DOI: 10.1111/eufm.12517

ORIGINAL ARTICLE

EUROPEAN FINANCIAL MANAGEMENT WILEY

The role of inventory in firm resilience to the Covid-19 pandemic

Olga Dodd[1] | **Shushu Liao**[2]

[1]Department of Finance, Auckland University of Technology, Auckland, New Zealand

[2]Department of Leadership and Management, Kühne Logistics University, Hamburg, Germany

Correspondence
Shushu Liao, Department of Leadership and Management, Kühne Logistics University, Hamburg, Germany.
Email: Shushu.Liao@klu.org

Abstract

We study the role of inventory in corporate resilience to Covid-19 in 2020, which triggered exogenous shocks to consumer demand, commodity prices and supply chains. Unexpected drops in consumer demand and commodity prices increase the costs of inventory. Conversely, inventory holdings can buffer against supply disruptions. Empirically, US firms with higher inventory experienced more negative stock market responses early in the crisis due to falling consumer demand. However, since May 2020, inventory has become valuable as a hedge against supply disruptions, improving firm performance. During Covid-19, unlike other crises, inventory played a unique role as a hedge against supply disruptions.

KEYWORDS
commodity price shock, consumer demand shock, Covid-19, inventory, supply chain disruption

JEL CLASSIFICATION
G31, G32, G01

We would like to thank John A. Doukas (the editor) and an anonymous referee for helpful comments. We also would like to thank Marcel Prokopczuk, Leibniz University Hannover, Jing Yu, University of Sydney, Alireza Tourani-Rad, Auckland University of Technology and other participants of the seminar at Kühne Logistics University, Germany, and 2021 New Zealand Finance Meetings for their helpful comments and suggestions. Open Access funding enabled and organized by Projekt DEAL.

1 | INTRODUCTION

Firms hold inventory to manage stockout and input price risks (Bianco & Gamba, 2019) and hedge against supply chain disruptions (Gao, 2018; Kulchania & Thomas, 2017). In the last several decades, a significant reduction in US firms' inventory holdings, mainly due to supply chain management deregulation and innovation, has increased the risk of disruptions (Kulchania & Thomas, 2017).[1] With historically low inventory holdings, firms face high costs of stockout, input price fluctuations, and supply chain disruption and rely more on their supply chains (Bianco & Gamba, 2019; Kulchania & Thomas, 2017). On the flip side, lower inventory holdings reduce storage and service costs, free up working capital and enable an increase in cash holdings (Bates et al., 2009). In this study, we examine inventory holdings' role in corporate resilience to the Covid-19 pandemic associated with exogenous shocks to consumer demand, commodity prices and supply chains.

The Covid-19 pandemic in 2020 affected the human population due to the rapid spread of the SARS-CoV-2 virus around the globe. In addition to significant health and social costs, this pandemic had substantial economic implications. With the introduction of measures to contain the spread of the virus, including “stay-at-home” orders and mandatory social distancing in the first part of 2020, consumer demand for discretionary products and services had plunged. Bekaert et al. (2020) posit that two-thirds of the drop in gross domestic product in the first quarter of 2020 was ascribed to the negative shock to aggregate demand. High levels of uncertainty have further contributed to reduced consumption and investment among consumers and firms (Ozili & Arun, 2020). With the sharp reduction in demand for oil and the following oil price war between Saudi Arabia and Russia, oil prices collapsed by more than 20% in a single day on 9 March 2020 (Albulescu, 2020).

Furthermore, public health measures, such as “stay-at-home” orders, social distancing rules and isolation requirements, led to manufacturing facilities working at a reduced capacity or even closing down, causing significant supply chain disruptions. In February 2020, China was the first country to shut down factories to prevent the spread of the virus, hampering global supply chains, particularly for firms relying on Chinese suppliers (Haren & Simchi-Levi, 2020; Meier & Pinto, 2020; The Economist, 2020). As the pandemic progressed, supply chain disruptions became more severe and widespread (Helper & Soltas, 2021), which potentially had devastating financial consequences for firms (Hendricks & Singhal, 2003, 2005a, 2005b). The distinct nature of supply chain disruptions during the Covid-19 pandemic sets it apart from previous crises, prompting research on corporate resilience in the context of this global pandemic.

In this study, we examine firm performance during different stages of the Covid-19 pandemic to assess the value of inventory holdings. Covid-19 has triggered unexpected exogenous shocks to consumer demand, commodity prices and global supply chains.[2] On the one hand, due to the plunge in consumer demand and sales in the first part of 2020, the value of inventory as a hedge against stockout had significantly diminished. Also, the concurrent collapse of

[1]Several studies report a decrease in inventory holdings over the last 50 years, for example, Rajagopalan and Malhotra (2001) and Chen et al. (2005).

[2]Covid-19 was an exogenous shock that had no bearing on corporate inventory holdings before the outbreak. Ramelli and Wagner (2020) provide a timeline of the key events. The first cases of the virus were reported to the WHO on 31 December 2019. Human-to-human transmission was not confirmed until 20 January 2020, and the WHO issued the first report on the outbreak on 22 January 2020.

commodity prices further diminished the value of inventory by reducing its benefit as a hedge against input price risk. On the other hand, inventory was valuable in safeguarding against global supply chain disruptions during the Covid-19 pandemic. Moreover, inventory carries storage and opportunity costs. Therefore, the net effect of inventory holdings on firm performance during the Covid-19 crisis remains an empirical question. The net effect can be negative if the value of inventory holdings as a hedge against stockout, rising commodity prices and supply chain disruptions is outweighed by its holding costs. This is what we find in the first part of 2020 when consumer demand and commodity prices plummeted, and supply chain issues just began to emerge.

The economic conditions changed in May 2020, when the US total business and retail sales recovered quickly to the precrisis levels after hitting their lowest level in April 2020. Following the recovery in consumer demand, commodity prices rebound from May 2020. In the environment of rising sales and input prices, we expect the inventory value to become positive. Moreover, as the Covid-19 pandemic continued, supply chain issues became more prominent (Helper & Soltas, 2021). Inventory value as a hedge against supply chain disruptions is manifested more during this time. Indeed, we find that higher inventory holdings warranted better firm performance in May–December 2020, particularly for firms experiencing supply chain disruptions in 2020.

Our sample includes all publicly traded US firms from Compustat with available firm-level data, excluding financial, real estate and utilities firms—3429 firms in total. We examine the determinants of the firm financial and operating performance in 2020. We split our analysis into two parts: (1) an analysis of the Covid-19 *crisis* using the January–April 2020 sample, and (2) a longer-run analysis of the Covid-19 pandemic using the full year 2020 with a focus on the later stage of the pandemic in May–December 2020 that featured a strong recovery in consumer demand and commodity prices, but also severe and widespread supply chain disruptions.[3] We measure the severity of Covid-19 using the change in the number of daily cases in each US state reported by USAFacts. To construct our inventory holdings variable, we use the firm's inventory position before the onset of the Covid-19 crisis. This approach addresses the concern that concurrent inventory holdings may be endogenous to unobservable firm-specific factors that could explain firm performance during the Covid-19 pandemic (see, e.g., Duchin et al., 2010).

We document that in January–March 2020, firms with higher precrisis inventory levels experienced a more negative stock market response to the growth in Covid-19 cases, suggesting that when consumer demand and commodity prices are falling, the costs of carrying inventory outweigh its benefits. The negative impact of inventory in January–March 2020 is economically significant. One standard deviation increase in inventory holdings leads to a 0.024% decline in daily stock returns, holding the growth rate of Covid-19 cases at the mean, which represents a 15.42% decrease over the absolute value of the unconditional mean of daily stock returns of 0.156%.

The negative impact of inventory holding on stock returns in January–March 2020 remains significant when we control for the impact of cash holdings and other firm characteristics documented in the literature as significant determinants of stock market response to Covid-19,

[3]We select the sample time periods based on the economic conditions such as consumer demand, commodity prices and global supply chain disruptions discussed in Section 2 "Economic backdrop during the Covid-19 pandemic in 2020".

including cash holdings, leverage, growth opportunities, profitability, firm size, cash flow (Ding et al., 2021; Ramelli & Wagner, 2020) and other variables that potentially influence stock returns, including S&P500 index return, stock return from the previous day, share turnover and daily range. Our main result is also robust to using alternative methods to estimate stock market performance (risk-adjusted returns, weekly and monthly returns, and buy-and-hold abnormal returns), a more restrictive sample period (1 January–20 March 2020, before the Federal Reserve Board [Fed] intervention announcement), and alternative inventory measures, including inventory-to-sales ratio, inventory-days ratio and abnormal inventory.

The documented negative impact of inventory on firm performance during the Covid-19 crisis is arguably driven by consumer demand and commodity price shocks. To test this proposition, we exploit a significant variation across industries in the degree of the shock to demand and commodity prices during the Covid-19 crisis (Ozili & Arun, 2020; Ramelli & Wagner, 2020). On the basis of the sales changes in Q1 2020, consumer discretionary, energy, industrials and materials industries are significantly adversely affected by Covid-19, while consumer staples, information technology, health care and communication services industries are less affected. The negative impact of inventory holds only for firms in highly affected industries, showing that the negative value of inventory is associated with the drop in consumer demand and commodity prices during the Covid-19 crisis.

Next, to disentangle the effects of consumer demand shock and commodity price shock, we consider different components of inventory—raw materials, work-in-progress and finished goods. We find that the finished goods component predominates the negative impact of inventory holdings in January–March 2020, implying that the drop in consumer demand can explain the negative impact of inventory holdings during the Covid-19 crisis. To reinforce our findings on the role of consumer demand shocks, we also provide evidence (in Supporting Information Appendix) that inventory holdings negatively affect firm performance during two other crises accompanied by significant adverse demand shocks: the 9/11 terrorist attacks and the 2007–2008 Global Financial Crisis.

One advantage of inventory holdings is protection against supply chain disruptions caused by Covid-19 (Haren & Simchi-Levi, 2020; Helper & Soltas, 2021). In the first part of 2020, the Covid-19 outbreak forced many factories in China to shut down, causing disruptions for firms that rely on Chinese supplies (Haren & Simchi-Levi, 2020; Meier & Pinto, 2020). We use the Hoberg and Moon Text-based Offshoring Network Database (Hoberg & Moon, 2017, 2019) to identify firms *with Chinese suppliers*. We find that in January–March 2020, the negative impact of inventory is mitigated by the benefits of inventory holdings as a hedge against supply chain disruption for firms *with Chinese suppliers*.

The second part of our investigation, the longer-run analysis, covers the full year 2020. It focuses on the role of inventory holdings in firms' resilience to the Covid-19 pandemic in the later stage of the Covid-19 pandemic in May–December 2020. During this period of rebounding consumer demand and rising commodity prices but disrupted supply chains, we document a reversal in the impact of inventory holdings. We find that firms with higher precrisis inventory holdings experience higher stock market returns in May–December 2020. The positive impact of inventory in May–December 2020 is economically significant. One standard deviation increase in inventory holdings leads to a 0.063% increase in daily stock returns, holding the growth rate of Covid-19 cases at the mean, which represents a 30.7% increase over the absolute value of the unconditional mean of daily stock returns in May–December 2020 of 0.206%.

While the first part of 2020 witnessed a breakdown of global supply chains caused mainly by shutdowns of factories in China, later in 2020, with the spread of the pandemic in the United

States and globally, supply chain issues are not limited to firms *with Chinese suppliers*. To capture global supply chain disruptions, we construct a broader measure, the number of mentions of "supply chain" in the firm's annual 10-K file in 2020. We find that firms that experience significant supply chain issues benefit more from higher inventory holdings in May–December 2020, when supply chain issues became more severe and widespread. This finding confirms the vital role of inventory holdings as a risk management tool against supply chain disruptions in the later stage of the Covid-19 pandemic.

Finally, we examine the impact of inventory holdings on firms' operating performance in 2020, measured using quarterly seasonally adjusted return on assets and sales growth. In line with the findings on stock market performance, precrisis inventory is a positive determinant of firms' operating performance in quarters two, three and four of 2020. The operating performance analysis reinforces our argument that inventory holdings became valuable in the later stage of the Covid-19 pandemic in 2020 when consumer demand and commodity prices recovered, but supply chain issues worsened.

Our study contributes to two strands of literature. First, it contributes to the literature on the economic impacts of the Covid-19 pandemic, particularly on corporate factors that determine a firm's resilience to the Covid-19 pandemic (e.g., Albuquerque et al., 2020; Ding et al., 2021; Fahlenbrach et al., 2020; Ramelli & Wagner, 2020). Several studies on the economic consequences of Covid-19 point to the importance of inventory and global supply chain management. Demers et al. (2021) report that the industry-adjusted inventory turnover ratio (costs of goods sold divided by inventory holdings) is a significant positive determinant of a firm's stock performance resilience in the first part of 2020. This evidence aligns with our finding that lower inventory levels are value-adding in the early days of the Covid-19 pandemic. Ramelli and Wagner (2020) report that internationally oriented US firms, especially those exposed to China, experienced worse stock market performance in the early stage of the Covid-19 pandemic in January–February 2020 when China had lockdown restrictions in place. Furthermore, they find the effect of exposure to China became positive and significant in February–March 2020 when the pandemic in China was getting more under control. For a global sample, Ding et al. (2021) show that firms with suppliers located in countries more affected by Covid-19 experienced more significant stock price declines in the first quarter of 2020, highlighting the importance of exposure to global supply chains during the Covid-19 pandemic. Meier and Pinto (2020) show that US industries with high exposure to imports from China experienced a significant decline in economic activities in March–April 2020 due to supply chain disruption issues. Cheema-Fox et al. (2021) examine companies' media responses to Covid-19 in February–March 2020 regarding their supply chain, among other factors. They find that companies with more positive sentiment in their responses experience less negative stock market returns. They argue that companies more committed to supplier relationships may respond more quickly to modify their supply chains to minimise the adverse effects of supply chain disruptions. We contribute to this literature by providing an in-depth analysis of the importance of inventory holdings conditional on the exposure to Covid-19 shocks, including supply chain disruptions, during the Covid-19 pandemic.

Second, our study contributes to the literature on working capital management that explores the role of inventory as a risk management tool. Inventory management is recognised as vital for improving operational flexibility and business growth (e.g., Chalotra, 2013; Prater et al., 2001). For instance, Wang (2019) reports that a high cash conversion cycle (i.e., the time a firm takes to sell its inventory or collect its receivables) leads to poor stock market performance. In contrast, Carpenter et al. (1994) and Kashyap et al. (1994) document that inventory holdings have liquidity value for financially constrained firms. More recently, Dasgupta et al. (2019) find that constrained firms deplete inventory more aggressively in response to adverse shocks. Bianco and Gamba (2019) show that firms hold inventory to mitigate commodity input price and cash flow risks. Bo (2001) and Caglayan et al. (2012) posit that firms with heightened demand uncertainty build up inventory to avoid stockout. Research also documents the opportunity costs of holding inventory due to a substitution effect between inventory and cash holdings. For instance, Bates et al. (2009) and Kulchania and Thomas (2017) argue that the dramatic decline in inventory explains the trend of increasing cash holdings for US firms. Gao (2018) shows that firms can shift resources from inventory to cash holdings due to switching to a just-in-time (JIT) inventory system. Our study contributes to this literature by focusing on the costs and benefits of inventory holdings in corporate resilience to a global pandemic.

The rest of the paper is organised as follows. Section 2 discusses stock market prices, consumer demand, commodity prices and supply chain issues as an economic backdrop of the Covid-19 pandemic. Section 3 provides the theoretical background and expectations on the role of inventory in general and during the Covid-19 pandemic. Section 4 describes our data and sample and report summary statistics. Section 5 discusses the empirical strategy and the results in detail. Section 6 concludes.

2 | ECONOMIC BACKDROP DURING THE COVID-19 PANDEMIC IN 2020

The spread of the Covid-19 pandemic has triggered a drop in stock prices in the first part of 2020. Panel (a) of Figure 1 plots the S&P500 daily prices from Compustat from 1 December 2019 to 31 December 2020. We observe a sharp and considerable drop in stock prices in February–March 2020, with a strong recovery in the second part of 2020.

As a result of "stay-at-home" orders,[4] business activities and consumer demand dropped substantially in April 2020. Panel (b) of Figure 1 plots monthly total business sales in 2020 reported by the U.S. Census Bureau. The total business (retail) sales declined from $1,347,262 ($418,734) million in January 2020 to $1,165,203 ($377,210) in April 2020 before rebounding to $1,274,361 ($462,286) in May 2020 (The U.S. Census Bureau). According to the National Bureau of Economic Research, the US economy was in a deep but short recession in March–April 2020 and started expanding in May 2020.[5]

The depressed demands during this period led to commodity prices, particularly crude oil used for gasoline and fuel, collapsing (e.g., Albulescu, 2020). Panel (c) of Figure 1 plots the Bloomberg Commodity index and West Texas Intermediate (WTI) crude oil prices from 1 December 2019 to 31 December 2020. It shows that the Commodity Index and the WTI crude oil prices recorded a continuous decline since the beginning of the Covid-19 outbreak and a crash in March 2020. Furthermore, the oil prices plunged below zero on 20 April 2020, falling

[4]In March–April 2020, most US states issued "stay-at-home" orders prescribing that people limit their movements to essential activities and ordering nonessential businesses to shut down. On 3 April 2020, 90% of the US population was living under "stay-at-home" orders. *Source*: https://www.pbs.org/newshour/politics/most-states-have-issued-stay-at-home-orders-but-enforcement-varies-widely.

[5]https://www.nber.org/news/business-cycle-dating-committee-announcement-july-19-2021 and also https://www.cnbc.com/2021/07/19/its-official-the-covid-recession-lasted-just-two-months-the-shortest-in-us-history.html

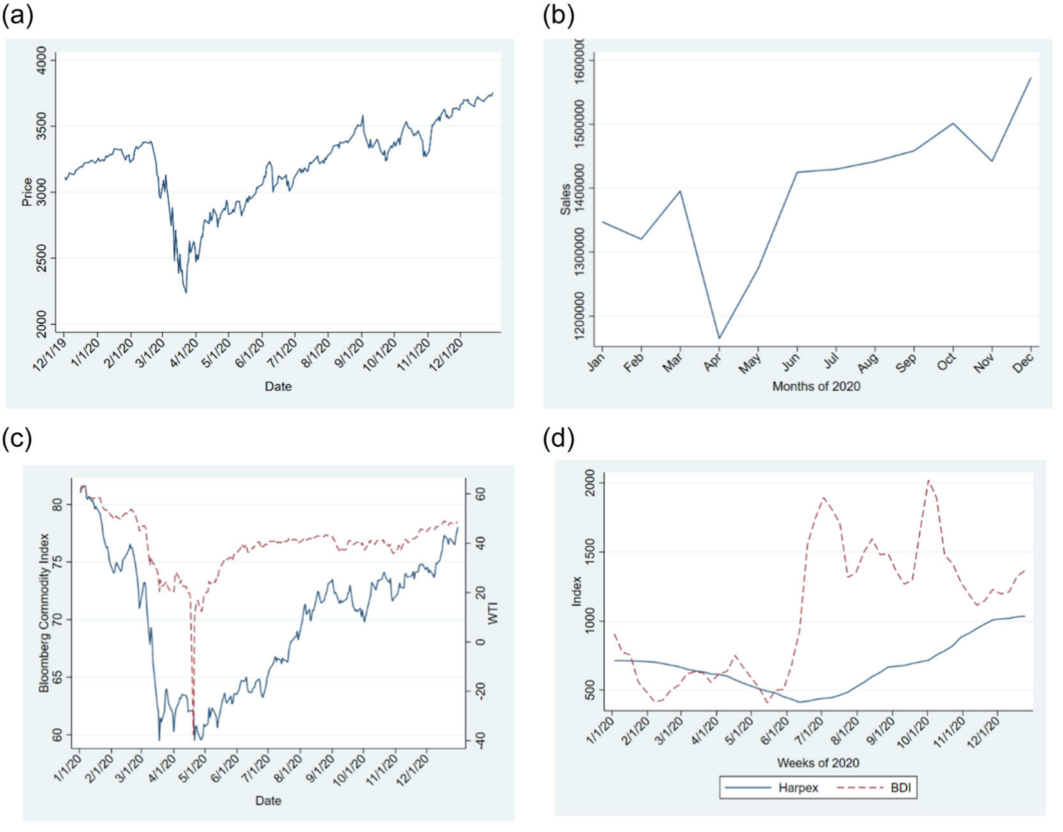

FIGURE 1 Economic conditions during the Covid-19 pandemic in 2020. Panel (a) Stock market performance. Panel (a) plots the S&P500 index daily prices from 1 December to 31 December 2020 (*Source*: Thomson Reuters). Panel (b) Consumer demand and sales. Panel (b) plots total business sales in January–December 2020 reported by the U.S. Census Bureau. Sales are in millions of dollars (*Source*: The U.S. Census Bureau https://www.census.gov/mtis/index.html). Panel (c) Commodity price index and WTI oil prices. Panel (c) plots the Bloomberg Commodity index (left *y*-axis) and WTI crude oil prices (right *y*-axis) from 1 December 2019 to 31 December 2020 (*Source*: Thomson Reuters' website). Panel (d) Supply chains in 2020—global transportation costs. Panel (d) plots the weekly movements of the Harpex index in the solid line and Baltic Dry Index (BDI) in the dashed line. The Harpex (Harper Petersen Charter Rates Index) reflects the worldwide container shipping rate changes in the charter market for container ships. The BDI is the global average cost of transporting dry bulk materials (*Sources*: Harper Petersen Holding GmbH and Baltic Exchanges). WTI, West Texas Intermediate. [Color figure can be viewed at wileyonlinelibrary.com]

into negative oil price territory for the first time in history. Commodity prices recovery started in May 2020.

Supply chain disruptions caused by Covid-19 were reflected in the global transportation costs. Panel (d) of Figure 1 plots the weekly movements of two global transportation costs indices: the Harpex index (Harper Petersen Charter Rates Index), which reflects the worldwide container shipping rate changes in the charter market for container ships, and the Baltic Dry Index (BDI), which is a global average cost of transporting dry bulk materials. Both indices rose in the second part of 2020, indicating a substantial increase in global transportation costs due to supply chain disruptions during the Covid-19 pandemic. According to the report by GEP, in

2020, the total cost of supply chain disruptions for US and European businesses was \$4tn, with 45% of firms reporting that Covid-19 significantly disrupted their supply chain.[6]

3 | THEORETICAL BACKGROUND AND PREDICTIONS

3.1 | The role of inventory holdings

Firms hold inventory to avoid stockout, hedge against rising input prices and mitigate supply chain disruptions. According to the stockout-avoidance theory, firms invest in inventory to avoid stockout and loss of prospective sales when they experience an unanticipated increase in demand since production takes time (e.g., Dasgupta et al., 2019; Eichenbaum, 1989; Wen, 2005).[7]

For hedging purposes, firms hold more inventory when anticipating a rise in input prices. Chen et al. (2005) argue that high inflation incentivises firms to buy inputs earlier. Bianco and Gamba (2019) posit that firms hold inventory as an operational hedge, and using inventory as a risk management tool adds more value when commodity prices are rising.

Finally, firms hold inventory to hedge against supply chain disruptions (Gao, 2018; Kulchania & Thomas, 2017; Tomlin, 2006). Supply chain disruptions can be very costly for firms that are unprotected. Hendricks and Singhal (2003, 2005a, 2005b) document a significant deterioration in financial and operating performance and a lasting increase in the cost of capital for firms that experience supply chain disruption events. One strategy to hedge supply risk is to hold higher inventory levels as a buffer. However, in the last several decades, US firms significantly reduced their inventory holdings due to supply chain management deregulation and innovation and the use of JIT inventory management practices (Gao, 2018; Kulchania & Thomas, 2017). Moreover, US firms are less vertically integrated than in the past and more reliant on offshore suppliers (Snyder et al., 2016). Low inventory holdings and high reliance on suppliers imply that firms may face substantial supply chain disruption risks.

Economic literature defines inventory cost as a function of the distance between the actual inventory holdings and the target inventory level determined by the firm's sales (e.g., Blanchard, 1983; Eichenbaum, 1989).[8] This definition reflects two main types of inventory costs. The first type is the costs of holding inventory that increase with inventory levels. Inventory holding costs include investment opportunity costs, physical storage costs, staffing costs, inventory service costs (e.g., insurance and taxes) and inventory risk or depreciation costs (e.g., obsolescence or theft of inventory) (La Londe & Lambert, 1977). The second type is stockout costs, which are high when the inventory levels are low, or the sales levels (and thereby target inventory levels) are high. Therefore, inventory holding is a trade-off between the benefits of avoiding stockout and the costs of holding inventory.

This definition can be extended to include costs of rising input prices and costs of potential supply chain disruptions. Firms hold additional inventory as a buffer against rising input costs

[6]https://www.cips.org/supply-management/news/2021/march/total-cost-of-supply-chain-disruption-in-2020-was-4tn/

[7]Firms with convex production costs face a more rapid rise in production costs when demand is favourable. Therefore, firms need to accumulate inventory as they would underproduce when demand is high and overproduce when demand is low.

[8]Blanchard (1983) defines the costs of holding inventory as $G_t = d/2\left(I_t - I_t^*\right)^2$, where I_t is the inventory holdings, and $I_t^* = aS_t$ is the target inventory level determined by sales S_t. When I_t is significantly higher than I_t^*, firms face the holding costs. When I_t is significantly lower than I_t^*, firms face the costs of stockout.

and supply uncertainties. However, holding additional inventory is costly for firms. As a result, inventory holding is a trade-off between the benefits of avoiding stockout and protecting against rising input costs and supply chain disruptions and the costs of holding inventory.

3.2 | Covid-19 and inventory holdings

Covid-19 has triggered unexpected adverse shocks to consumer demand, commodity prices and global supply chains, all at once. First, Covid-19 adversely affected consumer demand. Consumer demand for discretionary products and services plunged markedly in the first part of 2020 (discussed in Section 2). A slump in sales decreases the target inventory levels and reduces the probability of stockout. The benefits of holding inventory to avoid stockout become inconsequential. On the contrary, excessive amounts of inventory increase inventory holding costs. If firms expect sales to rise in the future, they may continue holding inventory and face substantial costs. If firms expect sales to decrease, they may choose to liquidate inventory at a discounted price, given the depressed demand conditions. In either case, firms experience a decrease in valuation. Therefore, in the first part of 2020, we expect higher inventory levels to be associated with lower firm financial performance. However, during the consumer demand recovery stage (discussed in Section 2), the role of inventory holding is expected to reverse. As sales rebound, firms with higher inventory holdings are better positioned to meet the growing consumer demand and are expected to perform better. Therefore, during the consumer demand recovery stage, the value of inventory holdings is expected to be positive.

Second, Covid-19 adversely affected commodity prices. Oil and other commodity prices dropped significantly during the Covid-19 crisis in March–April 2020 (discussed in Section 2). In this deflationary environment,[9] inventory holdings became less critical as a hedge against input price risk while incurring substantial holding costs. However, in the later stage of the Covid-19 pandemic, as the commodity prices were rising, the value of inventory holdings is expected to become positive since firms with higher inventory holdings are less adversely affected by rising prices of inputs, which should translate into better financial performance.

Third, Covid-19 pandemic adversely affected supply chains. As a result of factories working at reduced capacity, Covid-19 caused significant supply disruptions (Haren & Simchi-Levi, 2020; Helper & Soltas, 2021; Meier & Pinto, 2020). Lower inventory holdings increase a firm's reliance on its suppliers, increasing the costs of supply chain disruptions (Kulchania & Thomas, 2017). We expect that during the Covid-19 pandemic, firms with higher inventory holdings to have better financial performance as they can use inventory as a buffer against supply disruptions to prevent sales losses and production interruptions.

To summarise, in the first part of 2020 (the Covid-19 crisis period), when consumer demand and commodity prices collapsed, the net value of inventory holdings is expected to be negative. During this period, the value of inventory as a hedge against stockout and rising commodity prices is not expected to offset the costs of holding inventory. Therefore, firms with higher inventory holdings are expected to underperform. As consumer demand and commodity prices bounce back, the role of inventory holdings is expected to change. From May 2020, firms with

[9]Inflation is negative in March (−0.22%) and April 2020 (−0.68%) (Cavallo, 2020). See also the discussion in https://www.reuters.com/article/us-usa-economy-inflation/u-s-inflation-subdued-with-economy-in-recession-idUSKBN23H1Y1

higher inventory holdings should perform better as they can use their inventory holdings to prevent stockout and sales loss and are less affected by the rising commodity prices. Furthermore, we expect inventory holdings to be valuable to offset supply shortages for firms exposed to supply chain disruptions as the Covid-19 pandemic continues.

4 | DATA, SAMPLE AND SUMMARY STATISTICS

To evaluate the role of inventory holdings during the Covid-19 pandemic in 2020, we examine determinants of firm financial and operating performance. Motivated by the distinct change in the economic conditions in May 2020 (discussed in Section 2), our analysis contains two parts to examine the role of inventory: (1) analysis of daily stock market returns in January–April 2020 (the Covid-19 crisis) and (2) analysis of daily stock market returns and firm operating performance in January–December 2020, with a focus on May–December 2020 (the later stage of Covid-19 pandemic).

Our sample includes all publicly traded firms incorporated in the United States from Compustat, excluding financials (Global Industry Classification Standard [GICS] industry sector 40), real estate (GICS industry sector 60) and utilities (GICS industry sector 55).[10,11] We extract daily stock prices from the Compustat Security Daily file. Stock prices are adjusted for dividends using the daily multiplication factor and the price adjustment factors provided by Compustat. To capture the development of the Covid-19 crisis in the first part of 2020, we obtain the number of daily confirmed cases of Covid-19 in each state of the United States from USAFacts.[12] Following Ding et al. (2021), we compute the daily growth rate of Covid-19 cases for each state as $[\log(1 + \#\text{Cases}_t) - \log(1 + \#\text{Cases}_{t-1})]$. We merge the daily growth rates of Covid-19 cases with firm-level data by date and state where the company is headquartered.

We retrieve accounting and financial firm-level variables from the Compustat Fundamental Annual file. Our main explanatory variable is corporate *Inventory* holdings, measured as total inventory divided by total assets.[13] Our *Inventory* variable is the average of the beginning- and end-of-year values in the 2019 calendar year, capturing a firm's "normal" level of inventory holdings.[14] We use predetermined (precrisis) inventory holdings because the changes in a

[10] We exclude financial, real estate and utility firms because these firms are highly regulated, and their financial and investment policies are less subject to the discretion of the companies.

[11] In unreported robustness tests, we also exclude services industries from our sample (i.e., Commercial & Professional Services, Transportation, Communication Services, Health Care Providers & Services, Life Sciences Tools & Services, Energy Equipment & Services, IT Services and Internet Software & Services) and show that our results hold.

[12] The data for the number of confirmed cases can be downloaded from https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/

[13] Total inventory as a measure of inventory holdings is widely used in the literature (e.g., Dasgupta et al., 2019; Kulchania & Thomas, 2017).

[14] We believe the average inventory in 2019 as a measure of inventory holdings fits our setting for two reasons. First, averaging is expected to smooth the ratios and to result in a more representative figure than that calculated from only the most recent financial statement (Edmister, 1972). Also, an average value might be a true indicator of a firm's use of inventory rather than the single-period measure (Ferri & Jones, 1979). Second, more than 40% of firms file their 10-K reports in April of the following year even though their last fiscal year end (FYE) is December (Fama et al., 1992). Hence asset-pricing studies typically require a 3-month to a 6-month gap between the FYE and return tests (Daniel et al., 2001; Hirshleifer & Jiang, 2010). Given that the information for the FYE 31 December 2019 is not available in the Covid-19 crisis period (January–April 2020) for a significant portion of firms, it is reasonable to assume that investors may react according to the available information for the FYE 31 December 2018. Nevertheless, our main findings hold when, in the regression, we use the inventory holdings variable at the end of 2019 instead of the average 2019 value.

firm's inventory positions during the crisis may be related to the stock market reactions to the inventory holdings.

Following Ding et al. (2021), we control for various firm-level characteristics, including *Cash holdings*, *Leverage*, market-to-book ratio (*MTB*), return on assets (*ROA*), *Firm size* and *Cash flow*. *Cash* is defined as cash and marketable securities divided by total assets. *Leverage* is the sum of total long-term and current liabilities and debt divided by total assets. *MTB* is the market value of assets divided by the book value of total assets. *ROA* is the ratio of operating income before depreciation divided by total assets. *Firm size* is measured as the natural logarithm of total assets. *Cash flow* is defined as income before extraordinary items plus depreciation and amortisation divided by total assets. Consistent with the *Inventory* variable, all firm-level variables are the average of the beginning- and end-of-year values in 2019. Additionally we include several explanatory variables to control for the market microstructure variations, including *SP500 return* (contemporaneous S&P500 index return), *Lag return* (stock return from the previous day) and *Share turnover* (measured as the daily trading volume, the number of shares traded and scaled by shares outstanding)—a proxy variable for stock liquidity (Chordia et al., 2001) and *Daily range* (measured as the difference between the high and low daily prices scaled by the closing price)—a proxy variable for daily volatility (Parkinson, 1980). Detailed variable definitions are provided in Supporting Information Appendix SA.1. To reduce the impact of outliers, we winsorise all variables at the 1st and 99th percentiles of their distributions.

After removing financial, real estate, and utilities firms and observations with missing values for the main and control variables, our sample has a total of 3429 firms. We report descriptive statistics for all variables in Table 1, including the number of observations (*N*), mean, standard deviation (SD), 25th percentile (p25), median and 75th percentile (p75). The average *Return* in *January–April 2020* is −0.156% with a large standard deviation, while the average *Return* in *May–December 2020* is 0.206%. The average daily growth rate of Covid-19 cases in January–April 2020 (*Covid19*) is 0.087. The mean value of *Inventory* is 0.091.[15] The average *Cash* is 0.267, and the average *Leverage* is 0.529. The *MTB*'s mean (median) value is 8.847 (1.802), displaying a highly skewed distribution.[16,17] The average logarithm of total assets (*Firm size*) is 5.489, and the mean *ROA* and *Cash flow* are negative, −0.506 and −0.655, respectively.

5 | EMPIRICAL STRATEGY AND RESULTS

5.1 | Short-run analysis of the Covid-19 crisis (January–April 2020)

This section examines the impact of inventory holdings on daily stock returns during the Covid-19 crisis in January–April 2020 (using various return estimation procedures) conditional

[15]The mean value for the inventory-to-assets ratio is comparable to that of Kulchania and Thomas (2017) for the year 2014.

[16]See, for example, Erickson and Whited (2000) for discussions of a highly skewed Tobin's *q*.

[17]We conduct (unreported) robustness analyses to show that our results are not influenced by the extreme values of the *MTB* variable. We re-estimate the baseline regression (1) without controlling for *MTB*, (2) capping the *MTB* variable to 10 (following Campello & Graham, 2013) and (3) deleting observations with book value of assets less than 1 million USD and *MTB* larger than 10. Our main results remain robust after mitigating the influence of *MTB* extreme values.

TABLE 1 Descriptive statistics.

This table reports the number of firm-day observations (*N*), mean, standard deviation (SD), 25th percentile (p25), median and 75th percentile (p75) of the daily growth rate of Covid-19 cases by state in January–April 2020 (Covid-19), daily stock returns in percentages (Return) in January–April 2020 and May–December 2020, firm-level variables and market microstructure variables. All variables are defined in Appendix A1.

Variables	*N*	Mean	SD	p25	Median	p75
Return January–April 2020 (%)	203,930	−0.156	8.427	−2.624	0.000	2.121
Return May–December 2020 (%)	430,004	0.206	4.145	−1.803	0.011	2.039
Covid19	203,930	0.087	0.169	0.000	0.000	0.115
Inventory	203,930	0.091	0.128	0.000	0.027	0.137
Cash	203,930	0.267	0.293	0.042	0.136	0.423
Leverage	203,930	0.529	1.409	0.056	0.236	0.440
MTB	203,930	8.847	34.561	1.192	1.802	3.398
ROA	203,930	−0.506	2.157	−0.276	0.064	0.129
Firm size	203,930	5.489	2.992	3.650	5.784	7.604
Cash flow	203,930	−0.655	2.651	−0.307	0.028	0.095
SP500 return	203,930	0.001	0.030	−0.011	0.000	0.011
Lag return	200,714	−0.130	8.426	−2.568	0.000	2.151
Share turnover	202,008	0.022	0.425	0.002	0.006	0.014
Daily range	203,788	0.128	2.580	0.031	0.061	0.113
Inventory_FG	166,797	0.046	0.084	0.000	0.004	0.052
Inventory_RM	165,081	0.026	0.049	0.000	0.000	0.033
Inventory_WIP	164,701	0.011	0.026	0.000	0.000	0.009

on Covid-19 cases growth rates in 2020. Then, we run tests to examine what drives the value of inventory holdings—consumer demand shock, commodity price shock or supply chain disruptions. Finally, we perform several robustness tests.

5.1.1 | Inventory and short-run stock market response to the Covid-19 crisis

We start our investigation with univariate analysis. Panel A of Table 2 reports the correlation matrix between inventory and other firm-level factors and cumulative stock returns over the period of the Covid-19 crisis (January–April 2020). It shows that inventory is negatively associated with cumulative returns in January–April 2020. *Cash*, *Firm size* and *ROA* display positive correlations, while leverage and MTB negatively correlate with cumulative returns. Panel B of Table 2 reports stock returns and their correlations with growth rates of Covid-19 cases in January–April 2020 for firms with low, medium and high inventory holdings. Firms with high pre-Covid-19 inventory holdings ("High") display lower mean stock returns during the pandemic than firms with low and medium inventory holdings. Also, the correlation between stock

TABLE 2 Stock market returns correlations.

This table reports the mean daily stock return from 1 January to 30 April 2020, the correlation between stock return and the growth rate of Covid-19 cases, and the corresponding p value for firms with low, medium and high precrisis inventory holdings assigned based on the sample terciles.The table presents the pairwise correlation matrix between cumulative stock returns over the period of Covid-19 crisis (1 January to 30 April 2020) and inventory holdings as well as other firm-level factors (the control variables). ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Pairwise correlation between cumulative stock returns and firm-level variables in January–April 2019

Variables	***Cumulative Return***	***Inventory***	***Cash***	***Leverage***	***MTB***	***ROA***	***Firm size***
Cumulative Return	1.000						
Inventory	−0.059***	1.000					
Cash	0.153***	−0.299***	1.000				
Leverage	−0.121***	−0.062***	0.024	1.000			
MTB	−0.072***	−0.081***	0.146***	0.543***	1.000		
ROA	0.107***	0.109***	−0.211***	−0.684***	−0.719***	1.000	
Firm size	0.058***	0.057***	−0.369***	−0.386***	−0.487***	0.559***	1.000
Cash flow	0.112***	0.097***	−0.186***	−0.694***	−0.695***	0.960***	0.542***

Panel B: Stock returns and correlations for firms low, medium and low inventory holdings

Inventory	**Low**	**Medium**	**High**
Stock return	−0.130	−0.131	−0.209
p Value (stock return)	(0.000)	(0.000)	(0.000)
Correlation between stock return and Covid-19 cases growth	−0.006	−0.011	−0.020
p Value (correlation)	(0.105)	(0.006)	(0.00)

returns and the growth rate of Covid-19 cases is more negative for high-inventory firms. This analysis provides initial evidence that firms with higher inventory holdings have lower stock returns in January–April 2020.

Next, we evaluate the role of inventory during the Covid-19 crisis using multivariate regression analysis. We employ a model specification with an interaction term of *Inventory* and *Covid19* variables that captures the effect of firms' precrisis inventory holdings on the stock market response to the severity of the Covid-19 crisis. We estimate the following model:

$$\begin{aligned} R_{it} = \alpha &+ \delta_1 Inventory \times Covid19_t + \delta_2 Covid19_t + \delta_3 Inventory + \varphi_1 X_i + \varphi_2 X_i \times Covid19_t \\ &+ \varphi_3 Z_i + Fixed\ \ effects + \varepsilon_{it}, \end{aligned} \tag{1}$$

where R_{it} is the daily stock log return for firm i and date t in January–April 2020; $Covid19_t$ is the daily growth rate of Covid-19 cases by state in January–April 2020; *Inventory* is the average of the beginning- and end-of-year ratios of total inventory to total assets in 2019. The main coefficient of interest isδ_1 that captures the impact of inventory on the stock market response during the Covid-19 crisis.

While estimating the impact of inventory holdings, it is essential to control for other explanations. Ramelli and Wagner (2020) and Ding et al. (2021) show that cash holdings and leverage are important determinants of the stock market reaction to Covid-19. That is, firms with stronger financial positions (e.g., higher cash holdings and lower leverage) before the pandemic experience a less negative stock market response. Furthermore, inventory and cash holdings can be substitutes, and lower inventory holdings are likely associated with higher cash holdings (Bates et al., 2009; Gao, 2018; Kulchania & Thomas, 2017). Hence, in Equation (1), we include the interactions between a vector of firm-level controls X_i and $Covid19_t$, including *Cash*, *Leverage*, *MTB*, *ROA*, *Firm size* and *Cash flow*.

We also control for other return factors Z_i that are known to predict daily returns, including share turnover (measured as the daily trading volume scaled by shares outstanding), daily range (measured as the difference between the high and low daily prices scaled by the closing price), contemporaneous *SP500 return* and *Lag return* (stock return from the previous day). Share turnover is informative about stock liquidity, which is an important predictor of the stock price (Chordia et al., 2001). The stock price daily range is an efficient estimator of daily volatility (Parkinson, 1980). We include a lagged return to control for potential market overreaction during the Covid-19 crisis by capturing short-term return reversal (e.g., Da et al., 2014).

Finally, we include different combinations of industry, state and firm fixed effects to control for unobserved heterogeneity. Standard errors are robust to heterogeneity and clustered at the firm level.

Table 3 reports the estimation results of Equation (1). Model 1 includes industry fixed effects using GICS industry classification and state fixed effects to control for unobserved heterogeneity at the state level, such as local financial conditions, changes in the state policy for lockdown regulations, and governmental support. Model 2 includes firm fixed effects and forces identification of the regression coefficients within a firm. Since all firm-level variables are measured only once per firm, firm fixed effects subsume the effect of inventory and other firm-level variables on their own (in Models 2–5) (see, e.g., Duchin et al., 2010).

The coefficient estimates on the interaction variable *Inventory* × *Covid19* are negative and statistically significant at the 5% level, suggesting that higher precrisis inventory holdings are associated with a more negative stock market response to Covid-19. As expected, the coefficient estimate on *Covid19* is negative and significant at the 1% level, capturing a negative market response to Covid-19 for all firms. The coefficient estimate on *Inventory* in Model 1 is positive but insignificant, showing that the effects of inventory on stock returns are not significant in normal times (beyond the Covid-19 pandemic). The negative and significant coefficient on *Inventory* × *Covid19* indicates that the overall impact of inventory holdings during the Covid-19 crisis is negative.

Regarding the impact of other firm characteristics (*Cash holdings*, *Leverage*, *MTB*, *ROA*, *Firm size* and *Cash flow*) on stock returns during the Covid-19 crisis, in Model 2, the coefficient estimates on the interaction terms of firm-level variables with the Covid-19 variable show that firms with higher cash holdings and more profitable firms before the Covid-19 pandemic experience significantly less negative stock returns, in line with the findings of Ramelli and Wagner (2020) and Ding et al. (2021).

TABLE 3 Inventory and short-run stock market response to the Covid-19 crisis.

This table reports the estimates of Ordinary Least Squares panel regressions of the impact of inventory on the response of stock returns to the growth of Covid-19 cases using daily returns in Panel A and weekly, monthly and buy-and-hold abnormal returns in Panel B. The sample period is from 1 January to 30 April 2020, except for Model 4 in Panel A, which employs the sample from 1 January to 20 March 2020. In Panel A, the dependent variable is the daily stock return (Models 1, 2, 3 and 5) and risk-adjusted daily stock return (Model 4). In Panel B, in Models 1 and 2 (3 and 4), the dependent variable is the weekly (monthly) stock returns, and the independent variables are all measured on a weekly (monthly) basis. In Model 5 of Panel B, the dependent variable is buy-and-hold abnormal returns over January–April 2020, computed using the Fama–French and Carhart four-factor model. *Covid19* is the growth rate of Covid-19 cases by state. *Inventory* is the average total inventory to total assets in 2019. All variables are defined in Appendix A.1. In Models 2–5 in Panel A and Models 1–4 in Panel B, firm-level variables are absorbed by firm fixed effects. In parentheses, we report robust standard errors clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Daily returns

	(1) Industry and state fixed effects	(2) Firm fixed effects	(3) With return factor controls	(4) Four-factor model	(5) 1 January–20 March 2020
Inventory × Covid19	−2.212**	−2.159**	−2.210**	−2.390**	−2.283**
	(1.01)	(1.02)	(1.03)	(1.05)	(1.10)
Covid19	−1.360***	−1.396***	−1.556***	−1.128**	−1.579***
	(0.46)	(0.46)	(0.48)	(0.49)	(0.49)
Cash × Covid19	0.727*	0.791*		0.948**	0.314
	(0.44)	(0.44)		(0.48)	(0.48)
Leverage × Covid19	0.001	0.001		−0.002	0.002
	(0.01)	(0.01)		(0.01)	(0.01)
MTB × Covid19	0.093	0.094		−0.068	0.280
	(0.21)	(0.22)		(0.26)	(0.23)
ROA × Covid19	0.131**	0.135**		0.072	0.090
	(0.05)	(0.05)		(0.06)	(0.06)
Firm size × Covid19	0.056	0.031		0.071	0.142
	(0.14)	(0.14)		(0.17)	(0.16)
Cash flow × Covid19	−0.100	−0.103		0.086	−0.169
	(0.16)	(0.17)		(0.20)	(0.17)
SP500 return			0.798***		
			(1.13)		
Lag return			−0.133***		
			(0.01)		
Share turnover			0.831		
			(0.60)		

(Continues)

TABLE 3 (Continued)

Panel A: Daily returns	(1) Industry and state fixed effects	(2) Firm fixed effects	(3) With return factor controls	(4) Four-factor model	(5) 1 January–20 March 2020
Daily range			−0.127		
			(0.07)		
Inventory	0.141				
	(0.14)				
Cash	0.081				
	(0.08)				
Leverage	−0.009				
	(0.02)				
MTB	−0.000				
	(0.00)				
ROA	−0.054				
	(0.04)				
Firm size	0.006				
	(0.01)				
Cash flow	0.040				
	(0.03)				
Industry and state fixed effects	Yes	No	No	No	No
Firm fixed effects	No	Yes	Yes	Yes	Yes
Observations	203,930	203,930	198,822	203,930	133,915
R^2	0.002	0.008	0.141	0.010	0.016

Panel B: Weekly, monthly or buy-and-hold returns	(1) Weekly stock returns	(2)	(3) Monthly stock returns	(4)	Buy-and-hold abnormal returns	(5)
Inventory × *Covid19*	−2.558**	−2.304**	−0.022***	−0.014*	*Inventory*	−0.201**
	(1.00)	(1.10)	(0.01)	(0.01)		(0.08)
Cash × *Covid19*	−2.423*	1.302	−0.123	0.088	*Cash*	0.008
	(1.40)	(1.47)	(0.10)	(0.10)		(0.04)
Leverage × *Covid19*	0.594	1.014	0.112	0.097	*Leverage*	−0.001
	(1.50)	(1.53)	(0.11)	(0.11)		(0.01)
MTB × *Covid19*	−0.586***	−0.187**	−0.012**	0.004	*MTB*	−0.000
	(0.09)	(0.09)	(0.01)	(0.00)		(0.00)

TABLE 3 (Continued)

Panel B: Weekly, monthly or buy-and-hold returns						
	(1)	**(2)**	**(3)**	**(4)**		**(5)**
	Weekly stock returns		**Monthly stock returns**		**Buy-and-hold abnormal returns**	
ROA × Covid19	−1.622***	−1.380**	−0.028	−0.018	*ROA*	−0.004
	(0.54)	(0.57)	(0.04)	(0.04)		(0.02)
Firm size × Covid19	−0.953	−1.523	−0.079	−0.087	*Firm size*	0.010***
	(1.21)	(1.23)	(0.09)	(0.09)		(0.00)
Cash flow × Covid19	−2.423*	1.302	−0.123	0.088	*Cash flow*	−0.006
	(1.40)	(1.47)	(0.10)	(0.10)		(0.01)
Covid19	−1.328***	−1.310***	−0.013***	−0.010***		
	(0.20)	(0.22)	(0.00)	(0.00)		
SP500 return		0.784***		0.538***		
		(1.71)		(0.02)		
Lag return		−0.171***		−0.289***		
		(0.01)		(0.01)		
Share turnover		0.201		0.000		
		(0.17)		(0.00)		
Firm fixed effects	Yes	Yes	Yes	Yes		No
Industry and state fixed effects	No	No	No	No		Yes
Observations	55,722	52,507	12,245	12,245		3072
R^2	0.054	0.134	0.274	0.385		0.145

The economic magnitude of the coefficient estimates on the interaction variable *Inventory × Covid19* is large. For example, in Model 2, one standard deviation increase in *Inventory* leads to a 0.024% (2.4 basis point) decline in daily stock returns holding the growth rate of Covid-19 cases, *Covid19*, at the mean $(0.087 \times 0.128 \times (-2.16) = -0.024)$. This result is economically significant as it represents a 15.42% decrease over the absolute value of the unconditional mean of daily stock returns of 0.156%.

Model 3 of Table 3 additionally includes market microstructure control variables. Daily stock returns are positively associated with S&P 500 returns and negatively with lag returns. Share turnover and daily range are insignificant determinants of stock returns. Notably, the coefficient on the interaction variable *Inventory × Covid19* remains negative and significant.

Overall, our baseline regression results indicate that firms with high pre-Covid inventory holdings performed worse in the stock market in the short run during the Covid-19 crisis. The results are consistent with our arguments that high amounts of inventory during the crisis are associated with reduced benefits of avoiding stockout and managing price risk and increased inventory holding costs.

Alternative methods of estimating stock returns

To show the robustness of our findings, we employ alternative methods to estimate stock market performance, including estimating risk-adjusted returns and using an alternative sample period before the central bank interventions in response to the Covid-19 crisis in March 2020. Additionally, we estimate stock returns using different frequencies of data, including weekly, monthly and buy-and-hold abnormal returns.

Our baseline model uses raw returns rather than risk-adjusted returns because adjusted returns rely on strict assumptions that exposures to risk factors remain unchanged (Ramelli & Wagner, 2020). As a robustness test, we estimate Equation (1) with risk-adjusted stock returns as the dependent variable estimated using Fama–French and Carhart four-factor model (Model 4).[18] We estimate a firm's factor loading by regressing daily returns on risk factors in 2019 and subtracting factor exposures times the factor returns from the raw returns. We find that the negative impact of inventory holdings remains significant when we use risk-adjusted stock returns to measure firm performance.

Next, we re-examine the effects of inventory during the Covid-19 crisis in the absence of central bank interventions. On Monday, 23 March 2020, the Fed announced two new facilities, a Primary Market Corporate Credit Facility and a Secondary Market Corporate Credit Facility, to provide credit to large corporations and ease liquidity strains (see the timeline described in Ramelli & Wagner, 2020). We re-estimate the baseline regression for an alternative sample period, from 1 January to 20 March 2020 (Friday before the Fed's announcement) and report the estimation results in Model 5 of Table 3. The coefficient estimate on *Inventory* × *Covid19* remains negative and statistically significant at the 5% level, confirming the robustness of our main finding.[19]

Finally, in Panel B of Table 3, we report the estimation results of models that use weekly, monthly and buy-and-hold abnormal returns. In Models 1–4 of Panel B, the explanatory and control variables, the same as in Models 2 and 3 of Panel A, are all measured on a weekly (monthly) basis. The estimation results for weekly and monthly returns are similar to those for daily returns reported in Panel A of Table 3. Model 5 of Panel B is a cross-sectional regression with the dependent variable as buy-and-hold abnormal returns over the period January–April 2020, computed using the Fama–French and Carhart four-factor model. The negative and statistically significant coefficient on *Inventory* reconfirms our main finding. The positive and significant coefficient on *Firm size* shows that larger firms are more immune to the pandemic.

Overall, our main finding that inventory holdings negatively impacted the stock market performance during the Covid-19 crisis is robust to using alternative estimation methods of stock market performance.

[18]The estimation results are similar when we use risk-adjusted returns estimated using capital asseting pricing model.

[19]We also estimate the impact of inventory holdings using (1) an alternative definition of the Covid-19 crisis as the period from 20 February to 23 March 2020 when the large-scale decline in returns occurred (Cheema-Fox et al., 2021) and (2) monthly stock returns (instead of daily returns) as the dependent variable for an extended period from 1 September 2019 to 30 April 2020 with the Covid-19 variable defined as a dummy variable that equals one for February and March 2020 and zero otherwise. The estimation results for the periods 20 February–23 March 2020 and 1 September 2019–30 April 2020 (not reported) confirm our main result that higher precrisis inventory holdings are associated with a more negative stock market response to the Covid-19 crisis.

5.1.2 | Explaining the negative impact of inventory holdings during the Covid-19 crisis

This section examines potential explanations of the documented negative impact of inventory holdings in January–March 2020. We exploit cross-sectional heterogeneity in firms' exposure to Covid-19 shocks and disruptions and examine the role of different components of inventory holdings to disentangle the role inventory holdings play in the face of consumer demand, commodity price and supply shocks.

Firm's exposure to Covid-19: Consumer demand shock and commodity price shock

First, we test the proposition that the adverse shocks to consumer demand and commodity prices during Covid-19 can explain the negative impact of inventory holdings during this crisis. To test this proposition, we use industry-level variation in the degree of exposure to Covid-19, discussed in Supporting Information Appendix SA.1. To empirically assess how severely Covid-19 affects different industries, we calculate the percentage sales changes from Q1 2019 to Q1 2020 by industry based on GICS two-digit industry codes (reported in Figure SA1 in Supporting Information Appendix SA.1). We document a significant drop in sales for consumer discretionary, energy, materials and industrials industries (GICS industry codes 25, 10, 15 and 20, respectively); therefore, we classify these industries as “High Covid-19 shock”. The “Low Covid-19 shock” industries have a less significant drop or an increase in sales in Q1 2020; they include consumer staples, information technology, health care and communication services (GICS industry codes 30, 45, 35 and 50, respectively). We expect the negative impact of inventory holdings to be more pronounced for “High shock” than “Low shock” industries.

Table 4 reports the estimation results of the baseline regression for the two subsamples: (1) firms operating in “High Covid-19 shock” industries (Model 1) and (2) firms operating in “Low Covid-19 shock” industries (Model 2). As expected, in Model 1, the interaction term *Inventory* × *Covid19* has a negative and significant coefficient estimate, indicating that the negative impact of inventory holdings is significant for firms that experience significant demand and commodity price shocks during the Covid-19 crisis. In Model 2, the coefficient estimate on *Inventory* × *Covid19* is insignificant, meaning that for firms less affected by Covid-19, inventory holdings do not have a significantly negative bearing on stock performance during the Covid-19 crisis. Overall, our results show that the negative role of inventory is associated with shocks to consumer demand and commodity prices in the first part of 2020.

Different components of inventory: Consumer demand shock versus commodity price shock

To further understand the role of inventory during the Covid-19 crisis, we examine whether the negative impact of inventory is primarily driven by the consumer demand shock or the commodity prices shock. To test this, we distinguish between different components of inventory holdings, including raw materials, work-in-progress and finished goods.[20] We assume that the consumer demand shock is impounded in finished goods while the commodity price shock is in raw materials.

In Table 5, we report the estimation results of Equation (1), where we employ different components of inventory variables instead of the total inventory holdings: Raw Materials (*Inventory_RM*) (Models 1 and 2), Work-in-Progress (*Inventory_WIP*) (Models 3 and 4) and

[20]This analysis has a reduced sample size due to the limited availability of data on individual inventory components.

TABLE 4 The role of inventory during Covid-19: High versus low Covid-19 shock.

This table reports the firm fixed effects panel regression estimates explaining the impact of inventory on the response of daily stock returns to the growth of Covid-19 cases for two subsamples: "High" and "Low" Covid-19 shock based on the sales decrease in Q1 2020 (Figure SA1). Firms in industries that suffered a significant decrease in sales, that is, consumer discretionary, energy, industrials and materials (Global Industry Classification Standard codes 10, 15, 20 and 25, respectively) are identified as "High Covid-19 shock". The firms in consumer staples, information technology, health care and communication services industries are identified as "Low Covid-19 shock". The sample period is from 1 January to 30 April 2020. The dependent variable is the daily stock return. Covid-19 is the growth rate of Covid-19 cases by state. Inventory is the average total inventory to total assets in 2019. Inventory variable on its own is absorbed by firm fixed effects. Firm-level controls include *Cash*, *Leverage*, *MTB*, *ROA*, *Firm size* and *Cash flow*. Return factor controls include *SP500 return*, *Lag return*, *Share turnover* and *Daily range*. All variables are defined in Appendix A.1. In parentheses, we report robust standard errors clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% probability levels, respectively.

	(1) **High Covid-19 shock**	(2) **Low Covid-19 shock**
Inventory × *Covid19*	−2.736**	−0.592
	(1.33)	(1.68)
Covid19	−1.589**	−1.796**
	(0.72)	(0.63)
Firm-level controls × *Covid19*	Yes	Yes
Return factor controls	Yes	Yes
Firm fixed effects	Yes	Yes
N observations	87,460	111,362
R^2	0.141	0.113

Finished Goods (*Inventory_FG*) (Models 5 and 6). We find that the negative impact is concentrated in the Finished Goods component of inventory, suggesting that the documented negative impact of inventory holdings during the Covid-19 crisis is mainly driven by the drop in consumer demand in the face of Covid-19. The collapse in consumer demand increases inventory holding costs and reduces the importance of inventory as a stockout hedge.

Other consumer demand shocks

To reinforce our findings on the role of a consumer demand shock, we also examine the role of inventory holdings during two other crises that were accompanied by significant adverse demand shocks: (1) the 9/11 terrorist attacks and (2) the 2007–2008 Global Financial Crisis. These tests (reported in Supporting Information Appendix SA.2) provide additional empirical evidence that the negative impact of inventory holdings can be attributed to adverse consumer demand shocks.

Shock to global supply chains

We have shown that the adverse shock to consumer demand reduces the value of inventory holdings for the affected firms. On the flip side, inventory holdings may be valuable for firms

TABLE 5 The role of inventory components during the Covid-19 crisis.

This table reports the firm fixed effects panel regression estimates explaining the impact of different components of precrisis inventory (Raw materials (*Inventory_RM*) in Models 1 and 2, work-in-progress (*Inventory_WIP*) in Models 3 and 4, and Finished goods (*Inventory_FG*) in Models 5 and 6 on stock market response to the growth of Covid-19 cases. The sample period is from 1 January to 30 April 2020. The dependent variable is the daily stock return. *Covid19* is the growth rate of Covid-19 cases by state. Firm-level controls include *Cash*, *Leverage*, *MTB*, *ROA*, *Firm size* and *Cash flow*. Return factor controls include *SP500 return*, *Lag return*, *Share turnover* and *Daily range*. All variables are defined in Appendix A.1. Firm-level variables are absorbed by firm fixed effects. In parentheses, we report robust standard errors clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% probability levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Inventory_RM × *Covid19*	−1.967	−0.631				
	(2.59)	(2.79)				
Inventory_WIP × *Covid19*			−1.852	0.082		
			(3.33)	(3.55)		
Inventory_FG × *Covid19*					−2.911**	−2.388*
					(1.31)	(1.43)
Covid19	−1.019***	−1.654***	−1.060***	−1.766***	−0.941***	−1.649***
	(0.13)	(0.50)	(0.13)	(0.49)	(0.13)	(0.49)
Firm-level controls × *Covid19*	No	Yes	No	Yes	No	Yes
Return factor controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N observations	169,452	160,569	169,039	160,194	171,293	162,324
R^2	0.113	0.111	0.113	0.111	0.114	0.112

exposed to the disruptions of global supply chains caused by Covid-19 (Haren & Simchi-Levi, 2020). Precrisis levels of inventory holdings could buffer against supply shortages during the crisis. To test this proposition, we examine firms that are more exposed to global supply chain disruptions versus firms less exposed to global supply chain disruptions.

Over the past several decades, China has risen as the world's major trading partner. During the Covid-19 outbreak, many factories in China shut down, causing global supply chain disruptions (Haren & Simchi-Levi, 2020). Therefore, we expect that inventory holdings benefit firms that rely on Chinese suppliers. For firms *with Chinese suppliers*, the benefits of inventory as a hedge against supply chain disruptions can offset the negative impact of inventory holdings due to the demand shock. Firms that do not have Chinese suppliers are less likely to be affected by global supply chain disruptions and, therefore, derive less value from inventory holdings as a hedge against supply chain disruptions.

We use an ex ante measure of firms' reliance on Chinese suppliers to capture the impact of supply chain disruptions. We refer to Hoberg and Moon Text-based Offshoring Network Database (Hoberg & Moon, 2017, 2019) and define firms that mention in their 10-K files "China" in relation to importing activities in the last decade as firms *with Chinese suppliers*. We use two variables from this database: (1) *INPUT*, which is the number of mentions of the firm purchasing inputs from China, and (2) *ININ*, which is the number of mentions of the firm purchasing inputs from China when the firm also mentions owning assets in China. We identify one-third of our sample firms with nonmissing values in *INPUT* and *ININ* variables as *with Chinese suppliers* and the rest as *without Chinese suppliers*.

We estimate Equation (1) for the two subsamples, (1) firms *with Chinese suppliers* and (2) firms *without Chinese suppliers,* and report the estimation results in Table 6. Models 1 and 2 present the regression estimates for the two subsamples based on the full sample. We observe that the "*without Chinese suppliers*" subsample size is twice as large as that for "*with Chinese suppliers*". To mitigate the impact of unbalanced subsamples, we rerun the estimation using a matched sample. We match each firm "*with Chinese suppliers*" with a firm "*without Chinese suppliers*" based on their GICS industry sector code, *Cash holdings*, *Firm size*, *MTB* ratio, *ROA* and *Leverage* (defined in Appendix A.1). Models 3 and 4 of Table 6 present the estimation

TABLE 6 The role of inventory during the Covid-19 crisis for firms *with* and *without Chinese suppliers*.

This table reports the firm fixed effects panel regression estimates explaining the impact of inventory on the responses of daily stock returns to the growth rate of Covid-19 cases for two subsamples: (1) firms *with Chinese suppliers* and (2) firms *without Chinese suppliers*. We classify a firm as *with Chinese suppliers* if it mentions China in its 10-K file in relation to importing activities, that is, the firm has nonmissing values in *INPUT* and *ININ* for China in Hoberg and Moon Text-based Offshoring Network Database (Hoberg & Moon, 2017, 2019). We classify the rest of the firms as "*without Chinese suppliers*". Models 1 and 2 present regression estimates for the two subsamples based on the full sample. Models 3 and 4 present the estimates for the subsamples of firms matched based on the Global Industry Classification Standard industry sector code and *Cash holdings*, *Firm size*, *MTB* ratio, *ROA* and *Leverage* (defined in Appendix A.1). The sample period is from 1 January to 30 April 2020. The dependent variable is the daily stock return. *Covid19* is the growth rate of Covid-19 cases by state. *Inventory* is the average total inventory to total assets in 2019. *Inventory* variable on its own is absorbed by firm fixed effects. Firm-level controls include *Cash*, *Leverage*, *MTB*, *ROA*, *Firm size* and *Cash flow*. Return factor controls include *SP500 return*, *Lag return*, *Share turnover* and *Daily range*. All variables are defined in Appendix A.1. In parentheses, we report robust standard errors clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% probability levels, respectively.

	(1)	(2)	(3)	(4)
	Full sample		**Matched sample**	
	with Chinese suppliers	***without Chinese suppliers***	***with Chinese suppliers***	***without Chinese suppliers***
Inventory × *Covid19*	0.028	−2.877**	−3.365**	0.028
	(2.27)	(1.16)	(1.39)	(2.27)
Covid19	−3.068***	−1.146**	−0.438	−3.068***
	(1.04)	(0.56)	(0.98)	(1.04)
Firm-level controls × *Covid19*	Yes	Yes	Yes	Yes
Return factor controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
N observations	63,487	135,332	63,487	63,337
R^2	0.164	0.100	0.136	0.164

results for the subsample "*with Chinese suppliers*" and the matched "*without Chinese suppliers*" subsample, respectively.

The analysis based on the full sample (Models 1 and 2) and the matched sample (Models 3 and 4) shows that the negative impact of inventory on the stock market response to the Covid-19 crisis is more pronounced for firms *without Chinese suppliers* than for firms *with Chinese suppliers*. This finding is consistent with our prediction that firms *without Chinese suppliers* gain less from inventory holdings as a hedge against supply chain disruptions. However, for firms *with Chinese suppliers* that are exposed to global supply chain disruptions in the first part of 2020, the negative impact of inventory holdings due to the demand shock is offset by the positive value of inventory as a hedge against supply chain disruptions.

5.1.3 | Robustness tests

Alternate measures of inventory

Our inventory holdings variable is the inventory-to-assets ratio, which is widely used in finance literature (e.g., Carpenter et al., 1994; Dasgupta et al., 2019; Kulchania & Thomas, 2017). As a robustness test, we re-estimate the baseline regression with different measures of inventory holdings, following Chen et al. (2005). First, we consider the inventory-to-sales ratio (*Inventory_sales),* calculated as the total inventory divided by sales; this ratio matters most for stockout. Second, we calculate the inventory-days ratio (*Inventory_days)* as 365 times the inventory divided by the costs of goods sold; this ratio measures how many days it takes to turn over the inventory into costs of goods sold and indicates inventory management efficiency. Third, we estimate abnormal inventory (*Inventory_abnormal*) based on a normalised inventory-to-assets ratio to account for the industry- and firm size-driven differences that may affect inventory holdings. We sort our sample firms based on firm size into quintiles and compute *Inventory_abnormal* as the deviation of the firm's inventory from the minimum value of firms' inventory in the same GICS industry sector and firm size quintile, divided by the distance between the maximum and the minimum value (min–max normalisation).

Table 7 reports the estimation results with the alternative inventory measures. The coefficient estimates on the interaction term of inventory measures with *Covid19* remain negative and statistically significant in all models. It indicates that our results are robust to using alternative measures of inventory holdings.

Placebo test

Inventory holdings in the previous year could be negatively correlated with firms' growth opportunities and stock market performance in the following year, irrespective of the Covid-19 pandemic. To address this concern, we run Covid-19 "experiments" around placebo (a random noncrisis) periods assigned in years preceding the Covid-19 crisis. Supporting Information Appendix SA.3 reports the placebo test details and the estimation results. We find that the negative effects of inventory holdings do not appear in noncrisis years when there are no negative demand shocks. Therefore, we can rule out the explanation that some unobservable firm characteristics drive the negative relationship between precrisis inventory holdings and stock market response to Covid-19 in January–March 2020.

TABLE 7 Alternative measures of inventory.

This table reports the firm fixed effects regression estimates explaining the impact of inventory on the response of stock market returns to the Covid-19 crisis. The sample period is from 1 January to 30 April 2020. The dependent variable is the daily stock return. *Covid19* is the growth rate of Covid-19 cases by state. *Inventory_sales* is the ratio of total inventory to sales. *Inventory_days* is the number of days it takes for the inventory to turn over and is calculated as 365 times the total inventory divided by the costs of goods sold. *Inventory_abnormal* is the ratio of total inventory to total assets normalised by industry within the firm size quintile. All inventory variables are calculated as the average values in 2019. All inventory variables on their own are absorbed by firm fixed effects. Firm-level controls include *Cash*, *Leverage*, *MTB*, *ROA*, *Firm size* and *Cash flow*. Return factor controls include *SP500 return*, *Lag return*, *Share turnover* and *Daily range*. All variables are defined in Appendix A.1. In parentheses, we report robust standard errors clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% probability levels, respectively.

	(1)	(2)	(3)
Inventory_sale × *Covid19*	−1.074*		
	(0.65)		
Inventory_days × *Covid19*		−0.002***	
		(0.00)	
Inventory_abnormal × *Covid19*			−0.978**
			(0.50)
Covid19	−1.783***	−1.772***	−1.649***
	(0.46)	(0.45)	(0.48)
Firm-level controls × *Covid19*	Yes	Yes	Yes
Return factor controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
N observations	203,930	198,822	202,095
R^2	0.116	0.123	0.116

5.2 | Longer-run analysis of the Covid-19 pandemic in 2020

In the first part of our analysis, we have established that in January–April 2020, inventory holdings have a negative value for firms due to the significant drop in consumer demand. In this section, we extend our analysis to include the full year 2020 and examine the impact of inventory holdings on firm performance in May–December 2020. In the longer-run analysis, we use the same multivariate analysis framework as in the short-run analysis. We estimate Equation (1) and report the estimation results in Table 8.

5.2.1 | Inventory holdings and stock returns in May–December 2020

Model 1 of Table 8 presents the estimation results of the regression of daily stock returns for all sample firms using the sample period from 1 January to 31 December 2020. In this part of the

TABLE 8 Inventory and stock returns in May–December 2020.

This table reports the firm fixed effects panel regression estimates explaining the impact of precrisis inventory holdings on the firm's daily stock returns in May–December 2020. The sample period is from 1 January to 31 December 2020. The dependent variable is the daily stock return. *May–December 2020* is a dummy variable equal to one for May–December 2020 and zero otherwise. *Inventory* is the average total inventory to total assets in 2019. High (low) *Covid19 shock* indicates industries that are more (less) severely affected by the Covid-19 crisis based on the sales decrease in Q1 2020 (as in Figure SA1 and Table 4). *Chinese Suppliers* indicate firms reliant on Chinese suppliers, as defined in Table 6. *SCD_10K* measures a firm's supply chain issues in 2020, defined as the total number of "Supply Chain" mentions in the firm's 10-K file in 2020. Firm-level controls include *Cash*, *Leverage*, *MTB*, *ROA*, *Firm size* and *Cash flow*. Return factor controls include *SP500 return*, *Lag return*, *Share turnover* and *Daily range*. All variables are defined in Appendix A.1. Firm-level variables are absorbed by firm fixed effects. In parentheses, we report robust standard errors clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% probability levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Covid-19 shock		Chinese suppliers		SCD_10K	
	Full sample	High	Low	With high risk	Without low risk	High	Low
Inventory × May–December 2020	0.306***	0.214	−0.235	0.442**	0.256*	0.393**	0.245
	(0.12)	(0.14)	(0.20)	(0.22)	(0.14)	(0.16)	(0.19)
May–December 2020	0.317***	0.426***	0.291***	0.320***	0.320***	0.350***	0.223**
	(0.06)	(0.10)	(0.07)	(0.12)	(0.07)	(0.09)	(0.09)
Firm-level controls × May–December 2020	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Return factor controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N observations	679,911	302,453	377,458	231,179	448,732	397,724	252,872
R^2	0.125	0.143	0.113	0.164	0.110	0.159	0.121

article, our main goal is to draw comparisons between the early and later stages of the pandemic. Hence, we use a *May–December 2020* dummy variable equal to one for May–December 2020 and zero otherwise. The main variable of interest is the interaction term of *May–December 2020* and *Inventory* variables; the coefficient estimate in this interaction term captures the impact of inventory on stock market performance in the later stage of the Covid-19 pandemic. We include the same set of control variables as in Table 3. We find that, on average, precrisis inventory holdings have a positive and statistically significant at the 1% level impact on stock market performance in May–December 2020.[21] This finding suggests that in the later stage of

[21]The firm performance in the second part of 2020 may also be affected by investment or divestment in inventory in the first months of 2020. To show the robustness of our findings in unreported results, we additionally control for inventory holdings in the first quarter of 2020. Our main inventory variable continues to exhibit a positive and significant impact on the stock market performance in May–December 2020 after controlling for the impact of inventory holdings in the first quarter of 2020.

the Covid-19 pandemic, higher precrisis inventory holdings are associated with a stronger stock market recovery.

The economic magnitude of the coefficient estimate on the interaction term is large. In Model 1 of Table 8, one standard deviation increase in *Inventory* leads to a 0.062% (=0.487×0.128) increase in daily stock returns compared to the crisis period (January–April 2020). This result is economically significant as it represents a 30.3% increase over the absolute value of the unconditional mean of daily stock returns in May–December 2020, which is 20.6 basis points.

This finding is in line with the fact that consumer demand and commodity prices start recovering in May 2020. In an environment of fast-recovering consumer demand and commodity prices, firms benefit from larger inventory holdings as a hedge against stockout and input price increases. Notably, the positive impact of inventory is consistent with the positive value of inventory holdings as a hedge against supply chain disruptions that deteriorate as the year 2020 progresses.

Explaining the impact of inventory holdings in May–December 2020

To explain the positive impact of inventory holdings in May–December 2020, we examine cross-sectional differences in the role of inventory using subsample analyses. We examine the role of inventory holdings as an operational hedge against stockout, input price increases and supply chain disruptions from May 2020.

We start with the analysis of the level of firms' exposure to the Covid-19 crisis as defined in Section 5.1.2 and Table 4. Columns 2 and 3 of Table 8 report the estimation results for firms significantly negatively affected by the Covid-19 crisis in Q1 2020 ("High Covid-19 shock") and firms that are less affected ("Low Covid-19 shock"), respectively. We observe that both groups experienced a significant recovery of stock return in May–December 2020, as indicated by the coefficient estimates on the *May–December 2020* variable. The coefficient estimate on the interaction term *Inventory* × *May–December 2020* is positive for "High shock" firms and negative for "Low shock" firms; however, both are insignificant. The results indicate that, compared to "Low Covid-19 shock" firms, "High Covid-19 shock" firms benefit more from higher inventory holdings during consumer demand and commodity price recovery in May–December 2020. This result provides (weak) evidence that inventory is beneficial as a hedge against stockout during this period.

Next, we examine the role of inventory holdings as a hedge against supply chain disruptions. To evaluate the role of inventory as a hedge against supply chain disruptions, we examine the differences in the impact of inventory between firms *with* and *without Chinese suppliers*. We replicate the analysis from Section 5.1.2 and Table 6 for the full year 2020, focusing on the May–December 2020 period. Columns 4 and 5 of Table 8 report the estimation results for the subsample of firms *with* and *without Chinese suppliers*. We find that both firms *with* and *without Chinese suppliers* experienced significant recovery in stock market returns in May–December 2020; that is, for both subsamples, higher inventory holdings are associated with higher stock returns. The positive impact of inventory is slightly stronger for firms *with Chinese suppliers* (High risk), providing preliminary support for the bright side of inventory used as a hedge against supply chain disruption. While the first part of 2020 witnessed a breakdown of global supply chains caused by shutdowns of factories in China, later in 2020, with the spread of the pandemic in the United States and globally, supply chain issues are not limited to firms *with Chinese suppliers*. Furthermore, China gradually lifted its lockdown restrictions in

March–April 2020,[22] easing supply chain tensions for firms that rely on Chinese suppliers. Therefore, we additionally use a broader measure of supply chain disruptions in 2020, namely, the number of mentions of "supply chain" in the firm's annual 10-K file in 2020. We use this measure of supply chain disruptions (*SCD_10K* variable) and estimate Equation (1) for two subsamples: (1) firms with "High" supply chain disruptions exposure (firms with the above-median number of mentions of "supply chain" in the firm's annual 10-K file) and (2) firms with "Low" supply chain disruptions exposure (firms with the below-median number of mentions of "supply chain" in the firm's annual 10-K file). Columns 6 and 7 of Table 8 report the estimation results for "High" and "Low" supply chain disruption exposure. The coefficient estimate on the interaction term *Inventory* × *May–December 2020* is positive and statistically significant at the 5% level for "High" supply disruptions firms and insignificant for "Low" supply disruptions firms. This finding indicates that firms that experience significant supply chain issues in 2020 benefit more from higher inventory holdings in May–December 2020 when supply chain issues become more significant and widespread. This finding confirms the essential role of inventory holdings as a risk management tool against supply chain disruptions in 2020.

5.2.2 | Inventory holdings and operating performance in 2020

In this section, we examine the role of inventory holdings in the operating performance of firms in the later stage of the Covid-19 pandemic in 2020 to supplement our analysis of the stock market performance. During the period of recovering consumer demand and commodity prices and disrupted supply chains, we expect companies with higher inventory levels to recover faster than those with lower ones. We measure firm operating performance using the firm's quarterly seasonally adjusted return on assets, *ROA_q*, and percentage change in sales, *Sales_growth*.

The sample period is the year 2020 (Q1 2020–Q4 2020), and the effects of inventory are estimated in the second, third and fourth calendar quarters (Q2, Q3 and Q4) of 2020. We estimate Equation (1) using quarterly operating performance observations and a dummy variable *Q2_to_Q4* equal to one (zero) for Q2, Q3 and Q4 of 2020 (Q1 of 2020). The *Inventory* variable is the precrisis inventory holdings, and all regressions include firm fixed effects. The control variables are the firm-level variables that reflect the firm's precrisis financial position, as in Table 3.

Table 9 reports the estimation results of the impact of inventory on a firm's operating performance in Model 1 for *ROA_q* and Model 2 for *Sales_growth*. In both models, the coefficient estimate on the interaction term *Inventory* × *Q2_to_Q4* is positive and statistically significant at the 1% for *ROA_q* and 5% level for *Sales_growth*, indicating that, on average, firms with higher precrisis inventory holdings perform better in the later stage of the Covid-19 pandemic in Q2-Q4 2020. These results align with the findings for stock market performance and highlight the positive value of inventory holdings when consumer demand and commodity prices rise while supply chain issues exacerbate. In this environment, firms benefit from inventory holdings as a hedge against stockout, input price increases and supply chain disruptions.

Overall, our analysis of the role of inventory holdings on operating performance in 2020 provides additional empirical support for our argument that inventory holdings became

[22]See https://www.bloomberg.com/news/articles/2020-03-24/china-to-lift-lockdown-over-virus-epicenter-wuhan-on-april-8

TABLE 9 Inventory holdings and operating performance in the post-Covid periods.

This table reports the firm fixed effects panel regression estimates explaining the impact of inventory holdings on firm operating performance. The dependent variable is the firm's quarterly seasonally adjusted return on assets, *ROA_q*, in Model 1 and the adjusted percentage change in sales, *Sales growth_q*, in Model 2. The sample period is the year 2020, and the effects of inventory are estimated in the second, third and fourth calendar quarters (Q2, Q3 and Q4) of 2020. *Inventory* is the average inventory to total assets in 2019. *Q2_Q4* is a dummy variable equal to one (zero) for Q2, Q3 and Q4 of 2020 (Q1 of 2020). All variables are defined in Appendix A.1. Firm-level variables are absorbed by firm fixed effects. In parentheses, we report robust standard errors clustered at the firm level. ***, ** and * indicate significance at the 1%, 5% and 10% probability levels, respectively.

	(1)	**(2)**
	ROA_q	***Sales growth_q***
Inventory × *Q2_Q4*	0.034***	0.161**
	(0.01)	(0.08)
Cash × *Q2_Q4*	0.020***	0.093
	(0.01)	(0.10)
Leverage × *Q2_Q4*	0.003	0.096
	(0.01)	(0.06)
MTB × *Q2_Q4*	−0.000	−0.002
	(0.00)	(0.01)
Size × *Q2_Q4*	−0.001*	0.003
	(0.00)	(0.01)
Cash flow × *Q2_Q4*	−0.015***	0.006
	(0.01)	(0.03)
Q2_Q4	−0.004	−0.091
	(0.01)	(0.06)
Firm fixed effects	Yes	Yes
N observations	9933	9045
R^2	0.028	0.218

valuable for firms in the later stage of the Covid-19 pandemic in 2020 when consumer demand and commodity prices recovered, but supply chain issues worsened.

6 | CONCLUSION

The financial and economic fallout of the Covid-19 pandemic is different from other crises, and the existing evidence on the determinants of firm performance during crises may not apply to the Covid-19 pandemic. While the Covid-19 crisis has caused adverse consumer demand and commodity price shocks like other financial crises (e.g., the 2007–2008 Global Financial Crisis), it also significantly disrupted supply chains worldwide. The supply shock is a distinctive feature of the Covid-19 pandemic. In this paper, we examine the role of inventory holdings in the resilience of US firms to the Covid-19 pandemic in light of consumer demand, commodity prices and supply shocks.

The Covid-19 crisis in the first part of 2020 provides a setting to assess the role of corporate inventory holdings under adverse consumer demand and commodity price shocks that reduce the likelihood of stockout, downplay its importance as a hedge against rising inputs prices, and increase the costs of holding inventory. We document that in January–April 2020, firms with higher precrisis inventory holdings experienced a more negative market response to the growth of Covid-19 cases. We show that this negative effect is likely driven by the drop in consumer demand. During this period, inventory holdings have a compensating effect for firms relying on Chinese suppliers as a buffer against supply chain disruptions.

Later in 2020, as the Covid-19 pandemic progressed, US businesses and consumers learnt to function in the pandemic, and the economic conditions changed. From May 2020, consumer demand and commodity prices started to recover; however, supply chain issues became more prominent and widespread. We document that in May–December 2020, the impact of inventory holdings on firms' resilience to the Covid-19 pandemic becomes positive, which is in line with the argument that inventory holdings are valuable as an operational hedge against potentially high stockout risk and supply chain disruptions. Specifically, we show that, in May–December 2020, firms with higher inventory holdings performed better than firms with lower inventory levels. The positive effect of inventory in the later stage of the pandemic can be explained by its value as a hedge against supply chain disruptions.

Our study reveals a novel link between corporate inventory holdings and firm performance during the Covid-19 pandemic and contributes to the literature on the economic impact of the Covid-19 health crisis. By showing that inventory holdings play a significant role in firm performance in different stages of the Covid-19 pandemic, we highlight the importance of inventory management as a risk management tool and provide important implications for corporate managers. Inventory management is an essential but often overlooked aspect of corporate risk management. Firms' experience with the Covid-19 pandemic and the resulting consumer demand and supply shocks may force managers to rethink their inventory management practices.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ORCID

Shushu Liao http://orcid.org/0000-0003-0663-0372

REFERENCES

Albulescu, C. (2020). Coronavirus and oil price crash. https://ssrn.com/abstract=3553452

Albuquerque, R., Koskinen, Y., Yang, S., & Zhang, C. (2020). Resiliency of environmental and social stocks: An analysis of the exogenous COVID-19 market crash. *The Review of Corporate Finance Studies*, *9*(3), 593–621.

Bates, T. W., Kahle, K. M., & Stulz, R. M. (2009). Why do U.S. firms hold so much more cash than they used to? *The Journal of Finance*, *64*(5), 1985–2021.

Bekaert, G., Engstrom, E., & Ermolov, A. (2020). Aggregate demand and aggregate supply effects of COVID-19: A real-time analysis. *Covid Economics*, 141.

Bianco, M., & Gamba, A. (2019). Inventory and corporate risk management. *The Review of Corporate Finance Studies*, *8*(1), 97–145.

Blanchard, O. J. (1983). The production and inventory behavior of the American automobile industry. *Journal of Political Economy*, *91*(3), 365–400.

Bo, H. (2001). Volatility of sales, expectation errors, and inventory investment: Firm level evidence. *International Journal of Production Economics*, *72*(3), 273–283.

Caglayan, M., Maioli, S., & Mateut, S. (2012). Inventories, sales uncertainty, and financial strength. *Journal of Banking & Finance*, *36*(9), 2512–2521.

Campello, M., & Graham, J. R. (2013). Do stock prices influence corporate decisions? Evidence from the technology bubble. *Journal of Financial Economics*, *107*(1), 89–110.

Carpenter, R. E., Fazzari, S. M., Petersen, B. C., Kashyap, A. K., & Friedman, B. M. (1994). Inventory investment, internal-finance fluctuations, and the business cycle. *Brookings Papers on Economic Activity*, *1994*(2), 75–138.

Cavallo, A. (2020). *Inflation with Covid consumption baskets* [Harvard Business School BGIE Unit Working Paper 20-124].

Chalotra, V. (2013). Inventory management & small firms growth: An analytical study in supply chain. *Vision*, *17*(3), 213–222.

Cheema-Fox, A., LaPerla, B. R., Wang, H., & Serafeim, G. (2021). Corporate resilience and response to COVID-19. *Journal of Applied Corporate Finance*, *33*(2), 24–40.

Chen, H., Frank, M. Z., & Wu, O. Q. (2005). What actually happened to the inventories of American companies between 1981 and 2000? *Management Science*, *51*(7), 1015–1031.

Chordia, T., Subrahmanyam, A., & Anshuman, V. R. (2001). Trading activity and expected stock returns. *Journal of Financial Economics*, *59*(1), 3–32.

Da, Z., Liu, Q., & Schaumburg, E. (2014). A closer look at the short-term return reversal. *Management Science*, *60*(3), 658–674.

Daniel, K., Titman, S., & Wei, K. C. J. (2001). Explaining the cross-section of stock returns in Japan: Factors or characteristics? *The Journal of Finance*, *56*(2), 743–766.

Dasgupta, S., Li, E. X. N., & Yan, D. (2019). Inventory behavior and financial constraints: Theory and evidence. *The Review of Financial Studies*, *32*(3), 1188–1233.

Demers, E., Hendrikse, J., Joos, P., & Lev, B. (2021). ESG did not immunize stocks during the COVID-19 crisis, but investments in intangible assets did. *Journal of Business Finance & Accounting*, *48*(3–4), 433–462.

Ding, W., Levine, R., Lin, C., & Xie, W. (2021). Corporate immunity to the COVID-19 pandemic. *Journal of Financial Economics*, *141*(2), 802–830.

Duchin, R., Ozbas, O., & Sensoy, B. A. (2010). Costly external finance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics*, *97*(3), 418–435.

Edmister, R. O. (1972). An empirical test of financial ratio analysis for small business failure prediction. *Journal of Financial & Quantitative Analysis*, *7*(2), 1477–1493.

Eichenbaum, M. (1989). Some empirical evidence on the production level and production cost smoothing models of inventory investment. *American Economic Review*, *79*(4), 853–864.

Erickson, T., & Whited, T. M. (2000). Measurement error and the relationship between investment and q. *Journal of Political Economy*, *108*(5), 1027–1057.

Fahlenbrach, R., Rageth, K., & Stulz, R. M. (2020). How valuable is financial flexibility when revenue stops? Evidence from the COVID-19 crisis. *The Review of Financial Studies*, *34*(11), 5474–5521.

Fama, E. F., French, K. R., Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, *47*(2), 427–465.

Ferri, M. G., & Jones, W. H. (1979). Determinants of financial structure: A new methodological approach. *The Journal of Finance*, *34*(3), 631–644.

Gao, X. (2018). Corporate cash hoarding: The role of just-in-time adoption. *Management Science*, *64*(10), 4858–4876.

Haren, P., & Simchi-Levi, D. (2020). How coronavirus could impact the global supply chain by mid-march. *Harward Business Review*, HBS No. February. Harvard Business School Publishing.

Helper, S., & Soltas, E. (2021). *Why the pandemic has disrupted supply chains*. The White House Blog, 17 June 2021. https://www.whitehouse.gov/cea/written-materials/2021/06/17/why-the-pandemic-has-disrupted-supply-chains/

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

Hendricks, K. B., & Singhal, V. R. (2005a). Association between supply chain glitches and operating performance. *Management Science*, *51*(5), 695–711.

Hendricks, K. B., & Singhal, V. R. (2005b). An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. *Production & Operations Management*, *14*(1), 35–52.

Hirshleifer, D., & Jiang, D. (2010). A financing-based misvaluation factor and the cross-section of expected returns. *Review of Financial Studies*, *23*(9), 3401–3436.

Hoberg, G., & Moon, S. K. (2017). Offshore activities and financial vs operational hedging. *Journal of Financial Economics*, *125*(2), 217–244.

Hoberg, G., & Moon, S. K. (2019). The offshoring return premium. *Management Science*, *65*(6), 2876–2899.

Kashyap, A. K., Lamont, O. A., & Stein, J. C. (1994). Credit conditions and the cyclical behavior of inventories. *The Quarterly Journal of Economics*, *109*(3), 565–592.

Kulchania, M., & Thomas, S. (2017). Cash reserves as a hedge against supply-chain risk. *Journal of Financial & Quantitative Analysis*, *52*(5), 1951–1988.

La Londe, B. J., & Lambert, D. M. (1977). A methodology for calculating inventory carrying costs. *International Journal of Physical Distribution*, *7*(4), 193–231.

Meier, M., & Pinto, E. (2020). Covid-19 supply chain disruptions. *Covid Economics*, *48*, 139–170.

Ozili, P. K., & Arun, T. (2020). Spillover of COVID-19: Impact on the global economy. In *Managing inflation and supply chain disruptions in the global economy* (pp. 41–61). IGI Global.

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *Journal of Business*, 61–65.

Prater, E., Biehl, M., & Smith, M. A. (2001). International supply chain agility-tradeoffs between flexibility and uncertainty. *International Journal of Operations & Production management*, *21*(5–6), 823–839.

Rajagopalan, S., & Malhotra, A. (2001). Have US manufacturing inventories really decreased? An empirical study. *Manufacturing & Service Operations Management*, *3*(1), 14–24.

Ramelli, S., & Wagner, A. F. (2020). Feverish stock price reactions to COVID-19. *The Review of Corporate Finance Studies*, *9*(3), 622–655.

Snyder, L. V., Atan, Z., Peng, P., Rong, Y., Schmitt, A. J., & Sinsoysal, B. (2016). OR/MS models for supply chain disruptions: A review. *IIE Transactions*, *48*(2), 89–109.

The Economist. (2020). *Covid carnage: Much of global commerce has ground to a halt*. The Economist, March 21. st https://www.economist.com/business/2020/03/21/much-of-global-commerce-has-ground-to-a-halt

Tomlin, B. (2006). On the value of mitigation and contingency strategies for managing supply chain disruption risks. *Management Science*, *52*(5), 639–657.

Wang, B. (2019). The cash conversion cycle spread. *Journal of Financial Economics*, *133*(2), 472–497.

Wen, Y. (2005). Understanding the inventory cycle. *Journal of Monetary Economics*, *52*(8), 1533–1555.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Dodd, O., Liao, S. (2024). The role of inventory in firm resilience to the Covid-19 pandemic. *European Financial Management*, 1–33. https://doi.org/10.1111/eufm.12517

APPENDIX A1: VARIABLE DEFINITIONS

The table provides the definition of the variables. Compustat items are in italic font.

Variable	Variable definition
Inventory	Total inventory (*invt*) divided by total assets (*at*), where total inventory includes raw materials, finished goods, work-in-progress and other inventory. The variable is the average of the beginning- and end-of-year inventory ratio values in 2019.
Covid19	The daily growth rate of Covid-19 cases by state in January–April 2020, measured as $[\log(1 + \#Cases_t) - \log(1 + \#Cases_{t-1})]$.
Return	Daily stock log return. Stock prices are adjusted for dividends using the daily multiplication factor and the price adjustment factors provided by Compustat.
Buy-and-hold abnormal return	Accumulated stock returns minus accumulated expected returns over the period of January–April 2020. Expected returns are computed using Fama–French and Carhart four-factor model with coefficients estimated using stock returns in the year 2019.
Cash	Cash and marketable securities (*che*) divided by total assets (*at*). The variable is the average of the beginning- and end-of-year values in 2019.
Leverage	The sum of total long-term debt (*dlt*) and debt in current liabilities (*dlcc*) scaled by total assets (*at*). The variable is the average of the beginning- and end-of-year values in 2019.
MTB	The market value of assets divided by book value of total assets (*at*), where the market value of assets is calculated as total asset (*at*) plus the market value of common equity ($prcc\_f \times csho$) minus the book value of common equity (*ceq*), and minus deferred taxes (*txdb*). The variable is the average of the beginning- and end-of-year values in 2019.
ROA	Operating income before depreciation (*oibdp*) divided by total assets (*at*). The variable is the average of the beginning- and end-of-year values in 2019.
Firm size	The natural logarithm of total assets (*at*). The variable is the average of the beginning- and end-of-year values in 2019.
Cash flow	Income before extraordinary items (*ib*) plus depreciation and amortisation (*dp*) divided by total assets (*at*). The variable is the average of the beginning- and end-of-year values in 2019.
SP500 return	Returns on the S&P500 index.
Lag return	Return from the previous day.
Share turnover	Trading volumes scaled by total shares outstanding.
Daily range	Difference between the daily high price and daily low price, scaled by the closing stock price.
Inventory_RM	Raw materials (*invtrm*) divided by total assets (*at*). The variable is the average of the beginning- and end-of-year values in 2019.
Inventory_FG	Finished goods (*invtfg*) divided by total assets (*at*). The variable is the average of the beginning- and end-of-year values in 2019.
Inventory_WIP	Work-in-progress (*invtwp*) divided by total assets (*at*). The variable is the average of the beginning- and end-of-year values in 2019.

Variable	Variable definition
Inventory_sale	Total inventory (*invt*) divided by sales (*sale*). The variable is the average of the beginning- and end-of-year values in 2019.
Inventory_days	365 times Total inventory (*invt*) divided by the costs of goods sold (*cogs*). The variable is the average of the beginning- and end-of-year values in 2019.
Inventory_abnormal	The deviation of the firm's total inventory (*invt*) from the minimum value of inventory in the same Global Industry Classification Standard industry sector and firm size quintile, divided by the distance between the maximum and the minimum values. The variable is the average of the beginning- and end-of-year values in 2019.
SCD_10K	The total number of "supply chain" mentions in the firm's 10-K file during the full year 2020.
ROA_q	Quarterly seasonally adjusted return on assets.
Sales growth_q	Quarterly seasonally adjusted percentage changes in sales (*saleq*).