-----|-----|-----|
| COVID policy      | 0.186 (0.160)                                 | 0.188 (0.160) | 0.534*** (0.196) | 0.554*** (0.197) |
| WFH ads share     | 0.071 (0.090)                                 |                |                |                |
| COVID policy - WFH ads share | -0.493*** (0.163) | -0.488*** (0.162) |                |                |

Observations: 26,935 26,935 26,935 26,805
Pseudo $R^2$: .010 .011 .011 .015
Year FE and Industry FE and city FE: Yes Yes Yes Yes
Controls: No Yes Yes Yes
Firm FE: No No No Yes

Note: This table presents the results of a difference-in-differences PPML estimation of the differential impact of COVID-19 policy shock on supply chains across firms with varying degrees of WFH capacities. The variable COVID policy is a weighted sum of the policy shocks on the focal firm and its suppliers and customers. WFH measures the focal firms’ WFH capacity in terms of the total share of job postings for WFH jobs before 2020. The controls include ln(employees), working capital, ROA, leverage ratio, and PB ratio. Robust standard errors are in parentheses. Singletons are dropped during the regressions. The significances are indicated as ***$p < .01$, **$p < .05$, and *$p < .1$.
| Dependent variables | (1) VolRev | (2) DNG | (3) DNG | (4) DeltaRank | (5) DeltaRank | (6) DeltaRank |
|---------------------|-----------|---------|---------|---------------|---------------|---------------|
| Panel (a). An alternative measure of COVID-19 shocks (total number of cases) | | | | | | |
| COVID cases | 0.077** | 0.079** | –0.072* | –0.086** | 0.051* | 0.050* |
| (0.031) | (0.034) | (0.043) | (0.034) | (0.029) | (0.029) | |
| WFH ads share | 0.149* | | –0.163 | | | | 0.077 |
| (0.078) | | (0.177) | | | | |
| COVID cases - WFH ads share | -0.062* | -0.064* | 0.091** | 0.109*** | -0.077*** | -0.076*** |
| (0.031) | (0.034) | (0.044) | (0.036) | (0.024) | (0.024) | |
| Observations | 2442 | 2442 | 820 | 816 | 26,935 | 26,805 |
| R-squared | .132 | .161 | .096 | .229 | .011 | .015 |
| Panel (b). An alternative measure of COVID-19 shocks (including shocks on subsidiaries) | | | | | | |
| COVID sub | 1.289*** | 1.363*** | –1.617*** | –1.668*** | 0.110** | 0.124** |
| (0.394) | (0.437) | (0.519) | (0.405) | (0.046) | (0.048) | |
| WFH ads share | 0.150* | | –0.201 | | | | 0.015 |
| (0.078) | | (0.176) | | | | |
| COVID sub - WFH ads share | -0.889** | -0.945** | 1.462*** | 1.599*** | -0.084*** | -0.085*** |
| (0.405) | (0.445) | (0.565) | (0.441) | (0.030) | (0.031) | |
| Observations | 2442 | 2442 | 820 | 816 | 27,105 | 27,105 |
| R-squared | .135 | .164 | .097 | .231 | .016 | .023 |
| Panel (c). An alternative measure of WFH (weighted by number of vacancies) | | | | | | |
| COVID policy | 1.458*** | 1.476*** | –1.585*** | –1.925*** | 0.329* | 0.345* |
| (0.389) | (0.428) | (0.535) | (0.401) | (0.185) | (0.187) | |
| WFH vacancy share | 0.130* | | 0.028 | | | | 0.101 |
| (0.072) | | (0.148) | | | | |
| COVID policy - WFH vacancy share | -0.890** | -0.911* | 1.254** | 1.714*** | -0.259* | -0.257* |
| (0.443) | (0.486) | (0.598) | (0.458) | (0.138) | (0.137) | |
| Observations | 2424 | 2424 | 814 | 810 | 26,785 | 26,660 |
| R-squared | .141 | .166 | .098 | .232 | .011 | .015 |
| Panel (d). An alternative measure of WFH (weighted by occupational time-use) | | | | | | |
| COVID policy | 1.476*** | 1.489** | –2.771*** | –2.852*** | 0.951*** | 0.982*** |
| (0.562) | (0.619) | (0.833) | (0.647) | (0.213) | (0.217) | |
| WFH time-use | 0.150 | | –0.311 | | | | 0.314** |
| (0.129) | | (0.325) | | | | |
| COVID policy - WFH time-use | -1.208 | -1.219 | 3.842*** | 3.93*** | -1.493*** | -1.505*** |
| (0.965) | (1.061) | (1.467) | (1.134) | (0.277) | (0.285) | |
| Observations | 2442 | 2442 | 820 | 816 | 26,935 | 26,805 |
| R-squared | 0.135 | 0.164 | 0.099 | 0.232 | 0.011 | 0.016 |
| Time FE and Industry FE and city FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | No | Yes | No | Yes | No | Yes |

Note: This table presents robustness checks on difference-in-differences estimation of the differential impact of COVID-19 on firms with varying degrees of WFH capacities. Panel (a) uses a measure of COVID shock, COVID cases, which is the natural logarithm of the weighted sum of cumulative COVID cases in local cities of the focal firm and its suppliers and customers. Panel (b) further includes COVID shock on firms’ subsidiaries as compared to the baseline measure. Panel (c) uses the share of listed firms’ total posted WFH vacancies before 2020 as the WFH measure. Panel (d) uses the share of WFH jobs weighted by time-use. Columns (1) and (2) examine firms’ resistance capacity as measured by the standardized standard deviation of operating revenue (VolRev). Columns (3) and (4) examine firms’ recovery as measured by the duration of negative growth (DNG). Columns (5) and (6) examine the stability of the supply chains as measured by a dummy that equals one if the rank of the listed firms’ customers/suppliers decreases (DeltaRank). The controls include ln(employees), working capital, ROA, leverage ratio, and PB ratio. Robust standard errors are in parentheses. Singletons are dropped during the regressions. The significances are indicated as ***p < .01, **p < .05, and *p < .1.
Table 4 presents the results of running regression Model (2) using data from Panel (c) of Table 1, with DeltaRank as the outcome variable. According to columns (1) and (2), the COVID shock increases the probability of the suppliers/customers' rank falling during the pandemic. However, this coefficient is small and statistically insignificant. The insignificance of this average effect could be attributable to the heterogeneous treatment effects across firms. Therefore, column (3) examines the impact of the COVID shock across buyer–supplier relationships with different degrees of WFH by the focal listed firms. The coefficient of COVID Policy is positive and significant, supporting Hypothesis 1b. However, the interaction term is negative and statistically quite significant. This implies that if the focal firm has a higher share of WFH workers, the COVID-19 shock causes smaller disruptions to its supply chains by reducing the probability of its customer/supplier's rank falling. Column (4) also includes firm fixed effects. The coefficient becomes larger and remains significant. Therefore, with a higher share of WFH workers, the focal firm is more resilient in terms of its supply chains, consistent with H2a.

Together, the results from Tables 2, 3, and 4 suggest that firms face a tradeoff during the pandemic. On the one hand, WFH helps to increase firm resistance capacity and mitigates disruptions to supply chains. On the other hand, WFH prolongs the duration of the shock and extends the time taken for firms to return to normal.

5.2 Robustness checks

We conduct a battery of robustness analyses of the baseline results. First, instead of measuring firms' exposure to the COVID-19 shocks using data on local governments' anti-contagion policies, we measure the shocks using a weighted average of cumulative cases in the city of the listed firm and cities of its customers and suppliers. The results are presented in Panel (a) of Table 5. Second, the listed firms can have subsidiaries in cities different from the firm headquarters. It is also likely that shocks on the subsidiaries can spread within the firm. To deal with this possibility, Panel (b) includes policy shocks on the subsidiaries in addition to the baseline measure of COVID shock. Third, we measure firms' WFH capacity based on the share of WFH job ads before the pandemic in the baseline estimation. We now consider the number of vacancies mentioned in the job ads and measure WFH capacity by the share of WFH vacancies in total posted vacancies. The results are presented in Panel (c). Finally, Koren and Pető (2020) provided the share of workers who indicate they can WFH for each occupation, which allows us to construct an alternative measure of firms' WFH capacities. Panel (d) presents the estimation using this alternative WFH measure. Overall, the results are very similar to the baselines in Tables 2–4. Accordingly, we continue to find that WFH increases the resistance capacity of firms and the stability of their supply chains but slows their recovery. So far, we have used a continuous measure of the COVID shock. In Appendix B, we instead use a binary variable which equal one if the firm was hit by the COVID shock. The results in Table A1 are similar to the baseline results.

In addition, our DID strategy relies on the assumption that treated firms and non-treated firms are on parallel trends before the pandemic. Otherwise, the estimated results are biased. To examine whether the firms are on parallel trends, we group the firms into treated and non-treated groups. A firm is defined as treated if it or its customers or suppliers are from a city with travel bans or stay-at-home orders in 2020. Next, we run a DID estimation with time-varying coefficients. Figure 3 plots the estimated coefficients and their associated 95% confidence intervals. There is no significant difference between the treated and non-treated firms before the pandemic but a significant difference after the start of the pandemic in 2020.

6 Effect heterogeneity

So far, we have estimated the average effect of the COVID-19 pandemic and WFH across firms. However, the pandemic has had a significant differential effect across sectors and firms (Carletti et al., 2020). Moreover, as Section 4.3 indicates, the ability to WFH varies significantly across workers, occupations, and industries. Therefore, we expect to see heterogeneous effects of WFH across different groups of firms. Disentangling such heterogeneities help us better understand how WFH affects firms' resilience during the pandemic and provides better guidance for firms' operations.

6.1 Industries and firm size

We first examine how the effect varies across industries. We focus on manufacturing, service, and retail and conduct DID estimations of the baseline outcomes on interaction terms between the COVID-19 shock and industry dummies. Using service as the benchmark industry, we plot the estimated coefficients and their 95% confidence intervals in the upper panel of Figure 4. We find that COVID-19 increases the revenue volatility of manufacturing firms relative to service firms. However, manufacturing firms recover quicker than service firms, as the
duration of their negative growth is shorter on average than that of service firms. There are no significant differences in the stability of supply chains across industries. In addition, there is no significant difference between retailing firms and service firms in our outcomes. WFH also shows some differential effect, as the bottom panel of Figure 4 indicates. WFH reduces the revenue volatility of retailing firms more than that of service firms. WFH helps to stabilize the supply chains of manufacturing and retailing firms less than those of service firms. Finally, there is no significant difference in the effect of WFH on recovery capacity across industries.

To examine how the effect of WFH differs across firms with different sizes, we define a dummy Large for firms above the median size of employment. Next, we run a DID estimation interacting this dummy with the COVID-policy shock in the upper panel of Figure 5. The bottom panel presents triple-DID results that further interact with the WFH variable. We find that COVID-19 raises the revenue volatility of large firms by more, but large firms recover faster than small firms. There is no significant difference in the effect of COVID-19 on the stability of supply chains of large and small firms. As for WFH, overall, we find no significant difference in its impact on large versus small firms.

6.2 | Worker characteristics

To see the differential effect of WFH across different types of jobs, which can help firms create better plans to manage labor disruptions, we first refine our measure of
WFH according to the job characteristics indicated on the job ads posted by firms. For example, we observe a firm’s job postings by different departments within a firm. This allows us to measure the share of WFH workers in management, sales, administrative, finance, and engineering departments based on the ads posted by each department. Next, we extend baseline regression Model (1) to the following model,

$$y_{nt} = \alpha \text{Shock}_{nt} + \sum_{l} \beta_l \text{WFH}_{nl} + \sum_{l} \gamma_l \text{WFH}_{nl} \cdot \text{Shock}_{nt} + \sum_{k} \delta_k X_{nk} + C_n + I_n + T_t + F_n + \epsilon_{nt},$$

(3)

where we allow for the outcome to respond differentially to the share of WFH in each department ($WFH_{nl}$). The estimated $\gamma_l$ tells us which department’s WFH share matters the most during the pandemic. Similarly, we measure the share of WFH workers according to education and experience requirements. For example, we measured the share of WFH jobs requiring a college-and-above degree in total posted jobs. Next, we examine how the effect of WFH varies with the education of WFH workers.

Figure 6 plots the results of WFH based on workers’ education and job experience. There is no significant effect of education on either operating revenue volatility or recovery capacity, but there is a substantial and significant effect of job experience. For firms that hire more experienced WFH workers, their operating revenue volatility decreases more, but their recovery is also slower.

For stability of the supply chain, firms with more
educated and experienced WFH workers have more stable supply chains, although the effect is only marginally significant.

Figure 7 plots the effect of WFH across workers from different departments within the firm. There is a large differential effect across these departments. Operating revenue volatility declines by more if there are more WFH workers in the management, sales, clerical, and engineering departments. For recovery capacity, consistent with our baseline results, WFH continues to delay recovery, especially if there are more WFH workers in the management, sales, and IT departments. Finally, more WFH workers in the management, IT, and engineering departments help to stabilize the supply chains, whereas more WFH clerical workers destabilized supply chains.

**7 | DISCUSSION AND CONCLUSION**

**7.1 | Theoretical implications**

The COVID-19 pandemic is causing tremendous, unprecedented disruptions that call for more research to reveal what supply chains have learned and how to build upon those lessons to become more resilient and prepare for the next global mega-disruption (Flynn et al., 2021). Our study is one of the early attempts to investigate the impact of the pandemic-related disruptions on firm performance and strategies or remedies to enhance firm resilience. Unlike previously identified disruptions in the resilience literature, one of the most striking impacts of the COVID-19 pandemic has been profound disruptions of the labor supply and physical operations of both firms and their supply chain partners. We empirically investigate the impact of those disruptions by examining the effect of the COVID-19 pandemic on firms’ operations and transactions with their key supply chain partners. We also echo the call of Parker and Ameen (2018) for more research on different types of disruptions in the firm resilience research.

More importantly, we contribute to the resilience literature by identifying WFH as an effective capacity for firms to counteract disruptions such as those caused by the pandemic. The literature has generally suggested that WFH is a flexible work arrangement that substitutes for working on-site (Haddon & Lewis, 1994), but it is not designed as a coping strategy to deal with disruptions. However, the COVID-19 pandemic provides a good opportunity to rethink the role of WFH in firm resilience. We highlight the critical role of WFH in responding to disruptions caused by anti-contagion policies during the COVID-19 pandemic. Recently, WFH has been suggested as a new organizational design to cope with the pandemic (e.g., Foss, 2021), although it has been the subject of only limited empirical investigations (Zhang et al., 2022). For example, Trip.com Group, a NASDAQ-listed company, launched the “hybrid work model” policy that provides employees the options to work remotely since March 2022 (Trip.com Group, 2022). This type of organizational change is consistent with the “robust transformation” of organizational routines in dynamic environments (Lengnick-Hall & Beck, 2005). We attempt to examine this process using job postings data but cannot verify it as no other data are yet available. Because this type of transformation, implemented through the internal adjustment or redesign of work arrangements, may not be immediately flagged in a firm’s job ads.

Furthermore, as the pandemic lingers on, some firms
continue to struggle and have been unable to make fundamental transformations in a timely manner. We conjecture that there will be an increasing trend for many firms to transform to support more job positions to WFH in the post-pandemic stage, which calls for further investigations by future studies.

Our findings are also consistent with the panarchical thinking of social-ecological resilience (Wieland, 2021). The COVID-19 pandemic provides an account of the entanglement of the supply chain with other systems that operate at different levels. Our findings demonstrate a subtle link between anti-contagion policies at the political-economic level and firms’ adaptation through WFH strategies at the supply-chain level. Moreover, the flexible work arrangement of WFH may enable digital resilience by facilitating the application of digital technology in supply-chain operations. For example, virtual reality technology can help engineers work remotely to cooperate with their counterparts among their supply chain partners. From a social-ecological system perspective, organizational design changes at the company level can facilitate the digitalization process at the political-economic level, leading to digital transformation at the societal level (Wieland, 2021).

We also extend the resilience literature by studying the effect of WFH on resistance and recovery capacity. Interestingly, we find that WFH plays divergent roles in firm resilience under the impact of anti-contagion policies: it fosters firms’ resistance capacity but hinders their recovery capacity. As expected, WFH facilitates the resistance capacity of firm resilience. This result is consistent with the proactive role of resource redundancy in the resilience literature (Iftekhar et al., 2021). Surprisingly, WFH decreases the recovery capacity of firm resilience, which is a counterintuitive finding. Our results demonstrate the “dark side” of WFH for firm resilience, as firms may adhere to this reactive strategy, which prolongs their recovery time. Although it is easier for companies with high WFH feasibility to sustain normal operations in the face of labor disruption, these companies may have less of an incentive to adapt to this disruption, as they can temporarily use WFH to manage the problem. Because of the duration of the pandemic, the impact of labor disruption continues to affect firms and their supply chain partners. In contrast, companies with low WFH feasibility are significantly impacted by labor disruption. These companies may have to adjust their production and supply chain to adapt to this disruption (e.g., establish new businesses, search for local customers, provide new product/service solutions, and adjust production planning), which leads to unstable business performance but a rapid recovery from the labor disruption caused by anti-contagion policies. This finding indicates that slack resources may not always be beneficial to firm resilience. Overall, our findings contribute to the literature by providing a double-edged sword perspective on the role of WFH in firm resilience.

Additionally, our findings regarding the heterogeneous effect (industry type, firm size, and worker characteristics) of WFH on firm resilience enrich our knowledge of the interface between operations and human resources management (Boudreau et al., 2003). The OSCM literature has suggested that the production location decision related to operations efficiency is determined by the interdependence of production, the market, the supply chain, and product development (Ketokivi et al., 2017). Our results verify this conclusion by confirming the role of WFH and suggest potential contingency factors that release the tensions of interdependence during the COVID-19 pandemic. Industries with high level of customer co-production have been less likely to benefit from WFH as a response to disruptions during the pandemic. WFH is more suitable for companies that can separate production from customer consumption. Our results also indicate that WFH is more effective for employees in knowledge-intensive job positions (such as management, engineering, and jobs that require a high level of experience). WFH capacity in knowledge-intensive work provides companies with an opportunity to balance efficiency and resilience in their production location decisions.

7.2 | Managerial implications

WFH is a viable strategy that firms can use to build resilience to labor disruption. Specifically, there are several important lessons that managers can take from our study. First, as WFH capacity helps firms mitigate the pandemic-related disruptions by enhancing its resistance capacity, firms should consider establishing comprehensive policies and solid infrastructure for WFH in advance of such a crisis and practicing integral routines of WFH to foster better WFH capacity and prepare for similar disruptions in the future. Specifically, the acquirement of WFH capacity would require firms to redesign their work arrangement and workflow and provide introductory training sessions and essential working conditions, such as hardware and software to support telecommuting, communication, and collaboration.

Second, WFH is also a double-edged sword in the sense that it exerts a negative influence on firms’ recovery capacity by slowing down the recovery process. Given that a circumstance or mega-disruption like the COVID-19 pandemic is likely to persist (Barrero et al., 2021), it is necessary to consider the drawbacks of WFH when using it to cope with labor disruptions in the long run and seek
to alleviate its adverse impact on the pace of recovery. WFH’s mixed productivity effect has also been revealed in previous studies (Bloom et al., 2015; Gibbs et al., 2021). Since there is still insufficient evidence to inform practitioners on how to avoid its adverse effects effectively, they should be more cautious in pursuing a total replacement of working on-site by WFH. A hybrid model that combines working from home and on-site in proportion may be a good trade-off for establishing both resistance and recovery capacity.

Third, managers should be aware that WFH is not a one-size-fits-all approach to managing disruptions. More specifically, firms need to consider their industry type, company size, workers’ education and experience, and job positions when arranging WFH within their organizations. As shown, WFH is more effective in some situations than others. By piloting WFH for different job positions to apprehend the feasibility and efficiency of WFH in their business contexts, firms are more likely to find out their optimal WFH portfolio, given that the WFH effects vary across employees, firm, and industry.

**7.3 Limitations**

Although our study has interesting results, it also has limitations that should be addressed in future research. First, our data sample consists of listed firms in China, which may limit the potential generalizability of our findings to other contexts due to the following considerations. On the one hand, listed firms differ from non-listed firms, at least to an extent. Although we have taken account of the potential impacts of some observable heterogeneity among listed firms (e.g., testing the effect of firm size), whether our findings remain valid for non-listed firms remains to be explored. On the other hand, the experience of Chinese firms during the pandemic could be different from others in the rest of the world, as each country or region, divergent in its socio-economic conditions, has been struggling through the pandemic with different scales or waves and made its anti-contagion policies with different priorities or characteristics. Future research may consider expanding the data to cover more countries to verify the findings or conducting comparative studies between regions. Nevertheless, we believe that the essential finding that WFH can serve as a source of firm resilience against labor disruptions is likely to hold in more other contexts, given the consistent findings by other recent studies (Bai et al., 2020; Barrero et al., 2021).

Second, due to the scope of the study and the availability of necessary data, we measure WFH solely based on job postings data and focus the investigation on the short- and medium-run effects of COVID-19 and WFH. Future research should develop alternative measures using multi-faceted data from actual firm employment by occupation and examine their long-run effects. In addition, we find preliminary evidence of the negative effect of the WFH capacity on firms’ recovery capacity, and further studies should follow this line of research to reveal the underlying mechanism through which WFH has an adverse impact.

Third, our conceptualization and operationalization of firm resilience takes a narrow view of the concept, focusing on whether a firm can return to normal in the face of disruptions. However, from a broader view of firm resilience, WFH can help firms make permanent adaptations and achieve a new level of performance during and after disruptions. Therefore, future research should consider expanding our investigation from this perspective by incorporating measures that capture how firms adapt to disruptions and whether they can achieve new performance levels.

**7.4 Conclusion**

This study examines the role of WFH capacity in facilitating firms’ resilience to disruptions caused by the COVID-19 pandemic among Chinese listed firms. It considers the essence of such disruptions and their impacts on two types of firm resilience capacity. Using a DID strategy, we find that labor disruptions caused by the COVID-19 pandemic negatively affect firms’ operations and transactions with their supply chain partners and identify the effects of WFH capacity as a novel antecedent that enhances firms’ resistance capacity. In addition, contrary to our expectations, we find that WFH slows firms’ recovery. These results are robust to alternative measures of COVID-19 shocks on firms and WFH. The effects we identify are heterogeneous across firms from different industries, firms of different sizes, worker education and experience, and job functions. This study enriches our understanding of WFH, which has emerged as a novel antecedent of firm resilience capacity, and the findings have both theoretical and managerial implications.

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ENDNOTES

1 Data link: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/MR5JIN.

2 Overall, they examined seven indicators from the survey about work context and eight indicators from the survey about work activities.

3 We first matched the occupations based on the translated keywords using an algorithm. Next, we manually crosschecked the matching by consulting a few experts. Appendix A provides more details about the mapping.

4 As pointed out by Bai et al. (2020), these measures reflect the share of firm labor demand for which it is feasible to WFH. Although it does not capture layoffs during the pandemic, given our purpose of capturing firms’ pre-pandemic WFH capacity and the unexpected nature of the pandemic, we believe it serves as a second-best measure when we cannot directly measure the actual prevalence of WFH.

5 We also examined the level of operating revenue as an outcome. Consistent with Bai et al. (2020), we found that WFH helped dampen the negative effect of COVID-19 on firms’ operating revenue.

6 A firm might experience an episode of negative growth spreading across different natural years. By taking the average across a few years before the pandemic rather than measuring the negative growth duration within each year, we avoid this issue.

7 For the duration of negative growth, the data only have two periods. Therefore, we cannot create a similar figure. However, we also find no significant difference in the duration of pre-pandemic negative growth between the treated and the untreated firms.

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A.1 | TECHNICAL DETAILS OF THE WFH INDEXES

We first matched the Chinese listed firms with the online job postings data using the company name. We obtained 1904 listed firms that posted 790,762 job ads from January 1, 2017, to January 24, 2020. Next, we matched the occupation classifications on the online job posting platform with the O*NET classification. There were 1197 different occupations on the online platform. We mapped them into 380 O*NET occupations in 22 job families based on the keywords in the translated job names or skill requirements.

Dingel and Neiman (2020) classified the feasibility of WFH for all O*NET occupations using the Working Context Questionnaire and Generalized Work Activities Questionnaire. Following their results, we assigned the WFH feasibility of the occupations in our online job posting data based on the mapping with O*NET. Figure A1 demonstrates the average WFH index for the top-six job families, experience, and education requirements, based on the share of job advertisements that are WFH job advertisements.

We constructed an alternative WFH measure from another influential study by Koren and Pető (2020), who measured the share of workers in each occupation who told the American Time Use Survey that they can WFH. Similar to our baseline measure, we matched the occupations to our job postings data and computed the share of WFH job ads for each firm based on their pre-pandemic job posts. Figure A2 plots the two measures of firms’ WFH capacity based on pre-pandemic WFH job ads share. Although the two measures are based on different sources, they are highly correlated (correlation = .78).

**Figure A1** Share of posted jobs that are WFH jobs across major job families, experience, and education requirements

**Figure A2** Firms’ pre-pandemic WFH capacities. This figure plots two measures of firms’ WFH capacities using their pre-pandemic job posting data. The horizontal axis is a measure that computes the share of ads for WFH jobs; its WFH index of jobs is based on Dingel and Neiman (2020). The vertical axis also measures the share of WFH job ads for firms; its WFH index is based on Koren and Pető (2020).
APPENDIX B

B.1 | ADDITIONAL ROBUSTNESS CHECKS

Table A1.

| Dependent variables | (1) VolRev | (2) DNG | (3) DeltaRank | (4) (5) DeltaRank |
|---------------------|-----------|---------|--------------|------------------|
| COVID dummy         | 0.471***  | −0.701*** | −0.838***    | 0.534***         |
|                     | (0.167)   | (0.218)  | (0.166)      | (0.196)          |
| WFH ads share       | 0.141*    | −0.148   | 0.071        |
|                     | (0.079)   | (0.179)  |              |
| COVID dummy · WFH ads share | −0.342* | −0.355* | 0.567** | 0.690*** | −0.492*** | −0.488*** |
|                     | (0.178)   | (0.255)  | (0.196)      | (0.163)          |
| Observations        | 2442      | 2442     | 826          | 816              | 26,935 | 26,805 |
| R-squared           | 0.133     | 0.161    | 0.099        | 0.232            | 0.011  | 0.015  |
| Time FE and Industry FE and City FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls            | Yes       | Yes      | Yes          | Yes              | Yes    | Yes    |
| Firm FE             | No        | Yes      | No           | Yes              | No     | Yes    |

Note: This table presents robustness checks on difference-in-differences estimations of the differential impact of COVID-19 on firms with varying degrees of WFH capacities. The COVID-19 shock variable “COVID dummy” is a dummy variable that equals one if the firm (columns 1–4) or supplier-customer relationship (columns 5–6) is affected by COVID. A firm is defined as affected if the firm’s local cities or its buyers or suppliers imposed travel bans or home isolation policies. A supplier-customer is affected if the local cities of the customer or supplier imposed travel bans or home isolation policies. The significances are indicated as ***p < .01, **p < .05, and *p < .1.