2022

Pandemics and Cash

Mufaddal Baxamusa
University of St. Thomas, Minnesota, mufaddalb@stthomas.edu

Abu M. Jalal
Suffolk University, ajalal@suffolk.edu

Pandemics and Cash[1]

By:

Mufaddal Baxamusa

And

Abu Jalal

Abstract: We investigate the relationship between firms' cash holdings and pandemics. Our results show that as compared to tele-workable firms, whose employees can work remotely, non-tele-workable firms with more on-site employees increase cash during pandemics. This increase in cash comes from short-debt, preferred stocks, reduction in capital expenditures and discontinuation of some operations. Firms hold more cash as a reaction to higher default risk. For non-tele-workable firms, there is a positive relationship between abnormal stock returns and cash, suggesting that this increase in cash during pandemics is not driven by behavioral reasons, but by increases in uncertainty in labor productivity.

Keywords: Pandemic, Cash, Labor, Tele-workable, Working from home, Public health, Solvency, Liquidity, Risk, Financial constraint, Labor productivity, Labor uncertainty.

JEL Classifications: G30, G32, I10

[1] The previous version of this paper was titled "H1N1 Pandemic and Cash"

1. INTRODUCTION

Uncertainty in labor productivity has important consequences for the economy as it makes industries, wages, and employment less stable (Bai and Wang, 2003). Pandemics provide an experimental setting to test the impact of uncertainty in labor productivity since employees maybe incapacitated for varying lengths of time. To reduce the morbidity from a pandemic, employees may change their behavior and the governments may impose restrictions on businesses , which also increases this uncertainty (Baker et al. 2020).

According to Pinkowitz, Stulz, and Williamson (2016) and Opler, Pinkowitz, Stulz and Williamson (1999), firms react to uncertainty by holding more cash. As pandemics are spread through human interactions, firms that are more dependent on such interactions are likely to have a larger exposure to the uncertainties in labor productivity. In this research, we study the cash management policies of firms during pandemics, especially of those firms that are more dependent on human interactions and so more exposed to this uncertainty.

H1N1 and COVID are the most recent pandemics. Although COVID continues to have a stronger impact on everyday life and generates more economic disruptions, there are many similarities.[2] Both infected millions of people. According to the estimates from the Center for Disease Control and Prevention (CDC), about 60.8 million Americans were infected between April 2009 and March 2010 during the H1N1 pandemic.[3] Similarly, 114.6 million Americans are estimated to be infected with COVID between February 2020 and April 2021.[4] Firms were impacted, if the employees or their dependents fell ill, or the employees had to stay home if, for example, their children's schools closed or the class was quarantined.

[2] All our results hold if we only use the weaker H1N1 pandemic instead of pooling both the pandemics in our regressions.
[3] https://www.cdc.gov/flu/pandemic-resources/2009-h1n1-pandemic.html
[4] https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/burden.html

Since a pandemic affects the ability of people to stay healthy and work, the characteristics of the labor force becomes an important issue. Some firms need employees to be on site, such as the ones in the accommodation and food services industries; while others may allow a significant number of their employees to work from home, such as those in the information technology industries. Firms that need a large percentage of employees to be on-site are more likely to be affected by a disruption in labor arising from a pandemic, as the tasks performed by the employee are likely to remain pending if the employees are not physically present at the site. Uncertainty in labor productivity increases as an undetermined number of employees reduce effort for an unspecified number of days. In contrast, employees who can perform their tasks remotely may continue to be able to work while taking care of a sick dependent or even being moderately ill.

In our study, the firms in the treatment group belong to industries that need a large percentage of employees to be on-site (*Non-tele-workable*). We get this classification and data from Dingel and Neiman (2020). Propensity score matched firms that belong to the industries where the largest percentage of employees can work remotely constitute the control group (*Tele-workable*). Consistent with the argument that firms increase cash during the pandemic, our graph shows that over a fifteen-year period, which includes the financial crises and the trade war with China, cash holdings for *Non-tele-workable* firms reached the highest levels only during the pandemics – in the first quarter of 2010 and the fourth quarter of 2020.

For our analysis, we employ difference-in-difference estimation methodology. We create a dummy variable to indicate the time during the pandemic. The World Health Organization (WHO) declared H1N1 to be a pandemic in June 2009 and announced the end of the pandemic in August 2010. Our dummy variable *Pandemic* thus takes the value of one between the third quarter of 2009 and the third quarter of 2010. Correspondingly for COVID, the five quarters of the pandemic starts with the first quarter of 2020 when the WHO declared COVID a pandemic. Even though the COVID pandemic is still ongoing, we conclude our analysis in the first quarter of 2021 when the data available to us ends. For our pre-H1N1 period, we avoid the financial crisis and use data between the second quarter of 2006 and the second quarter of 2007. For the pre-COVID period, we use the last two quarters of 2018 and the first three quarters of 2019. We avoid using the last quarter of 2019 as there is some debate about when the COVID infections started. We use quarter-industry fixed effects to mitigate concerns about seasonal industry level dynamics.

Non-tele-workable firms increase cash during the pandemic by about 2.87% compared to the control group. Additionally, the cash holdings for the control and treated groups are not statistically different before the pandemic. The divergence in the cash balances of these two groups happens during the pandemic and occurs in each of the quarters during the pandemic. We also find that the increase in cash holdings seems to be concentrated amongst the firms that are the most vulnerable to liquidity shocks. *Non-tele-workable* firms that are financially constrained, have negative net income, high interest payments, high expenditures such as capital expenditures and SG&A, and pay no dividends increase their cash holdings more during the pandemic.

Next, we investigate how these firms finance their increase in cash holdings. We find that financially constrained *Non-tele-workable* firms increase their short-term debt. Acharya and Steffen (2020) suggest that a possible source of the short-term credit in a pandemic for financially constrained firms is a pre-existing line of credit, which the banks are contractually obliged to honor. Longer-term capital is raised through preferred stocks. On the operating side, the firms control expenses by reducing capital expenditure, discontinuing some operations, and paying less taxes.

Consistent with the asset pricing literature (see Baker et. al, 2020) we also find that volatility increases for firms during the pandemic. We find that the *Non-tele-workable* firms that experience greater increases in volatility and move closer to default are the ones that increase their cash holdings the most during the pandemic. Interestingly, the financially constrained *Non-tele-workable* firms experience a reduction in their long-term debt during the pandemic. Taken together, our results imply that increases in default risk may reduce the likelihood of the firms being able to borrow long-term debt.

We test three alternate explanations to our results. First, it is possible that firms increase cash for behavioral biases, such as managerial pessimism or risk aversion. To test it, we investigate how the shareholders react to increases in cash holdings. We find that during the pandemics, *Non-tele-workable* firms that increase cash holdings earn higher abnormal stock returns. These actions of the firm benefit the shareholders and so, do not appear to be motivated by agency or behavioral reasons. Second, the source of uncertainty affecting corporate cash policies could be demand risk during the pandemic. To test it, we generate a variable that takes the value of one if the firm has a large customer. A diversified customer base is less risky as the firm is not dependent on a single customer. The interaction term of this variable and pandemic does not mitigate the relationship of cash with *Non-tele-workable* firms during the pandemic. Third, a source of uncertainty can be supply risk. Again, we generate a dummy variable that takes the value of one if the firm has a large supplier. The interaction term of the presence of large supplier and pandemic is statistically insignificant in its relation to cash. This suggests that firms do not necessarily hold more cash in a pandemic because of supply uncertainty. However, the presence of a large supplier does not enhance the relationship between cash and *Non-tele-workable* firms in a pandemic.

This study contributes in four different ways. First, consistent with the literature, we find that firms hold more cash after a disaster (e.g. Dessaint and Matray 2017). We fundamentally diverge from the literature on the important question of why these firms hold more cash. The literature provides behavioral reasons for the increase in cash. In contrast we provide a neo-classical explanation. On the one hand, Dessaint and Matray (2017) attribute the increase in cash after hurricane strikes to biased managerial risk assessment. Bernile, Bhagwat, and Rau (2017) find that firms hold more cash because of early-life experiences of managers. Antoniou, Kumar, and Maligkris (2017) show that managerial pessimism leads firms to hold more cash after terrorist attacks. On the other hand, we hypothesize that firms rationally react to uncertainty in labor productivity arising from a pandemic and hold more cash in a bid to reduce default risk. In support of our hypothesis, we find that this increase in cash is beneficial to the shareholders and is not value destroying as suggested by these studies in the literature.

Second, the cash management literature suggests that cash increases with uncertainty (see Bates, Kahle, and Stulz, 2009). For instance, prior studies show that firms hold more cash under economic policy uncertainty (Duong et al. 2020), income uncertainty (Riddick and Whited, 2009), and financial crisis (Song and Lee, 2012). We add to this literature by showing that cash increases when uncertainty in labor productivity increases.

Third, our results suggest that tele-workability of employees provides a significant flexibility for firms, when it comes to their survival during a pandemic. Several studies confirm the benefits of tele-workability. For example, Mas and Pallais (2017) show that, even before the pandemic, workers value remote working arranging so much that they are willing to give up 8%

of compensation for this flexibility. Barrero, Bloom, and Davis (2021) find that there is a noticeable 20% shift towards working from home even after the pandemic ends and this trend will increase productivity by approximately 5%. We add to this strand of literature by showing that firms that have a large percentage of employees who tele-work are less susceptible to labor disruptions and thus, may not need to increase their cash holdings as much.

Finally, our findings have implications for policymakers. When faced with adverse shocks, policymakers often pass new regulations and design a slew of economic aid packages ranging from free money to interventions in the capital markets. This paper suggests that the policy responses should include support for the credit markets. The reason is that if the financially constrained firms can continue to borrow at a reasonable rate, then they are less likely to draw down short-term finance. Using large amounts of short-term finance puts stress on the lending banks and this stress can be transmitted through the banks to the wider economy, putting the economy at risk.

The rest of the paper is as follows. Section 2 reviews the literature and develops the hypothesis. Section 3 lays out the identification and testing strategy. Section 4 describes the sample and the variables used in the study. Section 5 presents the results. We conclude in Section 6.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

(i) Uncertainty in Labor Productivity in Pandemics

Uncertainty in labor productivity increases significantly during a pandemic. An employment contract stipulates the number of hours worked and the rate of pay for the employees. It typically lists a number of exemptions such as health and dependent care, under which the employee can temporarily reduce effort. Uncertainty in labor productivity increases when a large but unknown number of employees possibly reduce effort for a number of days while taking care of themselves or their dependents.

Emerging data and research on productivity of employees during the pandemic show this increase in uncertainty. De Vries, Erumban, and van Ark (2021) document a sharp decline in productivity in the hospitality and culture sectors, but an increase in productivity among digital intensive sectors. An International Labor Organization report by Kapsos (2021) finds that larger firms increase productivity, while smaller firms did the opposite as the smaller firms were more exposed to the economic effects of the pandemic. Regardless of the effects on the level of productivity, these data point towards an increase in the uncertainty associated with labor productivity.

From a firm's perspective, labor is a necessary component of its production and sales functions. In fact, none of the publicly traded corporations can produce anything without labor, despite significant advances in automation. The uncertainty in labor productivity flows from production to revenue and finally, to cash flows. This is important as the firm has on-going expenses such as interest, labor, and raw material that it needs to pay from these cash flows. Not being able to pay some of these expenses may result in financial distress. To reduce the likelihood of distress, firms are required to hold more cash to meet their liquidity needs.

Alternate work arrangements can be deployed to ease labor shortages and increase productivity. These arrangements include working from home, flexible schedules, and part-time work. Katz and Krueger (2017) document that these arrangements have grown since 2005 and have become more prevalent after 2008 (Mas and Pallais, 2017). An advantage of working remotely or tele-working is that it reduces an employee's contact with others.

(ii) Cash and Uncertainty

Opler, Pinkowitz, Stulz, and Williamson (1999) and Bates, Kahle, and Stulz (2009) find a positive relation between cash and growth intensive firms. They find this relation to persist for decades. Pinkowitz, Stulz, and Williamson (2016) find that R&D intensive firms hold more cash. Pinkowitz and Williamson (2007) provide evidence that investors favorably value cash held by more risky firms, possibly as this cash can be used to finance investments when the cost of external borrowing is high. Ghaly, Dang, and Stathopoulos (2017) notice that firms with more highly skilled employees, possibly employed in more growth-oriented companies, hold more cash. All these studies conclude that the motive for increasing cash holdings is uncertainty.

The behavioral literature also documents that firms hold more cash when perceived uncertainty increases (e.g. Dessaint and Matray, 2017). Bernile, Bhagwat, and Rau (2017) find that CEOs who experience downside consequences of disasters hold more cash. In our setting, the natural disaster is a pandemic as people become ill, incapacitated, or die because of the pandemic. Some managers may directly experience the negative impacts of the pandemics through illness. While other managers may experience the pandemic through the illness of family, friends, colleagues, and employees. As Bernile, Bhagwat, and Rau (2017) argue, this may lead the managers to behave more conservatively. One such action is to hold more corporate cash (e.g. Dessaint and Matray, 2017). In this research, firms with fewer tele-workable employees face larger adverse impact of the pandemic, so our hypothesis follows:

H1: Cash holdings increase more for firms with fewer tele-workable employees during a pandemic.

3. IDENTIFICATION STRATEGY

Our identification strategy employs the uncertainty in labor productivity arising from the H1N1 and the COVID pandemics. Pandemics are a good experimental setting, as the disease is spread by a highly contagious virus. Thus, the likelihood of falling ill is largely exogenous. The employee may also spend time on non-revenue generating activities such as washing hands and wearing masks. Furthermore, during pandemics the number of ill employees would be large enough to have a meaningful impact on the firms' behavior.

(i) Pandemic Timelines

(a) H1N1 Pandemic (The Swine Flu)

The first influenza pandemic of this century was caused by the novel-A (H1N1) virus in 2009. The WHO estimates that globally 100,000 – 400,000 people died in that year. Domestically, it was first reported in California on April 15, 2009. It quickly evolved into a multi-state outbreak. According to the CDC, at least one million Americans had been infected by mid-June. It disproportionately impacted children and young adults. The pandemic resulted in school closures for seven days if any of the students were infected, cancellation of sporting events, flight cancellations, and advisories to higher educational institutions and businesses. The first dose of an approved vaccine was administered on October 5. As this pandemic had a high publicity rate with coverage from almost all major news outlets, it changed the public behavior with fewer people choosing to go outside (Yoo, Kasajima and Bhattacharya, 2010). It also popularized the use of hand-sanitizers. Table 1 Panel A summarizes the timeline of this pandemic.

Figure 1 presents the weekly number of new infections confirmed by laboratory tests and reported to the CDC. The actual number of weekly infections is likely to be higher. The CDC estimates that 60.8 million Americans were infected resulting in 274,304 hospitalizations during the one year period April 2009 – March 2010.[5] Regardless, this graph is useful in the sense that it provides us with a timeline of the progress of the pandemic. H1N1 infected Americans in two distinct waves. The first wave peaked around the middle of June. The second wave was far stronger and peaked at the end of October. After the end of March, the number of weekly new infections was negligible.

(b) COVID Pandemic (SARS-CoV-2)

As the COVID pandemic is still recent and ongoing, our understanding of some basic facts is evolving. According to the CDC, the first case of community transmission of the disease in the United States occurred in February 2020. However, Basavaraju et al. (2020) find that COVID was possibly circulating in the United States in December 2019. In March, social distancing and the economic disruption had spread to large parts of the world including the United States. Table 1 Panel B summarizes the timeline of this pandemic in the United States.

CDC estimates that between February 2020 and April 14, 2021, 114.6 million Americans were infected, with 97.1 million being symptomatic, and 5.6 million Americans were

[5] https://www.cdc.gov/flu/pandemic-resources/2009-h1n1-pandemic.html

hospitalized.[6] About 604,882 Americans have died from this disease by the end of June 2021.[7] To reduce the death rates, many state governments mandated lockdown, with California being the first state to mandate a lockdown in March of 2020. The pandemic so far has had three distinct waves. The first wave peaked on April 9, 2020 and the second wave peaked on about July 21st. The third wave was the most severe and dwarfs the first two waves. The third wave peaked on about January 8th. Figure 2 presents the progression of this pandemic in the U.S.

(ii) Difference-in-Difference Estimation Model

A difference-in-difference testing strategy consists of two dummy variables. The first dummy variable takes the value of one for the treated group and the value of zero for the control group. The treated group uses the industry classification of Dingel and Neiman (2020). The industries that have the lowest percentage of tele-workable employees are more likely to require employees to be on-site. In a pandemic, if employees are not able to be physically present, then work designated for that employee is likely to remain pending. Thus, these firms are likely to be the most exposed to a pandemic. The variable *Non-tele-workable* takes the value of one if the firm belongs to the quartile of industries that are the least likely to be tele-workable.

The ideal control group should consist of firms that do not get affected at all by the pandemic. However, some employees in most firms are likely to either fall ill or be affected by school closures. So, we select the firms in industries that belong to the most tele-workable quartile, as these firms are the least likely to get affected by the pandemic. For instance, if these employees have to stay at home, they are more likely to be able to work from home or have

[6] https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/burden.html
[7] https://covid.cdc.gov/covid-data-tracker/#forecasting_cumulativedeaths

flexible schedules that allow them to complete the tasks during non-regular business hours. *Non-tele-workable* takes the value of zero for the firms in this group.

The second dummy variable is formed based on the pandemic timeline. It takes the value of one during the pandemic and zero beforehand. To select the periods, we turn to Table 1. This table reports that the WHO declared H1N1 a pandemic on June 11, 2009. Afterwards, according to the WHO, the pandemic ended on August 10, 2010. So, the variable *Pandemic* takes the value of one for five consecutive quarters starting on the third quarter of 2009 and ending on the third quarter of 2010.

Correspondingly for COVID, the five quarters of the pandemic are from the first quarter of 2020 to the first quarter of 2021. The first quarter of 2020 coincides with the WHO declaring COVID a pandemic on March 11. The data from Bureau of Economic Analysis shows that the economy contracted in the first quarter as well. A possible reason for this contraction is the mandated lockdown in many states. Anecdotal reports suggest that many industries started to experience declines in business because of COVID in January and February of 2020.[8] Demers, Hendrikse, Joos, and Lev (2021) also take Q1 2020 as the first quarter of the pandemic. Even though COVID pandemic is still ongoing, we are only able to include the first quarter of 2021 due to data availability.

Next, we need to find a period before the pandemic for comparison. The financial crisis of 2008 preceded the H1N1 pandemic. According to Taylor and Williams (2009), the events relating to the sub-prime mortgage crisis had already started on August 9, 2007. We attempt to avoid the confounding effects of the financial crisis and so, *Pandemic* takes the value of zero for

[8] Q4 2019 Ryman Hospitality Properties Inc. Earnings Call on Feb 25, 2020 (http://ir.rymanhp.com/static-files/1f0403d7-f5b2-46bf-a55d-2338af407eb1)

the five quarters starting on the second quarter of 2006 and ending on the second quarter of 2007. For COVID, we do not use the fourth quarter of 2019 to reduce confounding effects. Some studies suggest that the virus was already circulating in the United States in the fourth quarter of 2019 (see Basavaraju et al. 2020). Therefore, we use the five quarters immediately preceding it. These five quarters are the last two quarters of 2018 and the first three quarters of 2019. The estimation model is as follows:

$$Cash_{y,t} = \alpha + \beta_1 Pandemic_{y,t} * Non\text{-}Tele\text{-}workable_{y} + \beta_2 Pandemic_{y,t} + \beta_3 Non\text{-}Tele\text{-}workable_{y} + \beta_4 Controls_{y,t-1} + \beta_5 Quarter_t * Industry_t + \beta_6 Firm_y + \varepsilon_{y,t-1} \quad \ldots (1)$$

Cash is the cash and marketable securities held by firm y in time t, scaled by the book value of assets. The variable of interest is β_1, which estimates the interaction of the two dummy variables and thus, captures the difference-in-difference estimates. We are interested in learning the sign, magnitude, and statistical significance of the coefficient β_1. *Controls* is a vector of firm level controls and is lagged by one quarter. *Firm* and *Quarter*Industry* are firm and quarter*industry fixed effects and are included in almost all regressions. The impact of the seasonality of cash flows is mitigated by the *Quarter*Industry* fixed effects. Standard errors are clustered for both the firm and the quarter.

4. SAMPLE SELECTION AND VARIABLE CONSTRUCTION

The accounting data comes from Compustat's quarterly files. We delete firm-year observations without NAICS codes. The accounting information is then merged with the tele-workability data provided by Dingel and Neiman (2020) [9] using two-digit NAICS codes. Dingel and Neiman (2020) investigate which of the jobs can be performed from home. The authors study the answers to the questions "work context" and "generalized work activities" in two surveys of the Occupational Information Network. If the answers include "work outdoors" or "operating vehicles, mechanized devices, or equipment" on a daily basis, then this work may not be performed remotely from home. Once the tele-workability of each occupation has been determined, the dataset is then merged with Bureau of Labor Statistics data on the prevalence of these occupations in the two-digit NAICS industries. Dingel and Neiman (2020) are able to assign tele-workability scores to all twenty-four two-digit NAICS industries.

As Dingel and Neiman (2020) use a recent Occupation Information Network Survey, we check the accuracy of these classification for our analysis. We first manually check to see if this classification accurately reflects the tele-workability of employees. The least tele-workable industry in Table 2 Panel A is the Accommodation and Food Services industry followed by the Agriculture, Forestry, Fishing and Hunting industry. The most tele-workable is the Educational Services industry followed by the Professional, Scientific and Technical Services industry. These industries seem to reasonably reflect the tele-workability of employees during the pandemic. This classification is consistent with the findings of Mas and Palias (2008) and Katz and Krueger (2017) that tele-work became prevalent after 2005.

(i) Matched Sample

In a difference-in-difference experimental setting, we need two sets of firms. The first one consists of the treated group. In our study, these are the firms that belong to the quartile of

[9] https://github.com/jdingel/DingelNeiman-workathome/

industries that is the least tele-workable. The second set of firms is the control group. In an ideal setting, these control firms would be similar to the treated firms, except that they do not receive the treatment. In our sample, they are the firms least likely to be affected by the pandemic – i.e. they belong to the quartile of industries that is the most tele-workable.

To select the control firms that are similar in characteristics to the treated firms, we use propensity score matching technique. We use the firms that report data in the first calendar quarter of 2006 for the H1N1 sample and the second calendar quarter of 2018 for the COVID sample. We run the propensity score matching code separately for H1N1 and COVID. This way we can at least be assured that COVID affected firms are not being used as controls for firm observations from H1N1 period. This is necessary as there might be potentially different time trends present during the two different pandemics. The matching is without any replacement, and we select the nearest neighbor to the treated. The propensity score matching uses a logit model with caliper at 0.001. The matching is based on size and profitability of the firms. Our results are robust to using all the covariates in the matching criteria instead of size and profitability. Additionally, our results are robust if we use an alternative method, i.e. entropy balancing.

The matched sample for H1N1 is formed before the second quarter of 2006 – that is, before the beginning of our sample period. Similarly, for COVID, it is formed before the third quarter of 2018. To maintain a balanced panel and to make sure that firms exist after the financial crisis, we only keep firms that have data for all the quarters. Table 2 Panel B reports the number of firms in different industries that are in the sample. There are 797 firms in each of the treatment and the control groups. The largest number of firms in the treatment group belongs in the Transportation and Warehousing industry, followed by the Retail Trade. On the other hand, the largest number of firms in the control group belongs in Information industry, followed by

Real Estate and Rental Leasing industry. As mentioned before, we include firm and quarter*industry fixed effects in almost all our regressions to control for industry dynamics.

(ii) Variable Construction

(a) Dependent Variables

Our dependent variable of interest is *Cash*, defined as cash and marketable securities divided by total assets. It is widely used in the literature and the strictest measure of liquidity for a company. In Table 3, we show the average and median quarterly cash holdings of firms before and during the pandemics. Figure 3 shows the median cash holdings of tele-workable and non-tele-workable firms between a much longer period – 2006 Q2 and 2021 Q1.

Two observations can be made from these summary statistics. First, across all the quarters, including before and during pandemic periods, tele-workable firms tend to have higher cash balances. In unreported results, we find that tele-workable firms have higher probability of default in the pre-pandemic period. This is likely linked to the findings in the literature that more risky firms hold more cash (Bates, Kahle, and Stulz, 2009). Second, it is obvious from the average and median values, the cash balance of firms in the non-tele-workable group increased significantly during the pandemic periods. On the other hand, the cash balance remains about the same or even decreases during this period among the tele-workable firms.

In certain tests, we use cash cycle measures of liquidity as dependent variables. They are inventory period, payable period, receivable period, and cash cycle. Beyond liquidity, these measures account for the short-term capital management policies of firms (Richards and Laughlin, 1980). *Inventory Period* measures the time between the delivery of raw materials and the sale of finished goods. It is defined as the ratio of inventory to costs of goods sold (COGS).

Receivable Period is the time it takes for a firm to receive cash payments from the customers after making the sales. It is the ratio of account receivable to sales. The *Payable Period* is the time a company takes to pay its suppliers after receiving the invoice accompanying the raw materials. It is calculated by dividing accounts payable by COGS. Finally, *Cash Cycle* is calculated by subtracting accounts payable period from the sum of inventory and accounts receivable periods. Essentially, it is the time between when the company pays its suppliers and when it gets paid by its customers.

Additionally, we have used *Asset Volatility*, *Expected Default Frequency*, *Implied Volatility*, *Idiosyncratic Volatility*, and *Total Volatility* as dependent variables. *Asset Volatility* is the historical standard deviation of the percentage change of a firm's total value, which is the sum of the market value of equity and the total debt of the firm. *Expected Default Frequency* measures the probability that a company will not be able to honor interest and principal payments on its debt within a year. It is a forward-looking measure and is used by Moody's. This method is popularly called KMV-Merton method. We follow Bharath and Shumway (2008) in this respect. *Implied Volatility*, is the implied volatility of the firm's options and is used by Compustat to calculate the value of the options granted to executives of the firm. *Idiosyncratic Volatility* is the part of the total volatility that cannot be diversified away. It is calculated by subtracting the standard deviation of the market portfolio from the standard deviation of the equity returns. *Total Volatility* is the standard deviation of returns of a firm's equity. *Idiosyncratic Volatility* and *Total Volatility* measures are computed using daily return data from CRSP. Since Compustat accounting data are reported for fiscal years, to be consistent, we compute the volatility measure for fiscal years and annualize them. We present the summary statistics of the variables, including mean, median, standard deviation, minimum value, and maximum value in Table 4.

(b) Control Variables

We control for a number observable heterogeneity among the firms that have been shown by extant literature to affect cash holdings. We use two fixed effects. The firm fixed effect removes any firm level heterogeneity that does not vary with time. The second fixed effect is the interaction of the 6-digit NAICS code with the quarter. This fixed effect removes any dynamic changes in the industry such as those from the industry-wide changes in demand.

We additionally include *Size*, *Leverage*, *Market-to-Book*, *R&D*, *Profitability*, *Dividend Payer*, and *Collateral* as controls. *Size* is calculated as the natural logarithm of the book value of assets of the firm and controls for firm size on cash holdings. *Leverage* is the ratio of a firm's total liabilities to total assets. A higher level of leverage generates greater fixed claims on the income of the firm by the bondholders and thus, is associated with greater likelihood of default. *Market-to-book* is the ratio of market value of equity to book value of equity. It indicates the growth opportunity of the company. *R&D* is calculated by dividing the firm's research and development expenditures by total assets. R&D expenses are considered to have longer-term implications for a firm's profitability and growth. It is also subject to greater risk associated with the desired outcomes. *Profitability* is the ratio of earnings before interest and taxes and total assets. *Dividend Payer* is an indicator variable that takes the value of 1 if the company pays a positive dividend, 0 otherwise. It identifies firms that have enough earnings to pay cash dividends. *Collateral* is the ratio of property, plant, and equipment divided by total assets. A firm with higher levels of physical collateral can engage in higher levels of borrowing and have greater freedom in accessing financial markets when financing is needed. Again, the summary statistics of these variables are in Table 4.

(c) Other Sorting Variables

In our regression models, we use a number of variables to sort our sample into two groups to understand how the pandemic affects the cash holding conditional upon those particular characteristics of the firms. Then we estimate two regressions with these two sub-samples. An advantage of splitting the sample into two and using non-nested empirical models is that we allow the constant and the coefficients of other control variables to vary between these two groups of firms. These variables are *Financial Constraint*, *Interest Expense*, *Negative Income*, *Capex*, *Operational Expenses*, and *Dividend Payer*. *Financial Constraint* equals the value of the Kaplan-Zingales index (Kaplan and Zingales, 1997) of financial constraint, with higher values indicating greater difficulty in financing ongoing operations when market conditions tighten. *Interest Expense* is equal to the company's interest expenses divided by total debt. This measures the firm's interest payment obligations and thus, its flexibility in the use of available cash. *Negative Income* is a dummy variable that takes the value of 1 if the company has a negative net income during the quarter. It captures the firms that were unprofitable during the quarter. *Capex* is capital expenditures divided by total assets. It reflects the capital investment needs of the company, with higher values associated with greater requirement for cash. *Operational Expense* is equal to selling, general, and administrative expenses divided by total assets. This is one of the major non-production related expenses of a company. These types of obligations are less sensitive to the number of units of goods produced. *Dividend Payer* is as defined previously.

To explore the sources of financing during the pandemic, we compute *Long-term Debt, Short-term Debt*, and *Preferred Stocks* variables. *Long-term Debt* is defined as long-term debt divided by total assets and *Short-term Debt* is debt in current liabilities divided by total assets. Short-term debt has a maturity of less than one year and long-term debt matures in more than one year. In addition to lower costs and higher liquidity associated with it, short-term debt is also less sensitive to changes in assets risks (Barnea, Haugen, and Senbet, 1980). *Preferred Stocks* is the total par value of preferred stocks divided by total assets. In unreported tables, we notice no statistically significant differences between tele-workable and non-tele-workable groups when it comes to common equity offering.

A firm could also change its investments and operations to preserve cash. To understand such dynamics, we use *Capex*, *Discontinued Operations*, and *Taxes*. *Capex* is as defined previously. *Discontinued Operations* is computed by dividing the value of discontinued operations by total assets. *Taxes* is the total amount of taxes paid divided by sales. The summary statistics of these variables are in Table 4.

5. RESULTS

(i) Cash Holdings, Uncertainty in Labor Productivity and Pandemics

We begin our formal analyses by considering the change in the cash balances of firms before and during the pandemic. Our hypothesis states that driven by the shock arising from uncertainty in labor productivity, the firms will raise their cash holdings during the pandemic. Furthermore, firms that have a large contingent of labor that can tele-work are less likely to be affected by this shock as their employees could continue to perform the tasks remotely. Thus, they will not increase their cash holdings as much. Consequently, we would observe higher cash balances among firms in non-tele-workable industries during the pandemic.

We first explore this relation by taking advantage of a simple hypothesis testing using t-statistic. Table 5 Panel A shows the results. In columns (1) and (2), we provide the average cash holdings of firms in *Tele-workable* and *Non-tele-workable* groups before the pandemic. Column (3) shows that the difference between the two is negative and statistically significant. This means that *Tele-workable* firms hold more cash than the *Non-tele-workable* firms before the pandemic. In columns (4) and (5), we provide the average cash holdings of firms in *Tele-workable* and *Non-tele-workable* industries during the pandemic. Column (6) shows that the difference between the two is negative and statistically significant. This means that *Tele-workable* firms still hold more cash than the *Non-tele-workable* firms during the pandemic. However, it seems to be driven by lower cash holdings by *Tele-workable* firms and higher cash holdings by *Non-tele-workable* firms. Finally, the most important finding is presented in column (7), which shows the difference-in-difference, i.e. the difference between columns (3) and (6). It is positive and statistically significant. This indicates that the difference in cash holdings of *Tele-workable* and *Non-tele-workable* firms has decreased during the pandemic as compared to beforehand.

We estimate regression equations to formally control for observable and unobservable heterogeneity. Table 5 Panel B presents the results. The dependent variable is *Cash*. We specifically want to examine the coefficients of *Pandemic* and the interaction term *Pandemic* * *Non-tele-workable*. In columns (1) and (2), we estimate the regression equation for treatment and control firms separately. The coefficient of *Pandemic* is positive and statistically significant in the non-tele-workable treatment group – which means that there is a measurable and significant increase in cash holding among the *Non-tele-workable* firms during the pandemic. On the other hand, the coefficient of *Pandemic* is negative, but statistically insignificant in the *Tele-workable* group – meaning the change in cash holding among the tele-workable control group of firms is not significant. An F-test for the equality of the coefficients of *Pandemic* in columns (1) and (2) shows a statistically significant difference, which indicates that *Non-tele-workable* firms change their cash holding behavior significantly more than *Tele-workable* firms during the pandemic. In column (3), we estimate the regression equation for all firms in the sample. This allows us to estimate the coefficient of the interaction term *Pandemic * Non-tele-workable*, which turns out to be positive and statistically significant. It means that there is a statistically significant increase in cash holding among *Non-tele-workable* firms during the pandemic as compared to *Tele-workable* ones and as compared to before the pandemic. The coefficient of the interaction term is also economically significant. The estimate of 0.0287 implies that the *Non-tele-workable* firms increase their cash holding by 2.87% during the pandemic, as opposed to the control group. This compares to a median cash holdings of 6.7% and an average of 11.3% for the *Non-tele-workable* firms. As we use firm fixed effects and the industry interacted with quarter fixed effects our results can be interpreted to mean that after controlling for industry dynamics like changes in demand, *Non-tele-workable* still accounts for substantial increase in cash. These results confirm our hypothesis.

(ii) Robustness: Cross-sectional Tests Using Intensity of Exposure to Pandemic

Non-tele-workable is constructed at the industry level and so may capture industry effects in addition to the exposure to the pandemic. As a robustness check, we utilize an alternative measure of firm level exposure to the H1N1 and the COVID pandemics as developed by Hassan, Hollander, Lent, and Tahoun (2019). Using textual analysis of quarterly earnings calls, they count the number of times the disease is mentioned and construct variables to account for the risk-exposure of the firms. The variables *H1N1 Exposure* and *COVID Exposure* count the number of times the H1N1, COVID, or pandemic is mentioned in the quarterly earnings call. Higher values of the variable would indicate greater risk exposure of the firms. The references to the pandemic in the quarterly calls only occur after the pandemic has already started and varies with quarter. In our cross-sectional tests, we rank order the firms based on the exposure to the pandemic. This rank-ordering is based on the maximum number of times the particular pandemic has been referenced by the firm in the quarterly conference calls. We repeat this process separately for H1N1 and COVID pandemics. Afterwards, based on the rank order, we split our sample into two groups along the median.

We re-estimate the regression in Table 5, Panel B, Column (3). The results are presented in Table 5 Panel C. These are cross-sectional models to relate the intensity of exposure of firms to the pandemics to their cash holdings. The coefficients of *Pandemic * Non-tele-workable* are positive and statistically significant in columns (1) and (2). Consistent with our hypothesis, the coefficient estimate is higher among firms with greater intensity of exposure to pandemics. An F-test for the equality of the coefficients of *Pandemic * Non-tele-workable* in columns (1) and (2) shows that the difference is statistically significant. Thus, we can conclude that firms more exposed to the pandemics are likely to hold more cash.

(iv) Parallel Trends: Dynamic Analysis

The variable *Pandemic* takes the value of 1 and 0 to represent during pandemic and before pandemic periods, respectively. However, by doing this, we essentially average out the quarterly effects. That is, it does not show us the dynamic changes over the quarters due to the pandemic. To remedy this, we undertake a dynamic analysis and generate dummy variables indicating the quarter in relation to the beginning of the pandemic. They are Qtr-4, Qtr-3, Qtr-2, Qtr-1, Qtr1, Qtr2, Qtr3, Qtr4, and Qtr5. We estimate three regression equations as in the previous section and present the results in Table 6. Column (1) shows that there are statistically significant and positive changes in the cash holdings among the *Non-tele-workable* treatment firms after the pandemics began. On the other hand, there is no such pattern among the *Tele-workable* control firms in column (2). In column (3), the interaction terms *Qtr1 * Non-tele-workable*, *Qtr2 * Non-tele-workable*, *Qtr3 * Non-tele-workable*, and *Qtr4 * Non-tele-workable* are positive and statistically significant – indicating that *Non-tele-workable* firms had higher cash balances during the first four quarters after the beginning of the pandemic as compared to before and as compared to *Tele-workable* firms. The interaction term of *Qrt-4 * Non-tele-workable*, *Qtr-3 * Non-tele-workable*, *Qtr-2 * Non-tele-workable*, and *Qtr-1 * Non-tele-workable* are not statistically significant. These non-significance imply that the control and the treated firms did not have a statistically different trend before the pandemic. Therefore, the parallel trends assumption underlying the difference-in-difference estimation method conducted in the previous sub-section holds.

(v) Vulnerability to Liquidity Shocks

We explore how financial constraints and obligations affect the decisions of firms to change their cash balances. There are a number of indicators in the finance literature that have been utilized to identify the factors that bind or limit a firm's choices. In this section, we look at how six such factors affect the cash holding decisions of firms. They are: *Financial Constraint*, *Interest Expense*, *Negative Income*, *Capex*, *Operational Expense*, and *Dividend Payer*. A financially constrained firm may not be able to increase its cash holdings from external sources even if it wanted to. There are several measures of financial constraints. The Kaplan-Zingales index is one of the more widely used ones. Our results are also robust to using alternate measures of financial constraint such as that of Hadlock and Pierce (2010). High interest expense is an indicator of a firm in distress and thus, may not be able to easily increase its cash holdings. A firm with negative income has limited ability to increase its cash balances without resorting to external financing, likely at a high cost, or disposal of some of its assets under duress. A firm with significant capital expenditure plans will likely have to draw down its cash balances. High levels of operational expenses, which are often considered sticky, will prevent a firm from accumulating more cash. Finally, the ability to pay dividend sends a positive signal about the future profitability of the firm. We split our sample into two parts based on each of these six factors and estimate regressions with *Cash* as the dependent variable and the interaction term *Pandemic * Non-tele-workable* as the independent variable of interest. In the case of *Negative Income*, the sample is split based on whether firms have negative income or not. For *Dividend Payer*, we split the sample into dividend payers and non-payers. As for the rest, we divide the sample depending on high or low values of the indicator, split based on its median. The estimates are presented in Table 7.

In columns (1) and (2), we notice that firms with higher financial constraints have a positive and statistically significant coefficient of *Pandemic * Non-tele-workable*, while this coefficient is statistically insignificant for firms with lower financial constraints. An F-test for the equality of the coefficients of *Pandemic * Non-tele-workable* in columns (1) and (2) shows a statistically significant difference, which indicates that non-tele-workable firms with higher financial constraints increase their cash balances more during the pandemic. We observe similar results with high interest expenses. In columns (3) and (4), we find that non-tele-workable firms with higher interest expenses are more likely to increase their cash holdings during the pandemic. Similarly, non-tele-workable firms that have negative income (columns (5) and (6)), higher capital expenditure needs (columns (7) and (8)), higher operational expenses (columns (9) and (10)), and non-dividend payers (columns (11) and (12)) increase their cash holdings more during the pandemic. Additional results such as those sorted on other measures of financial constraint show consistent results but have not been reported because of space limitations.

(vi) Sources of External Debt Financing

In response to the liquidity shock associated with a pandemic, firms may seek external financing. We explore how firms obtain the funds to increase their cash balances. Specifically, we study whether firms differ in their short-term vs. long-term debt issuance behaviors. In Table 8 Panel A, we split our sample based on high vs. low financial constraints according to the median value of the Kaplan-Zingales index. In columns (1) and (2), the dependent variable is *Long-term Debt* and in columns (3) and (4), it is *Short-term Debt*. In column (1), the coefficient of *Pandemic * Non-tele-workable* is negative and statistically significant. On the other hand, in column (2), the coefficient of *Pandemic * Non-tele-workable* is statistically insignificant. Therefore, the non-tele-workable firms with higher financial constraints have less long-term debt during the pandemic. On the other hand, there are no significant differences in the long-term debts of the tele-workable and non-tele-workable firms when they have lower financial constraints. In contrast, the coefficient of *Pandemic * Non-tele-workable* is positive and statistically significant in column (3). The coefficient of *Pandemic * Non-tele-workable* is statistically insignificant in column (4). Thus, the non-tele-workable firms with higher financial constraints increase their short-term debt during the pandemic. There are no statistically significant differences between the firms with lower financial constraints. These findings indicate that non-tele-workable firms reduce their long-term debt, possibly to manage the increased risks of financial distress. The increase in short-term debt is consistent with the literature that finds firms to be more likely to draw down their credit lines when funding is scarce (Ivashina and Scharfstein, 2010; Bosshardt and Kakhbod, 2020). However, our finding adds to the literature by showing that the increase in short-term debt is driven by non-tele-workable firms.

In Panel B of Table 8, we replicate the results by using *Interest Expense*, as opposed to *Financial Constraint*, as the sorting variable. The findings are the same – non-tele-workable firms with higher interest expenses have less long-term debt during the pandemic and more short-term debt. On the other hand, there are no statistically significant differences in the long-term or the short-term debts of tele-workable and non-tele-workable firms during the pandemic.

(vii) Other Sources of Cash

In challenging times, in addition to seeking external funds, a corporation can delay capital investments or modify internal operations to generate needed cash. We explore what changes these firms undertake. Specifically, we consider capital expenditures, discontinued operations, and potential tax saving strategies. Delaying or reducing capital expenditures would help a firm reorient its future size and prepare for downward adjustments to its excess production capacity. Discontinuing some operations, whether it's in the form of closing down or divestments, would help reduce cash burn rate of the company. Reduced or delayed tax payments to the government would help the company preserve its cash holdings. Thus, we estimate regressions with *Capex*, *Discontinued Operations*, and *Taxes* as dependent variables. The independent variable of interest is *Pandemic*. To estimate the joint effects of *Pandemic* and *Non-tele-workable*, we include an interaction term of the two variables. The regressions estimates are presented in Table 9. In column (1), we notice a negative and statistically significant coefficient of *Pandemic * Non-tele-workable*, which indicates that non-tele-workable firms reduce their capital investments more during the pandemic. Similarly, we observe from that non-tele-workable firms have more discontinued operations (column (2)) and pay less in taxes (column (3)) when compared to the tele-workable firms. These strategies appear to help non-tele-workable firms preserve more cash during the pandemic.

We also explore the equity sources the firms may utilize to raise cash. Preferred stocks are especially popular among firms during natural disasters as they allow a company to obtain external financing without the need to sell ownership stakes at depressed valuations during a challenging time. The coefficient of *Pandemic * Non-tele-workable* in column (4) of Table 9 is positive and statistically significant. This indicates that non-tele-workable firms increase their preferred stock balance more during the pandemic. In unreported tables, we notice no statistically significant differences between tele-workable and non-tele-workable groups when it comes to common equity offering.

(viii) Risk and Cash Holding

The key argument underlying our hypothesis is that a pandemic increases the liquidity needs of firms, which translates into a greater risk of insolvency. In this section, we test this argument. Of course, there are several different types of risks proposed in the literature. We utilize five distinct measures of firm risks as dependent variables in regression models – *Asset Volatility*, *Expected Default Frequency*, *Implied Volatility*, *Idiosyncratic Volatility*, and *Total*

Volatility. The independent variable of interest is *Pandemic * Non-tele-workable*. The regressions estimates are presented in Table 10 Panel A. In each of the regressions, the coefficient of *Pandemic * Non-tele-workable* is positive and statistically significant. This indicates that across various measures of volatility, *Non-tele-workable* firms experience a significant increase in risk during a pandemic.

Next, we explore whether these increases in risks affect the cash holdings of firms. To this end, we divide our sample depending on high or low values of the risk indicator, split based on its median. Instead of repeating this exercise for all the risk measures, we present only two – *Asset Volatility* and *Implied Volatility*. In unreported results, we make the same conclusion for the remaining measures. The dependent variable is *Cash* and the independent variable of interest is *Pandemic * Non-tele-workable*. Additionally, we consider the variable *Collateral*, as it has implications on raising cash through the disposal of physical assets. The results are presented in Table 10 Panel B.

In column (1), we notice that firms with higher asset volatility have a positive and statistically significant coefficient of *Pandemic * Non-tele-workable*. However, for the firms with lower asset volatility, in column (2), there is a statistically insignificant coefficient of the interaction term *Pandemic * Non-tele-workable*. An F-test for the equality of the coefficients of *Pandemic * Non-tele-workable* in columns (1) and (2) shows a statistically significant difference, which indicates that *Non-tele-workable* firms with higher asset volatility increase their cash balances more during the pandemic. We find a similar conclusion from columns (3) and (4) that *Non-tele-workable* firms with higher implied option volatility increase their cash balances more during the pandemic. From columns (5) and (6), we notice that non-tele-workable firms that have lower *Collateral* are more likely to increase their cash balances during the pandemic. Essentially, the firms that can potentially pledge higher levels of collateral to raise debt financing or dispose physical assets increase cash balances less than the firms that have lower levels of collateral. The results in Panel A and Panel B of Table 9 provide evidence that risk is the channel through which cash holding is affected by the pandemic.

(ix) Other Explanations

(a) Alternate Story: Behavioral Reasons

We explore whether changes in cash holdings in response to a pandemic are ultimately beneficial to the shareholders. This is an important issue as Dessaint and Matray (2017) notice that increased cash holdings due to managerial biases in response to hurricane strikes are suboptimal. We follow the methodology of Faulkender and Wang (2006) to estimate the marginal value of cash to the shareholders. For our sample of non-tele-workable and tele-workable groups, we estimate the excess stock returns over the benchmark of Fama-French 25 portfolio returns. As independent variables, we include ΔC, *Pandemic*, $Pandemic*\Delta C$, ΔE, ΔNA, ΔRD, ΔI, ΔD, C_{t-1}, L, NF, $\Delta C*C_{t-1}$, and $\Delta C*L$. These variables are estimated as in Faulkender and Wang (2006)[10]. Δ signifies first difference in the variables and all the variables except for market leverage (L) are deflated by the lagged market value of equity. C is cash and marketable securities. E is earnings before extraordinary items plus interest, deferred tax credits, and investment tax credits. Net assets NA is total asset minus cash. RD is research and development expenses. I is interest expense. D is total dividends. Market leverage L is calculated as market leverage divided by total liability plus market value of equity. Net financing NF is total equity issuance minus equity repurchases plus debt issuance minus debt redemption. The estimates are

[10] Model II in Table II, page 1973.

presented in Table 11. The coefficient of *Pandemic*ΔC* is positive and statistically significant among the non-tele-workable firms, while it is statistically insignificant among the tele-workable firms. Therefore, cash is more valuable for the non-tele-workable firms during a pandemic. It is worthwhile and rational for these firms to increase cash holdings at the onset of a pandemic.

(b) Alternate Story: Supply and Demand Risk

It is conceivable that the source of business uncertainty stems from the supply or demand disruptions. To measure these risks, we use the notion of diversification. If a firm has a diversified customer base, then it is less likely to be impacted if one of the customers decreases purchases from the firm. We generate two independent variables. *LargeCustomerSale* is the percentage of the firm's sales that is sold to all the large customers. The large customers are those that purchase more than 10% of the firm's products and are reported in Compustat. *LargeCutomerDummy* is an indicator variable that takes the value of one if the firm has any large customer. The results are reported in Table 12 Panel A. The coefficient of the interaction term of *Non-tele-workable* and *LargeCustomerSale* is not statistically significant. This result suggests that the non-tele-workable firms do not hold more cash during the pandemic because of customer risk. Additionally, the three-way interaction term of *Non-tele-workable*, *LargeCustomerSale*, and *Pandemic* is not statistically significant. This suggests that the customer risk does not appear to drive the relationship between cash and *Non-tele-workable* firms and pandemic. However, the interaction term of *Non-tele-workable* and *Pandemic* remains positive and statistically significant. Thus, the relationship between cash and the interaction of *Non-tele-workable* and *Pandemic* is not mitigated by customer risk. We get similar results when we substitute *LargeCutomerDummy* instead of *LargeCustomerSale* in our regression model.

Next we turn to supply risk. Again, we build on diversification. If a firm has a diversified supplier base, then it is less likely to be impacted if one of the suppliers is not able to deliver the materials to the firm. Similarly, we generate two variables. *LargeSupplierBuy* is the ratio of the firm's cost of goods sold that is bought from all the large suppliers. *LargeSupplierDummy* is an indicator variable that takes the value of one if the firm has any large supplier. The results are reported in Table 12 Panel B. The interaction term of *Pandemic* and *LargeSupplierBuy* is statistically insignificant. This result suggests that firms may not be increasing cash as a reaction to supplier risk during the pandemic. The three-way interaction term of *Non-tele-workable*, *LargeSupplierBuy*, and *Pandemic* is not statistically significant in column (1), but statistically significant in column (2) when more controls are added. However, the interaction term of *Non-tele-workable* and *Pandemic* is always statistically significant and is much larger than the coefficient of the three-way interaction term. These results suggest that the relationship between cash and the interaction of *Non-tele-workable* and *Pandemic* may not be driven by supplier risk. We get similar results when we substitute *LargeSupplierDummy* instead of *LargeSupplierBuy* in our regression model. These results suggest that demand and supply risks do not appear to mitigate or drive our results.

6. CONCLUSION

We study the cash holdings of firms during the H1N1 and COVID pandemics. We employ a difference-in-difference estimation methodology and select firms that have a large percentage of their employees who cannot tele-work as the treatment group (*Non-tele-workable*) and the firms whose employees can easily tele-work as the control group (*Tele-workable*). We hypothesize that the firms in the treatment group are more likely to be affected by uncertainty in labor productivity during a pandemic and thus, more likely to build up a cash balance. We find that *Non-tele-workable* firms increase their cash holdings during the pandemic more than the *Tele-workable* group.

Our results show that uncertainty in labor productivity during pandemics makes the firms riskier. *Non-tele-workable* firms become more volatile and move closer to default during the pandemics. These firms also experience a larger decline in long-term debt. We investigate how these firms finance their increase in cash holdings. Consistent with Acharya and Steffen (2020) we find that financially constrained *Non-tele-workable* firms increase their short-term debt. Other sources of cash include issuing preferred stocks, reducing capital expenditure, discontinuing some operations, and paying less taxes.

Our findings provide an understanding of the behavior of firms in response to pandemics. While pandemics have not been very frequent in the past, the ease with which people can travel both domestically and internationally means that a lot more of these diseases may become pandemics. As firms respond to such disruptions in the future, understanding successful corporate policies during pandemics will provide guidance to practitioners and policy makers.

REFERENCES

Acharya, V.V., Almeida, H. and Campello, M., 2007. Is cash negative debt? A hedging perspective on corporate financial policies. *Journal of financial intermediation*, *16*(4), pp.515-554.

Acharya, V.V. and Steffen, S., 2020. The risk of being a fallen angel and the corporate dash for cash in the midst of COVID. *CEPR COVID Economics*, *10*.

Almeida, H., Campello, M. and Weisbach, M.S., 2004. The cash flow sensitivity of cash. *The Journal of Finance*, *59*(4), pp.1777-1804.

Antoniou, C., Kumar, A. and Maligkris, A., 2017. Terrorist attacks, managerial sentiment, and corporate policies. *Managerial Sentiment, and Corporate Policies (February 20, 2017)*.

Bai, C.E. and Wang, Y., 2003. Uncertainty in labor productivity and specific human capital investment. *Journal of Labor Economics*, *21*(3), pp.651-675.

Baker, S.R., Bloom, N., Davis, S.J., Kost, K.J., Sammon, M.C. and Viratyosin, T., 2020. The unprecedented stock market impact of COVID-19, *National Bureau of Economic Research* (No. w26945).

Barnea, A., Haugen, R. and L. Senbet, 1980, A Rationale for Debt Maturity Structure and Call Provisions in the Agency Theoretic Framework, *Journal of Finance* 35(5), 1223-34.

Barrero, J.M., Bloom, N. and S.J. Davis, 2021. Why working from home will stick, National Bureau of Economic Research working paper no. w28731.

Bernile, G., Bhagwat, V. and Rau, P.R., 2017. What doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior. *The Journal of Finance*, *72*(1), pp.167-206.

Basavaraju, S.V., Patton, M.E., Grimm, K., Rasheed, M.A.U., Lester, S., Mills, L., Stumpf, M., Freeman, B., Tamin, A., Harcourt, J. and Schiffer, J., 2020. Serologic testing of US blood donations to identify severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2)–reactive antibodies: December 2019–January 2020. *Clinical Infectious Diseases*.

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

Bharath, S.T. and Shumway, T., 2008, Forecasting default with the Merton distance to default model. *The Review of Financial Studies*, *21*(3), pp.1339-1369.

Bosshardt, J. and A. Kakhbod, 2020, Why did Firms Draw Down their Credit Lines during the COVID-19 Shutdown? SSRN Working Paper#3696981.

Demers, E., Hendrikse, J., Joos, P., and B. Lev, 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), pp.433-462.

Dessaint, O. and Matray, A., 2017. Do managers overreact to salient risks? Evidence from hurricane strikes. *Journal of Financial Economics*, 126(1), pp.97-121.

de Vries, K., Erumban, A. and B. van Ark (2021), Productivity and the Pandemic: Short-term Disruptions and Long-term Implications: The impact of the COVID-19 Pandemic on Productivity Dynamics by Industry, *International Economics and Economic Policy*, Sep 14: 1-30.

Dingel, J.I. and Neiman, B., 2020. *How many jobs can be done at home?* (No. w26948). National Bureau of Economic Research.

Duong, H.N., Nguyen, J.H., Nguyen, M. and Rhee, S.G., 2020. Navigating through economic policy uncertainty: The role of corporate cash holdings. *Journal of Corporate Finance*, *62*, p.101607.

Ghaly, M., Anh Dang, V. and Stathopoulos, K., 2017. Cash holdings and labor heterogeneity: the role of skilled labor. *The Review of Financial Studies*, *30*(10), pp.3636-3668.

Hadlock, C. and J. Pierce, 2010, New evidence on measuring financial constraints: Moving beyond the KZ Index, *The Review of Financial Studies* 23(5), pp. 1909–1940.

Han, S. and Qiu, J., 2007. Corporate precautionary cash holdings. *Journal of Corporate Finance*, *13*(1), pp.43-57.

Hassan, T., Hollander, S., Lent, L., and Tahoun, A., 2019 Firm-Level Political Risk: Measurement and Effects, *Quarterly Journal of Economics* 134 (4), pp.2135-2202.

Ivashina, V. and D. Scharfstein, 2010, Loan Syndication and Credit Cycles, *American Economic Review* 100(2), 57-61.

Jalal, A. and Khaksari, S., 2019. Cash cycle: A cross-country analysis. *Financial Management*, forthcoming.

Kahle, K. and R. Stulz, 2013, Access to capital, investment, and the financial crisis, *Journal of Financial Economics* 110(2), pp. 280-299.

Kaplan, S. and L. Zingales, 1997, Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints? *The Quarterly Journal of Economics* 112(1), 169-215.

Kapsos, S. (2021), Why Would Labor Productivity Surge during a Pandemic?, ILOSTAT, https://ilostat.ilo.org/why-would-labour-productivity-surge-during-a-pandemic/.

Katz, L.F. and Krueger, A.B., 2017. The role of unemployment in the rise in alternative work arrangements. *American Economic Review*, *107*(5), pp.388-92.

Keynes, J.M., 1936. *The general theory of employment, interest, and money*. Springer.

Mas, A. and Pallais, A., 2017. Valuing alternative work arrangements. *American Economic Review*, *107*(12), pp.3722-59.

Opler, T., Pinkowitz, L., Stulz, R. and Williamson, R., 1999. The determinants and implications of corporate cash holdings. *Journal of financial economics*, *52*(1), pp.3-46.

Ozkan, A. and N. Ozkan, 2004, Corporate cash holdings: an empirical investigation of UK companies, *Journal of Banking and Finance* 28, 2103–2134.

Pinkowitz, L., Stulz, R.M. and Williamson, R., 2016. Do US firms hold more cash than foreign firms do?. *The Review of Financial Studies*, *29*(2), pp.309-348.

Pinkowitz, L. and R. Williamson, 2001, Bank power and cash holdings: Evidence from Japan, *Review of Financial Studies* 14, 1059–1082.

Pinkowitz, L. and R. Williamson, 2007, What is the market value of a dollar of corporate cash?. *Journal of Applied Corporate Finance*, *19*(3), pp.74-81.

Richards, V. and E. Laughlin, 1980, A cash conversion cycle approach to liquidity analysis, *Financial Management* 9(1), 32-38.

Riddick, L.A. and Whited, T.M., 2009. The corporate propensity to save. *The Journal of Finance*, *64*(4), pp.1729-1766.

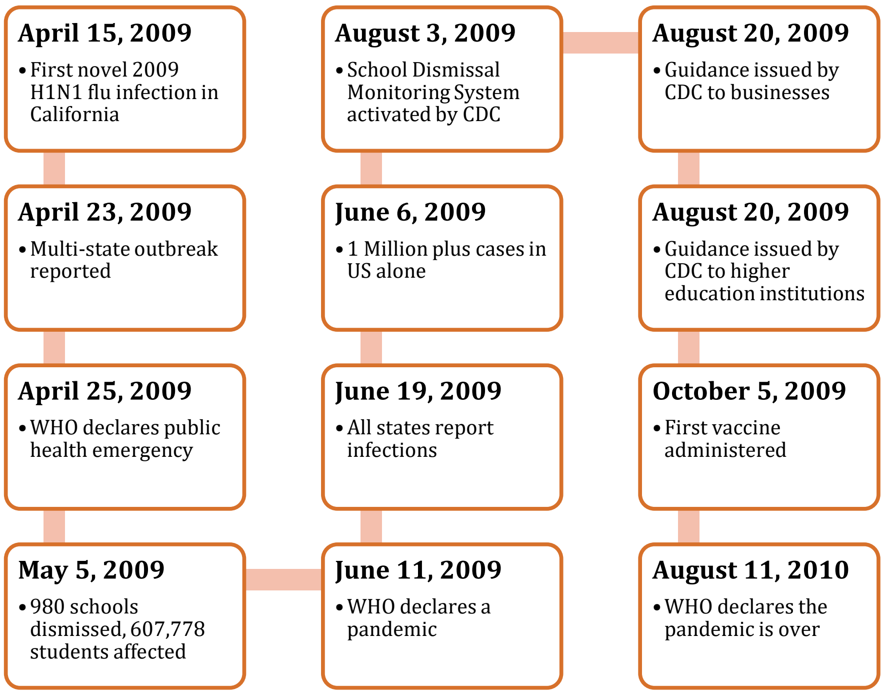
Song, K.R. and Lee, Y., 2012. Long-term effects of a financial crisis: Evidence from cash holdings of East Asian firms. *Journal of Financial and Quantitative analysis*, *47*(3), pp.617-641.

Taylor, J.B. and Williams, J.C., 2009. A black swan in the money market. *American Economic Journal: Macroeconomics*, *1*(1), pp.58-83.

Yoo, B.K., Kasajima, M. and Bhattacharya, J., 2010. *Public avoidance and the epidemiology of novel H1N1 influenza A* (No. w15752). National Bureau of Economic Research.

Table 1
Timeline of H1N1 and COVID-19 Pandemics

Panel A: H1N1 Timeline



Notes:

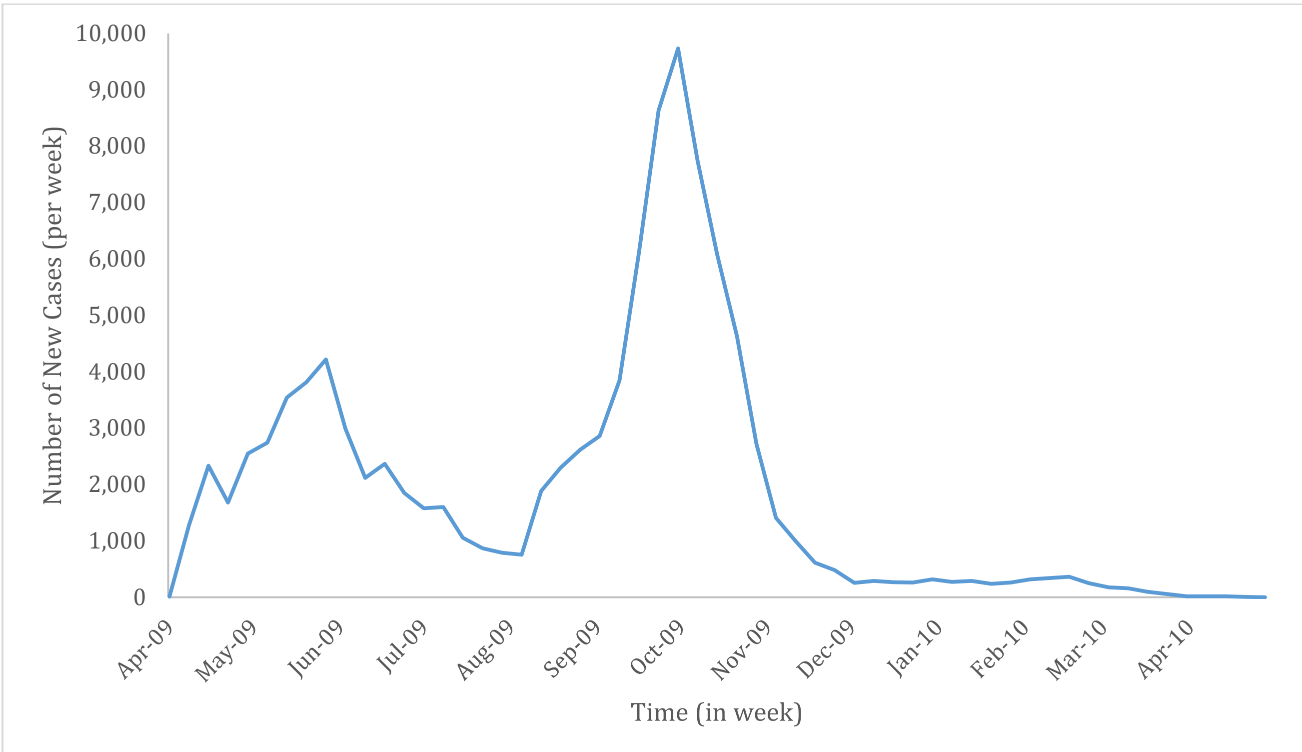
This table describes the timeline of H1N1 pandemic starting on April 15, 2009 and ending in August 11, 2010.

Panel B: COVID-19 Timeline

Notes:

The above table describes the timeline of COVID-19 pandemic starting on January 21, 2020.

Figure 1
Weekly H1N1 Confirmed New Infections

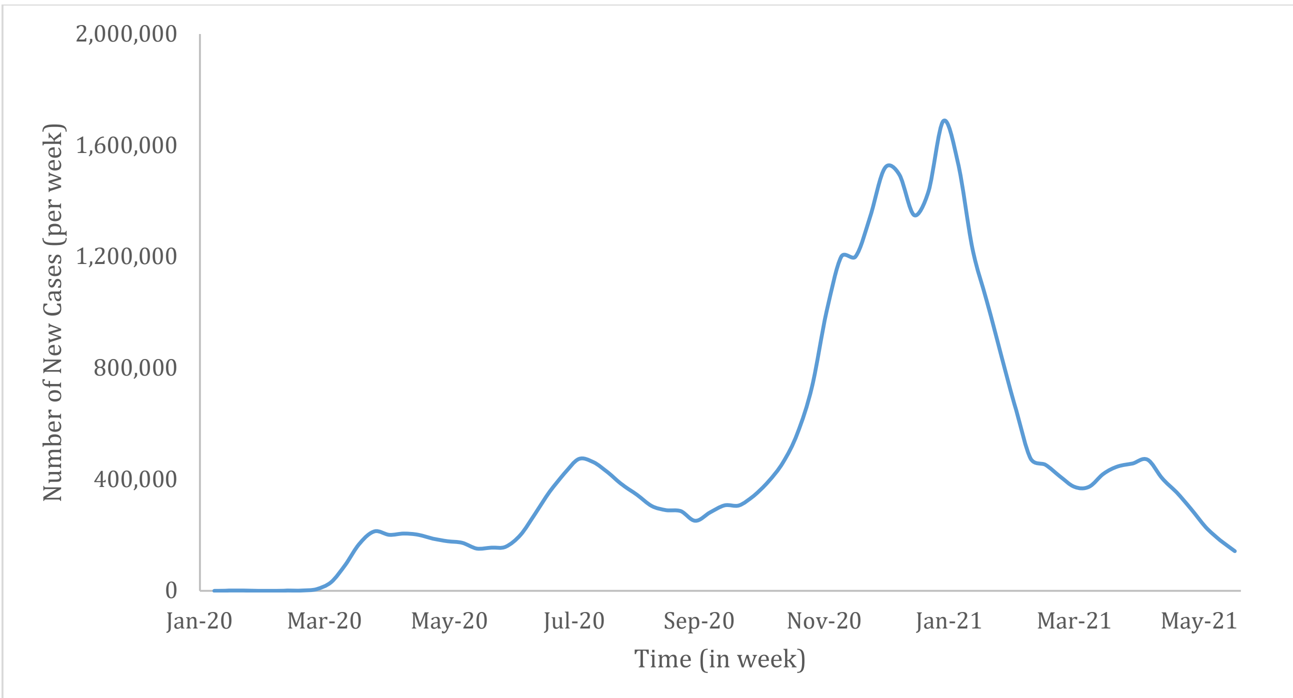


Notes:

The above graph plots the number of laboratory confirmed new cases for that week during the H1N1 pandemic period. Source: https://www.cdc.gov/flu/weekly/weeklyarchives2008-2009/weekly33.htm.

Figure 2

Weekly COVID New Infections



Notes:

The above graph plots the total number of new cases per week, including both actual and presumed cases, during the COVID pandemic period. https://covid.cdc.gov/covid-data-tracker/#datatracker-home.

Table 2

Tele-workability and Labor Vulnerability of Industries to Pandemics

Panel A: Non-tele-workable and Tele-workable Industries

Non-tele-workable Industries				Tele-workable Industries			
NAICS	**NAICS Title**	**Employees** (1)	**Wages** (2)	**NAICS**	**NAICS Title**	**Employees** (3)	**Wages** (4)
72	Accommodation and Food Services	3.54%	6.82%	61	Educational Services	82.65%	71.40%
11	Agriculture, Forestry, Fishing and Hunting	7.64%	13.14%	54	Professional, Scientific, and Technical Services	80.28%	86.35%
45	Retail Trade	14.34%	21.61%	51	Information	71.71%	79.79%
44	Retail Trade	14.33%	21.62%	42	Wholesale Trade	51.76%	66.87%
23	Construction	18.56%	22.28%	53	Real Estate and Rental and Leasing	41.81%	54.05%
48	Transportation and Warehousing	18.61%	24.68%	81	Other Services (except Public Administration)	31.24%	42.79%

Notes:
The above table describes the least and the most tele-workable industries, as identified by their 2-digit NAICS codes. The data is from Dingel and Neiman (2020). There are 24 industries based on 2-digit NAICS. Non-tele-workable and Tele-workable industries are identified as the bottom and top quarters of the industries based on the employees and wages that can be deployed through tele-work. Under the sub-heading Employees, in columns (1) and (3), we show the percentage of employees in that industry that could tele-work. Additionally, under the sub-heading Wages, columns (2) and (4) present the percentage of wages that are provided to tele-workable employees in that industry.

Panel B: Non-tele-workable and Tele-workable Firms in the Sample

Non-tele-workable Industries			Tele-workable Industries		
NAICS	**NAICS Title**	**No. of Firms** (1)	**NAICS**	**NAICS Title**	**No. of Firms** (2)
72	Accommodation and Food Services	125	61	Educational Services	12
11	Agriculture, Forestry, Fishing and Hunting	22	54	Professional, Scientific, and Technical Services	114
45	Retail Trade	115	51	Information	333
44	Retail Trade	182	42	Wholesale Trade	89
23	Construction	117	53	Real Estate and Rental and Leasing	225
48	Transportation and Warehousing	236	81	Other Services (except Public Administration)	24
	Total	797		Total	797

Notes:

The above table shows the number of firms in the sample that belong to the treatment and the control groups. The firms in the non-tele-workable industries are in the treatment group. The tele-workable firms were selected from the tele-workable industries based on propensity score matching on firm size and profitability.

Table 3

Cash-holding of Firms Before and During the Pandemics

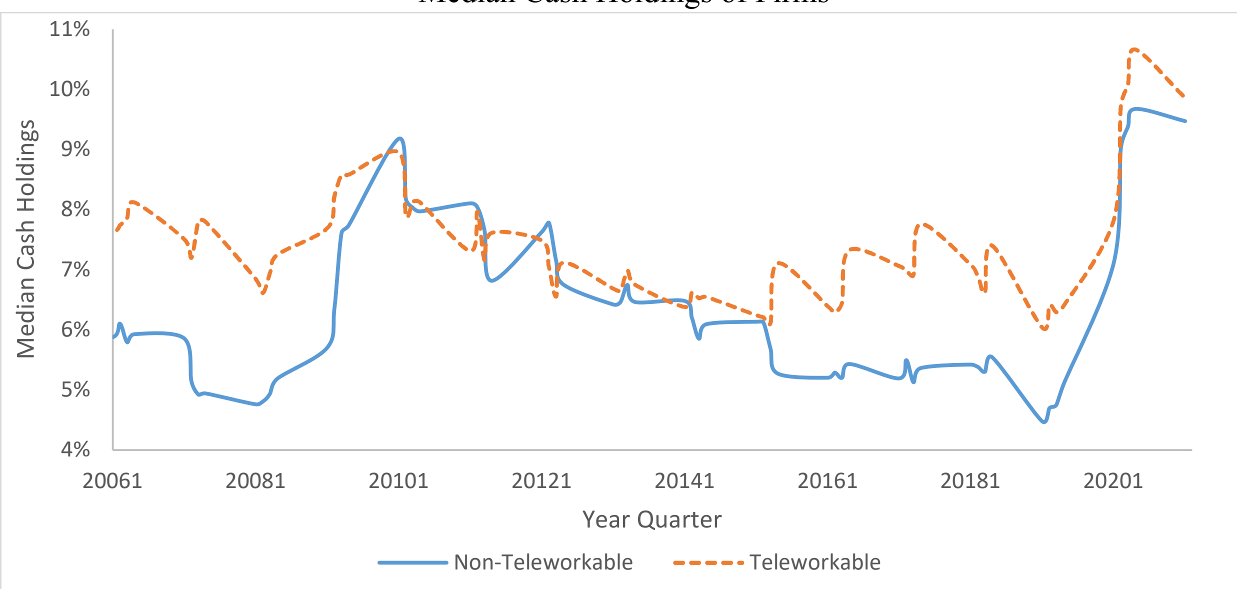
Pandemic	Quarters since the Beginning of Pandemic	Non-tele-workable Firms		Tele-workable Firms	
		Average (1)	Median (2)	Average (3)	Median (4)
	-5	0.1057	0.0545	0.1777	0.0742
	-4	0.1057	0.0537	0.1760	0.0746
Before	**-3**	0.1061	0.0535	0.1702	0.0734
	-2	0.1022	0.0491	0.1707	0.0718
	-1	0.0738	0.0419	0.1576	0.0718
	1	0.1114	0.0728	0.1644	0.0868
	2	0.1225	0.0849	0.1707	0.0912
During	**3**	0.1286	0.0906	0.1711	0.0942
	4	0.1234	0.0830	0.1663	0.0873
	5	0.1231	0.0858	0.1672	0.0863

Notes:

The above table shows the mean and median cash holding of firms five quarters before and five quarters during the H1N1 and the COVID pandemics. The variable *Cash* is defined as a ratio of cash and marketable securities to total assets of firms. Columns (1) and (3) show the average cash holdings, while columns (2) and (4) show the median cash holdings of firms.

Figure 3

Median Cash Holdings of Firms



Notes:

The above graph shows the median cash holdings of tele-workable and non-tele-workable firms during the period 2006 Q2 and 2021 Q1.

Table 4
Summary Statistics

Variable	Mean (1)	Median (2)	Std. Dev. (3)	Min (4)	Max (5)
Pandemic	0.5000	0.5000	0.5000	0.0000	1.0000
Non-tele-workable	0.5000	0.5000	0.5000	0.0000	1.0000
H1N1 Exposure	0.0231	0.0000	0.1748	0.0000	4.5616
COVID Exposure	0.2448	0.0000	0.6599	0.0000	7.3384
Non-tele-workable Index	13.3319	14.5000	5.8582	1.0000	24.0000
Size	6.9099	7.0798	2.0325	0.9719	10.8897
Leverage	0.6212	0.5698	0.7002	0.0523	1.9528
Market-to-Book	2.6298	1.8135	2.9817	0.3469	36.1023
R&D	0.0035	0.0000	0.0143	0.0000	0.0542
Profitability	-0.0016	0.0086	0.1429	-0.1848	0.1158
Dividend Payer	0.4959	0.0000	0.5000	0.0000	1.0000
Collateral	0.3173	0.2342	0.2725	0.0000	0.9734
Negative Income	0.2746	0.0000	0.4464	0.0000	1.0000
Interest Expenditure	0.0494	0.0136	0.2937	0.0000	0.7000
Intangibles	0.1648	0.0705	0.2066	0.0000	0.8295
Capex	0.0287	0.0135	0.0442	0.0008	0.7692
Inventory Period	0.8022	0.1197	8.6469	0.0000	748.8321
Receivables Period	0.3564	0.4276	6.9435	0.0000	399.5385
Payables Period	0.8328	0.4183	3.6576	-39.1471	234.8000
Cash Cycle	0.1388	0.0941	0.1392	0.0000	0.7165
Operational Expense	0.5208	0.1910	0.6697	0.0101	0.7173
Short-term Debt	0.0563	0.0083	0.2368	0.0000	0.6321
Long-term Debt	0.2583	0.1973	0.2710	0.0000	0.9170
Asset Volatility	0.5993	0.4795	0.4486	0.0515	6.3064
Expected Default Frequency	0.0849	0.0000	0.2166	0.0000	1.0000
Option Implied Volatility	49.2530	43.0000	27.0997	0.0000	491.0000
Idiosyncratic Volatility	0.02702	0.0216	0.0192	0.0059	0.1350
Total Volatility	0.0313	0.0254	0.0207	0.0095	0.1104
Discontinued Operations	0.00153	0.0000	0.0539	0.0000	0.1573
Taxes	0.3011	0.0144	0.7917	0.0000	0.5223
Preferred Stocks	0.1155	0.0000	0.1210	0.0000	0.5610

Notes:

Pandemic takes the value of 1 for the quarters, i.e. between third quarter of 2009 and the third quarter of 2010 for H1N1 and between the first quarter of 2020 and the first quarter of 2021 for COVID, the companies experienced a pandemic, and 0 for before. *Non-tele-workable* takes the value of 1 if the firm belongs to the treatment group, i.e. it is in an industry that is most likely to experience labor shock accompanying a pandemic. It takes the value of 0 if the firm belongs to the control group. *H1N1 Exposure* counts the number of times the disease is mentioned in the quarterly earnings call, as provided by Hassan, Hollander, Lent, and Tahoun (2019). Similarly, *COVID Exposure* counts the number of times the COVID pandemic is mentioned in the quarterly earnings call. *Non-tele-workable Index* ranks the two-digit NAICS industries from most tele-workable to least tele-workable by counting from 1 to 24. *Size* is calculated as the natural logarithm of the book value of assets of the firms and controls for firm size on cash holdings. *Leverage* is the ratio of a firm's total liabilities to total assets. Market-to-book is the ratio of market value of equity to book value of equity. *R&D* is calculated by dividing the firm's research and development expenditures by total assets. *Profitability* is the ratio of earnings before interest and taxes and total assets. *Dividend Payer* is an indicator variable that takes the value of 1 if the company pays a positive dividend, 0 otherwise. *Collateral* is the ratio of property, plant and equipment divided by total assets. *Negative Income* is a dummy variable that takes the value of 1 if the company has a negative net income during the quarter. *Interest Expenditure* is equal to the company's interest expenses divided by total debt. *Intangibles* is calculated as intangible assets divided by total assets. *Capex* is capital expenditures divided by total assets. *Cash* is defined as cash and marketable securities divided by total assets. *Inventory Period* defined as the ratio of inventory to costs of goods sold (COGS). *Receivable Period* is the ratio of account receivable to sales. *Payable Period* is calculated by dividing accounts payable by COGS. *Cash Cycle* is calculated by subtracting accounts payable period from the sum of inventory and accounts receivable periods. *Operational Expense* is equal to selling, general, and administrative expenses divided by total assets. *Short-term Debt* is debt in current liabilities divided by total assets. *Long-term Debt* is long-term debt divided by total assets. *Financial Constraint* equals the value of the Kaplan-Zingales index. *Asset Volatility* is the volatility of the firm's market value which is the sum of the firm's market capital and total debt. *Expected Default Frequency* is computed as in Bharat and Shumway (2009) and is the implementation of the KMV-Merton model. *Implied Volatility* is the implied volatility of the firm's options used in calculating the executive compensation by Compustat. *Idiosyncratic Volatility* is calculated by subtracting standard deviation of the market portfolio from the standard deviation of the equity returns. *Total Volatility* is the standard deviation of returns of a firm's equity. *Discontinued Operations* is discontinued operations divided by total assets. *Taxes* is calculated by dividing taxes paid by sales. *Preferred Stock* is the par value of preferred stocks divided by total assets. There are 15,940 observations.

Table 5

Cash Holdings during Pandemics

Panel A: Difference-in-Difference in Cash Holdings

	Before Pandemic			During Pandemic			Diff-in-Diff
	Tele-workable	Non-tele-workable	(2)-(1)	Tele-workable	Non-tele-workable	(5)-(4)	(6)-(3)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cash	0.174	0.105	-0.069***	0.168	0.122	-0.046***	0.022***

Notes:

Cash is defined as a ratio of cash and marketable securities to total assets of firms. Non-tele-workable and Tele-workable industries are identified as the bottom and top quarters of the industries based on the employees and wages that can be deployed through tele-work. During pandemic is the period between the third quarter of 2009 and the third quarter of 2010, when the H1N1 pandemic took place and between the first quarter of 2020 and the first quarter of 2021 for COVID. The period between the second quarter of 2006 and the second quarter of 2007 is the before H1N1 pandemic period and the period between the third quarter of 2018 and the third quarter of 2019 is the before COVID period. There are 7,970 observations each for before pandemic and during pandemic periods.

Panel B: Difference-in-Difference Regression Analysis

Sample	Non-tele-workable	Tele-workable	All Firms
	(1)	(2)	(3)
Pandemic	0.0295	-0.0058	0.0018
	(6.662)***	(-1.064)	(0.328)
Pandemic * Non-tele-workable			0.0287
			(5.471)***
Non-tele-workable			(drop)
Size	-0.0277	-0.0420	-0.0335
	(-3.950)***	(-3.116)***	(-3.763)***
Leverage	-0.0051	-0.0356	-0.0022
	(-2.232)**	(-2.994)***	(-0.932)
Market-to-Book	0.0002	-0.0002	-0.0003
	(1.748)*	(-2.411)**	(-0.641)
R&D	2.8882	0.0657	0.1469
	(3.444)***	(0.252)	(0.365)
Profitability	0.0097	0.1356	0.0762
	(0.257)	(2.751)**	(1.718)

Dividend Payer	-0.0003	-0.0145	-0.0051
	(-0.052)	(-1.742)*	(-0.981)
Collateral	-0.2511	-0.2277	-0.2401
	(-4.422)***	(-3.331)***	(-5.059)***
Constant	0.4001	0.5324	0.4445
	(6.509)***	(8.344)***	(9.510)***
Firm Fixed Effects	Yes	Yes	Yes
Quarter*Industry Fixed Effects	Yes	Yes	Yes
P-value of test for equality of the coefficients of Pandemic in (1) and (2)	0.0022**		
Adj R^2	0.74	0.85	0.82
N	7,970	7,970	15,940

Notes:

The dependent variable *Cash* is defined as a ratio of cash and marketable securities to total assets of firms. *Pandemic* takes the value of 1 for the quarters, i.e. between third quarter of 2009 and the third quarter of 2010 for H1N1 and between the first quarter of 2020 and the first quarter of 2021 for COVID, the companies experienced a pandemic, and 0 for before. *Non-tele-workable* takes the value of 1 if the firm belongs to the treatment group, i.e. it is in an industry that is most likely to experience labor shock accompanying a pandemic. It takes the value of 0 if the firm belongs to the control group. The control variables used are the following. *Size* is calculated as the natural logarithm of the book value of assets of the firms and controls for firm size on cash holdings. *Leverage* is the ratio of a firm's total liabilities to total assets. *Market-to-book* is the ratio of market value of equity to book value of equity. *R&D* is calculated by dividing the firm's research and development expenditures by total assets. *Profitability* is the ratio of earnings before interest and taxes and total assets. *Dividend Payer* is an indicator variable that takes the value of 1 if the company pays a positive dividend, 0 otherwise. *Collateral* is the ratio of property, plant and equipment divided by total assets. Industry follows the 6-digit NAICS code. OLS regression with firm and quarter*industry fixed effects. Standard errors are clustered at the firm and quarter level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Panel C: Robustness Tests: Cross-sectional Regression Using the Intensity of the Pandemic

Sample	Higher Intensity (1)	Lower Intensity (2)
Pandemic	0.0078	0.0069
	(0.248)	(0.673)
Pandemic * Non-tele-workable	0.0394	0.0147
	(3.667)***	(2.083)*
Non-tele-workable	(drop)	

Size	-0.0414	-0.0174
	(-5.667)***	(-1.564)
Leverage	-0.0055	-0.0014
	(-0.387)	(-0.536)
Market-to-Book	-0.0001	-0.0005
	(-0.663)	(-2.100)**
R&D	0.4480	0.3146
	(0.477)	(0.575)
Profitability	0.0828	0.0570
	(0.748)	(0.972)
Dividend Payer	-0.0076	-0.0033
	(-0.872)	(-0.380)
Collateral	-0.1734	-0.2877
	(-2.432)**	(-5.714)***
Constant	0.5003	0.3211
	(7.180)***	(4.606)***
Firm Fixed Effects	Yes	Yes
Quarter*Industry Fixed Effects	Yes	Yes
P-value of test for equality of the coefficients of Pandemic in (1) and (2)	0.0782*	
Adj R^2	0.80	0.80
N	7,970	7,970

Notes:
The dependent variable *Cash* is defined as a ratio of cash and marketable securities to total assets of firms. *H1N1 Exposure* counts the number of times the disease is mentioned in the quarterly earnings call, as provided by Hassan, Hollander, Lent, and Tahoun (2019). Similarly, *COVID Exposure* counts the number of times the COVID pandemic is mentioned in the quarterly earnings call. We split our sample into Higher Intensity and Lower Intensity based on the median value of *H1N1* or *COVID Exposure*. The rest of the control variables are defined in Table 5 Panel B. Industry follows the 6-digit NAICS code. OLS regression with industry fixed effects. Standard errors are clustered at the firm and quarter level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Table 6
Dynamic Analysis of Cash Holdings

Sample	Non-tele-workable	Tele-workable	All Firms
	(1)	(2)	(3)
Qtr-4	-0.0077	-0.0007	-0.0009
	(-1.014)	(-0.158)	(-0.123)
Qtr-3	-0.0068	-0.0064	-0.0069
	(-0.809)	(-0.694)	(-0.633)
Qtr-2	-0.0038	-0.0004	-0.0017
	(-0.518)	(-0.080)	(-0.265)
Qtr-1	0.0014	0.0034	0.0012
	(0.265)	(0.976)	(0.246)
Qtr1	0.0182	0.0016	-0.0028
	(3.133)***	(0.372)	(-0.545)
Qtr2	0.0266	0.0061	0.0015
	(2.665)**	(0.747)	(0.180)
Qtr3	0.0315	0.0089	0.0035
	(3.223)***	(1.087)	(0.414)
Qtr4	0.0258	0.0029	-0.0022
	(3.101)***	(0.369)	(-0.295)
Qtr5	0.0267	0.0050	0.0003
	(2.430)**	(0.459)	(0.027)
Qtr-4 * Non-tele-workable			-0.0066
			(-1.357)
Qtr-3 * Non-tele-workable			0.0030
			(1.568)
Qtr-2 * Non-tele-workable			0.0069
			(1.381)
Qtr-1 * Non-tele-workable			0.0049
			(1.568)
Qtr1 * Non-tele-workable			0.0295
			(5.767)***
Qtr2 * Non-tele-workable			0.0276
			(5.595)***
Qtr3 * Non-tele-workable			0.0111
			(2.268)**
Qtr4 * Non-tele-workable			0.0051
			(1.705)*
Qtr5 * Non-tele-workable			0.0010

			(0.374)
Size	-0.0281	-0.0422	-0.0338
	(-4.011)***	(-5.088)***	(-5.802)***
Leverage	-0.0052	-0.0359	-0.0022
	(-2.224)**	(-3.000)***	(-0.928)
Market-to-Book	0.0000	-0.0000	-0.0000
	(1.847)*	(-1.793)*	(-0.517)
R&D	2.8842	-0.0624	0.1486
	(3.424)***	(-0.239)	(0.369)
Profitability	-0.0105	0.1362	0.0763
	(-0.278)	(2.761)**	(1.704)
Dividend Payer	0.0006	-0.0144	-0.0049
	(0.091)	(-1.726)	(-0.950)
Collateral	-0.2511	-0.2286	-0.2406
	(-4.394)***	(-3.326)***	(-5.048)***
Constant	0.4063	0.5353	0.4487
	(6.642)***	(8.407)***	(9.696)***
Firm Fixed Effects	Yes	Yes	Yes
Quarter*Industry Fixed Effects	Yes	Yes	Yes
Adj R^2	0.74	0.85	0.82
N	15,940	15,940	15,940

Notes:
The dependent variable *Cash* is defined as a ratio of cash and marketable securities to total assets of firms. *Pandemic* takes the value of 1 for the quarters, i.e. between third quarter of 2009 and the third quarter of 2010 for H1N1 and between the first quarter of 2020 and the first quarter of 2021 for COVID, the companies experienced a pandemic, and 0 for before. *Non-tele-workable* takes the value of 1 if the firm belongs to the treatment group, i.e. it is in an industry that is most likely to experience labor shock accompanying a pandemic. It takes the value of 0 if the firm belongs to the control group. Qtr-4, Qtr-3, Qtr-2, Qtr-1, Qtr1, Qtr2, Qtr3, Qtr4, and Qtr5 are indicator variables in relation to the beginning of the pandemic. We use the same controls as in Table 5 Panel B. Industry follows the 6-digit NAICS code. OLS regression with firm and quarter*industry fixed effects. Standard errors are clustered at the firm and quarter levels. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Table 7

Effects of the Pandemic on Firms Vulnerable to Liquidity Shocks

Sample	Financial Constraint		Interest Expense		Negative Income	
	High	Low	High	Low	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Pandemic	-0.0072	0.0251	-0.0083	0.0128	-0.0311	0.0088
	(-1.152)	(3.779)***	(-1.188)	(2.196)**	(-2.371)**	(2.021)*
Pandemic * Non-tele-workable	0.0293	-0.0187	0.0380	0.0114	0.0526	0.0204
	(4.385)***	(-1.034)	(4.396)***	(1.416)	(3.492)***	(1.123)
Non-tele-workable	(drop)	(drop)	(drop)	(drop)	(drop)	(drop)
Constant	0.3809	0.5477	0.5297	0.3477	0.3473	0.4699
	(6.154)***	(7.922)***	(6.927)***	(6.926)***	(3.751)***	(9.244)***
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter * Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value of test for the equality of the coefficients of *Pandemic* in odd and even columns	0.0366**		0.0479**		0.0005***	
Adj R^2	0.83	0.88	0.86	0.83	0.79	0.85
N	7,970	7,970	7,970	7,970	3,821	12,119

(table 7 continued …)

Sample	Capex		Operational Expense		Dividend Payer	
	High	Low	High	Low	No	Yes
	(7)	(8)	(9)	(10)	(11)	(12)
Pandemic	-0.0038	0.0009	-0.0068	0.0177	-0.0092	0.0146
	(-0.608)	(0.140)	(-0.961)	(4.811)***	(-0.974)	(4.212)***
Pandemic * Non-tele-workable	0.0342	0.0253	0.0331	0.0135	0.0395	0.0177
	(4.309)***	(3.940)***	(4.040)***	(2.405)**	(4.362)***	(2.460)**
Non-tele-workable	(drop)	(drop)	(drop)	(drop)	(drop)	(drop)
Constant	0.4329	0.4455	0.4729	0.3726	0.4962	0.2719
	(7.572)***	(9.015)***	(7.925)***	(7.700)***	(8.459)***	(6.327)***
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter * Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value of test for the equality of the coefficients of *Pandemic* in odd and even columns	0.0863*		0.0132**		0.0194**	
Adj R^2	0.82	0.84	0.82	0.82	0.80	0.82
N	7,970	7,970	7,970	7,970	9,332	6,608

Notes:

The dependent variable *Cash* is defined as a ratio of cash and marketable securities to total assets of firms. *Pandemic* takes the value of 1 for the quarters, i.e. between third quarter of 2009 and the third quarter of 2010 for H1N1 and between the first quarter of 2020 and the first quarter of 2021 for COVID, the companies experienced a pandemic, and 0 for before. *Non-tele-workable* takes the value of 1 if the firm belongs to the treatment group, i.e. it is in an industry that is most likely to experience labor shock accompanying a pandemic. It takes the value of 0 if the firm belongs to the control group. *Financial Constraint* equals the value of the Kaplan-Zingales index. *Interest Expense* is equal to the company's interest expenses divided by total debt. *Negative Income* is a dummy variable that takes the value of 1 if the company has a negative net income during the quarter. *Capex* is capital expenditures divided by total assets. *Operational Expense* is equal to selling, general, and administrative expenses divided by total assets. We use the same controls as in Table 5 Panel B. Industry follows the 6-digit NAICS code. OLS regression with firm and quarter*industry fixed effects. Standard errors are clustered at the firm and quarter levels. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Table 8

Sources of Debt Financing for Firms

Panel A: Using Kaplan-Zingales Index of Financial Constraint

Dependent Variable:	Long-term Debt		Short-term Debt	
Sample	Financial Constraint		Financial Constraint	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Pandemic	0.0361	0.0040	-0.0239	0.0001
	(6.904)***	(0.447)	(-2.432)**	(0.081)
Pandemic * Non-tele-workable	-0.0199	0.0028	0.0407	0.0032
	(-2.164)**	(0.499)	(3.657)***	(1.108)
Non-tele-workable	(drop)	(drop)	(drop)	(drop)
Constant	0.0029	0.2636	-0.1882	0.0533
	(0.060)	(4.632)***	(-2.136)**	(7.881)***
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Quarter * Industry Fixed Effects	Yes	Yes	Yes	Yes
P-value of test for the equality of the coefficients of *Pandemic* in odd and even columns	0.0364**		0.0280**	
Adj R^2	0.80	0.91	0.74	0.82
N	7,970	7,970	7,970	7,970

Notes:

The dependent variable *Long-term Debt* is long-term debt divided by total assets. The dependent variable *Short-term Debt* is debt in current liabilities divided by total assets. *Pandemic* takes the value of 1 for the quarters, i.e. between third quarter of 2009 and the third quarter of 2010 for H1N1 and between the first quarter of 2020 and the first quarter of 2021 for COVID, the companies experienced a pandemic, and 0 for before. *Non-tele-workable* takes the value of 1 if the firm belongs to the treatment group, i.e. it is in an industry that is most likely to experience labor shock accompanying a pandemic. It takes the value of 0 if the firm belongs to the control group. *Financial Constraint* equals the value of the Kaplan-Zingales index. We use the same controls as in Table 5 Panel B. Industry follows the 6-digit NAICS code. OLS regression with firm and quarter*industry fixed effects. Standard errors are clustered at the firm and quarter levels. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Panel B: Using Interest Expense

Dependent Variable:	Long-term Debt		Short-term Debt	
Sample	Interest Expense		Interest Expense	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Pandemic	0.0170	0.0205	-0.0277	-0.0044
	(4.603)***	(5.592)***	(-2.801)**	(-2.076)*
Pandemic * Non-tele-workable	-0.0209	-0.0066	0.0604	0.0010
	(-3.091)***	(-1.252)	(3.237)***	(0.306)
Non-tele-workable	(drop)	(drop)	(drop)	(drop)
Constant	-0.0685	0.0876	-0.1974	-0.1019
	(-2.259)**	(2.083)*	(-1.180)	(-3.512)***
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Quarter * Industry Fixed Effects	Yes	Yes	Yes	Yes
P-value of test for the equality of the coefficients of *Pandemic* in odd and even columns	0.0538*		0.0423**	
Adj R^2	0.83	0.84	0.72	0.96
N	7,970	7,970	7,970	7,970

Notes:

The dependent variable *Long-term Debt* is long-term debt divided by total assets. The dependent variable *Short-term Debt* is debt in current liabilities divided by total assets. *Pandemic* takes the value of 1 for the quarters, i.e. between third quarter of 2009 and the third quarter of 2010 for H1N1 and between the first quarter of 2020 and the first quarter of 2021 for COVID, the companies experienced a pandemic, and 0 for before. *Non-tele-workable* takes the value of 1 if the firm belongs to the treatment group, i.e. it is in an industry that is most likely to experience labor shock accompanying a pandemic. It takes the value of 0 if the firm belongs to the control group. *Interest Expense* is equal to the company's interest expenses divided by total debt. We use the same controls as in Table 5 Panel B. Industry follows the 6-digit NAICS code. OLS regression with firm and quarter*industry fixed effects. Standard errors are clustered at the firm and quarter levels. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Table 9
Other Sources of Cash

Dependent Variable:	Capex	Discontinued Operations	Taxes	Preferred Stocks
	(1)	(2)	(3)	(4)
Pandemic	-0.0059	-0.0009	-0.3527	0.0013
	(-4.543)***	(-1.605)	(-0.763)	(0.926)
Pandemic * Non-tele-workable	-0.0121	0.0010	-0.2886	0.0012
	(-6.206)***	(2.954)***	(2.588)**	(2.563)**
Non-tele-workable	(drop)	(drop)	(drop)	(drop)
Constant	0.0668	0.0019	-8.4648	0.0432
	(6.599)***	(0.337)	(-0.848)	(2.229)*
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Quarter * Industry Fixed Effects	Yes	Yes	Yes	Yes
Adj R^2	0.60	0.04	0.31	0.85
N	15,940	15,940	15,940	15,940

Notes:

The dependent variable *Capex* is capital expenditures divided by total assets. The dependent variable *Discontinued Operations* is discontinued operations divided by total assets. The dependent variable *Taxes* is calculated by dividing taxes paid by sales. The dependent variable *Preferred Stock* is the par value of preferred stocks divided by total assets. *Pandemic* takes the value of 1 for the quarters, i.e. between third quarter of 2009 and the third quarter of 2010 for H1N1 and between the first quarter of 2020 and the first quarter of 2021 for COVID, the companies experienced a pandemic, and 0 for before. *Non-tele-workable* takes the value of 1 if the firm belongs to the treatment group, i.e. it is in an industry that is most likely to experience labor shock accompanying a pandemic. It takes the value of 0 if the firm belongs to the control group. We use the same controls as in Table 5 Panel B. Industry follows the 6-digit NAICS code. OLS regression with firm and quarter*industry fixed effects. Standard errors are clustered at the firm and quarter levels. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Table 10

Risk and Cash Holding

Panel A: Pandemic and Risk of Firms

Dependent Variable:	Asset Volatility	Expected Default Frequency	Implied Volatility	Idiosyncratic Volatility	Total Volatility
	(1)	(2)	(3)	(4)	(5)
Pandemic	0.1497	0.0416	10.6665	0.0120	0.0168
	(1.873)*	(2.224)**	(12.195)***	(3.822)***	(3.986)***
Pandemic * Non-tele-workable	0.0732	0.0235	5.0996	0.0016	0.0011
	(6.051)***	(4.025)***	(6.628)***	(4.254)***	(3.220)**
Non-tele-workable	(drop)	(drop)	(drop)	(drop)	(drop)
Constant	1.2705	-0.224	118.6033	0.0790	0.0807
	(9.163)***	(-1.853)*	(15.618)***	(13.195)***	(13.695)***
Controls	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Quarter * Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.34	0.39	0.79	0.61	0.57
N	11,214	11,214	5,282	11,214	11,214

Notes:

The dependent variables are *Asset Volatility*, *Expected Default Frequency*, *Implied Volatility*, *Idiosyncratic Volatility*, and *Total Volatility*. *Asset Volatility* is the volatility of the firm's market value which is the sum of the firm's market capital and total debt. *Expected Default Frequency* is computed as in Bharat and Shumway (2009) and is the implementation of the KMV-Merton model. *Implied Volatility* is the implied volatility of the firm's options used in calculating the executive compensation by Compustat. *Idiosyncratic Volatility* is calculated by subtracting standard deviation of the market portfolio from the standard deviation of the equity returns. *Total Volatility* is the standard deviation of returns of a firm's equity. *Pandemic* takes the value of 1 for the quarters, i.e. between third quarter of 2009 and the third quarter of 2010 for H1N1 and between the first quarter of 2020 and the first quarter of 2021 for COVID, the companies experienced the H1N1 a pandemic, and 0 for before. *Non-tele-workable* takes the value of 1 if the firm belongs to the treatment group, i.e. it is in an industry that is most likely to experience labor shock accompanying a pandemic. It takes the value of 0 if the firm belongs to the control group. We use the same controls as in Table 5 Panel B. Industry follows the 6-digit NAICS code. OLS regression with firm and quarter*industry fixed effects. Standard errors are clustered at the firm and quarter level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Panel B: Cash Holding and Risk of Firms

Sample	Asset Volatility		Implied Volatility		Collateral	
	High	Low	High	Low	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Pandemic	-0.0283	0.0096	-0.0441	0.0043	-0.0022	0.0043
	(-2.897)***	(0.538)	(-2.596)**	(0.396)	(-0.338)	(0.885)
Pandemic * Non-tele-workable	0.0435	0.0121	0.0481	0.0207	0.0317	0.0104
	(4.759)***	(1.464)	(2.384)**	(1.102)	(3.071)***	(1.432)
Non-tele-workable	(drop)	(drop)	(drop)	(drop)	(drop)	(drop)
Constant	0.4467	0.3351	0.6041	0.5493	0.4768	0.2796
	(6.804)***	(7.601)***	(5.729)***	(3.426)***	(8.357)***	(6.293)***
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter * Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
P-value of test for the equality of the coefficients of *Pandemic* in odd and even columns	0.0086***		0.0272**		0.0104**	
Adj R^2	0.80	0.87	0.84	0.87	0.84	0.76
N	5,607	5,607	2,641	2,641	7,970	7,970

Notes:

The dependent variable *Cash* is defined as a ratio of cash and marketable securities to total assets of firms. *Pandemic* takes the value of 1 for the quarters, i.e. between third quarter of 2009 and the third quarter of 2010 for H1N1 and between the first quarter of 2020 and the first quarter of 2021 for COVID, the companies experienced a pandemic, and 0 for before. *Non-tele-workable* takes the value of 1 if the firm belongs to the treatment group, i.e. it is in an industry that is most likely to experience labor shock accompanying a pandemic. It takes the value of 0 if the firm belongs to the control group. *Asset Volatility* is the volatility of the firm's market value which is the sum of the firm's market capital and total debt. *Expected Default Frequency* is computed as in Bharat and Shumway (2009) and is the implementation of the KMV-Merton model. *Implied Volatility* is the implied volatility of the firm's options used in calculating the executive compensation by Compustat. We use the same controls as in Table 5 Panel B. Industry follows the 6-digit NAICS code. OLS regression with firm and quarter*industry fixed effects. Standard errors are clustered at the firm and quarter level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Table 11

Shareholder Benefits of Increased Cash Holdings

Sample	Non-tele-workable (1)	Tele-workable (2)
ΔC	-0.0433	0.1656
	(-0.173)	(2.687)**
Pandemic	0.0105	0.0160
	(0.519)	(0.549)
Pandemic*ΔC	0.1581	-0.0536
	(2.488)**	(-1.221)
ΔE	0.2198	-0.0114
	(3.506)***	(-1.351)
ΔNA	0.0187	-0.0080
	(0.357)	(-0.501)
ΔRD	0.2287	1.5758
	(0.099)	(1.873)*
ΔI	-0.3870	0.5573
	(-0.632)	(2.148)**
ΔD	0.1122	0.2260
	(0.318)	(1.304)
C_{t-1}	-0.0764	0.0358
	(-0.719)	(0.984)
L	0.0245	0.0006
	(2.823)**	(0.683)
NF	0.0475	0.0155
	(0.497)	(1.132)
$\Delta C*C_{t-1}$	0.0269	-0.0001
	(1.168)	(-0.093)
ΔC*L	-0.0077	0.0000
	(-1.148)	(0.022)
Constant	-0.0126	0.0048
	(-0.427)	(0.209)
Firm Fixed Effects	Yes	Yes
Quarter*industry Fixed Effects	Yes	Yes
Adj R^2	0.01	0.07
N	7,689	7,689

Notes:

The dependent variable is excess stock return over the benchmark of Fama-French 25 portfolio returns. *Pandemic* takes the value of 1 for the quarters, i.e. between third quarter of 2009 and the third quarter of 2010 for H1N1 and between the first quarter of 2020 and the first quarter of 2021 for COVID, the companies experienced a pandemic, and 0 for before. Δ signifies first difference in the variables and all the independent variables except for market leverage (L) and *Pandemic* are deflated by the lagged market value of equity. Subscript (t-1) denotes lagged values of the variable. C is cash and marketable securities. E is earnings before extraordinary items plus interest, deferred tax credits, and investment tax credits. Net assets NA is total asset minus cash. RD is research and development expenses. I is interest expense. D is total dividends. Market leverage L is calculated as market leverage divided by total liability plus market value of equity. Net financing NF is total equity issuance minus equity repurchases plus debt issuance minus debt redemption. Industry follows the 6-digit NAICS code. OLS regression with firm and quarter*industry fixed effects. Standard errors are clustered at the firm and quarter level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Table 12

Alternate Story: Demand and Supply Risk

Panel A: Controlling for Demand Disruptions

	(1)	(2)	(3)	(4)
Pandemic	-0.0050	-0.0026	-0.0048	-0.0034
	(-0.919)	(-0.471)	(-0.847)	(-0.587)
Pandemic * Non-tele-workable	0.0238	0.0293	0.0247	0.0294
	(4.169)***	(5.551)***	(4.139)***	(5.339)***
LargeCustomerSale	0.0131	0.0116		
	(2.285)**	(2.242)**		
Non-tele-workable * LargeCustomerSale	0.0026	0.0110		
	(0.215)	(0.893)		
Pandemic * LargeCustomerSale	-0.0098	-0.0087		
	(-1.762)*	(-1.564)		
Pandemic * Non-tele-workable * LargeCustomerSale	-0.0140	-0.0099		
	(-1.125)	(-1.021)		
LargeCustomerDummy			0.0111	0.0036
			(0.737)	(0.234)
Non-tele-workable * LargeCustomerDummy			0.0184	0.0021
			(0.899)	(0.103)
Pandemic * LargeCustomerDummy			-0.0089	-0.0127
			(-0.655)	(-0.970)
Pandemic * Non-tele-workable * LargeCustomerDummy			-0.0310	-0.0198
			(-1.652)	(-1.158)
Constant	0.1377	0.4424	0.1377	0.4452
	(38.045)***	(9.371)***	(35.391)***	(9.385)***
Controls	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Quarter*industry Fixed Effects	Yes	Yes	Yes	Yes
Adj R^2	0.80	0.82	0.80	0.82
N	15,940	15,940	15,940	15,940

Notes:

The dependent variable *Cash* is defined as a ratio of cash and marketable securities to total assets of firms. *Pandemic* takes the value of 1 for the quarters, i.e. between third quarter of 2009 and the third quarter of 2010 for H1N1 and between the first quarter of 2020 and the first quarter of 2021 for COVID, the companies experienced a pandemic, and 0 for before. *Non-tele-workable* takes the value of 1 if the firm belongs to the treatment group, i.e. it is in an industry that is most likely to experience labor shock accompanying a pandemic. It takes the value of 0 if the firm belongs to the control group. *LargeCustomerSale*, is the sales to all the large customers divided by total firm level sales. *LargeCustomerDummy* takes the value of 1 if firm reports sales to any large customer. Generally, these sales are more than 10% of the firm's sales. We use the same controls as in Table 5 Panel B. Industry follows the 6-digit NAICS code. OLS regression with firm and quarter*industry fixed effects. Standard errors are clustered at the firm and quarter level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Panel B: Controlling for Supply Disruptions

	(1)	(2)	(3)	(4)
Pandemic	-0.0056	-0.0022	-0.0063	-0.0016
	(-1.035)	(-0.404)	(-1.077)	(-0.271)
Pandemic * Non-tele-workable	0.0229	0.0289	0.0210	0.0282
	(3.959)***	(5.411)***	(3.430)***	(4.989)***
LargeSupplierSale	0.0029	0.0003		
	(0.198)	(0.027)		
Non-tele-workable * LargeSupplierBuy	-0.0067	-0.0049		
	(-0.416)	(-0.337)		
Pandemic * LargeSupplierBuy	0.0098	0.0062		
	(0.863)	(0.556)		
Pandemic* Non-tele-workable * LargeSupplierBuy	-0.0213	-0.0246		
	(-1.519)	(-1.852)*		
LargeSupplierDummy			-0.0019	-0.0004
			(-0.118)	(-0.023)
Non-tele-workable * LargeSupplierDummy			0.0071	0.0118
			(0.377)	(0.658)
Pandemic * LargeSupplierDummy			0.0056	0.0028
			(0.435)	(0.217)
Pandemic * Non-tele-workable * LargeSupplierDummy			0.0110	0.0043
			(0.744)	(0.301)
Constant	0.1392	0.4564	0.1392	0.4481
	(38.261)***	(9.724)***	(33.492)***	(9.527)***
Controls	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Quarter * Industry Fixed Effects	Yes	Yes	Yes	Yes
Adj R^2	0.80	0.82	0.80	0.82
N	15,940	15,940	15,940	15,940

Notes:

The dependent variable *Cash* is defined as a ratio of cash and marketable securities to total assets of firms. *Pandemic* takes the value of 1 for the quarters, i.e. between third quarter of 2009 and the third quarter of 2010 for H1N1 and between the first quarter of 2020 and the first quarter of 2021 for COVID, the companies experienced a pandemic, and 0 for before. *Non-tele-workable* takes the value of 1 if the firm belongs to the treatment group, i.e. it is in an industry that is most likely to experience labor shock accompanying a pandemic. It takes the value of 0 if the firm belongs to the control group. *LargeSupplierBuy* is the purchase from all the large suppliers divided by firm's total cost of goods sold. *LargeSupplierDummy* takes the value of 1 if firm reports large purchase from a supplier. We use the same controls as in Table 5 Panel B. Industry follows the 6-digit NAICS code. OLS regression with firm and quarter*industry fixed effects. Standard errors are clustered at the firm and quarter level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.