The impact of governmental COVID-19 measures on manufacturers' stock market valuations: The role of labor intensity and operational slack

Lujie Chen1 | Taiyu Li1 | Fu Jia2 | Tobias Schoenherr3

1International Business School Suzhou, Xi’an Jiaotong Liverpool University, Suzhou, Jiangsu, China
2The York Management School, University of York, York, UK
3Department of Supply Chain Management, Broad College of Business, Michigan State University, East Lansing, Michigan, USA

Correspondence
Fu Jia, The York Management School, University of York, Heslington, York YO10 5DD, UK.
Email: jeff_fujia@hotmail.com

Funding information
Natural Science Foundation of China, Grant/Award Number: 71902159

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

Abstract
This study investigates the impact of the Chinese government’s Level I emergency response policy on manufacturers’ stock market values. We empirically examine the roles of human resource dependence (labor intensity) and operational slack within the context of supply chain resilience. Through an event study of 1357 Chinese manufacturing companies, we find that the government’s emergency response policy triggered statistically significant positive abnormal returns for manufacturers. However, we also find that there exists a negative impact on abnormal returns for manufacturers that are labor-intensive, giving rise to arguments based in resource dependence theory. In addition, the results indicate the positive role played by operational slack (e.g., financial and inventory slack) in helping manufacturers maintain operations and business continuity, effectively mitigating risks and adding to the manufacturers’ resilience. With these findings, we contribute to operations and supply chain management by calling attention to the importance of human resource redundancy while at the same time identifying financial slack and inventory as supply chain resilience strategies that were able to mitigate pandemic-related risks.

KEYWORDS
COVID-19 pandemic, event study, labor intensity, operational slack, public policy, supply chain resilience

Highlights
- Although government policies and regulations are often central for supply chain risk mitigation, they may sometimes also carry secondary risks; manufacturers should monitor and ideally anticipate public policy interventions.
Slack financial resources provide greater flexibility in a company’s response to an unanticipated event and should thus be emphasized; nevertheless, the value of excess inventory should not be neglected.

A greater dependence on labor exposes manufacturers to greater risks, especially when public policy curtails travel and the movement of labor.

Governments should use policymaking as a means to provide guidance and support regarding the deployment of manufacturers' operational slack, especially financial slack.

1 | INTRODUCTION

The rapid spread of COVID-19 had a significant impact on everyday life and the global economy (Baker et al., 2020)—public transportation was curtailed and factories were shut down, limiting travel and halting production. The impact on manufacturers was considerable, both economically and operationally, as indicated by a survey conducted by the National Association of Manufacturers (NAM, 2020). Specifically, 78.3% of manufacturers said that they believed that the pandemic had a significant negative influence on their financial performance, with 35.5% having experienced some type of supply chain disruption. Though the sample for this survey came from the United States, similar challenges were experienced across the world. For instance, Chinese manufacturers were reported to experience a similar, or even worse, situation (Norouzi et al., 2020). These challenges were exacerbated by the associated global public health emergency, which led many governments to implement public policy measures aimed at limiting the spread of the virus. While there is anecdotal evidence of the impact of such measures on the economy, research that quantifies this impact is, to date, scarce. We aim to close this gap by investigating the impact of government measures designed to contain the virus on the stock market valuations of manufacturers, contributing to the research domain at the intersection of public policy and operations and supply chain management (OSCM; Darby et al., 2020; Spring et al., 2017; Tokar & Swink, 2019).

Granular insight is provided based on a manufacturer’s dependency on labor, as well as how resilience can be enabled by operational slack.

Our focus in this study is on the Chinese government’s “Level I public health emergency response,” which has been lauded as an effective response to the pandemic (cf. Ge et al., 2020). Starting from January 23, 2020, 31 provinces and provincial-level jurisdictions of mainland China announced the emergency response effective immediately. As a result, a series of strict policies were implemented in medical facilities and organizations to assist with disease control and epidemiological investigations, in addition to restrictions in the form of, for instance, social distancing and quarantine mandates. Because of the scope of this country-wide adoption of pandemic-response measures, China offers an intriguing context to investigate their impact on manufacturers’ stock market valuations. Based on the preventative nature of the measures (i.e., that they were intended to stop the spread of the virus), we theorize that their implementation signaled confidence to investors regarding the future trajectory.

However, at the same time, travel restrictions, social distancing, and quarantine mandates meant that workers could not return to their place of work (Baker et al., 2020; Norouzi et al., 2020). As a result, many manufacturers and their upstream suppliers struggled with labor shortages and relocations, eventually sending ripple effects through the supply chain (PwC, 2020). Evidence for this additional strain on manufacturing operations is provided by China’s average working hours falling from 46.7 h in January to 40.2 h in February 2020, with 49% of employees not being able to work in that same month (Zeng, 2020). As may be expected, this impact was particularly pronounced in labor-intensive industries, where labor is a critical, if not the most important, resource (Bechtold & Jacobs, 1991; Francas et al., 2011). The nature of work in labor-intensive industries is also often associated with an inability to perform the work remotely (Bhattacharya & Narayan, 2015), exacerbating the challenges faced by labor-intensive manufacturers. While labor has been identified as a key production input in OSCM (Nikookar & Yanadori, 2022), research that explores the implications of government policies on the ability of labor-intensive manufacturers to perform their tasks remains scarce. We do so in the present research and suggest, based on arguments founded on resource dependence theory, that the emergency response measures had a negative effect on the stock market valuations of labor-intensive manufacturers.
Given these challenges, our objective in the present research is also to identify firm resources that would be beneficial in addressing this unprecedented situation; that is, characteristics that would render a manufacturer more resilient. Supply chain resilience can enable a supply chain to reduce the impact of interruptions, respond quickly to emergencies, and recover from disruptions to operations (Christopher & Peck, 2004; Wieland & Wallenburg, 2013). Existing literature points to redundancy as one of the keys to building a resilient supply chain (Christopher & Peck, 2004; Scholten & Schilder, 2015), leading to better organizational performance under external disruptions (Hendricks et al., 2009). Given labor constraints such as those triggered by the government’s emergency response, what may be especially useful for a firm’s resilience is the availability of organizational redundancy in the form of operational slack—again invoking arguments based on resource dependency theory. Within this context, financial slack and excess inventory may enable the maintenance of daily operations and business continuity (cf. Azadegan et al., 2021; Kovach et al., 2015; Manikas & Patel, 2016; Wiengarten et al., 2017). While these issues have been investigated in situations of labor shortages before, there has never been an event in modern history that restricted movement to such a magnitude. COVID-19 caused unprecedented challenges for manufacturers, triggered by employee shortages, the stagnation of nonessential production, changes in demand and supply, and lack of access to financial capital (Govindan et al., 2020; Hassan et al., 2020). Research into operational slack and supply chain resilience within the context of public health events has thus been called for (Sarkis, 2020). We heed this call and investigate the dynamics inherent in human resource dependence and operational slack that allow the fostering of supply chain resilience in the face of disruptions. As such, we develop arguments to discern the role of human resource redundancy and operational slack in manufacturers’ stock market valuations in response to China’s Level I public health emergency response. Within this context, we position labor intensity and operational slack as determining a company’s resilience within its overall supply chain (cf. Hendricks et al., 2009).

To provide specific insights into the above, we conduct an event study with 1357 publicly traded manufacturing firms listed on the Shenzhen Stock Exchange, with the objective of providing answers to the following research questions:

**RQ1:** What is the impact of governmental policies, specifically China’s Level I public health emergency response, on manufacturers’ stock market valuations?

**RQ2:** What role does manufacturers’ labor intensity play in the impact of China’s Level I public health emergency response on stock market valuations?

**RQ3:** What role does manufacturers’ operational slack play in the impact of China’s Level I public health emergency response on their stock market valuations?

Within this context, the contributions of this study to the OSCM literature are threefold. First, anchoring our investigation at the intersection of public policy and OSCM, we investigate the effect of public policy mandates triggered by a public health emergency on manufacturers’ ability to weather the crisis. Specifically, we find that while the public policy mandates are able to generate confidence in the overall trajectory of the economy, as indicated by the overall positive impact on manufacturers’ stock market valuations, this effect is not experienced across the board. As such, our second contribution lies in the more granular insight that the stock market valuations of labor-intensive manufacturers react less positively in response to the government mandate, in line with the associated measures designed to curb the spread of the virus, including travel restrictions, social distancing, and quarantine mandates. This human dependence thus poses a significant risk to these manufacturers’ operations. Our third contribution is that the operational slack can offset some of the negative consequences caused by pandemic-related measures, including the challenge created by labor-intensive manufacturing processes coupled with the immobility of the workforce in line with the pandemic measures.

This paper proceeds as follows. Section 2 provides a brief background on related literature and develops the hypotheses. Section 3 reviews the methodology and the data. Sections 4 and 5 summarize the results and discuss the implications, respectively. Section 6 concludes.

## 2 | BACKGROUND AND HYPOTHESIS DEVELOPMENT

### 2.1 | Governmental policies and manufacturers’ stock valuations

Governments often play a significant role in a country’s emergency management and response through the implementation of policies and measures (Wang, 2007). Within this context, public policy refers to initiatives and measures implemented by governmental decision-makers and administrative agencies in response to challenges in the public domain, aimed at alleviating these for the best
overall outcome for society (Tokar & Swink, 2019). As such, we suggest that governmental initiatives to alleviate crises will also have a positive effect on improving market confidence. Specific measures implemented in China included delineating control areas, restricting traffic in severe outbreak areas, and suspending work, business, and in-person education. At the same time, to ensure social stability, the government guaranteed the supply of essential products and services and addressed price gauging and other illegal activities.

The potential harm caused by the pandemic was unpredictable in the early stages. Companies did not know what disruptions there might be on the horizon, making it increasingly difficult to have a positive market outlook. At this time of uncertainty, the government's emergency response measures helped reduce this market uncertainty and alleviated some of the stress and strain. While studies exist that examine the general impact of the pandemic on the stock market (He et al., 2020; Liu et al., 2020), the impact of specific pandemic-related governmental policies has been largely neglected. We therefore focus on the Chinese government's announcement of Level 1 public health emergency response measures and assess its impact on manufacturers' stock market valuations. We theorize a positive impact, as the government's public policy initiatives should foster confidence in the maintenance of the status quo and provide safeguards to ensure that the situation does not spiral out of control. This could also entail expectations that companies be provided with assistance in case of need, as was indeed the case across many countries. We formulate our first expectation, which serves as our baseline hypothesis, accordingly.

**H1. The government's Level I emergency response had a positive impact on the market valuations of manufacturers.**

### 2.2 Governmental policies and the role of labor in operations management

Our second hypothesis aims to provide greater granularity to this investigation by discerning how manufacturing firms' OSCM strategy, positioning and associated decisions enabled firms to better weather the crisis and respond to the disruptions. As such, we suggest that based on firms' operational and supply chain choices, the Chinese government's Level 1 emergency response had a stronger or weaker impact on these manufacturers' stock market valuations. We specifically focus in our next hypotheses on a firm's labor intensity, which is a strategic aspect driven by operations and supply chain management decisions. Within this context, we develop arguments on how firms are better able to respond to the governmental (public) policies considered herein in the presence of lower labor dependence.

The intersection of public policy and OSCM has been a topic of investigation in the past (e.g., Chandrasekaran et al., 2012; Sharma et al., 2020; Smith & Grimm, 1987). For example, Smith and Grimm (1987) found that the deregulation of transportation industries (e.g., airlines, rail, and motor carriers) not only created competition, but also dramatically changed the cost control and operating philosophies of logistics operators. In addition, Chandrasekaran et al. (2012) found that public-health-related policies affected clinical and experimental practices in healthcare supply chains by reshaping performance metrics. However, what has been largely neglected in the domain at the intersection of public policy and OSCM is the role played by labor. While governmental policy has certainly had a significant impact in areas such as minimum wages, as well as health and safety standards, these initiatives were generally anticipated and debated at length in advance, thus not triggering any significant stock market reactions once they were announced. However, we expect that there will be significant abnormal stock returns in response to labor-related restrictions imposed by the pandemic control measures. Prior to the pandemic, mandates such as social distancing and quarantining, as well as travel restrictions, were largely unheard of, and it is reasonable to expect that these served as a shock, especially to those manufacturing industries that are highly dependent on labor (Baker et al., 2020). We thus deem it prudent to investigate how pandemic-related governmental restrictions affected the ability of manufacturing firms to operate.

Labor is considered a key resource in OSCM and an integral part of a supply chain network's proper operations (Greenley & Oktemgil, 1998; Miller et al., 2000). Extant research has thus emphasized the importance of labor for operations and supply chain management. For example, Turnquist and Vugrin (2013) found that companies relying on and investing more in labor have a shorter recovery time after an interruption, representing a greater capacity to recover. Research highlighting the role of employee efficiency in the operations of supply chain service providers is also rich (e.g., Cook et al., 2002), with a key finding being that companies possessing greater employee productivity are able to reduce operating costs (Jacobs & Singhal, 2014). Labor is of course particularly critical for labor-intensive manufacturing industries, such as the clothing, fabric, and furniture industries, whose operational success hinges to a large degree on human resources. This is especially the case in industries that lack technological or
knowledge resources to maintain operations and build competitive advantage (Boxall, 2003).

Against this background, we leverage tenets from resource dependence theory (RDT) to develop our expectations about the stock market reactions of labor-intensive manufacturing firms to public policy aimed at curtailing the spread of COVID-19. OSCM has a strong tradition of emphasizing the criticality of the strategic and selective usage of resources in dealing with external uncertainties and improving organizational performance (Christopher & Peck, 2004; Park, Park et al., 2020), which is one of the notions of RDT. RDT, which goes back to Pfeffer and Salancik (2003), aims to provide guidance for organizations on how to design and manage their operations given external constraints (Hillman et al., 2009; Pfeffer & Salancik, 2003). The primary message of RDT is that organizational survival depends on resources that have their origin in the external environment (Hillman et al., 2009; Pfeffer & Salancik, 2003). As such, a greater dependence on external resources will destabilize firms’ operations when external disruptions occur that affect these resources. Firms are thus expected to minimize environmental uncertainty while maximizing performance by reducing their dependence on external resources (Davis & Adam Cobb, 2010; Hillman et al., 2009). We note that while the RDT was originally developed with a focus on resources that are indeed external to the firm, this understanding has been broadening over the last several decades, with RDT also being able to explain relationships within organizations (Medcof, 2001; Pfeffer & Salancik, 2003).

Overlaying our prior discussion with insights from the RDT perspective, labor-intensive manufacturing industries (i.e., those whose proper operations hinge to a large degree on human resources) can be considered more dependent on these resources than their counterparts in less labor-intensive manufacturing industries. While this dependence can generally be managed well under normal conditions, it is reasonable to expect that the Chinese government’s Level I emergency response put significant strain on companies in terms of operating successfully. In particular, the restrictions imposed on travel and movement (social distancing and quarantining) directly affected the ability of workers to come to work, jeopardizing stable and predictable operations (Baker et al., 2020; Norouzi et al., 2020). This was especially felt in industries that rely on front-line workers to operate (Baker et al., 2020; PwC, 2020).

In contrast, non-labor-intensive industries can to some degree alleviate their dependence on labor via, for instance, a high level of automation, rendering companies more resilient to labor disruptions (Cheung, 2020; PwC, 2020; Wuest et al., 2020). For example, JD.com leveraged unmanned vehicles to distribute supplies to hospitals and communities in Wuhan during the Level I response, with the related sorting, disinfection, and distribution not requiring any direct human contact (Cheung, 2020). Based on these notions, we theorize that the positive impact of the government’s Level I emergency response on the market valuations of manufacturers was weakened for manufacturers in labor-intensive industries. As such, while we still expect a positive impact, we theorize that it will be less strong than for manufacturers in less labor-intensive industries. This expectation is predicated on the inability of workers to support operations by their physical presence and labor on-site.

We further aim to provide more granular insight by focusing on a specific industry that is expected to rely on a great degree of automation, replacing dependence on labor. A category of companies that would fit this description comprises the SFPI SMEs. Companies in this category are small- and medium-sized enterprises (SMEs) that are specialized (the SME must focus on a core business and specialize in production and collaboration), fitted (the SME must possess advanced production process and manage independent intellectual property rights), peculiar (the SME’s product must be unique and rely on exclusive production processes), and innovative (the SME must distinguish itself by technological, management, and business model innovations). Since the inception of this company category in 2011, the Chinese government has been encouraging companies to meet these requirements and become certified as such an enterprise. Companies in this category distinguish themselves by their competitiveness, technological innovation, and supply chain resilience (Huang, 2021). The requirements for being recognized as an SFPI SME are extremely strict; for example, the company’s primary products should address current shortcomings in the manufacturing industry, and the companies should be located at key locations within an industry’s supply chain network (MIIT, 2021).

In keeping with these characteristics, SFPI SMEs generally have a higher degree of automation enabled by advanced technologies, and thereby rely less on traditional labor for front-line production and operations (Sivathanu & Pillai, 2018). In addition, due to the frequent high degree of digitalization and innovation of these companies, the likelihood is great that they are able to pivot in case of a disruption through their ability to innovate and transform current operations and production processes—examples in this vein include electronic purchasing, flexible telework, and collaborative systems (Favilukis et al., 2020; Sivathanu & Pillai, 2018; Von Krogh et al., 2020).
Based on these discussions, we theorize that the positive impact of the Chinese government’s Level I emergency response on the market valuations of manufacturers was weaker for manufacturers in labor-intensive industries. In contrast, the positive impact of the Chinese government’s Level I emergency response on the market valuations of manufacturers was enhanced for manufacturers certificated as SFPI SMEs, in line with their high degree of automation and innovation. We capture this formally in the following two hypotheses.

H2a. The positive impact of the government’s Level I emergency response on the market valuations of manufacturers was less for manufacturers in labor-intensive industries.

H2b. The positive impact of the government’s Level I emergency response on the market valuations of manufacturers was greater for manufacturers certificated as SFPI SMEs.

2.3 Operational slack as a supply chain resilience strategy

Supply chain resilience can be defined as the ability of a supply chain to return to its original state after suffering a significant shock (Christopher & Peck, 2004), or the ability of a company to quickly recover from a supply chain network interruption, thereby improving company performance (Sheffi & Rice, 2005). While definitions vary slightly, common to all is the ability to resume normal operations after an interruption. With manufacturers generally playing a critical role in supply chains, as they are providing key components for a final product valued by customers (Blackhurst et al., 2011), supply chain resilience is particularly critical. Extant research has confirmed this criticality by associating greater supply chain resilience with increased profitability (e.g., Hendricks et al., 2009; Wieland & Wallenburg, 2013).

One strategy for a firm to obtain higher supply chain resilience is to garner more operational slack, which can be contrary to a firm’s pursuit of resource efficiency. It has however been found to be able to mitigate unexpected threats and thus reduce the likelihood of operational failures (Indjejikian & Matejka, 2006). These notions can be traced back to the concept of organizational slack, which was a central element in early research on organizational behavior (Cyert & March, 1963). As such, the focus on resource utilization commonly pursued in lean production comes with potential operational risks (Holweg, 2007), calling attention to the comparison between frugality and redundancy of resources. The pursuit of operational slack is therefore a double-edged sword. On the one hand, firms aim to reduce operational slack since it is often indicative of redundancy (Wood et al., 2017) and a sign that resources are either not utilized efficiently or exceed the company’s resource requirements (Kovach et al., 2015; Wood et al., 2017). Firms therefore aim to reduce operational slack in their quest to become leaner and more efficient, and ultimately, more profitable. The flipside of this strategy is however that the firm becomes highly dependent on the proper functioning of these resources (Kovach et al., 2015). Therefore, on the other hand and in line with RDT, firms may decide to increase their operational slack to become less vulnerable to supply chain disruptions. Operational slack would thus make the firm less dependent on resources and serve as a means to increase resilience. This perspective has been applied in prior work, such as that examining the 2003 severe acute respiratory syndrome (SARS) epidemic or the Fukushima Daiichi nuclear disaster (Lee & Preston, 2012).

Weighing the advantages and disadvantages of operational slack, we view it as an alternate means to mitigate disruptions and thus strengthen a firm’s resilience (Hendricks et al., 2009). We consider this to be particularly important in light of the significant disruptions caused by the measures implemented in response to the COVID-19 pandemic, and the implications for labor immobility. As such, we expect operational slack to alleviate the strain on manufacturing firms arising from their own or suppliers’ workers not being able to perform their tasks in plants due to travel and movement restrictions imposed by government mandates aimed to stop the spread of the virus. If manufacturing workers are not able to perform their tasks in plants due to movement restrictions imposed by government mandates for an extended period of time, their firm will sooner or later not be able to meet its customers’ demands, putting its very survival in jeopardy. We thus expect that higher levels of operational slack may serve as one means to alleviate this potentially existential pressure on manufacturing firms.

Departing therefore from the notion that operational slack can help companies better confront production disruptions, especially those triggered by labor mobility restrictions, we consider two types of slack: financial slack and excess inventory. Financial slack is reflected in redundancy related to cash (Azadegan et al., 2013; Bortolotti et al., 2015; Kovach et al., 2015). A firm having sufficient funds to pay its liabilities for the upcoming year, especially during times of disruption, bodes well for the confidence of investors in the firm’s sustainability. Excess financial resources, for instance in the form of...
liquidity, can help a firm bridge periods of stress and maintain operations (Guo et al., 2020). As such, while financial slack may generally be interpreted as inefficient use of current financial resources, we suggest that companies with higher levels of financial slack have fewer financial constraints and perform better in response to sudden governmental mandates restricting operations management activities and thus curtailing business activities (Boso et al., 2017; Guo et al., 2020). Theoretical support is provided by the RDT, under which financial slack can be considered as making the firm less dependent on resources. We consider two measures to capture a firm’s financial slack: the quick ratio (also known as the acid-test ratio or a firm’s liquidity) and the receivables turnover ratio (cf. Azadegan et al., 2013; Bortolotti et al., 2015; Kovach et al., 2015; Wood et al., 2017). While the former is defined as the quick assets divided by current liabilities (Bortolotti et al., 2015; Campbell et al., 2008), the latter is defined as net sales divided by average accounts receivables (Wood et al., 2017). Specifically, we position that firms with more available liquidity, as indicated by a more favorable (higher) quick ratio, possess greater financial slack. As such, we expect market valuations of manufacturers with more favorable (higher) quick ratios to react more positively to the government’s Level I emergency response. Similarly, while a higher receivables turnover ratio is generally a sign of good performance, since it indicates the firm collecting its debt efficiently, in this instance we position it as a negative aspect as it would be indicative of the firm not having large outstanding accounts receivables. However, having large outstanding accounts receivables can be a sign of the firm’s financial slack, as it can expect the funds to flow in sooner or later. As such, we expect market valuations of manufacturers with higher accounts receivables turnover ratio to react more negatively to the government’s Level I emergency response.

In addition to financial slack, excess inventory may also improve firms’ resilience when facing unexpected events. While the literature on lean manufacturing cautions against retaining excess inventory due to its associated costs, excess inventory is a common form of operational slack to guard against disruptions; for instance, when facing an unexpected increase in demand (Azadegan et al., 2013). In addition, keeping an inventory of standard subcomponents or subassemblies, as opposed to final products, can create additional flexibility in addressing isolated disruptions that affect only selected types of products, enabling the firm to respond to multiple forms of supply chain disruption (Azadegan et al., 2013; Kovach et al., 2015; Voss et al., 2008). As such, inventory has the potential to effectively respond to a broad range of production-related problems, ranging from raw material shortages to demand fluctuations (Azadegan et al., 2013; Kovach et al., 2015). Similar to the arguments above and framing excess inventory within an RDT perspective, excess inventory has the ability to make the firm less dependent on resources. To operationalize excess inventory, we utilize a firm’s operating cycle and inventory turnover as proxies (cf. Azadegan et al., 2013; Eroglu & Hofer, 2011; Guide & Srivastava, 1998; Kovach et al., 2015). While the former is defined as the average length of time from when the inventory is acquired to when the accounts receivables are collected, the latter is derived by dividing sales divided by the average inventory (Azadegan et al., 2018). Specifically, while a longer operating cycle is generally a sign of poorer performance, since it indicates that the firm requires a longer time to convert inventory into cash, in this instance we position it as a favorable property as the firm is likely to have larger inventories. As such, we expect market valuations of manufacturers with higher operating cycles to react more positively to the government’s Level I emergency response. Similarly, while a higher inventory turnover is generally associated with better performance, since the firm is able to sell its inventory quickly, in this instance, having a slower inventory turnover is theorized to be beneficial, since the firm can likely benefit from more inventory still in stock. As such, we expect market valuations of manufacturers with higher operating cycles to react less positively to the government’s Level I emergency response.

Overall, our expectation is that firms with greater operational slack in the form of financial slack and excess inventory benefited more from the Chinese government’s Level I emergency response to the pandemic, and that this will be indicated by a more positive market reaction than expected. Thus, we set out our last set of four propositions:

**H3a.** The positive impact of the government’s Level I emergency response on the market valuations of manufacturers was greater for manufacturers with a higher quick ratio.

**H3b.** The positive impact of the government’s Level I emergency response on the market valuations of manufacturers was less for manufacturers with a higher receivables turnover ratio.

**H3c.** The positive impact of the government’s Level I emergency response on the market valuations of manufacturers was greater for manufacturers with a higher operating cycle.
H3d. The positive impact of the government’s Level I emergency response on the market valuations of manufacturers was less for manufacturers with a higher inventory turnover ratio.

3 | SAMPLE AND METHODOLOGY

The overall research framework is presented in Figure 1. We now proceed with a description of how the sample data were compiled, followed by an overview of the event study methodology and ensuing cross-sectional analysis.

3.1 | Data

Financial data were compiled from the WIND financial database, which is maintained by one of the most comprehensive financial information service providers in China. Several prior works have used this database for financial analyses (e.g., Zhou et al., 2018). Within the database, we focus on all manufacturing firms listed on the Shenzhen Stock Exchange—one of the largest and most regulated stock exchanges in China (cf. Bai et al., 2021; Villena et al., 2021). We choose to focus on just one exchange as the existing literature indicates that the single-index model (Mills et al., 1996) is reliable for an event study. Additionally, the Shenzhen and Shanghai Stock Exchanges have markedly different market returns and indexes, and thus, studying both may induce sample errors. Similar research designs are applied by existing studies that focus on one market (Lease et al., 1991; Ma et al., 2005). We choose the Shenzhen Stock Exchange rather than the Shanghai Stock Exchange in light of evidence that the Shenzhen Stock Exchange performs better in market efficiency tests (Mahmood et al., 2011).

Our initial sample included all stocks from the Shenzhen stock exchange listed under the manufacturing category, which yielded 1635 firms. To ensure the reliability of our estimations, we removed all stocks that joined or exited the exchange during the estimation window and those that had fewer than 120 returns. To apply the market model for the calculation of abnormal returns (ARs) and cumulative abnormal returns (CARs), daily returns were collected. This was complemented with the daily returns of the Shenzhen Component Index to capture the market return as the benchmark. In addition, we collected data on firm characteristics and other financials from the same database for the ensuing cross-sectional analysis. At this stage, we excluded additional six firms due to missing data on our variables of interest. These data were compiled from the China Stock Market & Accounting Research Database (CSMAR), in line with previous work also leveraging this database to provide insights into ARs (Liu et al., 2020) and firm innovation (Gao et al., 2020). This approach yielded a final sample of 1357 manufacturers.

3.2 | Event study methodology

Under the efficient market hypothesis (Fama, 1970), the event study methodology is a highly reliable approach for measuring the influence of an event on a firm’s market value. Event studies have been widely used in operations and supply chain management research, with particular
emphasis given to supply chain disruptions. Work in this domain has for instance shown that product delays affect market values (Hendricks & Singhal, 1997) or that U.S. companies’ reshoring decisions can affect shareholder wealth (Brandon-Jones et al., 2017). As such, we deemed the event study approach an appropriate method for quantifying the direct and indirect influence of external shocks on the market values of firms.

The first step in an event study is to determine the event window. Since we aim to examine the influence of the Chinese government’s Level I emergency response on stock market valuations of manufacturers, we consider the announcement of this initiative as the event. As the Chinese government’s Level I emergency response was announced on January 23, 2020, we consider this day 0. This is consistent with Ding et al. (2018), who noted that for an event with such a long-term impact, in line with market efficiency assumptions, information can be considered to be reflected in the market since the occurrence of the earliest event. Following previous studies (Jacobs & Singhal, 2014), the event window then includes the trading day before day 0, day 0, and the trading day after day 0, denoted by (−1, 1). To assess the robustness of our results, we set two additional event windows of (−1, 0) and (0, 1).

We further follow guidance of prior event studies (Jacobs & Singhal, 2014) and use our sample firms’ ARs to quantify the impact of the shock due to the unexpected Level I emergency response. In line with previous studies (e.g., MacKinlay, 1997), the estimation period for calculating the AR includes 120 trading days, ending 11 days prior to the event window, denoted by (−130, −11). The estimation window thus ranges from July 18, 2019 to January 10, 2020. For the robustness tests, we set an additional estimation window of 150 trading days, ending 11 days prior to the event window, denoted by (−160, −11; cf. Brandon-Jones et al., 2017), capturing the time window from June 05, 2019 to January 10, 2020.

With the event and estimation windows set, we calculate ARs, defined as actual returns minus expected returns, with the latter representing the value of the stock in a no-event scenario. With only the actual return being observed in practice, we rely on a market model for the estimation of the expected return. Specifically, for stock $i$, the observed return $R_{it}$ on day $t$ is as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it}$$

where $R_{mt}$ is the market return for day $t$, $\epsilon_{it}$ is the prediction error, and $\alpha_i$ and $\beta_i$ are firm-specific parameters. The Shenzhen Component Index return is used as a proxy for the market return $R_{mt}$, which cannot be directly observed. However, with all sample firms being listed on the Shenzhen Stock Exchange, this assumption seems reasonable. Now substituting return rates for each stock in the estimation period, we obtain the estimated parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$. Consequently, we define the expected return for stock $i$ on day $t$ as follows:

$$E(R_{it}) = \hat{\alpha}_i + \hat{\beta}_i R_{mt}.$$ 

With the expected return, the difference between the actual return and the expected return for stock $i$ on day $t$ can be calculated as:

$$AR_{it} = R_{it} - E(R_{it}).$$

We calculate the CAR over the three-day event window (Ba et al., 2013; Hendricks et al., 1995) and set a 2-day event window as a robustness check. The CAR from day $−1$ to day 1 for firm $i$ is defined as follows:

$$CAR_i = \sum_{t=−1}^{0} AR_{it},$$

where $CAR_{it=(-1,0)}$ and $CAR_{it=(0,1)}$ are defined as the CARs over the windows (−1, 0) and (0, 1), respectively.

We conduct a standard $t$-test to determine the statistical significance of the abnormal performance. All ARs in our sample set were examined, with our reporting also including the $t$-test results for different estimation periods and event windows. To ensure the reliability of the analysis, we further conducted non-parametric tests and examined the CARs for different time windows to check if the results were consistent.

### 3.3 Cross-sectional analysis

In the cross-sectional analysis, we examine which factors exerted a significant impact on market values triggered by the Level I emergency response. We measure the dependence on human resources as Human Capital Return On Investment (HCROI) (Bassi & McMurrer, 2007; Becker, 1962; Bontis & Fitz-enz, 2002; Fitz-Enz, 2000; Schultz, 1961; Swanson et al., 2001), calculated as firm net income divided by total employee compensation and benefits. SFPI is a dummy variable that is 1 if a company is recognized as an SFPI SME by the Ministry of Industry and Information Technology of China, and 0 otherwise. A firm’s liquidity is captured by its quick ratio in the previous fiscal year (Bortolotti et al., 2015; Campbell et al., 2008), calculated as quick assets divided by current liabilities, with quick assets representing current assets...
minus the net inventory balance. The operating cycle (OC) refers to the average length of time from when inventory is acquired to when accounts receivables are collected. The receivables turnover ratio (RTR), net sales divided by average accounts receivables, measures how efficiently the company makes use of its current assets and receives its receivables. The inventory turnover ratio (ITR) is computed by sales divided by average inventory.

We control for four firm characteristics: firm age, firm size, firm profitability, and leverage (Ding et al., 2021). We consider firm age and size since companies with a longer history and greater business volume may be able to rely on greater experience and resources to manage disruptions. Similarly, firms that are more profitable are likely more robust and resilient. Last, greater leverage is also likely to serve as a foundation for greater resilience. We define firm age as the number of years since the firm's initial public offering (IPO), firm size is captured by the number of employees in the most recent fiscal year before the event (2019), profitability is measured by return on assets (ROA), and leverage is captured by the debt/asset ratio. Variable descriptions are provided in Table 1.

To test Hypotheses 2a, 2b, 3a, 3b, 3c, and 3d, CAR is set as the dependent variable. Our model is specified as

\[
    CAR = \beta_0 + \beta_1 \text{SFPI} + \beta_2 \text{OC} + \beta_3 \text{RTR} + \beta_4 \text{HCROI} + \beta_5 \text{QR} + \beta_6 \text{ITR} + \beta_7 \text{Age} + \beta_8 \text{Profitability} + \beta_9 \text{FirmSize} + \beta_{10} \text{Leverage},
\]

where OC represents operating cycle; RTR represents receivables turnover ratio; QR represents quick ratio and ITR represents inventory turnover ratio.

4 | RESULTS

We commence this section with the presentation of the event study. We then conclude with a presentation of the results derived in our cross-sectional analysis.

4.1 | Event study

Table 2 presents the results of the event study for the 1357 manufacturing firm observations, with ARs estimated with the 120 trading-day window ending 11 days prior to the event. Panel A describes daily ARs from day –1 through day 1. The mean AR for day –1 is –0.557 with negative t-statistic (–7.372), which implies that there are no significant positive ARs before the event. On
day 0, however, the mean AR is positive (0.396) with a significant t-statistic (4.619). This provides evidence that the stock market reacted significantly to the Level I emergency response. It also provides evidence that there was no investor prediction or prior information before the event. The mean AR for day 1 is 0.492, which is also significantly positive, indicating that the influence of the event on day 0 continued through day 1.

Panel B presents the 2-day CARs for the window \((-1, 0)\) and the window \((0, 1)\). The mean CAR for \((-1, 0)\) is 0.162, which is not significant, but the mean CAR for \((0, 1)\) of 0.887 is significantly positive with a t-statistic of 4.43. Panel C presents the three-day CARs for the entire window \((-1, 1)\), while the CAR is significantly positive at the 0.10 level. These results provide support for H1, suggesting that the Level I emergency response resulted in a positive market response for the manufacturing firms investigated.

To further assess the robustness of the results, we conducted three kinds of tests, summarized in Table 3. First, in panel A, we present the results for the Wilcoxon signed-rank test for daily ARs based on the 120 trading days estimation window. The results of the Wilcoxon signed-rank test are statistically significant. Second, in panel B, we extended the estimation period from 120 trading days to 150 trading days. The mean AR for day 1 is 0.492, which is also significantly positive, indicating that the influence of the event on day 0 continued through day 1. Third, we conducted the Wilcoxon signed-rank test for CARs for both the 120 trading days and 150 days estimation windows. The results are statistically significant. Thus, the results support the robustness of Table 2.

### 4.2 Cross-sectional regression results

We apply ordinary least squares (OLS) to estimate a multiple linear regression model to examine how the main and the control effects influence CARs over the event window from day \(-1\) to day 1. Observations with missing data were excluded, leaving a total sample size of 1291 (hence, CAR mean values are different in Table 4 versus Table 2). To test our hypothesis, the CAR is set as the dependent variable for each model. Descriptive statistics are presented in Table 4, with Table 5 providing the correlations. To avoid multicollinearity (Orzes et al., 2020), we constructed seven OLS models to perform stepwise regression analyses. Table 6 presents the estimation results for the seven regression models.

Model 1, which contains only control variables, is significant \((F = 3.024, p = .000)\). After adding our independent variables, the remaining models are significant at the .01 level \((F \geq 4.191, p \leq .000)\). Thus, our regression models are statistically valid. Further, as the independent variables are included sequentially, the \(R^2\) increases from 0.09 in Model 1 to 0.030 in Model 6. The F-statistic of the models also increases from 3.024 to 4.337 as variables are added. This improvement in performance indicates that the added variables strengthen the effectiveness of the regression analysis. The coefficient on HCROI is negative and statistically significant at the 0.01 level in

---

### Table 2 Abnormal returns for the 1357 manufacturing firms

| Event day | N  | Mean AR | SD  | t-Statistic | Cohen’s d |
|------------|----|---------|-----|-------------|-----------|
| \(-1\)     | 1357 | 0.557   | 2.785 | -7.372***  | -0.283    |
| 0          | 1357 | 0.396   | 3.155 | 4.619***    | 0.177     |
| 1          | 1357 | 0.492   | 5.268 | 3.439***    | 0.132     |

| Event window | N  | Mean CAR | SD  | t-Statistic | Cohen’s d |
|--------------|----|----------|-----|-------------|-----------|
| \((-1, 0)\)  | 1357 | -0.162   | 4.310 | -1.381      | -0.530    |
| \((0, 1)\)   | 1357 | 0.887    | 7.377 | 4.43***     | 0.170     |

| Event window | N  | CAR | SD  | t-Statistic | Cohen’s d |
|--------------|----|-----|-----|-------------|-----------|
| \((-1, 1)\)  | 1357 | 0.110 | 2.565 | 1.580*     | 0.061     |

Note: *, **, and *** indicate statistical significance at the .10, .05, and .01 levels. The estimation period covers 120 trading days, with day 0 selected as January 23, 2020.
Model 2 and also in the remaining models, suggesting that the positive impact of the government’s Level I emergency response measures were weakened. This provides support for H2a.

The coefficient for SFPI is positive and statistically significant at the 0.05 level in Models 3, 4, 5, 6, and 7, suggesting that firms categorized by MIIT as SFPI SMEs experienced a greater positive impact on their market values triggered by the government’s Level I emergency response compared to others. This provides support for H2b.

Further, the quick ratio (QR) is positive and statistically significant in Models 4, 5, 6, and 7, suggesting that manufacturers with a higher liquidity show a stronger reaction to the government’s Level I emergency response as reflected in their market values. This offers support for H3a.

Operating cycle (OC) was added in Models 5, 6, and 7; coefficients are both positive and significant at the 0.05 level, offering support for H3b. The receivables turnover ratio (RTR) was added in Models 6 and 7, and indicated a significant and positive effect, supporting H3c. Model 7 adds the inventory turnover ratio, whose coefficient is not statistically significant, offering no support for H3d; thus, a firm’s inventory turnover ratio appears to have no significant impact on its market valuation.

To ensure the robustness of our results, we applied two methods to assess the validity of the analysis. First, we applied a general linear model with autocorrelated errors (GLSAR; McKinney et al., 2011) to determine how the main and control effects influence CARs over the event window from day −1 to day 1. Models 1 and 2 in Table 7 present the associated results of the GLSAR models. Model 1, which includes all significant variables from Table 6, is significant at the .01 level (F = 4.332, p = .000), thus offering support for the results obtained above. The coefficient for ITR is added in Model 2, which is, similar as above results, not significant. Second, to offer a finer-grained interpretation of the results, we use CAR (0,1) as the dependent variable, with Model 3 in Table 7 presenting the results of CAR (0,1) with OLS regression analysis, and Model 4 presenting the results with the GLSAR approach. As can be seen, both models 3 and 4 are significant at the 0.01 level. Overall, all model results are consistent with the results presented above, confirming that our model is robust. As such, Hypotheses

**TABLE 3 Robustness checks**

| Event window | N  | t-Statistic | p   |
|--------------|----|-------------|-----|
| −1           | 1357 | 3.007*10^5 | .000|
| 0            | 1357 | 4.347*10^5 | .072|
| 1            | 1357 | 4.319*10^5 | .042|

**TABLE 4 Descriptive statistics**

| Variable | Mean | SD  | Min  | Max  |
|----------|------|-----|------|------|
| CAR      | 0.330| 7.696| −22.305| 44.413|
| Age      | 9.311| 6.498| 1.000 | 27.000|
| ROA      | 6.776| 10.573| −96.788| 57.822|
| Size     | 4971.871| 15465.192| −331.023| 276188.986|
| Lev      | 38.239| 18.513| 3.054 | 229.013|
| HCROI    | 77.608| 218.021| −3253.123| 1657.159|
| SFPI     | 0.077| 0.266| 0.000 | 1.000|
| QR       | 2.045| 2.133| 0.121 | 30.945|
| OC       | 259.767| 369.208| 11.641| 11899.122|
| RTR      | 16.759| 86.455| 0.121 | 2151.307|
| ITR      | 4.663| 6.826| 0.314 | 203.072|

Note: *** indicates statistical significance at .01 level. The estimation period is 150 trading days, with event day 0 set to January 23, 2020.
2a, 2b, 3a, 3b, and 3c are supported, while Hypothesis 3d is not supported.

5 | DISCUSSION

5.1 Impacts of governmental policy

The COVID-19 pandemic has disrupted daily life and business operations like no other event in modern history. Uncertainty has thus been ever-present, and challenges, including increased demand, production constraints, supply shortages, and financial constraints, have been multivariate and constant. Governments around the world have implemented pandemic-related policies and measures to create structure and stability. Such initiatives are reassuring not only for the public, but for financial investors, increasing their confidence in the future trajectory of business. We investigated these dynamics in this paper based on a sample of 1357 manufacturers, offering empirical support for the claim that government interventions can create confidence in the ability of businesses to weather crises. Specifically, our event study shows that the ARs of manufacturing firms were negative before the Level I emergency response, but turned positive following the government's intervention, suggesting that government measures reduced the perception of financial risk and uncertainty and contributed to manufacturers' stable operations and continuous business. Our findings demonstrate that in the face of large-scale disruptions, governments can serve as a powerful external actor and effectively use a variety of policies and regulations as a means to mitigate disruptions and ensure public safety.

5.2 The role of labor intensity

A further intriguing finding derived through our work is the empirical support for the impact of governmental mandates restricting travel and movement on the ability of labor-intensive manufacturers to perform. With labor being one of the most critical production inputs for the manufacturing industry (cf. Hendricks et al., 2009; Zhu et al., 2022), our study provides evidence that labor-intensive industries were more severely affected by the Level I emergency response. These companies have a greater dependence on onsite workers, who were not able to come to work due to the restrictions. Recognizing these challenges, investors discounted the effect of governmental initiatives for labor-intensive manufacturers. While the effect of the Level I emergency response measures was still positive, it was less positive for these manufacturers than

| TABLE 5 Correlations |
|----------------------|
| Variables            | 1       | 2       | 3       | 4       | 5       | 6       | 7       | 8       | 9       | 10      | 11      |
| CAR (1)              | 1.000   | 0.052*  | 0.482** | -0.078** | -0.062** | 0.134** | -0.459*** | 0.220*** | -0.103*** | 0.008*** | 0.067** |
| Firm age (2)         | 1.000   | 0.482** | 0.115** | 0.042    | 0.112**   | 0.080*** | 0.016***   | -0.155*** | -0.188*** | 0.061*** | 0.026   |
| Firm size (3)        | 1.000   | 0.115** | 1.000   | -0.700*** | -0.183*** | 0.983**  | 0.107***   | 0.107***   | 0.118***   | 0.087**  | 0.035   |
| ROA (4)              | 1.000   | -0.700*** | -0.183*** | 0.100    | 1.000     | 0.083**  | 0.016***   | -0.155*** | -0.188*** | 0.061*** | 0.026   |
| HCR (6)              | 1.000   | -0.183*** | 0.100    | 0.083**  | 0.100     | 1.000   | 0.083**   | 0.016***   | -0.155*** | -0.188*** | 0.061*** |
| LEV (5)              | 0.052*  | 0.134**  | 0.016*** | -0.155*** | -0.188*** | 0.061*** | 1.000     | 0.083**   | 0.016***   | -0.155*** | -0.188*** |
| ROA (6)              | 0.482** | 0.115**  | 0.100    | 0.083**  | 0.100     | 0.083** | 0.100     | 1.000     | 0.083**   | 0.016***   | -0.155*** |
| HCROI (7)            | -0.062**| 0.112**  | 0.080*** | 0.016*** | 0.100     | 0.080*** | 0.016*** | 0.100     | 1.000     | 0.083**   | 0.016*** |
| QF (8)               | 0.134** | 0.080*** | 0.016*** | 0.100    | 0.080*** | 0.016*** | 0.100     | 0.083** | 0.100     | 1.000     | 0.083** |
| QF (9)               | -0.459***| 0.220*** | -0.155***| -0.188***| 0.061*** | 0.026   | -0.155*** | -0.188*** | 0.061*** | 1.000     | -0.043  |
| QF (10)              | 0.220***| 0.112**  | 0.080*** | 0.016*** | 0.100     | 0.083** | 0.016*** | 0.100     | 0.083** | 1.000     | -0.043  |
| QF (11)              | 0.134** | 0.080*** | 0.016*** | 0.100    | 0.080*** | 0.016*** | 0.100     | 0.083** | 0.016*** | 1.000     | 0.083** |
| Note: *, **, and *** indicate statistical significance at the .10, .05, and .01 levels. |
| Variable  | Model 1 Parameter (t-statistic) | Model 2 Parameter (t-statistic) | Model 3 Parameter (t-statistic) | Model 4 Parameter (t-statistic) | Model 5 Parameter (t-statistic) | Model 6 Parameter (t-statistic) | Model 7 Parameter (t-statistic) |
|-----------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|
| Constant  | 3.608 (2.739)                  | 3.380 (2.569)                  | 2.661 (1.964)                  | 1.381 (0.914)                  | 0.4807 (0.306)                  | 0.1048 (0.066)                  | 0.034 (0.022)                  |
| Firm age  | −0.031 (0.816)                 | −0.019 (−0.491)                | −0.013 (0.348)                 | −0.012 (−0.315)                | −0.016 (−0.411)                 | −0.001 (−0.259)                 | −0.009 (−0.239)                |
| Firm size | −0.340 (−1.562)                | −0.336 (−1.544)                | −0.262 (1.195)                 | −0.241 (−1.095)                | −0.143 (−0.638)                 | −0.071 (−0.314)                 | −0.387 (−0.167)                |
| ROA       | −0.049 (−1.828)                | 0.049 (1.158)                  | 0.044 (1.033)                  | 0.045 (1.056)                  | 0.055 (1.277)                   | 0.056 (1.305)                   | 0.056 (1.305)                  |
| LEV       | −0.000 (−0.034)                | −0.000 (−0.012)                | 0.000 (0.014)                  | 0.017 (1.001)                  | 0.014 (0.825)                   | 0.011 (0.629)                   | 0.011 (0.624)                  |
| HCROI     | −0.006*** (−2.964)             | −0.006*** (−3.016)             | −0.006*** (−3.058)             | −0.007*** (−3.266)             | −0.001*** (−3.182)              | −0.007*** (−3.166)              |                                |
| SFPI      |                                | 1.758** (2.165)                | 1.757** (2.165)                | 1.766** (2.178)                | 1.750** (2.162)                 | 1.750** (2.162)                 |                                |
| QR        |                                |                                | 0.225* (1.891)                 | 0.225* (1.891)                 | 0.213* (1.796)                  | 0.215* (1.805)                  |                                |
| OC        |                                |                                |                                | 0.001** (2.025)                | 0.001** (2.071)                 | 0.001* (1.881)                  |                                |
| RTR       |                                |                                |                                |                                | −0.006** (−2.316)               | −0.006*** (−3.177)              |                                |
| ITR       |                                |                                |                                |                                |                                |                                | −0.382 (−0.677)                |

Observations: 1291

R²: 0.009

Adj. R²: 0.006

F-statistic: 3.024

p-Value (F-statistic): 0.000

Note: *, **, and *** indicate statistical significance at the .10, .05, and .01 levels. All test statistics are reported based on two-tailed tests.
for non-labor-intensive counterparts in our sample. This finding is consistent with those for other countries. Walmsley et al. (2021) found that, as a highly labor-intensive sector in the United States, the service sector suffered more severe negative impacts from COVID-19 prevention policies than other sectors. For regions dominated by labor-intensive industries, even if the government has announced effective COVID-19 prevention policies, the dependence on labor will imply the local area is affected more severely by the pandemic (Narula, 2020). These findings support our RDT-informed arguments above, in which suppliers’ labor is considered a critical element that many manufacturers are reliant on.

With this finding, we call attention to the impact of public policy on OSCM—an area we argue to be under-researched. China’s Level I emergency response policy restricted the mobility of labor, a key production factor in OSCM, which had a significant impact on manufacturers’ operations. We believe our study to be one of the first to identify the labor immobility issue triggered by public policy mandates, ultimately leading to a multitude of supply chain disruptions in labor-intensive industries, who rely heavily on labor availability throughout the supply chain. This echoes the tenet of RTD, which argues that a firm’s key resources may reside outside the boundary of the firm. In our case, too heavy a reliance on suppliers’ labor of multi-tier supply chains in labor-intensive industries causes vulnerability in their supply chain when facing the shock created by the Level I emergency response policy.

With this finding, we thus complement extant research that has assessed the impact of public policy within various contexts, such as procurement and inventory management (Darby et al., 2020; Harland et al., 2019), sustainable management (Tokar & Swink, 2019), supply chain financing (Chen et al., 2021; Tseng et al., 2018; Xue et al., 2018), supply chain innovation (Kusi-Sarpong et al., 2019; Pavitt & Walker, 1976), and supplier management (Min, 1994; Wu et al., 2014; Zheng et al., 2021).

5.3 The role of operational slack

Our study also highlights the importance of operational slack, which served as a means to strengthen a manufacturer’s supply chain resilience. Specifically, we found that operational slack in the form of a higher quick ratio, a lower receivables turnover ratio, and a shorter operating cycle jointly ensured a manufacturer’s stability. While operational slack is often discounted due to the associated idle resources and costs, it can serve as an important safeguard. Because of its flexible nature, it can easily be deployed, enabling companies to maintain their operations, and thus engendering greater supply chain

| Table 7 | Robustness check of the cross-sectional regression analysis |
|---------|-----------------------------------------------------------|
| Variable | Model 1 Parameter (t-statistic) | Model 2 Parameter (t-statistic) | Model 3 Parameter (t-statistic) | Model 4 Parameter (t-statistic) |
| Constant | 0.113 (0.071) | -0.514 (–0.559) | -0.155 (–0.104) | -0.163 (–0.110) |
| Firm age | -0.009 (–0.025) | 0.0013 (0.037) | 0.008 (0.136) | 0.104 (0.180) |
| Firm size | -0.073 (–0.323) | -0.000 (–1.663) | -0.000** (–2.039) | -0.000** (–2.048) |
| ROA | 0.056 (1.310) | 0.059 (1.396) | 0.102 (1.496) | 0.103 (1.501) |
| LEV | 0.010 (0.625) | 0.017 (1.012) | 0.021 (0.791) | 0.021 (0.784) |
| QR | 0.213* (1.791) | 0.230* (1.934) | 0.401** (2.086) | 0.400** (2.081) |
| HCROI | -0.007*** (–3.183) | -0.007*** (–3.164) | -0.013*** (–3.763) | -0.013*** (–3.766) |
| SFPI | 1.750** (2.161) | 1.756** (2.195) | 2.192* (1.697) | 2.193* (1.697) |
| OC | 0.001** (2.077) | 0.001** (1.854) | 0.002** (1.962) | 0.002** (1.970) |
| RTR | -0.006** (–2.320) | -0.006** (–2.185) | -0.009** (–2.230) | -0.009** (–2.237) |
| ITR | -0.306 (–0.551) | -0.072 (–0.798) | -0.072 (–0.807) | |
| Observations | 1291 | 1291 | 1291 | 1291 |
| R² | 0.030 | 0.032 | 0.040 | 0.040 |
| Adj. R² | 0.023 | 0.025 | 0.033 | 0.033 |
| F-statistic | 4.332 | 4.248 | 5.352 | 5.353 |
| p-Value (F-statistic) | <.001 | <.001 | <.001 | <.001 |

Note: *, **, and *** indicate statistical significance at the .10, .05, and .01 levels. All test statistics are reported based on two-tailed tests.
resilience (Azadegan et al., 2013; Kovach et al., 2015). For example, firms with financial slack are able to pay higher wages to recruit labor, enabling continuous operations during emergencies. In February 2020 when the travel restriction was partially lifted, there was a big wave of competition for labor, manufacturers in coastal areas such as Wenzhou used chartered flights to transport workers from their hometown to the production plants and paid much higher wages to attract labor. As such, manufacturers with greater operational slack in the form of financial slack and excess inventory were rewarded by investors by a more positive reaction to the Level I emergency response measures.

This result aligns well with RDT, with operational slack reducing some of the dependence manufacturers have on labor. With this finding, our research complements studies on operational slack that focus on risk in production, operations, or supplier management (e.g., Azadegan et al., 2013; Azadegan et al., 2018; Kovach et al., 2015; Wiengarten et al., 2017). Our study is the first that investigates operational slack within the context of public policy, positioning operational slack in the form of financial slack and excess inventory as a supply chain resilience strategy to mitigate COVID-19 related risks.

However, our hypothesis related to inventory turnover was not supported (H3d). This counterintuitive finding suggests that investors did not reward manufacturers with higher inventory turnover levels. This observation may be explained by the disruptions caused by the COVID-19 pandemic on all fronts. The literature suggests that physical inventory is often deployed to buffer against external fluctuations in demand (e.g., Azadegan et al., 2013; Wiengarten et al., 2017); however, the demand side experienced significant shocks as well, especially during the early phase of the pandemic, which saw a decrease in consumption of many goods and services (Baker et al., 2020). Except for a few selected product categories, such as medical supplies and household items, demand decreased across the board, rendering excess inventory unhelpful. Another possible explanation for the finding is that the sale and delivery of heavy equipment, for instance, relies to a large degree on physical labor, which was curtailed. Thus, even if equipment was in inventory, it could not get delivered. This is similar to the situation where there is a shortage of truck drivers globally in 2021. Future research is encouraged to investigate this counterintuitive finding further, and to develop strategies for the post-pandemic reality. Calls for this were also made by Queiroz et al. (2020), who indicated that a new operational and supply chain resilience framework is needed for the post-COVID-19 era. The authors suggested that supply chain resilience strategies, such as operational slack, digitization, and automation, may have different effects in terms of mitigating disruptions in different post-pandemic scenarios. Our work appears to provide evidence for this.

5.4 | Implications

5.4.1 | Theoretical implications

Our theoretical implications are threefold. First, even though the literature has confirmed the important role of government policy interventions within a supply chain management context (Chang et al., 2013), most studies focus on long-term economic policies, with few having focused on public health emergency policies. Our research fills this gap by unveiling the interaction between a government’s emergency response and investors’ confidence in manufacturers associated with their ability to weather the crisis. Our findings call the attention of OSCM scholars to further consider how short-term policy interventions by governments could uproot established operations.

Second, we contribute to the literature at the intersection of public policy and OSCM by considering the important role of labor. While studies exist that investigate the impact of governmental policies on OSCM within the context of organizational resources, research that looks at this from the perspective of labor is limited. Our results show that a too heavy reliance on labor in supply chains poses significant risks to firms—a dependence, which we theorized from the perspective of the RDT. As such, the positive impact of the government’s Level I emergency response for manufacturers in more labor-intensive industries on their market valuations was not as strong (H2a). We thus not only identify the impact of public policy on manufacturers’ ability to use labor, but also call attention to how current experiences are destined to further affect practices in the future. Specifically, while automation has been lauded to replace a lot of human labor, this has to be weighted with the often-significant investments needed to move into that direction. Nevertheless, we believe that these experiences of companies will further excel the progression toward Industry 4.0 and smart, interconnected companies. Initial evidence for this was provided by the positive impact of the government’s Level I emergency response for SFPI SMEs on their market valuations to be stronger (H2b). An added benefit of these constellations is also the ability to frequently control such operations remotely, lessening the reliance on labor physically present.

Third, we extend the literature on supply chain resilience by investigating the effects of two types of operational slack (i.e., financial slack and excess inventory).
Our research may be the first to highlight the significance of operational slack as a supply chain resilience strategy in the context of public policy responding to public health emergency, confirming that both financial slack and excess inventory can help manufacturers reduce their reliance on labor throughout the supply chain and strengthen their supply chain resilience within the context of unprecedented, large-scale disruptions. Specifically, we find support for the beneficial attributes of liquidity, but also for the benefits derived from a lower inventory turnover ratio. While the latter is generally a sign of poor performance, since it indicates the firm not being able to collect debt in an effective manner, having large amounts of accounts receivables outstanding may be a form of financial slack that created benefits during the crisis. Similarly, our results imply beneficial attributes associated with longer operating cycles. Again generally a sign of poor performance, taking a longer time to turn inventory into cash was a favorable property, since now inventory was on hand to be used. Contrary to our expectations, this theme did not manifest when considering inventory turnover, which did not have any statistically detectable impact in our analysis. Overall, these results offer intriguing insights into the dynamics associated with operational slack, as well as the associated benefits derived from a decoupling of the firm’s operations from (and, taking an RDT perspective, making the firm less dependent on) market environments in times of crises.

5.4.2 Managerial implications

From a managerial perspective, our findings reveal the potential risk created by government policies for manufacturers’ OSCM. Although government policies and regulations are often central for supply chain risk mitigation, they may sometimes also carry secondary risks, as highlighted in this study. Our study thus calls for manufacturers to monitor and ideally anticipate public policy interventions, especially if they have an impact on the manufacturer’s industry, so that they can better prepare for this.

In addition, we highlight the roles of financial slack and excess inventory, confirming their potential in contributing to supply chain resilience. In general, slack financial resources provide greater flexibility in a company’s response to an unanticipated event and should thus be emphasized. Nevertheless, the value of excess inventory should not be neglected.

We also found that a greater dependence on labor exposes manufacturers to greater risks, especially when public policy curtails travel and the movement of labor. This is especially of concern when workers commute greater distances to get to work. This observation suggests that manufacturers should think strategically about their labor footprint.

5.4.3 Policy implications

Governments and their associated public policy initiatives have played a major role in the fight against COVID-19. Our study confirms the effectiveness of such measures, not necessarily on their immediate intended outcome, but on peripheral aspects, such as investors’ confidence in manufacturers’ ability to weather the crisis. Much can be learned from the experiences to date, particularly in terms of the unintended consequences of manufacturers not being able to perform due to restrictions on the movement of labor.

As such, governments should take a broader perspective to risk evaluation and aim to assess not only the consequences for the intended population but also for other stakeholders that may be affected, either directly or indirectly. Our research, for instance, demonstrates that upstream manufacturers’ labor force shortages caused a ripple effect through the supply chain, leading to severe disruptions for focal manufacturers.

In addition, governments should use policymaking as a means to provide guidance and support regarding the deployment of manufacturers’ operational slack, especially financial slack, since this could ensure the stability of cash flow and inventory in emergencies, and thus mitigate supply chain disruptions. For instance, several countries offered tax breaks and forgivable loans to consumers and small businesses. These policies have been essential for firms to maintain their cash flow. Financial slack is particularly important to protect companies from liquidity issues and to improve supply chain resilience.

Further, governments should foster the development of a domestic industrial supply chain. For instance, governments could gradually promote the automation and digitization of supply chains through public policy and subsidies, improving the resilience of manufacturers. Several such initiatives are already underway in response to the pandemic across multiple countries, such as the U.S. executive order on America’s supply chains (The White House, 2021).

Finally, we expect governmental responses to have a great impact on the national economy and stock markets. Although some policy uncertainty is inevitable during emergencies (Darby et al., 2020), policymakers need to consider the economic impacts of their actions. For example, information gathering, as an important step in disaster prevention and mitigation, should be comprehensive, with data coming from different sources. This information
should be available for public consumption as soon as possible, allowing firms and investors to gauge potential responses from policymakers and to be prepared.

6 | CONCLUSIONS

By assessing the market values of 1357 Chinese manufacturing companies during the COVID-19 pandemic, we can draw the following conclusions. First, we found that manufacturers benefited from the government’s Level I emergency response. This provides evidence of an important relationship between public policy and manufacturers’ OSCM.

Second, in contrast to previous research on labor dependence in the supply chain can have negative consequences in a public health emergency context. The underlying reason is that workers’ movements are restricted, and thus, this has a greater impact on manufacturers that rely more heavily on onsite workers, especially if they come from other parts of the country. This high dependence on labor can reduce the responsiveness of manufacturers.

Further, manufacturers with more financial slack responded to emergencies more effectively and experienced lesser impacts from supply chain disruptions. This is because financial slack creates cash flow redundancies, which can be flexibly deployed as alternatives in the absence of critical resources. Our findings suggest that manufacturers should pay more attention to their financial flow stability and try to maintain a certain level of excess cash flow as a resilience strategy for future disruptions.

Overall, this study investigated the experiences of Chinese manufacturers during the COVID-19 pandemic. The associated economic recession reduced global demand for industrial production, while manufacturers also struggled against upstream supply disruptions and limited capacity. As most manufacturing industries cannot produce remotely, the stability of the current supply chain is not a given. The current pandemic has prompted companies to acknowledge that a heavy dependence on labor may have a negative impact on supply chain performance—especially if that labor is not available locally—while digital automated production may offer operability and convenience. Many organizations are thus expected to re-examine their OSCM strategies based on the experience gained during the pandemic. It is our hope that the present work provides inspiration and a starting point to further this discussion.

As such, to answer Helper’s et al. (2021, p. 795) call for more research at the intersection of public policy and OSCM, since “there is a large methodological, conceptual, and theoretical overlap between OSCM research and public policy,” it is critical to make that connection. Particularly, scholars and managers are encouraged to develop a better understanding of methods or strategies to anticipate government moves, so that firms can be better prepared.

Further, while RDT provided a useful and appropriate framework of our investigation, alternate theoretical perspectives may be able to uncover additional vantage points. For example, future research could draw on information processing theory to identify how public policy initiatives could be more effectively communicated to reduce uncertainty among manufactures (there was significant uncertainty at first as to exactly what all these mandates would imply). How to better improve the operating efficiency of manufacturers and increase their slack to better deal with unexpected events is also a topic that warrants future research (Chen et al., 2022; Li et al., 2022; Wang et al., 2021; Zhu et al., 2008; Zhu & Sarkis, 2004).

Finally, further studies on the positive and negative impacts of a heavy dependence on labor within the context of government policy implications are encouraged. Specifically, investigations are needed that focus on the trade-off between labor and automation costs. In this vein, it will be useful to distinguish different manufacturing industries in regard to their inherent slack, for example captured by their degree of automation or other characteristics, to develop finer-grained insight. Further, while China served as an intriguing context because of the large-scale initiatives as part of the Level I emergency response, it would be valuable to carry out comparison studies across multiple countries to assess the efficacy of public policy in addressing the COVID-19 pandemic.

ORCID

Lujie Chen https://orcid.org/0000-0002-4229-7194
Tatyt Li https://orcid.org/0000-0002-3033-3725
Fu Jia https://orcid.org/0000-0002-9830-121X
Tobias Schoenherr https://orcid.org/0000-0003-4958-189X

REFERENCES

Azadegan, A., Golara, S., Kach, A., & Mousavi, N. (2018). Corporate environmental investments: A cross-national study on managerial decision making. International Journal of Production Economics, 199, 47–64.

Azadegan, A., Modi, S., & Lucianetti, L. (2021). Surprising supply chain disruptions: Mitigation effects of operational slack and supply redundancy. International Journal of Production Economics, 240, 108218.

Azadegan, A., Patel, P. C., & Parida, V. (2013). Operational slack and venture survival. Production and Operations Management, 22(1), 1–18.
Ba, S., Liscic, L. L., Liu, Q., & Stallaert, J. (2013). Stock market reaction to green vehicle innovation. *Production and Operations Management, 22*(4), 976–990.

Bai, C., Gao, W., & Sarkis, J. (2021). Operational risks and firm market performance: Evidence from China. *Decision Sciences, 52*(4), 920–951.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K. J., Sammon, M. C., & Viratayosin, T. (2020). *The unprecedented stock market impact of COVID-19*. National Bureau of Economic Research.

Bassi, L., & McMurrer, D. (2007). Maximizing your return on people. *Harvard Business Review, 85*(3), 115–124.

Bechtold, S. E., & Jacobs, L. W. (1991). Improvement of labour utilisation in shift scheduling for services with implicit optimal modelling. *International Journal of Operations & Production Management, 11*(2), 54–69.

Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of Political Economy, 70*(5, Part 2), 9–49.

Bhattacharya, M., & Narayan, P. (2015). Output and labor productivity in organized manufacturing: A panel cointegration analysis for India. *International Journal of Production Economics, 170*, 171–177.

Blackhurst, J., Dunn, K. S., & Craighead, C. W. (2011). An empirically derived framework of global supply resiliency. *Journal of Business Logistics, 32*(4), 374–391.

Bontis, N., & Fitz-enz, J. (2002). Intellectual capital ROI: A causal map of human capital antecedents and consequences. *Journal of Intellectual Capital, 3*(3), 223–247.

Bortolotti, B., Fotak, V., & Megginson, W. L. (2015). The sovereign wealth fund discount: Evidence from public equity investments. *The Review of Financial Studies, 28*(11), 2993–3035.

Boso, N., Danso, A., Leonidou, C., Uddin, M., Adeola, O., & Hultman, M. (2017). Does financial resource slack drive sustainability expenditure in developing economy small and medium-sized enterprises? *Journal of Business Research, 80*, 247–256.

Boxall, P. (2003). HR strategy and competitive advantage in the service sector. *Human Resource Management Journal, 13*(3), 5–20.

Brandon-Jones, E., Dutoirdoir, M., Neto, J. Q. F., & Squire, B. (2017). The impact of reshoring decisions on shareholder wealth. *Journal of Operations Management, 49*, 31–36.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *The Journal of Finance, 63*(6), 2899–2939.

Chandrasekaran, A., Senot, C., & Boyer, K. K. (2012). Process management impact on clinical and experiential quality: Managing the pandemic outbreaks: A case study of coronavirus disease 2019 (COVID-19). *Transportation Research Part E: Logistics and Transportation Review, 138*, 101967.

Cheung, M. C. (2020). Coronavirus’ Impact on Consumers and Businesses in China. https://www.emarketer.com/content/coronavirus-china-us-covid-19-impact-retail-travel
international coproduction study of public procurement. *Journal of Supply Chain Management, 55*(2), 6–25.

Hassan, T. A., Hollander, S., Van Lent, L., Schwedeler, M., & Tahoun, A. (2020). Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1 (No. w26971). National Bureau of Economic Research.

He, P., Sun, Y., Zhang, Y., & Li, T. (2020). COVID-19's impact on stock prices across different sectors—An event study based on the Chinese stock market. *Emerging Markets Finance and Trade, 56*(10), 2198–2212.

Helder, S., Gray, J. V., Hughes, M. M., & Roman, A. V. (2021). Public policy and operations management. *Journal of Operations Management, 67*(7), 780–802.

Hendricks, K. B., & Singhal, V. R. (1997). Delays in new product introductions and the market value of the firm: The consequences of being late to the market. *Management Science, 43*(4), 422–436.

Hendricks, K. B., Singhal, V. R., & Wiedman, C. I. (1995). The impact of capacity expansion on the market value of the firm. *Journal of Operations Management, 12*(3–4), 259–272.

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

Hillman, A. J., Withers, M. C., & Collins, B. J. (2009). Resource dependence theory: A review. *Journal of Management, 35*(6), 1404–1427.

Holweg, M. (2007). The genealogy of lean production. *Journal of Operations Management, 25*(2), 420–437.

Huang, H. (2021). Enhancing the resilience of the supply chain of the industrial chain must strengthen technological innovation. MIIT https://sme.miit.gov.cn/cypd/zjgd/art/2021/art_85e763b27483491983dba5a70d5794b2.html

Indjejikian, R. J., & Matejka, M. (2006). Organizational slack in decentralized firms: The role of business unit controllers. *The Accounting Review, 81*(4), 849–872.

Jacobs, B. W., & Singhal, V. R. (2014). The effect of product development restructuring on shareholder value. *Production and Operations Management, 23*(5), 728–743.

Jacobs, B. W., & Singhal, V. R. (2020). Shareholder value effects of the Volkswagen emissions scandal on the automotive ecosystem. *Production and Operations Management, 23*(5), 728–743.

Kovach, J. J., Hora, M., Manikas, A., & Patel, P. C. (2015). Firm performance in dynamic environments: The role of operational slack and operational scope. *Journal of Operations Management, 37*, 1–12.

Kusi-Sarpong, S., Gupta, H., & Sarkis, J. (2019). A supply chain sustainability innovation framework and evaluation methodology. *International Journal of Production Research, 57*(7), 1990–2008.

Lam, H. K., Zhan, Y., Zhang, M., Wang, Y., & Lyons, A. (2019). The effect of supply chain finance initiatives on the market value of service providers. *International Journal of Production Economics, 216*, 227–238.

Lease, R. C., Masulis, R. W., & Page, J. R. (1991). An investigation of market microstructure impacts on event study returns. *The Journal of Finance, 46*(4), 1523–1536.

Lee, B., & Preston, F. (2012). *Preparing for high-impact, low-probability events: Lessons from Eyjafjallajökull*. Chatham House.

Li, T., Chen, L., Jia, F., & Tang, O. (2022). The Development of an Industry Environment for the Internet of Things: Evidence From China. *IEEE Transactions on Engineering Management, Early Access*, 1–13.

Liu, H., Manzoor, A., Wang, C., Zhang, L., & Manzoor, Z. (2020). The COVID-19 outbreak and affected countries stock markets response. *International Journal of Environmental Research and Public Health, 17*(8), 2800.

Lo, C. K., Pagell, M., Fan, D., Wiengarten, F., & Yeung, A. C. (2014). OHSAS 18001 certification and operating performance: The role of complexity and coupling. *Journal of Operations Management, 32*(5), 268–280.

Ma, Y., Tang, A. P., & Hasan, T. (2005). The stock price overreaction effect: Evidence on Nasdaq stocks. *Quarterly Journal of Business and Economics, 44*(3/4), 113–127.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature, 35*(1), 13–39.

Mahmood, F., Xia, X., Ali, M., Usman, M., & Shahid, H. (2011). How Asian and global economic crises prevail in Chinese IPO and stock market efficiency. *International Business Research, 4*(2), 226–237.

Manikas, A. S., & Patel, P. C. (2016). Managing sales surprise: The role of operational slack and volume flexibility. *International Journal of Production Economics, 179*, 101–116.

McKinney, W., Perktold, J., & Seabold, S. (2011). Time series analysis in Python with statsmodels. Jarrod Millman Com.

Medcof, J. W. (2001). Resource-based strategy and managerial power in networks of internationally dispersed technology units. *Strategic Management Journal, 22*(11), 999–1012.

MIIT. (2021). MIIT’s notice on the construction of the third batch of SEPI SMEs. MIIT http://www.gov.cn/zhengce/zhengceku/2021-04/22/content_5601309.htm

Miller, J. L., Craighead, C. W., & Karwan, K. R. (2000). Service recovery: A framework and empirical investigation. *Journal of Operations Management, 18*(4), 387–400.

Mills, T. C., Coutts, J. A., & Roberts, J. (1996). Misspecification testing and robust estimation of the market model and their implications for event studies. *Applied Economics, 28*(5), 559–566.

Min, H. (1994). International supplier selection: A multi-attribute utility approach. *International Journal of Physical Distribution & Logistics Management, 24*(5), 24–33.

NAM (National Association of Manufacturers). (2020). *Economic and operational impacts of COVID-19 to manufacturers*. National Association of Manufacturers. https://www.nam.org/coronasurvey/

Narula, R. (2020). Policy opportunities and challenges from the COVID-19 pandemic for economies with large informal sectors. *Journal of International Business Policy, 3*(3), 302–310.

Nikookar, E., & Yanadori, Y. (2022). Preparing supply chain for the next disruption beyond COVID-19: Managerial antecedents of supply chain resilience. *International Journal of Operations & Production Management, 42*(1), 59–90.

Norouzi, N., de Rubens, G. Z., Choubanpishehzafar, S., & Enevoldsen, P. (2020). When pandemics impact economies and climate change: Exploring the impacts of COVID-19 on oil and electricity demand in China. *Energy Research & Social Science, 68*, 101654.

Orzes, G., Moretto, A. M., Moro, M., Rossi, M., Sartor, M., Caniato, F., & Nassimbeni, G. (2020). The impact of the United
Nations global compact on firm performance: A longitudinal analysis. International Journal of Production Economics, 227, 107664.

Park, S., Choi, G. J., & Ko, H. (2020). Information technology–based tracing strategy in response to COVID-19 in South Korea—Privacy controversies. JAMA, 323(21), 2129–2130.

Pavitt, K., & Walker, W. (1976). Government policies towards industrial innovation: A review. Research Policy, 5(1), 11–97.

Pfeffer, J., & Salancik, G. R. (2003). The external control of organizations: A resource dependence perspective. Stanford University Press.

PwC. (2020). COVID-19: What it means for industrial manufacturing. PwC https://www.pwc.com/us/en/library/covid-19/coronavirus-impacts-industrial-manufacturing.html

Queiroz, M. M., Ivanov, D., Dolgui, A., & Wamba, S. F. (2020). Does the impact of slack resources and environmental threat on product exploration and exploitation. Academy of Management Journal, 51(1), 147164.

Walmsley, T. L., Rose, A., & Wei, D. (2021). Impacts on the US macroeconomy of mandatory business closures in response to the COVID-19 pandemic. Applied Economics Letters, 28(15), 1293–1300.

Wang, L. (2007). Overview of the HIV/AIDS pandemic, scientific research and government responses in China. AIDS, 21, S3–S7.

Wang, Y., Xu, X., & Zhu, Q. (2021). Carbon emission reduction decisions of supply chain members under cap-and-trade regulations: A differential game analysis. Computers & Industrial Engineering, 162, 107711.

Wieland, A., & Wallenburg, M. C. (2013). The influence of relational competencies on supply chain resilience: A relational view. International Journal of Physical Distribution & Logistics Management, 43(4), 300–320.

Wiemengen, F., Fan, D., Lo, C. K., & Pagell, M. (2017). The differing impacts of operational and financial slack on occupational safety in varying market conditions. Journal of Operations Management, 52, 30–45.

Wood, L. C., Wang, J. X., Olesen, K., & Reiners, T. (2017). The effect of slack, diversification, and time to recall on stock market reaction to toy recalls. International Journal of Production Economics, 193, 244–258.

Wu, Z., Ellram, L. M., & Schuchard, R. (2014). Understanding the role of government and buyers in supplier energy efficiency initiatives. Journal of Supply Chain Management, 50(2), 84–105.

Wuest, T., Kusiak, A., Dai, T., & Tayur, S. R. (2020). Impact of COVID-19 on manufacturing and supply networks—The case for ai-inspired digital transformation. https://ssrn.com/abstract=3593540

Xu, X., Chen, X., Jia, F., Brown, S., Gong, Y., & Xu, Y. (2018). Supply chain finance: A systematic literature review and bibliometric analysis. International Journal of Production Economics, 204, 160–173.

Zeng, X. (2020). China’s Job Market under the Impact of COVID-19. Xinhuanet. http://www.xinhuanet.com/fortune/2020-09/28/c_1126550429.htm

Zheng, X., Li, D., Liu, Z., Jia, F., & Lev, B. (2021). Willingness-to-cede behaviour in sustainable supply chain coordination. International Journal of Production Economics, 240, 108207.

Zhou, X., Pan, Z., Hu, G., Tang, S., & Zhao, C. (2018). Stock market prediction on high-frequency data using generative adversarial nets. Mathematical Problems in Engineering, 2018, 1–11.

Zhu, Q., & Sarkis, J. (2004). Relationships between operational practices and performance among early adopters of green supply chain management practices in Chinese manufacturing enterprises. Journal of Operations Management, 22(3), 265–289.
Zhu, Q., Sarkis, J., & Lai, K. H. (2008). Confirmation of a measurement model for green supply chain management practices implementation. *International Journal of Production Economics, 111*(2), 261–273.

Zhu, X., Zhang, Z., Chen, X., Jia, F., & Chai, Y. (2022). Nexus of mixed-use vitality, carbon emissions and sustainability of mixed-use rural communities: The case of Zhejiang. *Journal of Cleaner Production, 330*, 129766.

**How to cite this article:** Chen, L., Li, T., Jia, F., & Schoenherr, T. (2022). The impact of governmental COVID-19 measures on manufacturers' stock market valuations: The role of labor intensity and operational slack. *Journal of Operations Management, 1*–22. [https://doi.org/10.1002/joom.1207](https://doi.org/10.1002/joom.1207)