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

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ABSTRACT

We study the role of inventory holdings in corporate resilience to the Covid-19 crisis that triggered exogenous shocks to consumer demand, commodity prices, and global supply chains. The sharp, unexpected drop in consumer demand and commodity prices increases the costs of holding inventory. On the flip side, inventory holdings provide a buffer against supply chain disruptions. Empirically, we find that U.S. firms with higher inventory levels experience a more negative stock market response to Covid-19. The negative impact of inventory is more profound for firms with greater exposure to the slump in demand and commodity prices and a higher degree of financial constraints. Nonetheless, for firms that experience supply chain disruptions during Covid-19, the benefits of holding inventory offset its storage costs. We reconfirm that inventory carries significant costs using two other demand shocks – the 9/11 terrorist attacks and the global financial crisis.

KEYWORDS: Covid-19, inventory, working capital management, global pandemic, consumer demand shock, commodity price shock, global supply chain disruption, stockout risk, hedging

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1. Introduction

Firms hold inventory to manage the stockout and input price risks (Bianco and Gamba, 2018) and hedge against supply chain disruptions (Kulchania and Thomas, 2017; Gao, 2018). A significant reduction in U.S. firms' inventory holdings in the last several decades, mainly due to supply chain management deregulation and innovation, has increased the risk of disruptions (Kulchania and Thomas, 2017).[1] With historically low inventory holdings, firms have higher stockout risks, input price fluctuations, and supply chain disruption costs and rely more on other firms in the supply chain (Bianco and Gamba, 2018; Kulchania and Thomas, 2017). On the flip side, lower inventory holdings reduce physical storage costs, free up working capital, and enable an increase in cash holdings (Bates, Kahle, and Stulz, 2009). In this study, we examine the role that inventory holdings play in corporate resilience to the Covid-19 pandemic, which is associated with exogenous shocks to consumer demand, commodity prices, and global supply chains.

The COVID-19 pandemic affects a plethora of human population due to the rapid spread of SARS-CoV-2 around the globe. The first case of Covid-19 in the United States was recorded on January 20th, 2020 (Holshue et al., 2020), and on March 11th, 2020, the World Health Organization characterized the Covid-19 outbreak as a pandemic.[2] In addition to major health and social costs, this pandemic has had substantial economic implications. With the introduction of various measures to contain the spread of the virus, including lockdowns and mandatory social distancing, consumer demand for non-essential products and services has plunged. Bekaert, Engstrom, and Ermolov (2020) also posit that two-thirds of the drop in GDP in the first quarter of 2020 is ascribed to the negative shock to aggregate demand. High levels of uncertainty have further contributed to reducing consumption and investment among consumers and firms (Ozili and Arun, 2020). With the sharp reduction in demand for oil and, as a result, the oil price war between Saudi Arabia and

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

[2] https://www.who.int/emergencies/diseases/novel-coronavirus-2019/events-as-they-happen

Russia, oil prices collapsed by more than 20% in a single day on March 9th, 2020 (Albulescu, 2020).[3] At the same time, in China and later other countries, the outbreak has forced factories to shut down, causing major disruptions to global supply chains (Haren and Simchi-Levi, 2020; "Covid carnage" 2020).

In efficient markets, the costs and benefits of corporate inventory holdings are impounded into stock prices (e.g., Duchin et al., 2010). Thus, we exploit the U.S. stock market response to the Covid-19 pandemic to study the role of inventory. Covid-19 has triggered unexpected adverse exogenous shocks to consumer demand, commodity prices, and global supply chains. First, a significant drop in consumer demand is expected to increase the costs of holding inventory. The net effect of inventory is a trade-off between the benefits of avoiding stockout and the costs of physical storage. During the Covid-19 crisis, in light of reduced consumer demand and sales, the value of inventory as a hedge against stockout has diminished, while storage costs have increased. Therefore, the costs of inventory holdings might outweigh its benefits. Second, inventory is more valuable as a risk management tool when input price is rising. Hence, the collapse of commodity prices during Covid-19 further increases the costs of holding inventory by reducing its importance as a hedge against input price risk. On the other hand, inventory holdings are valuable to safeguard against global supply chain disruptions during the Covid-19 crisis. The above competing arguments raise the question regarding the net effect of inventory holdings on corporate resilience during the Covid-19 crisis – that is, as a hedge against stockout and price risks vs. a hedge against supply chain disruptions.

Our sample includes all publicly traded U.S. firms from Compustat, excluding financial, real estate, and utilities firms, with available firm-level data - 3,429 firms in total. We examine the determinants of the sample firms' daily stock returns from January 1st, 2020 to April 30th, 2020. Our focus is the response to the severity of Covid-19, which we define as the change in the number

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[3] Reuters Business News, "Coronavirus, oil collapse erase $5 trillion from U.S. stocks," March 10, 2020.

of daily confirmed cases of the virus in each U.S. state as reported by USAFacts. We use the firm's inventory position before the onset of the Covid-19 crisis to address the concern that inventory holdings may be endogenous to unobservable firm-specific factors that could explain stock price movements during the Covid-19 downturn (see e.g., Duchin, Ozbas, and Sensoy, 2010).

We find that firms with higher inventory levels before the pandemic experience a more negative stock market response to the Covid-19. The documented negative impact suggests that the costs of carrying inventory during the period of depressed consumer demand and commodity prices outweigh the benefits of inventory holdings as a buffer against supply chain disruptions during this pandemic. The negative impact of inventory is economically significant. One standard deviation increase in inventory holdings leads to a 0.029% decline in stock returns holding the growth rate of Covid-19 cases at the mean, representing an 18.3% increase over the absolute value of the unconditional mean of daily stock returns of 0.156%.

Arguably, inventory is a substitute for cash holdings, and higher inventory holdings are likely to be associated with lower cash holdings (Bates et al., 2009; Kulchania and Thomas, 2017; Gao, 2018). Therefore, the documented negative impact of inventory might be driven by a positive impact of cash holdings on the stock market response to Covid-19. Ramelli and Wagner (2020) and Ding, Levine, Lin, and Xie (2021) document that firms with stronger financial positions (e.g., higher cash holdings, lower leverage) before the pandemic experience less negative stock market response to Covid-19. We control for the impact of various firm characteristics and find a positive impact of cash holdings and firm size on stock returns during the Covid-19 crisis. However, our main result, the negative impact of inventory, remains significant.

The documented negative relationship between inventory and stock returns may be endogenous if the 2019 average inventory values are not sufficiently predetermined and independent of the

Covid-19 event.[4] To address this endogeneity concern, we employ an instrumental variable approach with lagged inventory variables and the interaction terms of lagged inventory and Covid-19 as the instruments (Aghion, Howitt, and Mayer-Foulkes, 2005; Wooldridge, 2002). We find that our main result holds after correcting for endogeneity.

To further examine the role of inventory, we compare its impact on firms affected differently by the Covid-19 crisis. The degree of the shock to demand and commodity prices during Covid-19 has varied across industries (Ramelli and Wagner, 2020; Ozili and Arun, 2020). We use industry-level heterogeneous exposure to the crisis to classify the sample firms as more or less affected. We find that inventory holdings negatively impact firms operating in industries significantly affected by the adverse consumer demand and commodity price shocks (transportation, energy, materials, and consumer discretionary industries). In contrast, the impact of inventory is insignificant for firms operating in less affected industries (consumer staples, information technology, communication services, and health care services).

One advantage of inventory holdings is protection against supply chain disruptions to avoid sales shortfalls and production interruptions. Covid-19 has disrupted global supply chains (Haren and Simchi-Levi, 2020), and pre-crisis inventory holdings can provide a buffer for firms that experience supply chain disruptions during the pandemic. The Covid-19 outbreak forced many factories in China to shut down, causing disruptions for U.S. firms that rely on Chinese supplies (Haren and Simchi-Levi, 2020). We use the Hoberg and Moon Text-based Offshoring Network Database (Hoberg and Moon, 2017 and 2019) to identify firms with Chinese suppliers. We find that for firms with Chinese suppliers, the negative impact of inventory is mitigated by the benefits of inventory holdings as a hedge against supply chain disruption. The negative effect of inventory

[4] It is a possibility that companies that were better informed about the developing Covid-19 situation in China have strategically reduced their inventory holdings at the end of 2019.

is more pronounced for firms that do not have Chinese suppliers and extract fewer benefits from inventory as a hedge against supply chain disruptions during the global pandemic.

The impact of adverse shocks can be magnified by corporate liquidity constraints. Even during normal times, financially constrained firms hold more inventory as a hedge against price risks (Bianco and Gamba, 2018). While financially constrained firms may use inventory as a source of liquidity during a crisis (e.g., Carpenter, Fazzari, and Peterson, 1994; Kashyap, Lamont, and Stein, 1994; Dasgupta, Li, and Yan, 2019), higher pre-crisis levels of inventory may also indicate higher storage costs during a crisis. Financially unconstrained firms, however, have better access to money and capital markets and can borrow to tide themselves over a crisis. Constrained firms with limited access to external funds may have to engage in value-destroying inventory "fire sales" to cut inventory storage costs even if they have growth potential in the future. Empirically, we find that the negative impact of inventory during Covid-19 is more profound for financially constrained firms.

We run several robustness tests. First, we employ alternate inventory measures, including inventory-to-sales ratio, inventory-days ratio (the number of days it takes to clear the inventory), and abnormal inventory (adjusted for industry and state averages). Second, we use alternative methods to estimate the market response to Covid-19. We re-examine the effects of inventory during the Covid-19 crisis in the absence of central bank interventions, using monthly and cumulative daily returns. We find that the negative effects of inventory withstand alternative inventory measures and definitions of stock market response. Furthermore, placebo tests using random non-crisis periods preceding the Covid-19 crisis yield no negative effects of inventory holdings, confirming the validity of our findings.

Finally, to broaden the interpretation of our findings beyond the Covid-19 crisis, we examine the role of inventory using two other events – the 9/11 terrorist attack and the 2007-2008 global financial crisis, both accompanied by adverse consumer demand shocks due to fear or economic hardship and uncertainty (Tong and Wei, 2008; Duchin et al., 2010). For both events, we find a negative market perception of high levels of inventory during adverse demand shocks, reconfirming our arguments for the Covid-19 crisis.

Our study broadly contributes to two strands of literature. First, it contributes to the budding literature on the economic impacts of the Covid-19 pandemic. Beck (2020) suggests that Covid-19 underlines the need for appropriate responses from regulatory authorities to help struggling firms, and Hoseini and Beck (2020) show that government emergency loans can boost the consumption of non-durable and semi-durable goods in Iran. Ding et al. (2021) find that firms with stronger financial positions, less reliance on global supply chains, higher CSR engagement, and less entrenched executives are more immune to Covid-19. Ramelli and Wagner (2020) report the stock market underperformance of internationally oriented U.S. firms, especially those with exposure to China. Li, Liu, Mai, and Zhang (2020) show that firms with a strong corporate culture are more likely to engage in cost-cutting, community engagement, and digital technology and have thereby been performing better during the pandemic. Demers, Hendrikse, Joos and Lev (2021) provide evidence that firms with investments in internally generated intangible asset are more capable of dealing with the Covid-19 outbreak. Carlett, Oliviero, Pagano, Pelizzon, and Subrahmanyam (2020) find that the Covid-19 lockdown in Italy led to a slump in profits and equity shortfall. We contribute to this research by highlighting the role of corporate inventory management during a crisis and showing that inventory is an important determinant of a firm's stock market response to Covid-19.

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 recognized as vital for improving operational flexibility and business growth (e.g., Prater, Biehl, and Smith, 2001; Chalotra, 2013). Consistent with our findings, Aktas, Croci, and Petmezas (2015) argue that working capital management overinvestment increases financing and investment opportunities costs and can lead to value destruction for shareholders. Molina and Preve (2011) show that firms that markedly increase their trade payable face an additional fall of at least 11% in financial distress. Wang (2019) also contends high cash conversion cycle (i.e., time a firm takes to sell their inventory or collect their receivables) leads to poor subsequent firm returns. On the other hand, Fazzari and Petersen (1993), Gertler and Gilchrist (1994), Carpenter et al. (1994), Kashyap et al. (1994), and Guariglia (1999) document that inventory has liquidity value for financially constrained firms. More recently, Dasgupta et al. (2019) find that constrained firms deplete inventory more aggressively in response to negative shocks. Bianco and Gamba (2019) show that firms hold inventory to mitigate commodity input price risk and cash flow risk. Bo (2001) and Caglayan et al. (2012) posit that firms that face heightened demand uncertainty build up inventory to avoid stockout. Research also documents 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 U.S. 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 is different as we focus on the costs and benefits of inventory holdings on corporate resilience to a global pandemic.

The rest of the paper is organized as follows. In section 2, we discuss the theoretical background and expectations on the role of inventory in general and during the Covid-19 crisis. In section 3, we present stock and commodity prices as an economic backdrop of the Covid-19 crisis. In section 4, we describe our data and sample and report summary statistics. In section 5, we discuss in detail our empirical strategy and discuss the empirical results. In section 6, we make conclusions.

2. Theoretical background and predictions

2.1 The role of inventory holdings

Firms hold inventory for purposes of avoiding stockout, hedging against rising input prices, providing liquidity, and mitigating supply chain disruptions. Firms carry inventory to smooth production levels in the face of fluctuating demand and sales (e.g., Blinder, 1986; Caglayan, Maioli, and Mateut, 2012). Specifically, firms hold inventory to avoid stockout and loss of sales when they experience an unanticipated increase in demand because strong consumer demands can be associated with high production costs[5] (e.g., Eichenbaum, 1989; Dasgupta et al., 2019).

Economic literature broadly defines inventory cost as a function of the distance between the inventory holdings and the target inventory level determined by the firm's sales (e.g., Eichenbaum, 1989; Blanchard, 1983).[6] This definition manifests two types of costs. The first type is the physical costs of carrying inventory or storage costs that increase with inventory levels. The second type is the stockout costs that are higher when the inventory levels are low, or the sales levels (and thereby target levels of inventory) are high. Therefore, inventory holding is a trade-off between the benefits of avoiding stockout and the costs of storage.

For hedging purposes, firms hold more inventory when they anticipate a rise in the input prices. Chen, Frank, and Wu (2005) argue that high inflation incentivizes firms to buy inputs earlier. Bianco and Gamba (2019) also posit that firms hold inventory as an operational hedge, and this risk management tool adds more value when commodity prices are on the rise.

Moreover, inventory, a current asset on a balance sheet, may act as a source of liquidity for financially constrained firms that can sell inventory to get over adverse states (e.g., Carpenter et al., 1994; Dasgupta et al., 2019). On the other hand, extant literature documents a negative relationship between inventory and cash holdings. Gao (2018) and Kulchania and Thomas (2017)

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

[6] Blanchard (1983) defines the costs of holding inventory as $G_t = d/2(I_t - I_t^*)^2$, 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 costs of storage. When I_t is significantly lower than I_t^*, firms face the costs of stockout.

show that inventory reduction due to supply chain management innovations prompts firms, as a precaution against future supply-chain disruptions, to retain the freed-up capital from inventory as cash reserves. The negative relationship between cash and inventory indicates that higher inventory levels may reduce firms' abilities and incentives to hold cash, which is the most liquid asset.

Finally, firms hold inventory to hedge against supply chain disruptions (SCD) (Tomlin, 2006). Chen et al. (2005) and Gao (2018) attribute the documented decrease in inventory levels over the past several decades to supply chain innovations. Low inventory holdings increase the costs of SCD and increase a firm's reliance on others in the supply chain (Kulchania and Thomas, 2017).

2.2 Covid-19 and inventory holdings

Covid-19 has triggered unexpected adverse shocks to consumer demand, commodity prices, and global supply chains, all at once. The first adverse shock of Covid-19 is a shock to consumer demand. Due to lockdowns and mandatory social distancing, consumer demand for non-essential products and services has plunged markedly. The slump in sales moves down the target levels of inventory and reduces the probability of stockout. The benefits of holding inventory to avoid stockout become inconsequential. On the contrary, excessive amounts of inventory increase the physical costs of holding inventory. If firms expect sales to rise in the future, they may continue to hold inventory and incur high storage costs. If firms expect sales to decrease in the future, they may choose to liquidate inventory at a discounted price given the depressed demand conditions. In both cases, firms experience a decrease in valuation either because of the "fire sales" decision or the cash outflows due to inventory storage costs.

The second adverse shock of Covid-19 is a shock to commodity prices. A sharp decline in consumption and economic activities contributes to the drop in oil and other commodity prices during the Covid-19 pandemic.[7] The drop and expected further downward trend in commodity prices eclipse the hedging benefits of inventory holdings. Inventory becomes less critical as a hedging tool during the Covid-19 deflationary environment[8] while it incurs high physical storage costs, making inventory holding more costly than that in normal periods.

Overall, due to the adverse consumer demand and the depressed commodity prices, we expect high inventory holdings to be detrimental during the Covid-19 crisis. At the same time, the impact of shock during Covid-19 varies significantly across industries (Ramelli and Wagner, 2020; Ozili and Arun, 2020). Due to social distancing and travel restrictions, transportation companies, such as airlines, suffer a catastrophic drop in revenues due to mass travel cancellations,[9] and high levels of inventory, such as fuel, may incur significant storage and maintenance costs. In addition, a significant drop in fuel prices eclipses the role of inventory holdings as a price risk hedging tool for transportation companies. Similarly, the energy sector (including the oil industry) and materials sector (including the mining industry) are highly exposed to the decline in commodity prices, which, combined with the reduced demand, makes inventory a burden due to high physical storage costs. The lockdown efforts aimed at reducing the spread of the virus, such as "stay-at-home" policies, and job uncertainties associated with this crisis, have significantly reduced consumer discretionary expenditure, such as spending on hotels, restaurants, and leisure services (Charm et al., 2020). High inventory levels for the consumer discretionary sector increase the inventory storage costs while the stockout risk is low owing to the demand slump. Therefore, we expect a stronger negative impact of inventory for firms operating in transportation, energy, materials, and consumer discretionary industries.

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7 We discuss in section 3 and show in Panel B of Figure 1 that the Covid-19 health crisis has led to a collapse in commodity prices.

8 Based on Cavallo (2020), inflation is negative in March and April of 2020 according to the change of Consumer Price Index (a fall of 0.22% in March and a fall of 0.68% in April). See also the discussion in https://www.reuters.com/article/us-usa-economy-inflation/u-s-inflation-subdued-with-economy-in-recession-idUSKBN23H1Y1

9 See https://www.businessinsider.com.au/what-happens-airline-mass-canceled-flight-2016-8?r=US&IR=T

Some industries, however, are less affected by the Covid-19 crisis. While consumer discretionary spending has decreased during the Covid-19, spending on consumer staples, such as food, beverage, and household and personal products, has maintained the pre-crisis levels or increased (Charm et al., 2020). Information technology and communication services firms are better set up to work remotely and are less affected by social distancing rules. They may even experience an increase in demand for their services during the pandemic due to the increased importance of online communications and digital tools.[10] Finally, the health care services sector faces a surge in demand from Covid-19 patients during the pandemic, although it experiences a reduction in revenues from elective surgeries that are postponed due to Covid-19 (Ozili and Arun, 2020). We hence expect a less significant negative impact of inventory for firms operating in consumer staples, information technology, communication services, and health care services industries.

The third adverse shock of the Covid-19 pandemic is to global supply chains as many factories, first in China and later in other countries, are forced to shut down their operations during the pandemic outbreak (Haren and Simchi-Levi, 2020). The high reliance of U.S. firms on outsourcing and overseas suppliers increases the supply chain disruption risk. In this case, high pre-crisis inventory holdings are valuable to prevent sales losses and production interruptions due to supply shortages.

To summarize, for firms more affected by the decline in consumer demand and commodity prices during the Covid-19 crisis, we expect the cost of holding inventory to outweigh the benefits. However, for firms that are more exposed to global supply chain disruptions, we expect inventory holdings to be valuable to offset supply shortages. The costs and benefits of corporate inventory holdings are incorporated into firms' stock prices in an efficient stock market (see, e.g., Duchin et

[10] For example, the video conferencing market players, such as Zoom Video Communications, Inc., gained traction during the Covid-19 outbreak as video conferencing has been viewed as an ultimate solution to remotely connect with employees and customers at the times of social distancing. https://www.businesswire.com/news/home/20200416005739/en/Impact-COVID-19-Video-Conferencing-Market-2020--

al., 2010). How the stock market perceives the net impact of inventory holdings during Covid-19 is an empirical question that we aim to address in this study.

3. Economic backdrop during Covid-19: stock prices and oil and commodity prices

The first case of Covid-19 in the U.S. was reported on January 20th, 2020, and since then, the U.S. has seen exponential growth in the number of cases. The spread of the pandemic has triggered a drop in stock prices. In Panel A of Figure 1, we plot the number of confirmed Covid-19 cases and the daily cumulative returns of an equally weighted portfolio of all U.S. publicly traded firms sourced from Compustat from December 1st, 2019, to April 30th, 2020, a period in which most of states in the US are undergoing their first Covid-19 lockdown. [11] There is a sharp and considerable drop in stock returns starting from February 2020, and the cumulative returns had not recovered by May 1st, 2020.

The collapse in oil and other commodity prices is due to the depressed demands during this period (e.g., Albulescu, 2020). Panel B of Figure 1 plots the Bloomberg Commodity index and West Texas Intermediate (WTI) crude oil prices from December 1st, 2019 to April 30th, 2020. Crude oils, used for gasoline and fuels, have seen a drastic fall in global demand. U.S. firms cannot buy and store oil with their capacity filled up, causing a slump in oil prices. The graph below shows that the WTI crude oil futures contract prices and the Bloomberg Commodity Index record a continuous decline since the beginning of the Covid-19 outbreak and then a crash in March 2020. Furthermore, the oil prices plunged below zero on April 20th, 2020, falling into negative oil price territory for the first time in history.

[Insert Figure 1 about here]

[11] Information of "stay-at-home" enforcement in the US is reported at: https://www.pbs.org/newshour/politics/most-states-have-issued-stay-at-home-orders-but-enforcement-varies-widely

4. Data, sample, and summary statistics

Our primary interest is the stock market response to Covid-19. 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+#Cases$_t$)-log(1+#Cases$_{t-1}$)].

Our sample includes all publicly traded firms incorporated in the U.S., from Compustat, excluding financials (GICS industry sector 40), real estate (GICS industry sector 60), and utilities (GICS industry sector 55).[13] We extract daily stock prices from January 1st, 2020, to April 30th, 2020, from the Compustat Security Daily file.[14] Stock prices are adjusted for dividends through the daily multiplication factor and the price adjustment factors provided by Compustat. We use unadjusted (log) returns rather than CAPM-adjusted or Fama-French three-factor adjusted returns because adjusted returns rely on strict assumptions that exposures to risk factors remain unchanged (Ramelli and Wagner, 2020).[15] We merge the daily stock returns data with the daily growth rates of Covid-19 cases according to date and the state in which the company is headquartered.

We retrieve accounting and financial firm-level variables from Compustat Fundamental Annual file. Our main variable in explaining stock market response to Covid-19 is corporate *Inventory,* measured as total inventory (Compustat item *invt*)[16] divided by total assets (*at*), where total

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

[13] 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. Also, the nature of their inventory may be different from companies in other industries.

[14] We focus on the period January - April 2020 as there was a strong rebound in retail sales and stock market rally in May after record sales decline on April. See, for example, https://www.nytimes.com/2020/06/16/business/stock-market-today-coronavirus.html#link-2edeba1c

[15] In our untabulated output, we find that the main results are similar when we use CAPM-adjusted, Fama French three-factors adjusted and Cahart four-factors adjusted stock returns.

[16] Inside the parenthesis, we provide the Compustat item name.

inventory includes raw materials, finished goods, work-in-progress, and other inventory.[17] Our *Inventory* variable is the average of the beginning- and end-of-year values in the calendar year of 2019. We use inventory holdings before the Covid-19 crisis because the changes in inventory levels during the Covid-19 crisis may be correlated with unobserved changes in the firm's hedging demands and financial conditions that could also affect the firm's stock price. The advantage of using the average inventory value is to address the concern that firms might have anticipated the crisis by observing China's situation at the end of 2019 and then started making inventory adjustments.[18]

We control for various firm-level characteristics, following Ding et al. (2021), all measured as the average of the beginning- and end-of-year values in 2019, in line with the *Inventory* variable. *Cash* is defined as cash and marketable securities (*che*) divided by total assets (*at*). *Leverage* is the sum of total long-term debt (*dlt*) and debt in current liabilities (*dlcc*) scaled by total assets (*at*). *MTB* is the market value of assets divided by book value of total assets (*at*), where market value of assets is calculated as total asset (*at*) plus the market value of common equity (*prcc_f* × *csho*) minus the book value of common equity (*ceq*), and minus deferred taxes (*txdb*). Return on assets, *ROA*, is the ratio of operating income before depreciation (*oibdp*) divided by total assets (*at*). *Firm size* is measured as the natural logarithm of total assets (*at*). *Cash flow* is defined as income before extraordinary items (*ib*) plus depreciation (*dp*) divided by total assets (*at*). To reduce the impact of outliers, all variables are winsorized at the 1st and 99th percentiles of their distributions.

After removing financial, real estate, and utilities firms and deleting observations with missing values for the main and control variables (defined above), there is a total of 3,429 firms with 203,930 firm-day observations in our sample. We report descriptive statistics for all variables in Table 1, including mean, standard deviation (SD), 25th percentile, median and 75th percentile. The

[17] We use total inventory following most of the finance literature (e.g., Kulchania and Thomas, 2017; Bianco and Gamba, 2018; Dasgupta et al., 2019).
[18] The use of average value is also consistent with the textbook formula of computing inventory efficiency ratio.

average daily growth rate of Covid-19 cases is 0.087, and the daily stock return is on average negative -0.156% with a large standard deviation. The mean value of *Inventory* is 0.091.[19] The average *Cash* is 0.267, and the average *Leverage* is 0.529. The mean (median) value of *MTB* is 8.847 (1.802), displaying a highly skewed distribution.[20] The average logarithm of total assets is 5.489, and the mean of *ROA* and *Cash flow* are negative, -0.506 and -0.655, respectively.

[Insert Table 1 about here]

5. Empirical strategy and results

5.1 Inventory and stock market response to Covid-19

We aim to explore the impact of corporate inventory on stock returns during the Covid-19 crisis. We start our analysis by forming portfolios based on the average inventory holdings in 2019. The high-inventory portfolio is in the top tercile, while the low-inventory portfolio is in the bottom tercile of the inventory levels. Table 2 reports stock returns and their correlations with the growth rate of Covid-19 cases, 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 returns and the growth rate of Covid-19 cases is more negative for high-inventory firms.

[Insert Table 2 about here]

Figure 2 shows the stock market performance for the low-inventory portfolio (the dotted line) and high-inventory portfolio (the dashed line). To highlight the differences, we plot the low-minus-high portfolio returns (the solid line). The differences are mainly positive during our sample

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[19] The mean value for inventory-to-assets ratio is very close to that in Bianco and Gamba (2018) and that in Kulchania and Thomas (2017) for the year of 2014.

[20] For example, see Erickson and Whited (2000) for discussions of a highly skewed Tobin's q.

period. Overall, the results in Table 2 and Figure 2 provide initial evidence that firms with low inventory holdings outperform those with high inventory holdings during the Covid-19 crisis.

[Insert Figure 2 about here]

Next, we evaluate the role of inventory in worsening or alleviating the adverse impact of Covid-19 using multivariate regression analysis. We employ a model specification with an interaction term of *Inventory* and *Covid-19* that captures the effects of firms' pre-crisis inventory levels on the stock market response to the severity of the Covid-19 crisis. Specifically, we estimate the following model:

$$R_{it} = \alpha + \delta_1 Inventory \times Covid19 + \delta_2 Inventory + \delta_3 Covid19 + \varphi X_{it} + Fixed\ effects + \varepsilon_{it}, \tag{1}$$

where R_{it} is daily stock log return for firm i and date t; *Covid19* is the growth rate of Covid-19 cases by state, measured as $[\log(1+\#Cases_t)-\log(1+\#Cases_{t-1})]$; *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 is δ_1 that captures the impact of inventory on stock market response during the Covid-19 crisis. X_{it} is a vector of firm-level control variables, which may correlate with stock returns. Specifically, we include the cash-to-assets ratio, leverage, market-to-book ratio, ROA, firm size, and cash flow as control variables. 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 main estimation results of Eq. (1). In Model (1), we control for industry fixed effects using GICS industry classification. In Model (2), we include state fixed effects to control for unobserved heterogeneity at the state level, such as local financial conditions, changes in state policy for lockdown regulations, and governmental support. In Model (3), we control for industry and state fixed effects. Finally, in Model (4), we include firm fixed effects and force identification of the regression coefficients within a firm. Since all firm-level variables, including inventory, are measured only once per firm, firm fixed effects subsume the effect of inventory (see, e.g., Duchin et al., 2010).

The coefficient estimates on the interaction variable *Inventory*×*Covid19* are negative and statistically significant at the 1% level in all model specifications, suggesting that higher pre-crisis inventory holdings are associated with a more negative stock market response to Covid-19. As expected, the coefficient estimate on *Covid19* is negative and statistically significant at the 1% level in all models, capturing a negative market response to Covid-19 for all firms. The coefficient estimates on *Inventory* are positive but insignificant in all model specifications. The absolute value of the coefficient estimates on *Covid19* is significantly smaller than those on *Inventory*×*Covid19*, implying that the overall impact of inventory holdings is negative.

The economic magnitude of the coefficient estimates on the interaction variable *Inventory*×*Covid19* is large. For example, in Model (4) of Table 3 that includes firm fixed effects, one standard deviation increase in *Inventory* leads to a 0.029% (2.9 basis point) decline in daily stock returns holding the growth rate of Covid-19 cases, *Covid19,* at the mean (0.087 × 0.128 × (-2.577) = -0.029). This result is economically significant as it represents an 18.3% increase over the absolute value of the unconditional mean of daily stock returns, which is 0.156%. Overall, our baseline regression results indicate that firms with high pre-Covid inventory holdings perform worse in the stock market during the Covid-19 pandemic. The results are consistent with our arguments that high amounts of inventory during the Covid-19 crisis are associated with reduced benefits of avoiding stockout and managing price risk and increased physical costs of carrying inventory.

[Insert Table 3 about here]

5.1.1 Ruling out other explanations

Ramelli and Wagner (2020) and Ding et al. (2021) show that corporate cash holdings and leverage are important determinants of the stock market reaction to Covid-19, that is, firms with stronger financial positions (e.g., with higher cash holdings, lower leverage) before the pandemic experience a less negative stock market response. Several studies suggest that inventory and cash holdings can be considered substitutes, and lower inventory holdings are likely to be associated with higher cash holdings (Bates et al., 2009; Kulchania and Thomas, 2017; Gao, 2018). Zeng, Zhong, and He (2020) directly show that firms reduce their inventory holdings following heightened economic policy uncertainty to free up capital for cash.

If inventory and cash holdings are negatively correlated, then the documented negative effect of inventory holdings may be driven by the impact of cash holdings. Therefore, cash holdings and other aspects of firm heterogeneity, which may be correlated with inventory holdings before the crisis, could underline the relation we observe so far. In order to rule out other explanations for the documented impact of inventory, we control for the impact of cash holdings and other firm-level characteristics, such as leverage, growth opportunities (MTB), profitability (ROA), firm size, and cash flow by including in Eq. (1) the additional interaction terms of *Covid19* and these firm-level variables.

Table 4 reports the estimation results of the impact of the inventory holdings on the stock market response, controlling for the interaction term with cash holdings, leverage, MTB, ROA, firm size, and cash flow, individually (Models (1) – (6)), and simultaneously in one regression (Model (7)). We find that firms with higher cash holdings and larger firms experience a significantly less negative stock market response to Covid-19, in line with the findings of Ramelli and Wagner (2020) and Ding et al. (2021). Nevertheless, the coefficient estimates on the *Inventory*×*Covid19* remain negative and statistically significant after controlling for the impact of firms' financial positions. This analysis shows that the observed negative effect of corporate inventory on stock performance during the Covid-19 crisis does not capture the impact of the firm's financial conditions before the crisis.

[Insert Table 4 about here]

5.1.2 Addressing endogeneity concerns

A potential endogeneity concern is that the 2019 average values of inventory holdings may not be sufficiently predetermined and independent of the Covid-19 event. Companies that were better informed about the Covid-19 situation in China in late 2019 may have strategically reduced their inventory holdings right before 2020. The anticipation of the crisis may confound the interpretation of our results. To address this concern, we employ an instrumental variable approach. We follow Aghion et al. (2005) and use lagged inventory as the instrument for *Inventory* and the interaction term of the lagged inventory, and *Covid-19* as the instrument for *Inventory*×*Covid19* (see also Wooldridge, 2002). Table 5 reports the second stage estimates of the instrumental variables regressions explaining the impact of corporate inventory on the responses of daily stock returns to the growth rate of Covid-19 cases. The *Inventory* in the main variable of interest *Inventory*×*Covid19* is the average of the beginning- and end-of-year inventory in 2019. Model (1) of Table 5 uses the average inventory in 2017 as the instrument. The coefficient on *Inventory*×*Covid19* remains negative and significant at the 5% level. The results are robust when we use the average inventory in 2016 as the instrument in Model (2). In Model (3), with the average inventory in 2015 as the instrument, the coefficient estimate on *Inventory*×*Covid19* is still negative, albeit slightly insignificant. In the last column (Model (4)), we report results with the average inventory levels in 2015, 2016, and 2017 as a set of instruments. *J* statistics for the test of overidentification restrictions show that our set of instruments is likely to satisfy the exclusion criteria. The coefficient on *Inventory*×*Covid19* remains negative and statistically significant, confirming the robustness of the documented negative impact of inventory holdings.

[Insert Table 5 about here]

5.2 Cross-sectional heterogeneity on the impact of inventory

5.2.1 Shock to consumer demand and commodity prices

We argue that the negative shocks to consumer demand and commodity prices during Covid-19 can explain the negative impact of inventory holdings during this crisis. To test the above proposition, we evaluate and compare the impact of inventory holdings for firms in industries that have experienced a significant negative shock to consumer demand and commodity prices with that for firms in less affected industries.

Based on the discussion in section 2.1, we classify the following industries as ones that suffer a significant negative demand and commodity price shock ("High shock"): transportation (GICS industry group 2030), energy (GICS sector 10), materials (GICS sector 15), and consumer discretionary (GICS sector 25). We classify the following industries as industries less affected by the Covid-19 in terms of demand for their product and services ("Low shock"): consumer staples (GICS sector 30), information technology (GICS sector 45), communication services (GICS sector 50), and health services (GICS industry sector 35). We expect the negative impact of inventory holdings to be more pronounced for "High shock" than "Low shock" industries.

Table 6 reports the estimation results of the baseline regression for the two sub-samples: (1) firms operating in "High shock" industries (Model (1)), (2) firms operating in "Low 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 have experienced 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 that have not experienced a significant negative demand shock, 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.

[Insert Table 6 about here]

5.2.2 Shock to global supply chain

We have shown that the adverse shock to demand and commodity prices reduces the value of inventory holdings for the affected firms. On the flip side, inventory holdings during the Covid-19 crisis may be valuable for firms subject to the disruptions of global supply chains caused by the pandemic (Haren and Simchi-Levi, 2020). Pre-crisis levels of inventory holdings could buffer against shortages in the supply of raw materials and finished goods during the crisis. To empirically test this proposition, we examine the role of inventory during Covid-19 for firms that have experienced more significant supply chain disruptions (SCD) vs. firms that have experienced less significant SCD.

Over the past several decades, China has risen as the world's major trading partner. During the Covid-19 outbreak, many factories in China were shut down, causing global supply chain disruptions (Haren and Simchi-Levi, 2020). We expect inventory holdings to be beneficial for firms that rely on Chinese suppliers and, therefore, are more likely to miss their sales target due to the global SCD during Covid-19. For these firms, the negative impact of inventory holdings should be mitigated by the benefits of inventory as a hedge against supply chain disruptions. Firms that do not have Chinese suppliers experience less significant supply chain disruptions. We expect the negative effects of inventory during Covid-19 to be more pronounced for firms without Chinese suppliers than firms with Chinese suppliers.

We refer to Hoberg and Moon Text-based Offshoring Network Database (Hoberg and Moon, 2017 and 2019) and define firms with Chinese suppliers (*Chinese suppliers*) as firms mentioning China in their 10-K related to importing activities. 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 non-missing values in *INPUT* and *ININ* in the last decade as *Chinese suppliers* and the rest as *Non-Chinese suppliers*.

We estimate the baseline regression for the two sub-samples: (1) firms that have Chinese suppliers (High SCD - Chinese suppliers); (2) firms that do not have Chinese suppliers (Low SCD – no Chinese suppliers) and report the estimation results in Table 7. Models (1) and (2) of Table 7 present the regression estimates for the two sub-samples based on our full sample. We find that the negative impact of inventory on stock market response to the Covid-19 crisis is more pronounced for "Low SCD" firms than for "High SCD" firms, consistent with our prediction.

We observe that the "Low SCD" sub-sample size is twice as large as that for "High SCD." To mitigate the impact of unbalanced sub-samples, we re-run the estimation using a matched sample. We match each "High SCD" firm with a "Low SCD" firm based on their beginning- and end-of-year average cash, firm size, market-to-book ratio, ROA, and leverage in 2019. Models (3) and (4) of Table 7 present the estimation results for the "High SCD" sub-sample and the matched "Low SCD" sub-sample, respectively. The results for the matched sub-samples are similar to those based on the full sample (Models (1) and (2)), indicating that the differences in sample size do not drive the differences in the impact of inventory holdings between "High SCD" and "Low SCD" firms.

[Insert Table 7 about here]

5.2.3 Financial constraints

We have shown that it is costly for firms to carry inventory during Covid-19 due to the significant drop in consumer demand and commodity prices. At the same time, firms experience a slump in corporate revenues and cash flows. Financially unconstrained firms have better access to borrowing and external funding to cover their inventory holding costs and are thus more resilient to the crisis. Financially constrained firms, however, may have to engage in value-destroying inventory "fire sales" to cover the storage costs. Therefore, we expect that the negative impact of inventory holdings during the Covid-19 pandemic is more profound for financially constrained firms than unconstrained ones.

To examine the cross-sectional variation, we first estimate firms' ex-ante financial constraints status. We use five variables: WW index (Whited and Wu, 2006), KZ index (Lamont et al., 2001), HP index (Hadlock and Pierce, 2010), bond ratings, and dividend payout ratio.[21] These measures are standard in corporate finance literature (e.g., Almeida et al., 2004; Denis and Sibilkov, 2010). We classify firms that have WW index, KZ index and HP index above (below) the sample median as financially constrained (unconstrained) firms. We classify firms with (without) bond ratings in the past decade as financially unconstrained (constrained) firms.[22] We classify firms with a dividend payout ratio below (above) the sample median as financially constrained (unconstrained) firms.

We estimate our baseline regression for the sub-samples of financially constrained and unconstrained firms based on the five measures described above and report the estimation results in Table 8. For all five measures of financial constraints, the coefficient estimates on

[21] WW index is computed as 0.091 CF/AT-0.062 DIV_POS + 0.021 TLTD/AT - 0.044 LNTA + 0.102 ISG - 0.035 SG where CF/AT is the ratio of cash ow to total asset, TLTD is the ratio of the long-term debt to total assets, LNTA is natural log of total assets, DIV_POS is an indicator that takes the value of one if the firm pays cash dividends, ISG is the firm's three-digit SIC-based industry sales growth, SG is firm's sales growth.
KZ index is computed as -1.002 CF/K + 0.283 MB + 3:139 LEV – 39.368 DIV – 1.315 CH/K where CF/K is the ratio of cash flow to capital stock, MB is market-to-book of asset ratio, LEV is total debt (debt in current liabilities plus long-term debt) scaled by stockholder's equity, DIV is the ratio of total dividends (common dividends plus preferred dividends) to capital stock, CH/K is the ratio of cash holdings to capital stock.
HP index is computed as – 0.737 Firmsize + 0.043 Firmsize^2 – 0.040 Age where Firmsize is equal to the natural log of GDP-deflated total asset, Age is the number of years firms are active with a non-missing stock price in Compustat. Dividend payout ratio is the ratio of total dividends (common dividends plus preferred dividends plus repurchases) to income before extraordinary items.
[22] Credit rating data from S&P suffer a significant amount of missing information in 2017-2019, therefore, we use rating information in the past ten years (starting from 2010). We classify firms that have a non-missing long-term issuer credit rating (*splticrm*) in any year starting from 2010 as financially unconstrained. The results remain if we classify firms as financially unconstrained based on non-missing long-term issuer credit rating in any year starting from 2015.

Inventory×*Covid19* for financially constrained firms are negative and statistically significant while they are negative but statistically insignificant for financially unconstrained firms. This result suggests that for firms with a higher degree of financial constraints, it is more costly to hold inventory during the Covid-19 crisis.

[Insert Table 8 about here]

5.3 Robustness tests

5.3.1 Alternate measures of inventory

So far in our analysis, we have focused on the measure of inventory holdings, the inventory-to-assets ratio, commonly used in finance literature (e.g., Carpenter et al. 1994; Kulchania and Thomas 2017; Dasgupta et al. 2019;). In this section, 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 it indicates inventory management efficiency. Third, we estimate abnormal inventory (*Inventory_abn*) to control for industry and state characteristics that may affect inventory holdings (e.g., storage capacity could be more limited in certain states). We define *Inventory_abnormal* as the deviation of the firm's inventory from the state- and GICS industry group- average scaled by its standard deviation. All inventory variables are calculated as the average of the beginning- and end-of-year values in 2019. We estimate the baseline regression with the alternative inventory measures and report the estimation results in Table 9. The coefficients on the product term of different measures of inventory with *Covid19* stay negative and statistically significant. It indicates that our results are robust to alternate measures of inventory holdings.

[Insert Table 9 about here]

5.3.2 Alternative sample periods and measures of returns

In this section, we test the robustness of our findings to alternative methods to estimate the market response to Covid-19. First, we aim to re-examine the effects of inventory during the Covid-19 crisis in the absence of central bank interventions. On Monday, March 23rd, 2020, the Federal Reserve Board (Fed) announced two new facilities, a Primary Market Corporate Credit Facility (PMCCF) and a Secondary Market Corporate Credit Facility (SMCCF), to provide credit to large corporations and ease liquidity strains (see the timeline described in Ramelli and Wagner, 2020). We re-estimate the baseline regression for an alternative sample period, from January 1st, 2020, to March 20th, 2020 (Friday).[23] The estimation results are reported in Table 10, Model (1). The coefficient estimate on *Inventory*×*Covid19* remains negative and statistically significant at the 1% level, confirming the robustness of our main finding.

Next, instead of daily returns, we use monthly returns for a longer period, from September 2019 to April 2020, as the dependent variable to re-evaluate the impact of inventory on the stock market response during the crisis. We define the first four months of 2020 (Jan-Apr 2020) as the crisis period and the last four months of 2019 (Sep-Dec 2019) as the pre-crisis period. Model (2) in Table 10 reports the regression estimates. *After* is a binary variable equal to one for the crisis period and zero for the pre-crisis period. The negative and significant (at the 1% probability level) coefficient on *Inventory*After* indicates that monthly stock returns decline more significantly during the Covid-19 crisis for firms with higher pre-crisis inventory holdings.

Finally, we employ cumulative daily returns from January 1st, 2020 to April 30th, 2020, as the dependent variable in a cross-sectional regression to explain the impact of inventory on the

[23] The results are similar if we use an alternative sample period from January 20th, 2020 (when the first case was recorded) to March 20th, 2020 (Friday before the Fed's announcement).

response of stock market returns to the Covid-19 crisis. Model (3) in Table 10 reports the regression estimates. The negative and statistically significant coefficient on *Inventory* reconfirms our main finding.

[Insert Table 10 about here]

5.3.3 Placebo test

A potential concern with our results is that inventory holdings one year before could be negatively correlated with firms' growth opportunities and stock market performance in the following year, irrespective of the crisis. This could explain the negative relationship between inventory and stock market performance that we document. To address this concern and show the robustness of our findings, we run a Covid-19 "experiment" around a placebo (a random non-crisis) period assigned in years preceding the Covid-19 crisis. We use stock returns during two placebo sample periods (1) Jan – Apr 2019, and (2) Jan – Apr 2018, and assign the number of cases to the same day and month in 2019 and 2018, respectively. Additionally, as a third placebo test, we randomly assign the number of Covid-19 cases to the same day and month in any of the years between 2014 and 2019. We re-estimate the baseline regression for these placebo samples to examine the impact of the year-before inventory holdings during the placebo periods. Table 11 reports the estimation results.

In Models (1) and (2) of Table 11 that report the estimates for the 2019 and 2018 placebo periods, respectively, the coefficients on *Inventory*Placebo* are positive, indicating that higher inventory holdings a year before do not generate negative stock market performance in the following year. Model (3) shows the impact of the assigned number of cases randomly selected in the years between 2014 and 2019 and the average inventory one year before. The coefficient on *Inventory*Placebo* is nearly zero and statistically insignificant. Overall, the negative effects of inventory holdings do not appear in non-crisis years when there are no negative demand shocks.

The placebo tests help us rule out the explanation that some other unobservable characteristics drive the negative relationship between pre-crisis inventory holdings and stock market response to Covid-19.

[Insert Table 11 about here]

5.4 Other adverse demand shocks

We have documented that firms with higher pre-crisis inventory experience a more negative market response to Covid-19 due to the adverse consumer demand shock that increases inventory storage costs and reduces its importance as a stockout hedge. To interpret our findings beyond the Covid-19 crisis, we examine the role of inventory holdings exploiting two other events that were accompanied by significant adverse demand shocks: (1) the 9/11 terrorist attacks and (2) the global financial crisis (GFC).

5.4.1 The 9/11 terrorist attacks

The 9/11 terrorist attacks caused a negative shock to consumer confidence and a sharp downturn in consumer spending (Tong and Wei, 2008; Duchin et al., 2010). Tong and Wei (2008) argue that the market response to the 9/11 terrorist attacks was mainly driven by the negative consumer demand shock. Therefore, it provides a setting to examine the value of inventory holdings during negative demand shocks.

To gauge the impact of the 9/11 attacks, we follow Chesney, Reshetar, and Karaman (2011) and Brounen and Derwall (2010) and employ cumulative abnormal returns (CAR) over the 11-day event window from September 11th, 2001 (the event date). We compute daily abnormal returns as $(R_{it} - \overline{R_i})$, where $\overline{R_i}$ is the average stock i's return in the (-120, -11) estimation period. Table 12 presents the regression results for the 9/11 terrorist attacks in Model (1). The coefficient on *Inventory* is negative and significant, suggesting a negative market perception of higher levels of inventory holdings during this adverse consumer demand shock.

5.4.2 The global financial crisis

The GFC led to a significant economic downturn and a deep contraction in consumer spending (Mian, Rao, and Sufi, 2013; Mian, Sufi, and Verner, 2017; Benguria and Taylor, 2019). It arguably caused a shock to consumer demand through bank's reduction in the supply of credit to households (Ramcharan, Verani, and Van den Heuvel, 2016). To measure the stock market reaction to the GFC, we use the log monthly stock returns from January 2006 to March 2009. Models (2) and (3) of Table 12 present the regression results. Model (2) presents the baseline results, and Model (3) shows the impact of inventory after controlling for the interaction terms of other firm-level variables with *After*. *After* is a binary variable equal to one for the crisis period (July 2007 - March 2009) and zero for the pre-crisis period (January 2006 - June 2007).[24] The coefficients on *Inventory*After* are negative and statistically significant at the 1% level in both specifications. Once again, we find strong empirical support for our argument that the negative impact of inventory holdings is attributed to adverse demand shocks.

[Insert Table 12 about here]

6. Conclusion

The Covid-19 pandemic provides an experiment to assess the role of corporate inventory holdings under the adverse consumer demand and commodity price shocks that reduce the likelihood of stockout, increase the storage costs of inventory, and downplay its importance as a hedge against

[24] We follow the timeline of the GFC from Duchin et al., (2010).

inputs price increases. We document that firms with higher pre-crisis inventory holdings experience a more negative market response to Covid-19. We identify the causal effects of inventory holdings on firm performance during the Covid-19 crisis by controlling for unobserved firm heterogeneity and other firm characteristics and employing the instrumental variables approach. In the cross-industry analyses, we show that firms that face a greater reduction in consumer demand and are more susceptible to falling commodity prices perform worse during the Covid-19 crisis.

On the flip side, pre-crisis inventory holdings provide a buffer against global supply chain disruptions during the Covid-19. We find that for firms that experience supply chain disruptions during Covid-19 due to their reliance on global suppliers (i.e., having Chinese suppliers), inventory holdings have compensating effects. We also find that the negative impact of high inventory holdings is more pronounced for financially constrained firms. Our results are robust to various inventory measures and different definitions of stock market response, and we confirm the validity of our inferences with placebo tests.

Our research reveals a novel link between corporate inventory and the Covid-19 pandemic and contributes to the burgeoning literature on the Covid-19 health crisis's economic impact. By suggesting that inventory plays a significant role in influencing the stock market responses to the Covid-19 crisis, we point out the importance of inventory management and provide essential implications for corporate managers to manage inventory holdings. Understanding the effects of inventory is also essential for policymakers to provide financial aid for firms to navigate crises.

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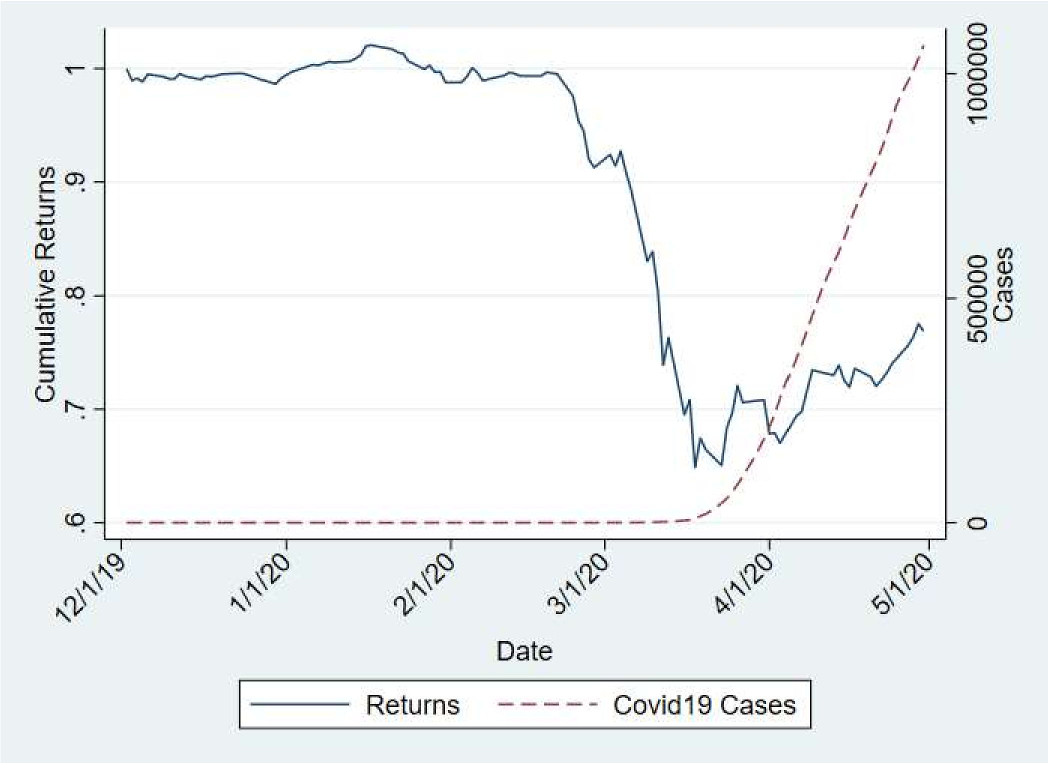
Figure 1. Stock price performance and commodity prices around Covid-19 pandemic

Panel A. Equally weighted cumulative returns

Panel A plots the daily cumulative equally weighted returns of 3,429 U.S. public firms (left y-axis) and the number of Covid-19 cases in the U.S. (right y-axis), from December 1st, 2019 to May 1st, 2020 (Sources: Compustat, USAFacts).



Panel B. Commodity price index and WTI oil prices

Panel B plots Bloomberg Commodity index (left y-axis) and WTI crude oil prices (right y-axis), from December 1st, 2019 to May 1st, 2020 (Source: Thomson Reuters' website).

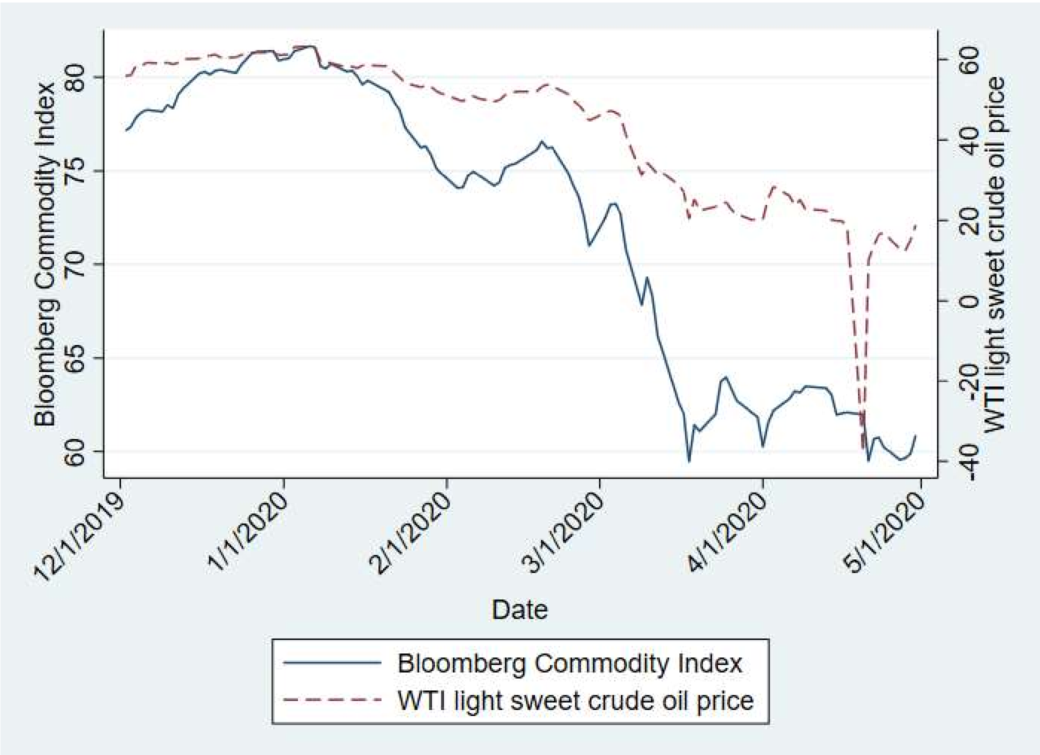


Figure 2. Inventory-sorted portfolio returns

The figure shows daily cumulative equally weighted returns for low-inventory and high-inventory portfolios in early 2020 (excluding financial, real estate, and utility firms), and the difference between the low- and high- inventory portfolios. We sort firms into high-inventory (top tercile) and low-inventory (bottom tercile) portfolios based on the average of the beginning- and end-of-year ratios of total inventory to total assets in 2019.

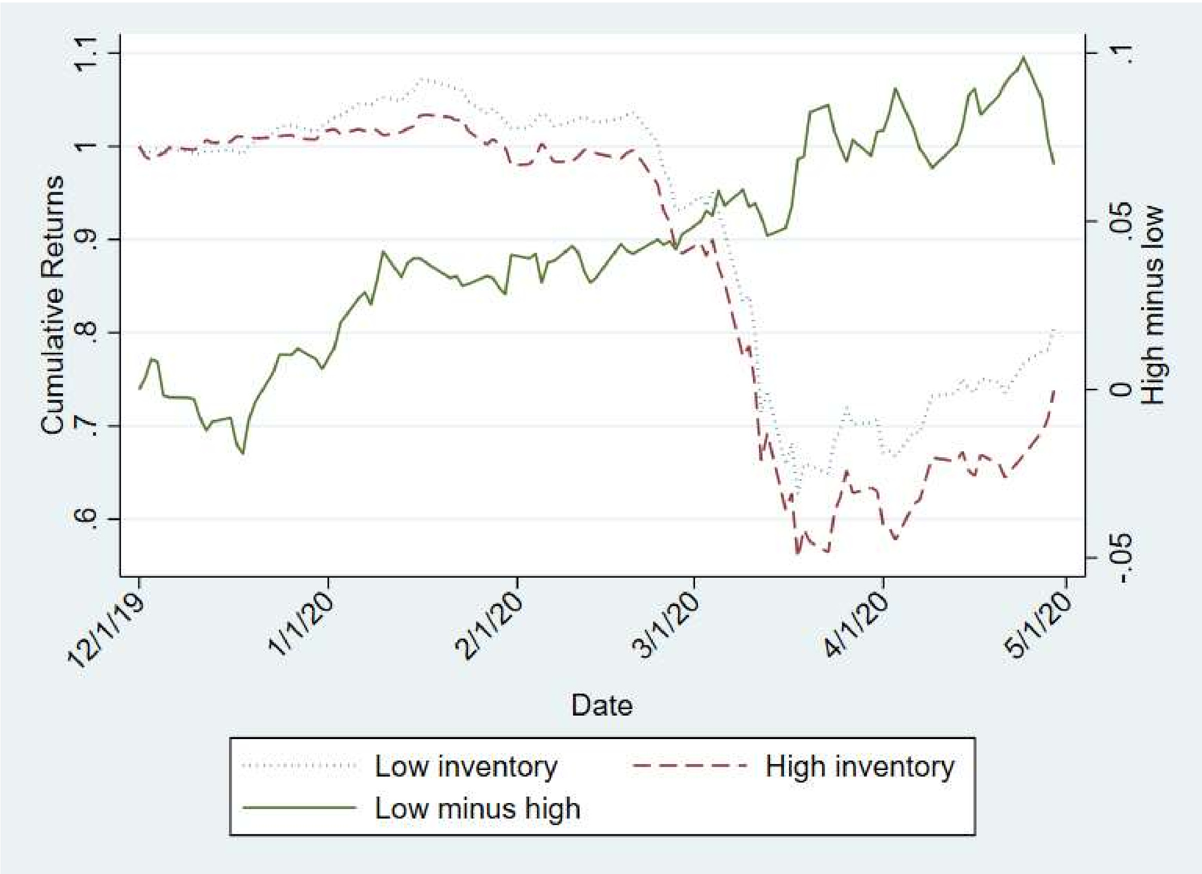


Table 1. Descriptive statistics

The 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 measured as [log(1+#Cases$_t$)-log(1+#Cases$_{t-1}$)] (Covid19), daily stock returns in percentage term (Return), and firm-level variables measured as the average of the beginning- and end-of-year values in 2019 (the definitions of all variables are provided in section 4).

Variables	N	Mean	SD	p25	Median	p75
Covid19	203,930	0.087	0.169	0.000	0.000	0.115
Return	203,930	-0.156	8.427	-2.624	0.000	2.121
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

Table 2. Stock returns for high versus low pre-Covid inventory

The table reports the mean of stock returns from January 1st, 2020 to April 30th, 2020, the correlation between stock returns and the growth rate of Covid-19 cases, and the corresponding *p*-value for firms with low, medium, and high pre-Covid inventory holdings assigned based on the sample terciles.

Inventory	Low	Medium	High
Stock returns	-0.130	-0.131	-0.209
p value (stock returns)	(0.000)	(0.000)	(0.000)
Correlation between stock returns and Covid19 cases growth	-0.006	-0.011	-0.020
p value (correlation)	(0.105)	(0.006)	(0.00)

Table 3. Inventory and stock market response to Covid-19

The table reports the OLS panel regression estimates of the impact of inventory holdings on the responses of daily stock returns to the growth rate of Covid-19 cases. The sample period is from January 1st, 2020, to April 30th, 2020. The dependent variable is daily stock returns. *Covid19* is the growth rate of Covid-19 cases by state measured as [log(1+#Cases$_t$)-log(1+#Cases$_{t-1}$)]. *Inventory* is the average of the beginning- and end-of-year ratios of total inventory to total assets in 2019. All variables are defined in section 4. In model (4), firm-level variables are absorbed by firm fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Inventory×Covid19	-2.593***	-2.611***	-2.602***	-2.577***
	(0.95)	(0.95)	(0.95)	(0.95)
Covid19	-0.363***	-0.364***	-0.364***	-0.365***
	(0.13)	(0.13)	(0.13)	(0.13)
Inventory	0.139	0.137	0.174	
	(0.14)	(0.14)	(0.14)	
Cash	0.171**	0.127**	0.143**	
	(0.07)	(0.06)	(0.07)	
Leverage	-0.004	-0.006	-0.004	
	(0.02)	(0.02)	(0.02)	
MTB	-0.000	-0.000	-0.000	
	(0.00)	(0.00)	(0.00)	
ROA	-0.051	-0.044	-0.047	
	(0.03)	(0.03)	(0.03)	
Firm size	0.018**	0.014*	0.018**	
	(0.01)	(0.01)	(0.01)	
Cash flow	0.036	0.030	0.031	
	(0.02)	(0.02)	(0.02)	
Constant	-0.261***	-0.225***	-0.255***	-0.104***
	(0.07)	(0.06)	(0.07)	(0.01)
Industry fixed effects	Yes	No	Yes	No
State fixed effects	No	Yes	Yes	No
Firm fixed effects	No	No	No	Yes
Obs.	203,930	203,930	203,930	203,930
R-squared	0.000	0.000	0.000	0.008

Table 4. The role of inventory during Covid-19: Controlling for other explanations

The table reports the OLS panel regression estimates explaining the impact of corporate inventory on the responses of daily stock returns to the growth rate of Covid-19 cases with additional firm-level control variables. The sample period is from January 1st, 2020, to April 30th, 2020. The dependent variable is daily stock returns. *Covid19* is the growth rate of Covid-19 cases by state measured as [log(1+#Cases$_t$)-log(1+#Cases$_{t-1}$)]. All variables are defined in section 4. Firm-level variables are the averages of the beginning- and end-of-year values in 2019. Firm-level variables on their own are absorbed by firm fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% probability level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Inventory×Covid19	-2.437**	-2.600***	-2.609***	-2.634***	-2.672***	-2.610***	-2.159**
	(1.01)	(0.96)	(0.96)	(0.96)	(0.96)	(0.96)	(1.02)
Covid19	-0.433**	-0.349**	-0.350**	-0.346**	-0.820***	-0.352***	-1.396***
	(0.19)	(0.14)	(0.14)	(0.14)	(0.30)	(0.14)	(0.46)
Cash×Covid19	0.229						0.791*
	(0.38)						(0.44)
Leverage×Covid19		-0.027					0.031
		(0.12)					(0.14)
MTB×Covid19			-0.002				0.001
			(0.00)				(0.01)
ROA×Covid19				0.031			0.094
				(0.09)			(0.22)
Firm size×Covid19					0.083*		0.135**
					(0.04)		(0.05)
Cash flow×Covid19						0.016	-0.103
						(0.08)	(0.17)
Constant	-0.105***	-0.104***	-0.104***	-0.104***	-0.104***	-0.104***	-0.105***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	203,930	203,930	203,930	203,930	203,930	203,930	203,930
R-squared	0.008	0.008	0.008	0.008	0.008	0.008	0.008

Table 5. Controlling for endogeneity: Instrumental variables regressions

The table reports the second stage estimates of the fixed effects instrumental variables regressions explaining the impact of corporate inventory on the responses of daily stock returns to the growth rate of Covid-19 cases. The sample period is from January 1st, 2020, to April 30th, 2020. Inventory holdings in 2017, 2016, and 2015 are used as instruments in Model (1), Model (2), and Model (3), respectively. In Model (4), we use inventory in 2015, 2016, and 2017 as a set of instruments and report statistics and its associated *p*-value for the test of overidentification restrictions. The dependent variable is daily stock returns. *Covid19* is the growth rate of Covid-19 cases by state measured as [log(1+#Cases$_t$)-log(1+#Cases$_{t-1}$)]. *Inventory* is the average of the beginning- and end-of-year ratios of total inventory to total assets in 2019. *Inventory* variable on its own is absorbed by firm fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% probability level, respectively.

	(1)	(2)	(3)	(4)
	IV: Inventory in 2017	IV: Inventory in 2016	IV: Inventory in 2015	IVs: Inventory in 2015, 2016, and 2017
Inventory×Covid19	-2.359**	-2.094**	-1.485	-1.935*
	(1.00)	(0.98)	(1.04)	(1.00)
Covid19	-0.421***	-0.446***	-0.481***	-0.418***
	(0.14)	(0.15)	(0.16)	(0.15)
Constant	-0.104***	-0.102***	-0.105***	-0.103***
	(0.01)	(0.01)	(0.01)	(0.01)
Firm fixed effects	Yes	Yes	Yes	Yes
Obs.	196,159	185,847	175,131	173,867
J statistics of overidentifying restrictions (*p* value)				2.595 (0.27)
Wald statistics	39.429***	39.301***	32.509***	32.377***

Table 6: The role of inventory during Covid-19: High vs. low shock to consumer demand and commodity prices

The table reports the fixed effects panel regression estimates explaining the impact of corporate inventory on the responses of daily stock returns to the growth rate of Covid-19 cases for two sub-samples: (1) industries that suffer significant negative demand and commodity price shocks, i.e., transportation, energy, materials, and consumer discretionary (GICS industry groups and sectors 2030, 10, 15, and 25, respectively), and (2) industries that face less significant demand and commodity price shocks, i.e., consumer staples, information technology, communication services, and health services, (GICS industry sectors 30, 45, 50, and 35, respectively). The sample period is from January 1st, 2020, to April 30th, 2020. The dependent variable is daily stock returns. *Covid19* is the growth rate of Covid-19 cases by state measured as [log(1+#Cases$_t$)-log(1+#Cases$_{t-1}$)]. *Inventory* is the average of beginning- and end-of-year ratios of total inventory to total assets in 2019. *Inventory* variable on its own is absorbed by firm fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% probability level, respectively.

	(1)	(2)
	High shock	Low shock
Inventory×Covid19	-3.560**	-1.422
	(1.54)	(1.55)
Covid19	-0.258	-0.399**
	(0.28)	(0.17)
Constant	-0.160***	-0.071***
	(0.02)	(0.01)
Firm fixed effects	Yes	Yes
Obs.	61,097	111,178
R-squared	0.008	0.008

Table 7. The role of inventory during Covid-19: high vs. low supply chain disruptions

The table reports the fixed effects panel regression estimates explaining the impact of corporate inventory on the responses of daily stock returns to the growth rate of Covid-19 cases for two sub-samples: (1) firms that experience significant supply chain disruption (SCD) during Covid-19, i.e., firms that have Chinese suppliers (*High SCD - Chinese suppliers*); (2) firms that experience less significant SCD during Covid-19, i.e., firms that do not have Chinese suppliers (*Low SCD - no Chinese suppliers*). We classify a firm as having *Chinese suppliers* if the firm mentions China in its 10-K in relation to importing activities, i.e., the firm has non-missing values in *INPUT* and *ININ* for China in Hoberg and Moon Text-based Offshoring Network Database (Hoberg and Moon, 2017 and 2019). We classify the rest of the firms as "*no Chinese suppliers*." Models (1) and (2) present regression estimates for the two sub-samples based on the full sample. Models (3) and (4) present the estimation results for the "High SCD" sub-sample and the sub-sample of "Low SCD" firms matched based on the beginning- and end-of-year average cash, firm size, market-to-book ratio, ROA, and leverage in 2019. The sample period is from January 1st, 2020, to April 30th, 2020. The dependent variable is daily stock returns. *Covid19* is the growth rate of Covid-19 cases by state measured as [log(1+#Cases$_t$)-log(1+#Cases$_{t-1}$)]. *Inventory* is the average of beginning- and end-of-year ratios of total inventory to total assets in 2019. *Inventory* variable on its own is absorbed by firm fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% probability level, respectively.

	(1)	(2)	(3)	(4)
	Full sample		Matched samples	
	High SCD - Chinese suppliers	Low SCD - no Chinese suppliers	High SCD - Chinese suppliers	Low SCD - no Chinese suppliers
Inventory×Covi	-0.201	-3.550***	-0.201	-3.258**
	(1.98)	(1.10)	(1.98)	(1.27)
Covid19	-0.646**	-0.303**	-0.646**	-0.378
	(0.29)	(0.15)	(0.29)	(0.24)
Constant	-0.145***	-0.086***	-0.145***	-0.073***
	(0.02)	(0.01)	(0.02)	(0.02)
Firm fixed	Yes	Yes	Yes	Yes
Obs.	64,521	139,405	64,521	64,522
R-squared	0.007	0.008	0.007	0.007

Table 8. The role of inventory during Covid-19: Financially constrained vs. financially unconstrained firms

The table reports the fixed effects panel regression estimates explaining the impact of corporate inventory on the responses of daily stock returns to the growth rate of Covid-19 cases for two sub-samples: (1) financially constrained firms (*Const.*) and financially unconstrained firms (*UnConst.*). We use five variables to evaluate the degree of financial constraints: WW index, KZ index, HP index, bond ratings, and dividend payout ratio. We classify firms that have WW index, KZ index and HP index above (below) the sample median as financially constrained (unconstrained) firms. We classify firms with (without) bond ratings in the past decade as financially unconstrained (constrained) firms. We classify firms that have a dividend payout ratio below (above) the sample median as financially constrained (unconstrained) firms. The sample period is from January 1st, 2020, to April 30th, 2020. The dependent variable is daily stock returns. *Covid19* is the growth rate of Covid-19 cases by state measured as [log(1+#Cases$_t$)-log(1+#Cases$_{t-1}$)]. *Inventory* is the average of beginning- and end-of-year ratios of total inventory to total assets in 2019. *Inventory* variable on its own is absorbed by firm fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% probability level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	WW index		KZ index		HP index		Bond ratings		Dividend payout	
	Const.	UnConst.	Const.	UnConst.	Const.	UnConst.	Const.	UnConst.	Const.	UnConst.
Inventory×Covid19	-3.679***	-1.428	-3.020***	-1.314	-4.087***	-1.857	-3.192***	-0.898	-5.208***	-0.352
	(1.31)	(1.54)	(1.16)	(1.60)	(1.49)	(1.40)	(1.09)	(2.02)	(1.57)	(1.20)
Covid19	-0.482**	-0.132	-0.427*	-0.363**	-0.264	-0.139	-0.432***	-0.199	-0.119	-0.335*
	(0.23)	(0.21)	(0.22)	(0.17)	(0.19)	(0.21)	(0.16)	(0.27)	(0.19)	(0.19)
Constant	-0.154***	-0.165***	-0.167***	-0.049***	-0.175***	-0.153***	-0.087***	-0.156***	-0.203***	-0.120***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	77,121	76,623	94,553	95,019	92,940	77,263	154,464	49,462	99,528	74,632
R-squared	0.010	0.006	0.008	0.006	0.010	0.006	0.008	0.005	0.010	0.005

Table 9. Alternative measures of inventory

The table reports the fixed effects regression estimates explaining the impact of corporate inventory on the response of stock market returns to Covid-19. The sample period is from January 1st, 2020, to April 30th, 2020. The dependent variable is daily stock returns. *Covid19* is the growth rate of Covid-19 cases by state measured as [log(1+#Cases$_t$)-log(1+#Cases$_{t-1}$)]. *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 adjusted for the industry- and state- average. All inventory variables are calculated as the average of beginning- and end-of-year values in 2019. All inventory variables on their own are absorbed by firm fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% probability level, respectively.

	(1)	(2)	(3)
Inventory_sale×Covid19	-1.276*		
	(0.67)		
Inventory_days×Covid19		-0.003***	
		(0.00)	
Inventory_abnormal×Covid19			-0.237**
			(0.11)
Covid19	-0.470***	-0.413***	-0.632***
	(0.13)	(0.12)	(0.11)
Constant	-0.104***	-0.104***	-0.105***
	(0.01)	(0.01)	(0.01)
Firm fixed effects	Yes	Yes	Yes
Obs.	203,930	203,930	183,833
R-squared	0.007	0.007	0.007

Table 10. Alternative sample periods and measures of returns

The table reports the regression estimates explaining the impact of corporate inventory on the stock market response to Covid-19. In Model (1), the dependent variable is daily stock returns, and the sample period is from January 1st, 2020 to March 20th, 2020; *Covid19* is the growth rate of Covid-19 cases by state measured as [log(1+#Cases$_t$)-log(1+#Cases$_{t-1}$)]. In Model (2), the dependent variable is monthly stock returns, and the sample period is from September 2019 to April 2020; *After* is a binary variable equal to one for the crisis period (Jan-Apr 2020) and zero for the pre-crisis period (Sep-Dec 2019). Model (3) is a cross-sectional regression with cumulative daily stock returns from January 1st, 2020 to April 30th, 2020, as the dependent variable. *Inventory* is the average of beginning- and end-of-year ratios of total inventory to total assets in 2019. In Models (1) and (2), *Inventory* variable on its own is absorbed by firm fixed effects. All variables are defined in section 4. Robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% probability level, respectively.

	(1)	(2)	(3)
	Daily returns January 1st, 2020 – March 20th, 2020	Monthly returns September 2019 – April 2020	Cumulative returns January 1st, 2020 – April 30th, 2020
Inventory×Covid19	-2.860***		
	(1.04)		
Covid19	-0.962***		
	(0.15)		
Inventory×After		-2.428***	
		(0.93)	
After		-0.476***	
		(0.13)	
Inventory			-0.087*
			(0.05)
Cash			0.140***
			(0.02)
Leverage			-0.016***
			(0.01)
MTB			0.001**
			(0.00)
ROA			0.008
			(0.01)
Firm size			0.012***
			(0.00)
Cash flow			0.001
			(0.01)
Constant	-0.540***	-0.172***	-0.280***
	(0.01)	(0.06)	(0.02)
Firm fixed effects	Yes	Yes	Yes
Obs.	136,965	22,247	3,213
R-squared	0.015	0.151	0.036

Table 11. Placebo test

The table reports the placebo regression estimates explaining the impact of corporate inventory on the stock market performance. The dependent variable is daily stock returns. In these placebo tests, we assign the number of Covid-19 cases to the same day and month in 2019 (Model (1)) and 2018 (Model (2)). In Model (3), we randomly assign the number of cases to the same day and month in any of the years between 2014 and 2019. *Placebo* denotes the growth rate of Covid-19 cases by state assigned to the placebo year based on the same day and month. The growth rate of Covid-19 cases by state is measured as [log(1+#Cases$_t$)-log(1+#Cases$_{t-1}$)]. *Inventory* is the average of beginning- and end-of-year ratios of total inventory to total assets in the year before the placebo year. *Inventory* variable on its own is absorbed by firm fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% probability level, respectively.

	(1)	(2)	(3)
	Jan – Apr 2019	Jan – Apr 2018	2014 - 2019
Inventory×Placebo	1.221**	0.020***	0.001
	(0.62)	(0.00)	(0.01)
Placebo	-0.560***	-0.001	-0.002*
	(0.10)	(0.00)	(0.00)
Constant.	0.073***	-0.002***	0.001***
	(0.01)	(0.00)	(0.00)
Firm fixed effects	Yes	Yes	Yes
Obs.	176,326	92,302	93,804
R-squared	0.012	0.026	0.030

Table 12. Other adverse demand shocks: 9/11 terrorist attacks and 2007-2008 GFC

The table reports the regression estimates explaining the impact of corporate inventory on the stock market responses to the 9/11 terrorist attacks (Model (1)) and the 2007-2008 global financial crisis (GFC) (Models (2) and (3)). In Model (1), the dependent variable is the cumulative abnormal return (CAR) over the 11-day event window from September 11th, 2001. In Models (2) and (3), the dependent variable is monthly stock returns; *After* is a binary variable equal to one for the crisis period (July 2007 - March 2009), and zero for the pre-crisis period (January 2006 - June 2007). All variables are defined in section 4. Firm-level variables are calculated as the average of beginning- and end-of-year values before the event (before 2001 for the 9/11 terrorist attacks and before 2006 for GFC). Robust standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% probability level, respectively.

	(1)	(2)	(3)
	9/11 terrorist attacks	Global Financial Crisis	
Inventory×After		-0.020***	-0.022***
		(0.01)	(0.01)
Inventory	-0.025*	-0.043***	-0.050***
	(0.01)	(0.00)	(0.00)
After		0.027	0.032
		(0.03)	(0.03)
Cash	-0.023*	-0.017	-0.017
	(0.01)	(0.01)	(0.01)
Leverage	-0.002	0.037***	0.058***
	(0.01)	(0.01)	(0.01)
ROA	-0.002**	-0.022***	-0.022***
	(0.00)	(0.00)	(0.00)
MTB	0.003	-0.022	-0.026*
	(0.03)	(0.01)	(0.01)
Firm size	-0.006***	-0.052***	-0.055***
	(0.00)	(0.00)	(0.00)
Cash flow	0.014	-0.025***	-0.030***
	(0.03)	(0.01)	(0.01)
Cash×After			0.001
			(0.01)
Leverage×After			-0.026***
			(0.00)
MTB×After			0.000
			(0.00)
ROA×After			0.005
			(0.01)
Firm size×After			0.002***
			(0.00)
Cash flow×After			0.009
			(0.01)
Constant	-0.034***	0.372***	0.386***
	(0.01)	(0.02)	(0.02)
Firm fixed effects	No	Yes	Yes
Obs.	4,796	168,528	168,528
R-squared	0.009	0.056	0.056