Work from Home, Managerial Sentiment, and Corporate Liquidity Management under COVID-19

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ABSTRACT

COVID-19 pandemic lockdowns and mobility restrictions have forced many individuals to work from home, leading to diverse isolation-induced mental health consequences. Using the granularity of foot traffic data, we show that prolonged work from home during the COVID-19 outbreak dampens managerial sentiment. This baseline result is robust to the identification strategy exploiting the staggered implementation of stay-at-home orders across the United States. Further analyses indicate that the induced negative sentiment elevates managers' perceived risk, driving them to accumulate more cash in response to the unprecedented COVID-19 cash-flow shock. But this increase in cash destroys shareholder value.

Keywords: COVID-19, Work from Home, Managerial Sentiment, Corporate Cash Policy

JEL Classification Number: G02, G32, G39

"We want our people to feel an attachment to our firm... Loneliness is not a great feeling. ... the blurring of lines between work and home is "simply not sustainable.""

Citigroup Inc. CEO Jane Fraser[1]

"Working from home all the time is very isolating. It's not just that you're working 100 hours – you don't have the team around you, you don't have the camaraderie."

BLK Consulting founder Geoff Blades[2]

The abrupt shift to working from home under the COVID-19 pandemic has taken an unprecedented toll on the public's mental health.[3] *The Lancet*'s task force reviews the explosion of COVID-related research on mental health and finds much evidence of increased anxiety, depression, and distress, especially during the early months of the pandemic (Aknin et al. 2021).[4] Despite being mentally resilient individuals, corporate executives are not immune to COVID-19 psychological consequences, an important determinant of their sentiment. A 2020 global survey finds that 85% of C-suite executives have struggled with significant remote work challenges and that 53% have suffered from mental health issues in the workplace more than their employees (45%).[5] Given that managers' decisions are inherently subjective, their emotional states could have profound economic consequences. Thus, it is crucial to understand how managerial sentiment changes under the COVID-19 work-from-home environment. Our study addresses this important issue. We investigate the impact of remote work on managerial sentiment and how the induced sentiment influences corporate responses to the immense COVID-19 cash-flow shock.[6]

[1] "Citigroup chief Jane Fraser calls for reset of working life." https://www.ft.com/content/f3a54eee-c741-4ced-9572-ac02b3990db9

[2] "Wall Street Loosens Up as 100-Hour Weeks in Pandemic Take a Toll." https://www.bloomberg.com/news/articles/2021-03-23/citigroup-ceo-bans-zoom-calls-on-friday-encourages-vacations.

[3] The American Psychological Association's (APA's) 2020 survey finds that nearly eight in 10 adults claimed that the pandemic is a significant source of stress, causing the APA to sound the alarm of a national mental crisis (Stress in America^{TM} 2020: A National Mental Health Crisis, American Psychological Association, October 2020.)

[4] These findings are consistent with earlier psychology literature (e.g., Lerner and Keltner 2001; Hawryluck et al. 2004; Goldmann and Galea 2014) documenting that exposure to any natural or human-made disasters can evoke strong negative feelings of fear, anxiety, and depression. Focusing on the 2003 severe acute respiratory syndrome (SARS) outbreak, Hawryluck et al. (2004) show evidence of a high prevalence of psychological distress following the quarantine measures necessary for infectious disease containment. Lerner and Keltner (2001) and Kuhnen and Knutson (2011) further find that individuals in negative emotional states tend to express pessimistic risk assessments in their economic choices.

[5] "Mental Health At Work Requires Attention, Nuance, and Swift Action," Oracle and Workplace Intelligence (2020) (https://www.oracle.com/a/ocom/docs/hcm-ai-at-work-volume-2.pdf).

[6] Throughout this study, we use "remote work" to refer to working from home.

There are opposing views on how remote work may affect managerial sentiment. On the one hand, corporate management plays a highly interactive role and spends a significant amount of their time at in-person meetings (e.g., Drucker 1967; Mintzberg 1973; Bandiera, Prat, Hansen, and Sadun 2020).[7] Switching to remote work with the loss of support of key personnel physically located in a centralized office upends their conventional work style, intensifying their already demanding job pressure (Borgschulte, Guenzel, Liu, and Malmendier 2021). Many business leaders grapple with workplace isolation, work stress, and the loss of workplace culture. On the other hand, some business leaders embrace a remote work environment to save their commuting time and enable a better work-life balance.[8] We expect that involuntary remote work performed under challenging circumstances leads to overall adverse psychological outcomes for management and hence reduces their sentiment. This hypothesis is grounded in the extensive work in psychology that individuals exposed to calamitous events are prone to negative psychological consequences,[9] and that social isolation is a distressing experience.[10]

Prior studies further suggest that managerial sentiment influences corporate decisions (e.g., Antoniou, Kumar, and Maligkris 2017; Chhaochharia, Kim, Korniotis, and Kumar 2019) and that negative emotions induce managers to express pessimistic risk assessments and make risk-averse choices. This evidence is rooted in earlier psychology and economics research that individuals' emotions affect their risk perception and shape their economic decisions (see, for e.g., Lerner and Keltner 2001; Loewenstein, Weber, Hsee, and Welch 2001; Kuhnen and Knutson 2011). Motivated by this strand of literature, we explore the economic consequences of managers' work-from-home-(WFH-)induced sentiment and risk assessment. The COVID-19 cash-flow shock provides a natural setting to study managerial risk perception as reflected by their corporate cash policy. The virus outbreak creates a sudden sizeable negative shock to firm cash flows, thus plunging a vast majority

[7] These studies stress the importance of in-person communication activities in the coordination of complex organizations. Bandiera, Prat, Hansen, and Sadun's Figure 1A shows that a median CEO spends more than 50% of her time in face-to-face meetings but less than 5% in virtual communications via videoconferences, emails, or phone calls.

[8] In a media's article titled, "Mark Zuckerberg plans to work remotely for at least half of the next year," Facebook CEO Zuckerberg wrote "I've found that working remotely has given me more space for long-term thinking and helped me spend more time with my family, which has made me happier and more productive at work." (https://edition.cnn.com/2021/06/09/tech/zuckerberg-facebook-remote-work-memo/index.html).

[9] See Goldmann and Galea (2014) for a comprehensive survey of the literature.

[10] Aknin et al. (2021) find this evidence, as previously supported by earlier studies such as Perlman and Peplau (1981), Hawryluck et al. (2004), and Cacioppo, Hawkley, and Thisted (2010).

of firms into a liquidity crisis. During economic crises, corporate cash policy is a critical risk-management tool.[11] We expect that remote managers primed with negative sentiment embody stronger precautionary motives, driving their firms to accumulate cash beyond actual needs.

Our empirical study employs newly available daily foot traffic data from SafeGraph,[12] which has aggregated anonymized location data from millions of mobile devices since the beginning of the pandemic in January 2020, to investigate the work-from-home effect on managers' sentiment. SafeGraph provides social distancing information that allows us to determine the fraction of time residents stay at home in a particular county. We use a county's stay-at-home ratio (hereafter WFH_C) as our proxy for the proportion of time a firm's employees and management work from home.[13] Figure 1 depicts the distribution of WFH_C on the U.S. map for each quarter of 2020 and illustrates how stay-at-home time varies across U.S. counties as these counties impose, relax, and reinstate social distancing restrictions. Our analysis also utilizes Hassan, Hollander, van Lent, and Tahoun's (2020) measures of managerial sentiment constructed using a textual analysis of companies' quarterly earnings conference calls during this crisis period. After merging the above two primary databases and the information on control variables, our final sample contains 8,444 sentiment observations from 2,314 unique firms.[14]

Our analysis implicitly assumes that social isolation and mobility restrictions arising from the imposed home workplace impact corporate managers' mental well-being. However, one might argue that the proliferation of video conferencing tools (e.g., Zoom and Skype) and cloud-based team collaboration technologies (e.g., Google docs and Microsoft Teams) could facilitate virtual communications even under pandemic lockdowns and refute our assumption. Given that an individual's mental state is unobservable, we validate our work-from-home construct, WFH_C, a stressor for the manager, by correlating WFH_C with the individual's observable actions. Our first validation

[11] Recent studies produce consistent evidence of swift corporate liquidity management in the wake of the COVID-19 outbreak (Acharya and Steffen 2020; Li, Strahan, and Zhang 2020). Other previous studies that underscore the importance of liquidity management during crises include Almeida, Campello, and Weisbach (2004), Berg (2018), and Campello, Giambona, Graham, and Harvey (2011).

[12] Chang et al. (2021), Goolsbee and Syverson (2021), and Liu and Lu (2021) are examples of recent studies that employ SafeGraph data in their analyses.

[13] Our findings remain robust even when we use the average stay-at-home ratio at the state level.

[14] Hassan et al.'s (2020) sample consists of 13,297 managerial sentiment observations of 3,135 unique U.S. public companies. Our final sample results from excluding financial firms and after merging the sentiment data with different sources of databases required in the study.

test draws from the integration of media psychology literature and conservation of resources theory (Hobfoll 1989) that high levels of COVID-related news consumption are linked to negative mood or emotions and poorer mental health (Andel, Arvan, and Shen 2021). Prior research uses Google search trends to capture households' economic concerns, a proxy for investor sentiment (Da, Engelberg, and Gao 2015). We also use such large amounts of public search data that afford us a valuable opportunity to study sentiments and attitudes. Our findings indicate a positive and statistically significant relationship between WFH_C and Google searches on COVID-related topics, suggesting that enforced remote work is associated with economic anxiety and mental distress. The other validation test applies the Latent Dirichlet Allocation (LDA) topic modeling algorithm to a sample of online employee reviews from Glassdoor in 2020.[15] We find a significant increase in Glassdoor's employee concerns about workplace communication, suggesting that the restricted work-from-home environment creates a collective deficit in workplace social connection. Such disconnection can be particularly salient to managers who embrace in-person communication (Coase 1937; Drucker, 1967; Mintzberg, 1979).

Next, our baseline analysis suggests that work from home induces managers to become more pessimistic. We show that WFH_C exhibits a robust negative association with managerial sentiment while controlling for firm-specific characteristics, the county-level COVID-19 infection risk, and different combinations of county, industry, firm, calendar-quarter, and industry$\times$quarter fixed effects. From an economic perspective, a rise in WFH_C from its pre-pandemic to pandemic-mean level explains 51% of the drop in managerial sentiment during the pandemic. Furthermore, using the staggered adoption of stay-at-home orders across different U.S. states as a source of exogenous variation in the work-from-home environment, we find managerial sentiment to be significantly lower in treated firms from mandated states than their peers in non-mandated states on the entire sample and in subsamples of firms whose operations are less likely to be affected by the mandate. This evidence confirms the causal mental effect of the COVID-19 work-from-home environment.

We explore two possible psychological channels through which remote work can exacerbate managers' mental stress. The first channel stems from limits of social interactions when managers are

[15] See Blei, Ng, and Jordan (2003) for a list of LDA applications and its effectiveness. Bandiera, Prat, Hansen, and Sadun (2020) apply this algorithm to study CEO behavior.

confined to working at home. In his seminal paper, Maslow (1943) theorizes a man's fundamental need to socialize. Subsequent psychology evidence suggests that social interactions promote positive affect, but social isolation induces negative feelings and compromises an individual's mental well-being (e.g., Perlman and Peplau 1981; Hawryluck et al. 2004; Kesselring et al. 2021). In particular, Hawryluck et al. suggest that the need for social support is most significant in times of adverse situations and that mobility restrictions threaten an individual's sense of connectedness and undermine mental health. Kesselring et al. find that an individual's positive affect increases with in-person, but not virtual, interaction time. We posit that the effect of social isolation is more pronounced for managers who often engage in face-to-face communications in a physical workplace prior to the pandemic. The second psychological mechanism may be operative through the increased work stress. Classic management research suggests that executives' main task is to communicate and coordinate internal activities in complex organizations (Coase 1937; Drucker 1967; Mintzberg 1979). But the remote work environment with a physically dispersed workforce depresses the natural channels of face-to-face communication, reducing informal communication opportunities, and raising coordination costs (DeFilippis et al. 2020). Thus, we expect increased undue work stress for management working from home.

Given the unobservable nature of psychological attributes, we can only provide suggestive indirect evidence on the mechanisms by identifying managers who are more prone to these two psychological effects. Our results show that the negative remote work effect is more pronounced for firms managed by CEOs with a strong desire for social interactions (i.e., young CEOs) and teamwork-intensive firms, supporting the social isolation mechanism. We also find that the adverse impact of work from home is more significant in firms managed by CEOs with a shorter tenure and firms having less experience with pre-pandemic teleworking arrangements, indicative of the work stress mechanism.

Sentiment influences risk assessments and subjective judgment. We infer managers' risk perception by evaluating their cash policy response to the exogenous cash-flow shock during the pandemic. Our results demonstrate that as WFH-induced managerial sentiment dampens, managers accumulate more cash through external capital market financing, indicating their increased perceived liquidity risk. Further analyses suggest that the stock market places a lower value on sentiment-driven cash holdings. Overall, our evidence supports the notion that WFH-induced sentiment drives managers to hoard excess cash for a precautionary motive that, in turn, hurts shareholder value.

Finally, we conduct several robustness tests to further substantiate our baseline evidence. First, our baseline findings might be open to two alternative explanations. Work from home might reduce managerial sentiment simply because remote work causes a sudden business disruption, worsens firm performance, and raises uncertainty (the performance effect). However, our results show that the adverse work-from-home effect persists across subsamples of firms resilient and vulnerable to the pandemic, indicating that the adverse WFH_C effect on managerial sentiment is independent of a firm's operating uncertainty during the pandemic. Our main evidence may also be consistent with managerial opportunism when managers intentionally associate their negative news with similar news from other underperforming firms during the pandemic and attribute their poor performance to the health crisis (Tse and Tucker 2010; Acharya, DeMarzo, and Kremer 2011) (the opportunistic effect).[16] But our analysis of insider trading activity during the 2020 pandemic year is inconsistent with this conjecture. We find that WFH_C has a strongly negative impact on insider purchases and net trades while no impact on insider sales. This finding is more in line with a psychological interpretation than an opportunism argument. Second, we show that our key evidence is robust to various alternative measures of managerial pessimism biases, including managerial earnings forecast bias (*MFBIAS*), pessimism (negative *MFBIAS*), optimism (positive *MFBIAS*), forecast precision, and orthogonalized managerial sentiment. Lastly, our primary findings cannot be explained by socioeconomic differences and supply chain disruptions caused by the COVID-19 outbreak.

Corporate managers perform cognitively challenging tasks and require significant in-person communication to facilitate decision-making.[17] Our study is the first to present evidence that the COVID-19-imposed work from home has taken a toll on the mental health of corporate management.

[16] Bilinski (2021) reports that analysts revise all forecasts downwards from March to June 2020, suggesting that the cost of managing market expectations during the pandemic is markedly low as weak market conditions become public knowledge.

[17] Künn, Seel, and Zegners (2020) compare the performance of elite professional chess players competing online under the pandemic with off-line pre-pandemic and show a statistically and economically significant fall in performance when competing online compared to competing offline. This evidence suggests that teleworking has an adverse effect on individuals performing cognitive tasks.

In contrast, other research on the remote work environment catalyzed by the pandemic examines the feasibility of work from home (Dingel and Neiman, 2020; Barrero, Bloom, and Davis 2021), its effect on worker benefits (Barrero, Bloom, and Davis 2020), gender performance (Du 2021), firm performance (Bai et al. 2021), and productivity (Gibbs, Mengel, and Siemroth 2021).[18] Our work expands this strand of literature by showing the heterogeneity of job demands and highlighting the psychological consequences of remote work on management. More broadly, we contribute to the fast-growing literature that evaluates the economic and financial consequences of the COVID-19 crisis.[19] Given the role of sentiment in managerial decisions, our evidence suggests the potentially considerable indirect economic cost of the pandemic through its mental impact on firms' decision-makers.

Our research also advances the behavioral corporate finance literature that evaluates the effect of psychological factors on corporate managers' decisions (see Baker and Wurgler (2012) for a comprehensive literature review). In particular, one stream of the literature suggests that managers' exposures to disastrous events, such as the Great Depression (Malmendier, Tate, and Yan 2011), natural disasters (Bernile, Bhagwat, and Rau 2017; Dessaint and Matray 2017), and terrorist attacks (Antoniou, Kumar, and Maligkris 2017), can shape their corporate policies. Our study shows how the prolonged, wide-ranging COVID-19-imposed mobility restrictions can influence managerial sentiment, attributable to social isolation and stress. The resulting pessimistic risk assessment, in turn, leads to a suboptimal corporate cash policy in response to the cash-flow shock during the COVID-19 crisis.

Finally, our study adds to the rich literature on corporate liquidity management during economic crises (e.g., Almeida, Campello, and Weisbach 2004; Berg 2018; Campello, Giambona, Graham, and Harvey 2011). Prior studies find that in response to the COVID-19 cash-flow shock, firms accumulate cash by drawing down bank credit lines (Acharya and Steffen 2020), raising external

[18] Prior studies investigate similar issues primarily on samples of low-skilled employees (Bloom, Liang, Roberts, and Ying 2015; Mas and Pallais 2017). Duchin and Sosyura (2020) study remote CEOs whose roundtrip commute from home to firm headquarters exceeds 100 miles. They report the underperformance of remote CEOs and attribute the poor performance to serving their private interests at the expense of shareholders.

[19] See Baldwin and di Mauro (2020), Cochrane (2020), Davis, Liu, and Sheng (2020), and Fetzer, Hensel, Hermle, and Roth (2020) for evidence on the pandemic's macroeconomic damage, and Baker et al. (2020) and Ding, Levine, Lin, and Xie (2021) on financial market responses.

financing (Darmouni and Siani 2020; Hotchkiss, Nini, and Smith 2020), and canceling dividends and suspending share repurchases (Pettenuzzo, Sabbatucci, and Timmermann 2021). Darmouni and Siani further suggest that firms that increase bond issuances tend to hoard cash rather than invest in real assets and attribute these findings to low-cost financing facilities available. We, however, show that the subjective biases of remote managers partly contribute to the increased corporate cash holdings.

The paper proceeds as follows. Section 1 describes the data and validates the work-from-home measure as a stressor of mental health consequences. Section 2 presents our empirical findings, and Section 3 explores the impact of WFH-induced managerial sentiment on corporate liquidity management. Section 4 conducts a host of robustness tests, followed by the conclusion.

1. Data and Sample Construction

Our study uses data from several different sources: (1) work-from-home duration from SafeGraph's daily foot traffic information; (2) managerial sentiment measures from Hassan et al. (2020); (3) managerial earnings forecast information from the I/B/E/S database; (4) corporate insider transactions from Thomson/Refinitiv Insiders data; (5) financial accounting information and corporate headquarters from Compustat; and (6) stock trading data from CRSP. Our sample covers the period from January through December 2020, which includes the day (March 11, 2020) when the World Health Organization declared the novel coronavirus (COVID-19) outbreak a global pandemic.

Our initial sample consists of 9,182 managerial sentiment observations of 2,478 unique nonfinancial U.S. public companies that issued earnings calls in 2020. We merge this sample of firms with SafeGraph's county-level foot traffic data in the following manner. First, we use firm headquarters' zip codes reported in Compustat to map headquarters onto their corresponding counties using the Office of Policy Development and Research's link table. This mapping allows us to identify 2,324 firms. For the remaining 154 firms, we manually search these firms' official websites and determine the county locations of 116 firms. The resulting sample consists of 2,440 firms with 9,056 sentiment observations and identifiable county information. Merging this sample with SafeGraph's data and other control variables from different data sources leads to our final selection of 8,444 sentiment observations from 2,314 unique firms. Below we describe the construction of our main variables, together with their summary statistics, and relegate the definition of all the key variables to Appendix Table 1.

1.1 Measuring work-from-home duration

Our key variable of interest is a measure of the corporate management work-from-home duration. To construct this measure, we first determine the county in which a firm is headquartered and assume that the firm's management resides in this county. We next employ the county's work-from-home ratio (WFH_C) as a proxy for the duration a firm's management is working from home. While WFH_C is a coarse measure of management work-from-home duration, it should work against us finding any relationship between WFH_C and managerial sentiment.

We compute WFH_C using the daily foot traffic data from SafeGraph.[20] SafeGraph obtains opt-in consent from more than 45 million mobile users to collect anonymized mobile device location data. To better understand individual movements during the pandemic, the company generously makes two datasets available to researchers: Places Patterns and Social Distancing Metrics. The first dataset maps mobile devices' hourly movement from census block groups to specific points of interest. This dataset is particularly informative of individuals' essential activities at physical retail locations such as restaurants, grocery stores, and religious establishments (Chang et al. 2021). Our information on the time homebound management spends working from home is from the Social Distancing Metrics database. SafeGraph updates daily details on the average home-dwelling time and non-home dwelling time at the census block level, assuming that each mobile device's common nighttime location over a six-week period is the device's home. We compute the daily work-from-home ratio for each census block by dividing the daily home staying time by the daily sum of home staying time and non-home staying time.

Notably, the SafeGraph data could contain a few sampling biases that might mislead our em-

[20] https://www.safegraph.com

pirical analysis. For example, mobile users might work at nighttime, or mobile users who permit to collect their location data might not represent the U.S. population. We mitigate these sampling errors by aggregating the home staying time across census blocks to a county level. Specifically, our daily WFH_C is calculated as the average work-from-home ratio of all five-digit census blocks in a given county. By this geographic unit, SafeGraph covers a comprehensive list of 3,229 counties and reports a high Pearson correlation coefficient of 0.97 between its sample of mobile devices and the U.S. census population.[21] As we control for time fixed effects, the sampling errors associated with WFH_C, presumably persistent over time, should not affect the direction of our results.

Figure 1 illustrates the distribution of WFH_C on the U.S. map across four quarters of the year 2020. In the first quarter, there is only sporadic compliance of social distancing mostly observed in the Western and Northeastern states (the blue zone on the map), where the first few COVID-19 cases in the U.S. are reported. Time spent at home rises sharply in the second quarter as the first wave of the pandemic swells across the U.S., and many states impose legal social restrictions. As local governments gradually lift the social bans and allow firms to resume pre-pandemic activity in the third quarter, there is increased outdoor time across the country (the red zone on the map). While the stay-at-home time rises again in the last quarter relative to that in the third quarter as winter looms, it still falls below the second quarter's level, consistent with a gradual adaptation to the pandemic. Figure 2 depicts time-series patterns of average daily WFH_C and new COVID-19 cases across four U.S. geographic regions. The dynamics of WFH_C seem tied to but do not perfectly correlate with those of the emerging infection risk. Figure 2a shows that WFH_C ratios peak in April across all four U.S. regions, following the World Health Organization's declaration of a pandemic in mid-March. Except for the Northeastern region, the sharp rise of WFH_C pre-empts the surge in infection cases in the other areas. Furthermore, while WFH_C falls gently during the summer, it starts trending up again in September as a new COVID-19 wave hits the country.

Our analysis may also subject to the bias that not all firm managers and senior employees reside in their corporate headquarter county. We cannot rule out this bias without knowing the specific home addresses of corporate managers. However, we can somewhat alleviate this concern

[21] https://www.safegraph.com/blog/what-about-bias-in-the-safegraph-dataset

using an alternative work-from-home ratio measured at the state level (WFH_S). We assume that managers heavily involved in day-to-day business operations are most likely to live in the state of their corporate headquarters. For a given state, WFH_S is computed as the average of county-level work-from-home ratios weighted by the number of mobile devices used in a county.

In subsequent analyses, we employ an event study setting to capture the immediate effect of work-from-home duration on managerial sentiment, where an event is an earnings call or a managerial earnings forecast. Accordingly, we compute the management work-from-home duration over the [-30, -1] window prior to the earnings call date or managerial forecast date. Table 1 reports the summary statistics of our key constructs and control variables that we employ in this study. The mean (median) WFH_C is 88.9% (90.3%), indicating that firm managers spend an unprecedented amount of time at home during the pandemic year. These statistics closely resemble those at the state level. The mean and median WFH_S are 87.9% and 88.7%, respectively.

1.2 Measuring managerial sentiment

We retrieve the primary managerial sentiment variable directly from Hassan et al.'s (2020) website, and the authors construct the variable using a textual analysis of corporate earnings call transcripts released during 2020. Their overall managerial sentiment score (*Managerial Sentiment*) is defined as the number of positive words minus the number of negative words, divided by the total number of words in an earnings call transcript. The original score is then multiplied by 10^3. As shown in Table 1, *Managerial Sentiment* displays a considerable variation, ranging from 0.391 (at the 25th percentile) to 1.118 (at the 75th percentile) with its mean (median) value at 0.752 (0.747). The significant fluctuation in *Managerial Sentiment* reflects the swing in managers' mood as they increasingly face the danger of the COVID-19 crisis and experience the stress of working from home and the pandemic impact on their business operations.

Additionally, we construct another set of managerial sentiment indicators using managerial earnings per share forecasts available from I/B/E/S's management earnings guidance data. Unlike sentiment measures constructed from analyzing earnings call transcripts, managerial earnings forecasts are inherently forward-looking and involve significant estimation and judgment with little external monitoring. Hence, these forward-looking performance forecasts ought to reflect managers' sentiment even more (Chen, Wu, and Zhang 2020). But the downside of analyzing earnings guidance data is the significantly smaller sample of 603 managerial earnings forecasts issued in 2020.[22] With this caveat in mind, we follow prior literature and develop five different forecast variables to capture managerial mental biases. The first measure is the management forecast bias ($MFBias$), defined as the difference between management forecasts using point estimates or midpoint of range estimates and actual earnings per share, deflated by the previous quarter stock price. The pessimistic (optimistic) forecast dummy variable takes the value one if $MFBias$ is negative (positive) and zero otherwise. Following Cheng, Luo, and Yue (2013), we also consider forecast precision by examining the forecast range ($MFRange$) and horizon ($MFHorizon$). Conceivably, biased managerial forecasts should be less precise. $MFRange$ is calculated as the difference between the upper and lower ends of range estimates, and $MFHorizon$ is the log of one plus the number of calendar days between the forecast announcement date and forecast period end date. We expect managers who work long hours at home tend to issue more pessimistic earnings guidance and forecasts with a wider range and a shorter horizon (i.e., less precise forecasts).

1.3 Control variables

We control for a battery of county- and firm-specific characteristics in our analysis. The first critical control variable is the fear of COVID-19 infection. Prior studies suggest that fear of infection drives the voluntary compliance of social distancing even before the enforcement of mobility restrictions (Goolsbee and Syverson 2021) and panic stock selling by fund managers located in or socially connected with COVID-19 hotspots (Au, Dong, and Zhou 2020). Hence, it is plausible that managerial sentiment might be driven jointly by fear of infection and work from home. To rule out the fear of COVID-19 infection, our regression model includes a proxy for COVID-19 infection risk (*Infection*), which is computed as the log of the number of COVID-19 infection cases in a county at the previous month end preceding an earnings call.

[22] The extreme uncertainty surrounding the pandemic causes many firms to withdraw their earnings guidance in 2020. According to a FactSet report, more than one third of S&P firms withdrew their guidance for 2020. (https://www.factset.com/hubfs/Resources%20Section/Research%20Desk/Earnings%20Insight/EarningsInsight_062620.pdf.)

We also control for firm-specific characteristics that previous research has shown to determine managerial sentiment (Huang, Teoh, and Zhang 2014; Chen, Wu, and Zhang 2020). These characteristics are firm size (*Firm Size*; defined as the log of stock market capitalization), return-on-assets ratio (ROA; defined as the net income scaled by total assets), book-to-market ratio (BM; defined as book equity scaled by the market value of equity), previous-quarter stock return performance (*Past Return*; defined as buy-and-hold daily stock returns in the previous quarter), stock return volatility ($Volatility$; defined as the standard deviation of daily stock returns in the last quarter), and financial leverage (*Leverage*; defined as total liabilities scaled by total assets). We use current fiscal quarter accounting information to construct all the financial ratios, consistent with existing findings that current firm performance influences managerial sentiment (e.g., Chen, Wu, and Zhang 2020). We winsorize the control variables at the top and bottom 1% of the sample distribution to mitigate outliers' influences.

1.4 Validating the work-from-home construct

Our empirical design exploits anecdotal evidence by implicitly assuming that physical isolation arising from enforced work from home negatively affects the mental wellness of corporate management. As an individual's mental state is unobservable, we validate our work-from-home construct, WFH_C, by correlating it with the individual's observable actions.

Our first validation test builds on the psychology literature that news consumption is associated with an individual's emotional state (Hobfoll 1989; Andel, Arvan, and Shen 2021). Inspired by this literature, we evaluate individuals' mental stress through their COVID-related news search on the internet. A similar measure is used in Da, Engelberg, and Gao (2015). They construct a "Financial and Economic Attitudes Revealed by Search" ($FEARS$) index by aggregating the Google search volume of keywords related to households' economic concerns from Google Trends as an investor sentiment measure. We apply a slight modification to their Google search metrics. Instead of using self-selected keywords, we follow Fetzer et al. (2020) and use topic-based search queries to encompass a broader set of search terms. Furthermore, to better quantify individuals' perceived risk attitudes toward the pandemic, we focus on search topics indicative of COVID-related health and economic risks. Specifically, the three search topics we examine are coronavirus, lockdown, and recession, which, respectively, indicate the public's concerns about the virus spread, the virus containment, and the pandemic's economic impact. The queried terms in search of each topic are summarized in Online Appendix Table OA1. Our search-based metric, the Google Search Volume Index (SVI) at daily intervals, ranges from 0 to 100, with 100 representing the highest search interest for the queried terms in a specified area (i.e., U.S. states) and time frame (i.e., the year 2020).[23] Table 2 contains the correlation results with controls for state and calendar day fixed effects in place. We find a robustly strong positive correlation between WFH_S and *Google SVI* for each search topic. This finding suggests the general public's increased risk perception during this pandemic, thereby validating the public's reduced mental wellness associated with physical isolation from remote work.

The other validation test links WFH_C to employees' feedback on workplace communication based on their reviews posted on Glassdoor.com, the oldest employee review platform with one of the most complete employer coverage in the U.S.[24] Launched in 2007, this online platform allows employees to anonymously share their perceptions of various aspects of their firm, including company reviews, CEO approval ratings, salary reports, benefits reviews, and office photos. For each company review, an employee can rate the employer's overall quality on a 1-5 scale as well as ratings of the following five dimensions: Career Opportunities, Compensation&Benefits, Work/Life Balance, Senior Management, and Culture&Values. The employee can also enter free text responses on *Pros* and *Cons* sections of the review. Since workplace interaction is not explicit in any of the five dimensions, we draw employees' perceptions about workplace communication from Glassdoor's free text employee responses using a natural language processing technique LDA.[25] We apply the LDA topic modeling algorithm to our sample of employee reviews from 2019 to the first quarter

[23] We employ state-level search measures because the county-level equivalents are unavailable in Google Trends.

[24] As of January 2021, the website recorded 70 million employee reviews covering 1.3 million public and private employers located in the U.S. and elsewhere in the world.

[25] LDA is an unsupervised Bayesian machine-learning approach developed by Blei, Ng, and Jordan (2003) to identify topics in an entire set of documents. While the word embedding method is another popularly employed machine learning approach in the literature, it does not fit our research purpose. The method requires a set of keywords in close association with workplace communication. However, without much literature guidance on communication, the self-imposed keywords on this topic inevitably introduce a subjective bias. Instead, LDA is an unsupervised approach that requires no pre-specified keywords for categories' underlying taxonomy (latent topics).

of 2021 to estimate each review's probability in association with workplace communication. We then analyze 921 employee reviewers concentrated on communication issues and construct three variables at the reviewer level: *Negative Reviews*, *Positive Reviews*, and *Net Reviews*. *Negative Reviews* (*Positive Reviews*) represents the likelihood of a *Cons* (*Pros*) review on the communication issue, and *Net Reviews* indicates the difference between *Positive Reviews* and *Negative Reviews*.[26] We detail how the LDA topic modeling tool helps to generate these variables in Online Appendix Section OA1. Columns (1) and (2) of Table 3 show that WFH_C is positively and significantly associated with *Negative Reviews* but exhibits no significant relationship with *Positive Reviews*. Column (3) indicates a statistically significantly negative correlation between WFH_C and *Net Reviews* at the 5% level. The overall evidence is consistent with the notion that working from home increases employees' complaints on workplace communication. Given that managers are heavily reliant on workplace communication, this finding substantiates our implicit assumption.

2. Empirical Results

This section presents the empirical results of the work-from-home effect on measures of managerial sentiment, addresses any possible endogenous relationship between WFH_C and managerial sentiment using the staggered adoption of stay-at-home orders across U.S. states as the identification strategy, and explores channels through which remote work influences managerial sentiment.

2.1 Baseline evidence

To test the empirical relationship between remote work and managerial sentiment, we estimate the following regression Eq. (1):

$$Sentiment_{i,t+1} \quad = \quad \alpha + \beta_1 WFH_{C,t} + \beta_2 Infection_{C,t} + \lambda' Controls_{i,t} + \gamma_i + \theta_t + \epsilon_{i,t+1}. \qquad (1)$$

The dependent variable, $Sentiment_{i,t+1}$, denotes managerial sentiment (*Managerial Sentiment*) obtained using the textual analysis of an earnings call transcript issued by firm i at time $t+1$.

[26] The small number of communication-related employee reviews is limited by the less frequent mentioning of the keyword "communication" in the employee reviews relative to other more frequently used words such as "people", "management" and "employee" as shown in the word cloud in Online Appendix Figure OA1.

The main explanatory variable WFH_C is the average daily fraction of time managers working from home during the 30 days prior to an earnings call issued by firm i headquartered in county C. Our regression model also includes different combinations of firm, industry, county, calendar quarter, and industry $\times$ calendar quarter fixed effects. In all the regressions, we cluster our standard errors at the county level. To isolate the psychological effects arising from fear of infection, we explicitly account for the fear of COVID-19 virus spread using the log of the number of county-level infection cases (*Infection*). Firm i's control variables ($Controls_{i,t}$) include firm size (*Firm Size*), return-on-assets ratio (*ROA*), book-to-market ratio (*BM*), previous-quarter stock return (*Past Return*), return volatility (*Volatility*), and financial leverage (*Leverage*). We anticipate our key coefficient β_1 to be negative, suggesting that the longer managers work from home in isolation, the lower is their sentiment (i.e., the more pessimistic they become).

Table 4 reports the estimation results of Eq. (1). One distinct evidence is that WFH_C is robustly and negatively related to *Managerial Sentiment*, suggesting that prolonged work from home dampens managerial sentiment and induces managerial pessimism. Specifically, in Column (1), the estimated coefficient of WFH_C is -1.523 (t-stat = -10.13) while controlling for firm-specific characteristics but excluding any fixed effects. To effectively purge unobservable effects in our analysis, we include varying combinations of firm, industry, county, and calendar quarter fixed effects in Columns (2)-(5). With firm and calendar quarter fixed effects, Column (2) shows that the coefficient of WFH_C, while reduced in magnitude from -1.523 to -1.183, remains negative and statistically significant at the 1% level. When we factor in the psychological impact of COVID-19 infection risk ($Infection$) in Column (3), $Infection$ exhibits a negative and statistically significant impact on managerial sentiment, consistent with existing psychology evidence that the fear arising from traumatic events undermines one's mental wellness (Lerner and Keltner 2001; Goldmann and Galea 2014). More importantly, the significance of WFH_C (β_1 = -1.132 with t-stat = -5.30) is not subsumed by $Infection$. Our finding that corporate managers are susceptible to mental stressors during the pandemic is in line with the U.S. Centers for Disease Control and Prevention's findings that COVID-19 health risk and mobility restrictions have presented significant mental health challenges to the public.[27] The economic magnitude of WFH_C is also sizable. Based on the estimates from Column (3), an interquartile change in WFH_C (0.946 - 0.830 = 0.116) is associated with a -0.131 (-1.132 $\times$ 0.116) decline in *Managerial Sentiment*, which corresponds to a 17.4% fall relative to its sample average (0.131/0.752). Correspondingly, the WFH_C jump from its pre- to post-pandemic level explains 51% of the post-pandemic sentiment drop compared to its pre-pandemic level.[28]

The impact of social distancing under the pandemic is heterogeneous across industries. For example, essential industries that provide critical services and infrastructure are allowed to stay open during lockdowns, and industries that use computer-mediated communication in the past are adapted to virtual work during the pandemic. Also, certain counties have more stringent lockdown restrictions than others. To absorb industry and geographic effects, we control for time-invariant industry and county effects using industry, county, and calendar quarter fixed effects in Column (4) and time-varying industry characteristics using industry$\times$quarter and firm fixed effects in Column (5). Notably, the magnitude and statistical significance of the WFH_C coefficient are qualitatively similar after controlling for these fixed effects. It seems unlikely that our baseline results are driven by industries or geographic locations that are more vulnerable to social distancing. Therefore, for brevity, we only report results of regression models with calendar quarter (θ_t) and firm (γ_i) fixed effects (FE) in subsequent analyses.

Our tests rely on the assumption that senior managers reside in their firm headquarter county. As managers are responsible for daily operations, there is good reason to assume that they live close to their workplace to reduce travel costs and time. Similarly, the team supporting and assisting senior management may also choose to reside close to the firm for the same reason. As such, the county-level WFH_C measure arguably captures the influence of local work-from-home practice on managers and the team around them. However, it is plausible that the team and managers live in different counties and outside the workplace county. To ensure our results'

[27]The U.S. Centers for Disease Control and Prevention's August 2020 Morbidity and Mortality Weekly Report conducted in June 2020 ensuing the wide-ranging stay-at-home orders enforced across the U.S. states (https://www.cdc.gov/mmwr/volumes/69/wr/pdfs/mm6932a1-H.pdf)

[28]We deem January 2020 as the pre-pandemic period and the rest of the year as the post-pandemic period. The unreported pre- and post-pandemic means of WFH_C are 0.795 and 0.891, respectively, while their *Managerial Sentiment* counterparts are 0.962 and 0.749.

robustness to this possibility, we employ the state-level work-from-home ratio (WFH_S). This enlarged geographic coverage increases the likelihood of a match between a firm's headquarters and its managers' residences. For example, Yonker (2017) finds a significant link between a CEO's state of origin (i.e., birthplace) and her labor market outcome and infers that firms prefer to hire CEOs who reside in their firm's headquarter state. Column (6) shows that the state-level WFH_S remains significantly negative, substantiating our baseline finding of a negative association between WFH_C and managerial sentiment. Overall, the evidence supports the notion that homebound managers exhibit pessimistic feelings while working from home under COVID-19.

2.2 Identification strategy: staggered implementation of stay-at-home orders

Advances in video conferencing and telework technology have facilitated some businesses thriving with a remote and efficient workforce. Remote work has, thus, become an increasingly accepted practice for some companies to permit their employees to work from home part of the week. As firms can self-select to accommodate a remote workforce, the relationship between WFH_C and managerial pessimism may be endogenously determined.

To address this endogeneity concern, we use the staggered adoption of stay-at-home orders as an exogenous shock to firm-level work-from-home policy. Stay-at-home orders are a COVID-19 mitigation strategy widely implemented by different U.S. state governments. These orders require all residents to stay at home, except for essential tasks, and all workers at non-essential businesses to work from home.[29] The timing of issuing a stay-at-home order and its duration vary across states. 46 states adopted the stay-at-home order to combat the pandemic's first wave in 2020, with California being the first on March 19th and South Carolina the last on April 7th. Yet, the remaining states, including Arkansas, Iowa, Nebraska, North Dakota, South Dakota, did not implement any stay-at-home order for the whole duration. Appendix Table 2 lists the effective dates of stay-at-home mandates for all U.S. states.[30] Applying a difference-in-differences (DiD) identification strategy, we construct a cohort of treatment firms in states mandating stay-at-home

[29] https://www.cdc.gov/mmwr/volumes/69/wr/mm6935a2.htm.

[30] We obtain information on the stay-at-home orders from the New York Times website (https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html).

orders. In contrast, the cohort of the control sample contains the rest of the firms in our sample. Note that our choice of control firms may underestimate the treatment effect given that control firms might likely adopt the work from home policy voluntarily during the COVID outbreak.

We test the managerial psychological response to the stay-at-home order for treated versus control firms in the following regression model,

$$Sentiment_{i,t+1} = \alpha + \beta_1 Stay@Home_{i,S,t} + \lambda' Controls_{i,t} + \gamma_{i,cohort} + \theta_{t,cohort} + \epsilon_{i,t+1}, \quad (2)$$

where $Stay@Home$ is a binary variable that equals one for earnings calls released by treatment firms over the three months following the implementation of the stay-at-home order and zero if otherwise. The list of control variables is identical to that specified in Eq. (1). Following Gormley and Matsa (2011), we also include cohort-by-firm and cohort-by-quarter fixed effects to allow for unobservable differences between treatment and control firms to vary by cohort every quarter. Table 5 summarizes the estimation results of Eq. (2). Column (1) shows that managers of treated firms under forced lockdowns display more negative emotions than those of control firms. Under the stay-at-home order, *Managerial Sentiment* is, on average, 22.1% lower in treated firms than in control firms.

We also examine the dynamics of the decline in managerial sentiment surrounding the implementation of the stay-at-home order with a simple modification of Eq. (2). We replace $Stay@Home_{i,S,t}$ in Eq. (2) with a set of dummy variables, $Stay@Home_{i,S,t+k}$, where $k = -3, ..., +3$ ($k \neq 0$) represents the number of months relative to the order's enforcement date from three months before to three months after the order. Column (2) shows that the timing of the drop in managerial sentiment coincides with the increase in stay-at-home time. $Stay@Home$ time dummies are insignificant before implementing the order but turn statistically and economically significant following the ruling, indicating that managers of treated firms appear not to anticipate the impending stay-at-home mandate. The managerial sentiment of treated firms is 14.7%–36.3% lower than that of control firms over the three months following the stay-at-home order.

However, one might argue that stay-at-home orders represent a shock to both a firm's economic environment and its management's psychological wellness. Therefore, to possibly isolate the effect of business operations, we focus on firms with geographically dispersed operations and those with teleworking practices. We expect the stay-at-home order to be less disruptive when firms' operations are distributed across different states. Similarly, firms with teleworkable employees should be more adaptive during lockdowns to relocate their operations from office to home with limited economic costs. To implement our tests, we construct two subsamples of firms. The first subsample consists of firms with geographically dispersed operations across different states, allowing us to include their operations in other states that had not implemented a stay-at-home order when the headquarter state adopted the order. The degree of geographic dispersion of a firm's business operations is retrieved from García and Norli (2012) and defined as the count of each state's name mentioned in a firm's 10-K filings in 2008. The second subsample of firms comprises firms with an industry-level teleworkability index value above the sample median. The teleworkability index comes from Dingel and Neiman (2020) and measures the share of jobs that can be done at home weighted by the wage at the 2-digit NAICS level. We then perform our DiD analysis on these two subsamples of firms and report their results in Columns (3) and (4). The coefficients of $Stay@Home$ remain statistically significant and negative for firms that are more economically immune to the stay-at-home order.

Overall, the DiD results confirm our baseline evidence that the work-from-home effect on sentiment is causal and not subject to any omitted firm or industry characteristics, or a firm's economic environment.

2.3 Psychological mechanisms: social isolation and work stress

In this subsection, we seek to understand the psychological mechanisms through which remote work from home impacts managerial sentiment. As managers' psychological outcomes are unobservable, our results on the psychological mechanisms are thus exploratory. One critical way work from home distresses managers stems from the limits on social interactions when managers work alone in their home office. In his seminal work, Maslow's (1943) theory of human motivation posits that when survival and safety needs become satisfactorily met, there emerges a deep need for love and belonging, gratified by connecting physically and emotionally with other people. Subsequent psychology research (Perlman and Peplau 1981; Cacioppo, Hawkley, and Thisted 2010) suggests that social isolation induces negative feelings and undermines mental well-being. For example, Hawryluck et al. (2004) study the psychological consequences of instituting widespread quarantine measures during the 2003 SARS epidemic and find that a longer duration of quarantine is associated with an increased prevalence of psychological distress. In the work context, COVID-induced social-distancing measures disconnect employees from working in a centralized location and force them to rely on computer-mediated virtual communication. Furthermore, Kesselring et al. (2021) provide psychological evidence that in-person, but not virtual, communication increases positive affect. Following this literature, we expect that a geographically dispersed workforce adversely affects managers who spend much of their time in interpersonal interactions to perform their cognitively challenging tasks in normal times.

While it is impossible to directly gauge the impact of social isolation, we provide indirect evidence by identifying managers who are more susceptible to such psychological consequences. Our analysis employs two measures to proxy for the managerial demand for social interactions: CEO's age (*Age*) and a firm's reliance on teamwork (*Teamwork*). Psychology surveys consistently show that young, rather than old, adults are most vulnerable to increased mental distress during the pandemic,[31] in line with their stronger need for social interactions (Carstensen 1995) and weaker ability to regulate negative emotions (Gross et al. 1997). We, therefore, anticipate an amplifying effect of CEO young age. We define a binary variable, *Age*, which equals one if the CEO's age falls below the sample median and zero if otherwise. Information on CEO characteristics is retrieved from the ExecuComp database.

Moreover, sectors that require frequent face-to-face contact at the workplace and rely heavily on teamwork may suffer the most from the loss of social capital at work. We identify the teamwork-intensive industries following Koren and Petö (2020). In their study, teamwork within the firm is described as "working with team, providing consultation to others, coordinating the activities of others, guiding and motivating subordinates, and building and developing teams." Based on this

[31] The survey evidence includes the U.S. Census Bureau's December 2020 Household Pulse Survey (https://www.cdc.gov/nchs/covid19/pulse/mental-health.htm) and the U.S. Centers for Disease Control and Prevention's August 2020 Morbidity and Mortality Weekly Report conducted in June 2020 ensuing the wide-ranging stay-at-home orders enforced across the U.S. states (https://www.cdc.gov/mmwr/volumes/69/wr/pdfs/mm6932a1-H.pdf).

definition, they construct the teamwork intensity index by 2-digit NAICS industries based on the work context and work activity described by the Occupational Information Network (O*Net).[32] We predict a more pronounced WFH_C effect for teamwork-intensive industries. To test this hypothesis, we introduce a dummy variable, *Teamwork*, which takes the value of one if the firm belongs to one of the top five teamwork-intensive industries identified in Koren and Petö and zero if otherwise. The results in Columns (1) and (2) of Table 6 lend credence to the social isolation channel. For example, the coefficient of $WFH_C \times CEO\ Age$ is -0.344 (t-stat = -1.99), implying that the effect on the WFH-induced sentiment is stronger for managers with greater needs for social interactions. Turning to teamwork intensity, we find that $WFH_C \times Teamwork$ is -0.873 (t-stat = -3.68), suggesting an amplifying WFH_C effect for firms reliant on internal teamwork communications. The evidence collectively points to the detrimental effect of workplace social disconnection due to remote work.

The mental distress at an involuntary home workplace may also arise from increased work demands for managers in the wake of the abrupt switch to remote work under the pandemic. This channel is motivated by early findings in economics (Coase 1937; Drucker 1967; Mintzberg 1979) that emphasize the coordinating role of managers in complex organizations. Drucker, for example, suggests that knowledge workers (i.e., subordinate managers) demand more time with top management than manual workers. Mintzberg highlights the importance of informal communication in coordinating complex internal activities. Empirically, Bandiera et al. (2020) show that CEOs spend a greater fraction of their time on coordinating than operational activities. We, therefore, anticipate that virtual work arrangements under the pandemic stress managers by raising their coordination costs. The physically dispersed workforce inhibits the natural channels of face-to-face interactions, thereby reducing informal communication opportunities. While many managers have engaged in remote work prior to the pandemic (Duchin and Sosyura 2021), they often do so with key personnel co-located in a centralized office and come into the office for at least part of the week (Raghuram, Hill, Gibbs, and Maruping 2019).

To test the mediating effect of the management's work stress, we employ two measures: CEO tenure (defined as the time difference between the CEO appointment date and the 2020 year-end

[32] National Center for O*NET Development. O*NET OnLine dataset 2020.

date) and Dingel and Neiman's (2020) industry-level teleworkability index (*Teleworkability*). Prior literature (e.g., List 2003) shows that experienced individuals are less prone to behavioral biases. We argue that experienced CEOs familiar with internal operations and teamwork face fewer information barriers and communication challenges associated with work from home. Further, employees' ability and past experiences with work from home also matter. A firm may adapt to the COVID-induced remote work more efficiently if its employees have gained some pre-pandemic experiences with this work model. We employ Dingel and Neiman's (2020) teleworkability index to gauge the extent to which a firm uses telecommuting.[33] Columns (3) and (4) of Table 6 show results generally consistent with the work stress channel. The coefficient of $WFH_C \times CEO\ Tenure$ is positive and significant at the 1% level, whereas the coefficient of $WFH_C \times Teleworkability$ is positive and marginally significant, consistent with work experience alleviating the work stress associated with remote-work conditions. This evidence also implies that WFH_C exacerbates the adverse psychological effect on management having little experience with the firm or with a remote-work environment.

3. WFH-Induced Managerial Sentiment and Corporate Liquidity Management

In this section, we investigate whether WFH-induced managerial sentiment affects firm managers' risk tolerance. We exploit the pandemic-induced cash flow shock as a quasi-natural experiment to study managers' risk assessment through their corporate liquidity risk management. Since the onset of the pandemic, many firms have scaled back operations as a consequence of social distancing mandates, while others have adopted a large-scale shift to a remote workforce. In the face of sudden significant operational disruptions, firms are scrambling for cash to keep businesses afloat. Given the importance of cash policy in risk management in times of heightened cash flow uncertainty, corporate cash holdings and their sources should reflect managers' risk perception. Following prior literature, we expect a decline in WFH-induced managerial sentiment be associated with an increase in corporate cash holdings, reflecting managers' risk aversion.

We test the cash effect of WFH-induced managerial sentiment by estimating the following

[33] The index is constructed based on the share of jobs that can be done at home weighted by wage before the pandemic. It thus reflects the firm's past remote-work experiences.

regression specification Eq. (3):

$$
\begin{aligned}
\textit{Cash Holdings}_{i,t+1} \quad = \quad & \alpha + \beta_1 \widehat{Sentiment}_{C,t} + \beta_2 \textit{Infection}_{C,t} + \lambda' \textit{Controls}_{i,t} \\
& + \gamma_i + \theta_t + \epsilon_{i,t+1}.
\end{aligned} \tag{3}
$$

The dependent variable, $\textit{Cash Holdings}_{i,t+1}$, is defined as cash and cash equivalents scaled by total assets at the beginning of 2020. $\widehat{Sentiment}$ is the predicted *Managerial Sentiment* obtained from estimating Model (1), as shown in Column (3) of Table 4. Column (1) of Table 7 reports the estimates of Eq. (3) and shows that the β_1 estimate is -0.128 (t-stat = -2.48), indicating that reduced managerial sentiment is associated with larger cash reserves. This finding is consistent with our expectation that negative emotions induced by isolating work environments result in managers making more pessimistic risk assessments and hoarding more cash to buffer against the perceived liquidity risk.

A natural extension of this analysis is to understand how a firm raises the observed cash during the pandemic. The increased cash may arise from the following sources: an increase in revenues (*Sales Growth*) and operating profits (*Operating Margin*), a decrease in net working capital requirement (*Net Working Capital*), a cut in corporate investments (*Investment*), a drop in dividend payout (*Dividend*) or share repurchases (*Repurchases*), a surge in new financing via debt/equity (*New Financing*), or any combination of these sources. We construct these variables following Dessaint and Matray (2017) and relegate their definitions to Appendix Table 1. We investigate the different sources of cash by replacing the dependent variable in Eq. (3) with each source of cash variable in turn; the results are presented in Columns (2)-(8) of Table 7.

We find that only *New Financing*, while not other sources of cash, yields a statistically significant coefficient at the 1% level. The estimate of *New Financing* coefficient is -0.471 (t-stat = -2.71), suggesting that firm managers who exhibit low WFH-induced managerial sentiment tend to use equity and/or debt as a way to raise cash. This finding ties in with recent studies that examine corporate liquidity management during the pandemic. In particular, Darmouni and Siani (2020) and Hotchkiss, Nini, and Smith (2020) find that firms raise cash from equity and bond markets at record levels during the COVID-19 crisis. While Darmouni and Siani further suggest that the low external financing cost during the pandemic facilitates firms hoarding more cash, our findings show that remote managers' increased risk perception also contributes to corporate cash accumulation.

We now turn to evaluate whether this increase in cash holdings is optimal. Specifically, we investigate how the stock market assesses the value of cash that stems from the psychological biases of homebound managers. Suppose WFH-induced sentiment amplifies managers' perceived risk and leads them to hold more cash than their actual need. Then, we expect the dampened WFH-induced managerial sentiment to adversely affect the marginal value of cash (i.e., the market will discount the value of cash more). In other words, the value of cash will fall as the predicted sentiment declines. To test this prediction, we follow Faulkender and Wang's (2006) methodology by regressing stock i's return in quarter t, $R_{i,t}$,[34] on changes in firm-specific variables scaled by the previous quarter's equity value (i.e., firm earnings, net assets, R&D, and dividend payout) and levels of market leverage, new financing, and lagged cash holdings. Table 8 presents the findings.

Our focus is on the estimated coefficient of $\Delta Cash$, the ratio of unexpected change in cash to the previous quarter's equity value. Since the lagged equity value normalizes both the dependent and independent variables, the $\Delta Cash$ coefficient measures a one-dollar change in shareholder value associated with a one-dollar change in the amount of cash held by the firm. For example, Column (1) of the table shows that the coefficient of $\Delta Cash$ is 0.527 (t-$stat$ = 4.48), implying that a one-dollar increase in cash holdings is associated with a 53-cent increase in market value for the mean firm in our sample. We then augment our model by including the interaction term between $\Delta Cash$ and $\widehat{Sentiment}$. If managers' psychological biases lead to excess cash holdings, we expect the estimated coefficient of the interaction term to be positive. That is, the decline in WFH-induced sentiment is associated with a lower market value of cash. Column (2) shows a positive and statistically significant coefficient of $\Delta Cash \times \widehat{Sentiment}$, consistent with our expectations that when WFH-induced managerial sentiment falls, the lower is a firm's marginal value of cash. This evidence, therefore, implies that the excess cash holdings induced by managers' increased risk perception hurt shareholder value.

[34] We adopt the raw stock return as a dependent variable and time fixed effects as suggested by Gormley and Matsa (2014) and Dessaint and Matray (2017).

4. Additional Analyses

This section conducts a battery of robustness checks: (i) ruling out two alternative interpretations of our baseline evidence, (ii) using an alternative set of sentiment measures, (iii) controlling for county-level income inequality, and (iv) factoring supply chain disruptions.

4.1 Alternative interpretations

4.1.1 The performance effect

One might argue that transitioning to remote work could cause operational uncertainty and business disruption, weakening firm performance and, in turn, evoking negative managerial sentiment. As a result, managers exhibit negative sentiment manifested in their conference calls. It is, therefore, plausible that managerial pessimism is a rational outcome of weak firm performance instead of the psychological bias induced by remote work (the performance effect). To allay this concern, we exploit the industry heterogeneity in disaster times and examine the relationship between WFH_C and managerial sentiment conditioning on the firm-level vulnerability to the pandemic risk. While many firms adopt the work-from-home policy during the COVID crisis, not all are hit hard by the crisis. Some firms in the healthcare and technology sectors even thrive during the pandemic. Thus, if remote work evokes managerial pessimism, we expect a consistent homebound effect on managerial sentiment, independent of firms' financial conditions during the pandemic.

We employ two criteria to define a firm's vulnerability to the pandemic. The first criterion employs Pagano, Wagner, and Zechner's (2020) industry-level social distancing resilience index to partition our sample into two subsamples according to the sample median of industry-level disaster resilience score.[35] The other criterion divides the sample into two subsamples of firms operating in critical versus non-critical industries defined by Papanikolaou and Schmidt (2020).[36]

[35] Pagano, Wagner, and Zechner construct their industry-level resilience to social distancing index as one minus the percentage of workers in occupations that are communication-intensive and/or require a physical presence close to others based on Koren and Petö (2020).

[36] Papanikolaou and Schmidt (2020) provide a more conservative and accurate essential industry classification (termed as "critical industry" in their work) compared with other classifications made by state governments. They assume that an essential industry provides critical infrastructure and thus is allowed to stay open by local governments during the pandemic. Under this assumption, they refine Pennsylvania's list of essential industries at the four-digit NAICS level, formed based on The Cybersecurity and Infrastructure Security Agency's (CISA) guidance. The detailed

Critical industries are primarily in producing and selling food and beverages, utilities, pharmacies, transportation, waste collection and disposal, and some healthcare and financial services. Table 9 presents the results. Columns (1)-(2) show no statistical difference in the WFH_C effect on *Managerial Sentiment* between high- and low-resilence firms, but Columns (3)-(4) indicate a marginal difference in this effect between critical and non-critical businesses. We interpret the relatively weak WFH_C effect for critical industries as evidence that management in essential businesses works less at home than those in non-essential industries. It is plausible that when employees work on the frontline facing the COVID-19 crisis, management is physically in the office coordinating and supporting their workforce. Overall, our primary findings are robust to firms' varying exposures to COVID-induced mobility restrictions and, therefore, unlikely attributed to the weak performance effect.

4.1.2 The opportunistic effect

Opportunistic managers may blame the pandemic for their weak firm performance and strategically instill negative sentiment in corporate disclosures (Tse and Tucker 2010; Acharya, DeMarzo, and Kremer 2011) (the opportunistic effect). This argument would suggest that psychological biases do not drive managerial sentiment. To rule out the managerial opportunism argument, we investigate the work-from-home impact on insider trading behavior during the pandemic. The accounting literature (Cheng and Lo 2006; Rogers 2008) suggests that insider trading can motivate opportunistic disclosures; opportunistic managers are prone to disseminate negative information ahead of company stock purchases and vice versa. In contrast, if managerial pessimism is a natural, unintended outcome, the depressed feelings due to work from home should result in more insider sales and fewer purchases. To disentangle the two possible explanations, we investigate the WFH_C effect on subsequent insider transactions disclosed during 2020. We construct three insider trading variables: (1) firm-level insider purchases ($InsiderBuys$), defined as the dollar value of shares bought by corporate insiders in the quarter following an earnings call scaled by the previous quarter's market value of equity; (2) firm-level insider sales ($InsiderSales$), defined as the dollar

list of essential industries is reported in Appendix Table A.1 of their paper.

value of shares sold by corporate insiders in the quarter following an earnings call scaled by the previous quarter's market value of equity; and (3) net insider trades ($NetTrades$), which is the difference between $InsiderBuys$ and $InsiderSales$. Our tests are based on the three measures aggregated to the firm level.

We replicate our analysis using Eq. (1) but replacing the dependent variable by each insider measure. Table 10 presents the results, with Columns (1)-(3) showing the findings for *InsiderBuys*, *InsiderSales*, and *NetTrades*, respectively. The coefficients of *InsiderBuys* and *NetTrades*, while not *InsiderSales*, are negative and statistically significant at the 1% and 10% levels, respectively. The results suggest no evidence of managerial opportunism during the pandemic year, further supporting our main hypothesis that working from home induces managerial pessimism.

4.2 Alternative measures of managerial sentiment

We follow Chen, Wu, and Zhang (2020) and employ management earnings forecasts and their properties as alternative measures of managerial sentiment.[37] These measures are managerial forecast bias (*MFBias*), forecast pessimism (*MFPessimism*), forecast optimism (*MFOptimism*), forecast range (*MFRange*), and forecast horizon (*MFHorizon*). *MFBias*, *MFPessimism*, and *MFOptimism* gauge the extent of managerial sentiment affecting earnings forecasts, whereas *MFRange* and *MFHorizon* reflect the forecast precision, given that biased managers may issue less precise forecasts. We re-run Eq. (1) using each proxy as the outcome variable and report the results in Table 11. The coefficient of WFH_C is statistically significant for all proxies of managerial sentiment, except for *MFRange* in Column (4). WFH_C decreases managerial optimistic forecast bias (Column (1)), the probability of optimistic forecasts (Column (3)), and managerial earnings forecast horizon (Column (5)) but increases the probability of pessimistic forecasts (Column (2)). We also use an adjusted *Managerial Sentiment* measure to control for unobservable firm characteristics that may potentially confound the effect of WFH_C. Specifically, the adjusted sentiment measure, *Orthogonalized Sentiment*, is constructed by taking the residuals from estimating the regression of *Managerial Sentiment* on firm and calendar-quarter fixed effects. As shown in Column (6), WFH_C

[37] Prior accounting literature documents that management earnings forecasts are an influential source of forward-looking information in the capital market (Beyer, Cohen, Lys, and Walther 2010).

remains significantly and negatively related to *Orthogonalized Sentiment*.

In summary, these results substantiate our primary findings that managerial pessimism increases with the extended remote work, implying that an isolating home workplace under COVID-19 puts a mental toll on management.

4.3 Other robustness tests

We perform additional robustness tests that explicitly take into account variables that may drive our baseline evidence. First, recent studies show evidence of income inequality as important determinants of social distancing practices. For example, Chang et al. (2021) show that COVID-19 infection rates are higher among disadvantaged racial and socioeconomic groups because their visits to points of interest are more crowded and therefore associated with higher risk. It is possible that our work-from-home construct, WFH_C, reflects the county's household socioeconomic distribution. For robustness, we expand our base model by including a county's household socioeconomic status in Column (7) of Table 11. Specifically, Column (7) controls for the local socioeconomic status using county-level unemployment rate ($Unemployment$) and the log of median household income in 2019 (*Household Income*). We obtain the county-level economic statistics from the Bureau of Labor Statistics. Our primary results remain materially unaffected: WFH_C still bears a negative and statistically significant coefficient even in the presence of the additional county-level variables.

Second, the COVID-19 outbreak brings about unexpected supply chain disruptions as many businesses are forced to shut down or transition to remote work for the virus containment (Cheema-Fox et al. 2020; Ding et al. 2021). Therefore, one may argue that the supply chain exposure to the COVID-19 infection risk rather than the remote workplace influences the sentiment of corporate managers. To rule out this possibility, we introduce a binary variable, *Major Customer*, in the baseline regression model. *Major Customer* equals one if a firm's major customer, the largest customer in terms of the firm's revenues, is headquartered in a COVID-19 hotspot and zero if otherwise.[38] The customer-supplier pairs are identified using the Compustat's supply chain linking suite and merged into our main sample. Column (8) shows that the supply-chain risk exposure

[38]For a given month, a county is classified as a hotspot if the number of its month-end infection cases is above the county-level median number of infection cases in the United States.

has a slight dampening effect on managerial sentiment, where the coefficient on *Major Customer* is significant at the 5% level. More importantly, the negative WFH_C effect on managerial sentiment remains statistically significant at the 1% level. This result again confirms the robust mental effect of remote work on corporate managers.

5. Concluding Remarks

We exploit the mental health crisis in this global COVID-19 pandemic to examine the work-from-home effect on managerial sentiment and ensuing corporate liquidity management. Our results show that remote work adversely impacts managers' sentiment and exacerbates their pessimism biases. The increase in the work-from-home duration explains 51% of the fall in managerial sentiment during the pandemic relative to its pre-pandemic mean level. This evidence is robust to the staggered adoption of state-level stay-at-home orders, alternative interpretations, alternative managerial sentiment measures, county-level socioeconomic status, and firms' supply chain disruptions. Further analyses highlight social isolation and work stress as two potential psychological mechanisms through which work from home affects managerial sentiment. Moreover, the mental health effects of remote workplaces with mobility restrictions have important economic consequences. We find that remote managers, plagued by negativity and pessimism, tend to adopt a risk-averse cash policy and accumulate excess cash through external financing. However, this increase in cash is value-destroying.

The rapid digital transformation during the COVID-19 crisis has made remote work a possible new normal post-pandemic. While some businesses thrive and experience growth and success during COVID-19, others face the stress of managing a widely distributed workforce. For example, a recent McKinsey (2021) survey reports that more than three-quarters of 504 C-suite respondents are concerned about organizational culture and belonging under remote work and expect their employees to return to the office three or more days a week post-pandemic.[39] Our study echoes these concerns and suggests that the psychological outcomes of remote work can have consequential eco-

[39] https://www.mckinsey.com/business-functions/organization/our-insights/its-time-for-leaders-to-get-real-about-hybrid

nomic impacts. As COVID-19 social distancing rules start to ease following widespread vaccination campaigns, corporate executives must rethink the future of work. Our research would help business leaders better understand the potential cost of a virtual working environment in this transitioning process.

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Figure 1
Quarterly Distribution of Work-from-Home Ratios at the County Level on the U.S. Map in the Year 2020

This figure depicts the quarterly distribution of work-from-home ratios (WFH_C) at the county level on the U.S. map for the year 2020. It charts the public's time spent at home across U.S. states during this pandemic period and how stay-at-home time varies as many states impose, relax, and reinstate social distancing restrictions.

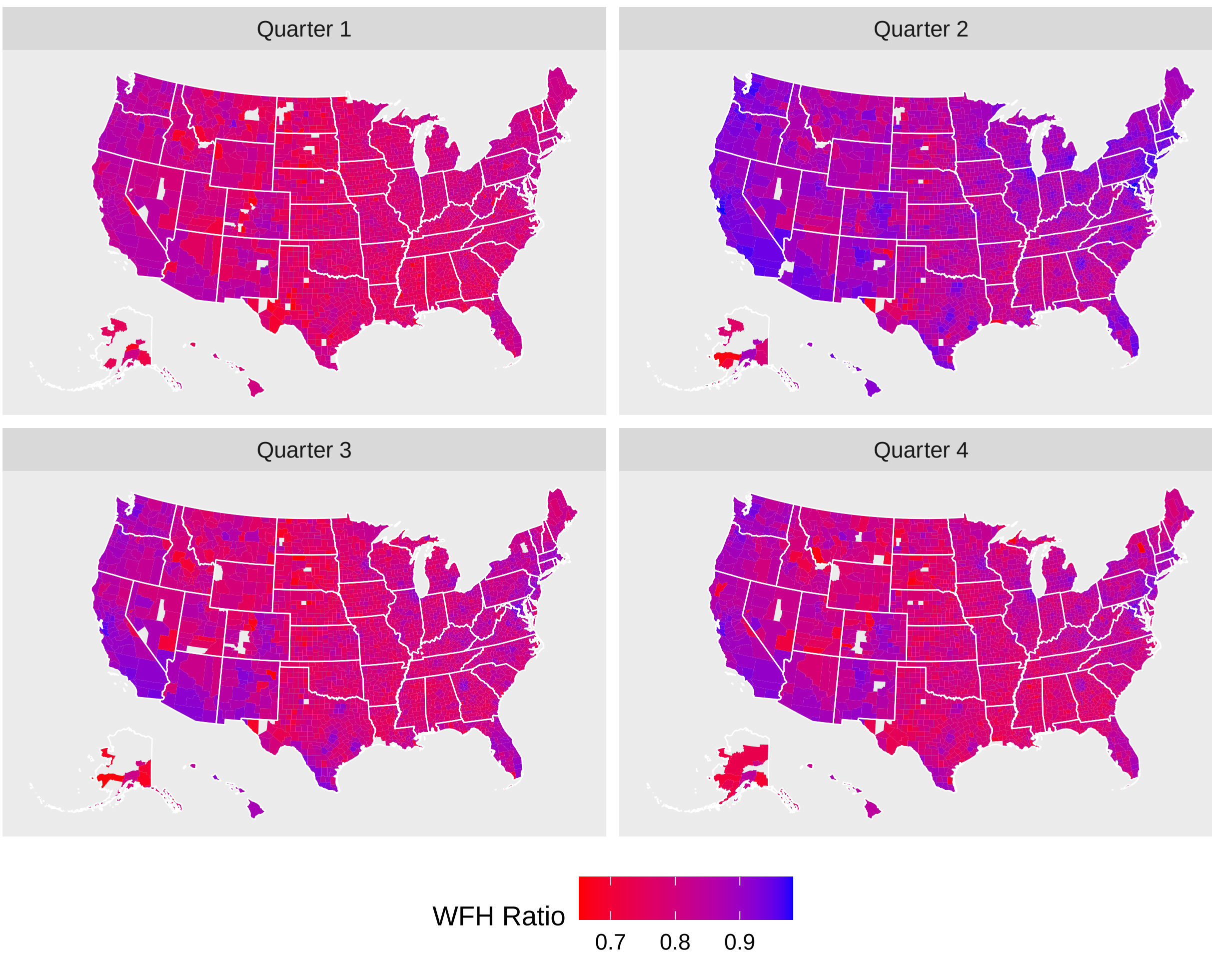

Figure 2
Time-Series Patterns of the Work-from-Home Ratio and New COVID-19 Infection Cases by U.S. Region

This figure depicts the time-series patterns of average daily work-from-home (WFH_C) ratios and number (in 10,000) of new COVID-19 infection cases across four different U.S. regions in the year 2020. For every given month, we compute the average daily WFH_C (Figure 2a) and number of new COVID-19 infection cases within each region (Figure 2b).

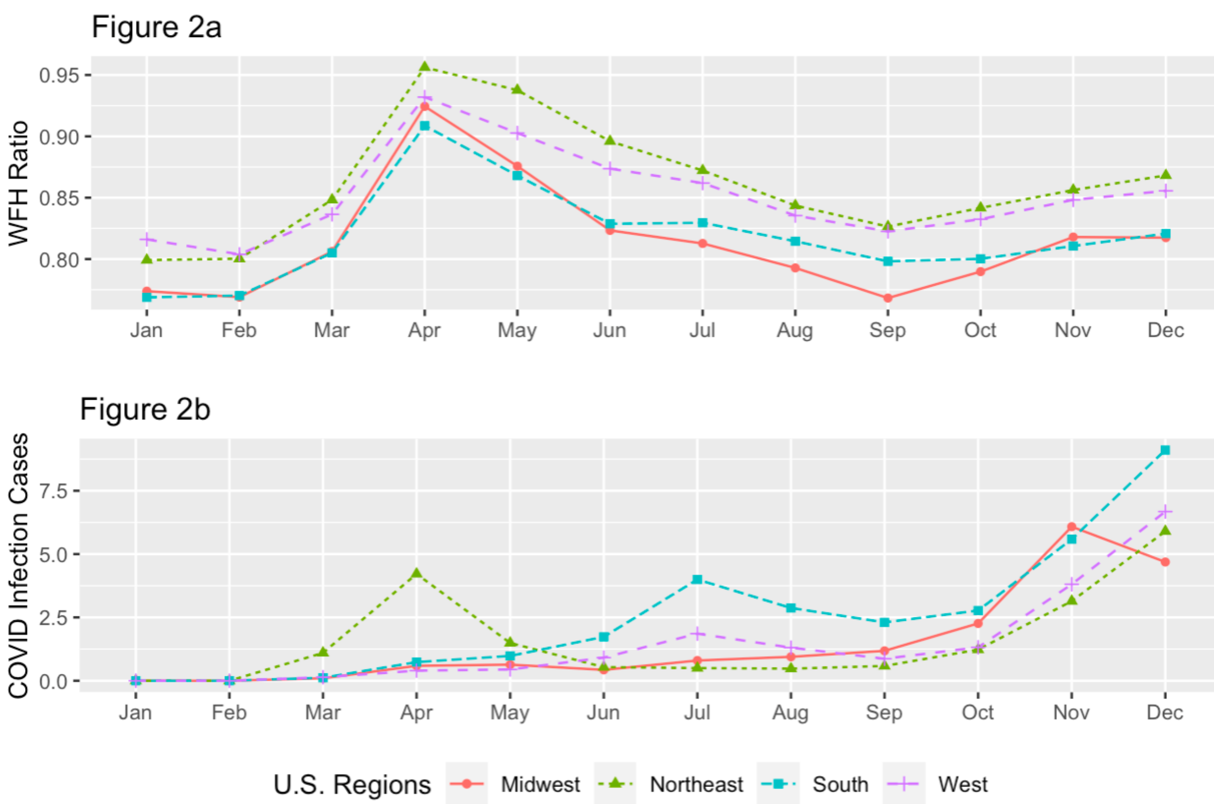

Table 1
Summary Statistics

This table reports descriptive statistics of key variables in our empirical analysis including mean (Mean), standard deviation (StdDev), 25th percentile (25th), median (Median), and 75th percentile (75th). The full sample consists of 8,444 firm-quarter observations of firms making quarterly earnings calls in year 2020. WFH_C represents the daily average work-from-home ratio in a given county in the [-30, -1] window relative to the earnings call date 0. WFH_S is the weighted average of county-level work-from-home ratios for a given state (by county-specific number of mobile devices). All continuous variables are winsorized at the top and bottom 1% of the sample distribution and defined in Appendix Table 1.

Variable	NObs	Mean	StdDev	25th	Median	75th
Working from Home Duration						
WFH_C	8,444	0.889	0.069	0.830	0.903	0.946
WFH_S	8,444	0.879	0.065	0.822	0.887	0.929
Managerial Sentiment Metrics						
Managerial Sentiment	8,444	0.752	0.539	0.391	0.747	1.118
MFBias	603	−0.004	0.016	−0.005	−0.002	−0.001
MFPessimism	603	0.837	0.369	1	1	1
MFOptimism	603	0.141	0.348	0	0	0
MFRange	603	0.003	0.006	0.000	0.001	0.002
MFHorizon	603	0.601	0.216	0.533	0.622	0.689
Other Variables						
Infection	8,444	6.849	4.133	2.773	8.596	10.002
Firm Size	8,444	7.033	2.121	5.539	7.093	8.459
ROA	8,444	−0.021	0.074	−0.029	0.002	0.015
BM	8,444	0.588	0.890	0.155	0.378	0.755
Past Return	8,444	0.119	0.472	−0.149	0.051	0.271
Volatility	8,444	0.044	0.025	0.026	0.040	0.056
Leverage	8,444	0.344	0.242	0.147	0.330	0.483
Cash Holdings	8,337	0.201	0.223	0.052	0.123	0.253
Sales Growth	8,138	0.096	0.586	−0.094	0.023	0.139
Operating Margin	6,802	−0.328	1.114	−0.040	0.009	0.032
Net Working Capital	6,629	−0.016	5.484	0.062	0.152	0.253
Investment	6,821	0.043	0.062	0.012	0.025	0.049
Dividend	6,840	0.034	0.116	0.000	0.000	0.032
Repurchases	6,840	0.001	0.007	0.000	0.000	0.000
New Financing	8,323	0.276	0.532	0.026	0.081	0.269

Table 2
Work from Home and Internet Search Attention

This table presents results from regressing a daily Google Search Volume Index (SVI) associated with each topic, namely Coronavirus, Lockdown, and Recession, separately, against the work-from-home ratio at the state level, WFH_S. WFH_S is computed as the daily average state-level work-from-home ratio over the previous 30 days. All regression models include state and day fixed effects (FE). Variable definitions are presented in Appendix Table 1. The t-statistics are reported in parentheses. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. NObs is the number of observations.

	Google Search Volume Index		
	Coronavirus	Lockdown	Recession
	(1)	(2)	(3)
WFH_S	0.022***	0.049***	0.025***
	(6.67)	(6.32)	(3.38)
State FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
NObs	18,300	14,214	18,088
Adj. R^2	0.781	0.274	0.191

Table 3
Work from Home and Employee Internet Reviews

This table reports the regression results of the likelihood of an employee review in association with the communication topic on the county-level work-from-home ratio (WFH_C) along with other control variables. *Negative Reviews* (*Positive Reviews*) denotes the likelihood of an employee's negaive (positive) review in association with the communication topic. *Net Reviews* equals the difference between *Positive Reviews* and *Negative Reviews*. Control variables include the log of the number of infection cases ($Infection$), firm size (*Firm Size*), return-on-assets ratio (ROA), book-to-market ratio (BM), previous-quarter stock return (*Past Return*), return volatility ($Volatility$), and financial leverage (*Leverage*). All control variables are winsorized at the top and bottom 1% of the sample distribution and defined in Appendix Table 1. The regression model also includes calendar-quarter and firm fixed effects (FE). The t-statistics reported in parentheses are based on heteroskedasticity-consistent and county-level clustered standard errors. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. NObs is the number of observations.

	Negative Reviews	*Positive Reviews*	*Net Reviews*
	(1)	(2)	(3)
WFH_C	2.450***	−0.149	−3.314**
	(2.57)	(−0.25)	(−2.22)
Infection	−0.009	0.004	0.013
	(−1.12)	(1.27)	(1.29)
Firm Size	−0.034	−0.031	−0.064
	(−0.26)	(−0.69)	(−0.38)
ROA	−0.313	0.044	0.516
	(−0.25)	(0.10)	(0.36)
BM	−0.022	−0.034	0.026
	(−0.32)	(−0.75)	(0.21)
Past Return	0.057	0.019	0.002
	(0.65)	(0.42)	(0.02)
Volatility	−1.439	1.603	2.884
	(−0.34)	(1.06)	(0.56)
Leverage	−0.052	−0.273	−0.230
	(−0.09)	(−1.29)	(−0.28)
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
NObs	921	921	921
R^2	0.650	0.610	0.597

Table 4
The Effect of Work from Home and Managerial Sentiment

This table presents the estimation results of the following baseline equation:

$$Sentiment_{i,t+1} \quad = \quad \alpha + \beta_1 WFH_t + \beta_2 Infection_{C,t} + \lambda' Controls_{i,t} + \gamma_i + \theta_t + \epsilon_{i,t+1},$$

where *WFH* alternatively represents the work-from-home duration ratio at the county-level (WFH_C) and state level (WFH_S). The control variables include the log of the number of infection cases (*Infection*), firm size (*Firm Size*), return-on-assets ratio (*ROA*), book-to-market ratio (*BM*), past-quarter stock return (*Past Return*), return volatility (*Volatility*), and financial leverage (*Leverage*). All control variables are winsorized at the top and bottom 1% of the sample distribution and defined in Appendix Table 1. The model also includes various combinations of calendar-quarter, firm, industry, county, and industry × quarter fixed effects (FE). The t-statistics reported in parentheses are based on heteroskedasticity-consistent and county-level clustered standard errors. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. NObs is the number of observations.

	(1)	(2)	(3)	(4)	(5)	(6)
WFH_C	−1.523***	−1.183***	−1.132***	−1.209***	−1.202***	
	(−10.13)	(−5.43)	(−5.30)	(−5.34)	(−5.88)	
WFH_S						−2.218***
						(−8.13)
Infection			−0.006**	−0.008**	−0.004	−0.005*
			(−2.26)	(−2.35)	(−1.37)	(−1.68)
Firm Size	0.008	−0.028*	−0.030*	0.019***	−0.042**	−0.027*
	(1.27)	(−1.79)	(−1.91)	(3.50)	(−2.39)	(−1.78)
ROA	0.038	0.651***	0.648***	0.159*	0.584***	0.660***
	(0.39)	(6.13)	(6.10)	(1.77)	(5.64)	(6.22)
BM	−0.034***	0.004	0.003	−0.004	0.007	0.004
	(−3.72)	(0.27)	(0.24)	(−0.45)	(0.42)	(0.27)
Past Return	0.222***	0.108***	0.109***	0.129***	0.101***	0.108***
	(14.23)	(8.15)	(8.19)	(8.35)	(7.20)	(8.23)
Volatility	−3.798***	−2.146***	−2.142***	−1.019**	−1.472***	−2.104***
	(−10.08)	(−5.55)	(−5.54)	(−2.56)	(−3.34)	(−5.43)
Leverage	0.050	−0.042	−0.040	0.067	0.017	−0.046
	(1.17)	(−0.48)	(−0.46)	(1.43)	(0.20)	(−0.53)
Firm FE	-	Yes	Yes	-	Yes	Yes
Industry FE	-	-	-	Yes	-	-
County FE	-	-	-	Yes	-	-
Industry×Quarter FE	-	-	-	-	Yes	-
Quarter FE	-	Yes	Yes	Yes	-	Yes
NObs	8,444	8,444	8,444	8,444	8,444	8,444

Table 5
Dynamic Effects of the Stay-at-Home Order on Managerial Sentiment

This table reports the dynamic effect of the state-level stay-at-home (Stay@Home) order on managerial sentiment using a difference-in-differences approach as specified below:

$$Managerial\ Sentiment_{i,t+1} \quad = \quad \alpha + \beta_1 Stay@Home_{i,S,t} + \lambda' Controls_{i,t} + \gamma_{i,cohort} + \theta_{t,cohort} + \epsilon_{i,t+1}.$$

The treatment sample consists of firms located in a state with a stay-at-home order in 2020, while the control sample contains the rest of the firms with no such orders. The dependent variable is the overall managerial sentiment score (*Managerial Sentiment*). In Column (1), the $Stay@Home$ dummy takes the value of one for earnings calls released by treatment firms over the three months following the implementation of the stay-at-home order and zero if otherwise. In Column (2), the $Stay@Home$ dummy is replaced by a set of dummy variables, $Stay@Home_{i,S,t+k}$, where where $k = -3, ..., +3$ $(k \neq 0)$ to test the effect of Stay@Home from month $k = -3$ to month $k = +3$ around the implementation of the order. In Columns (3) and (4), we repeat the analysis in Column (1) on subsamples of firms with geographically dispersed business activity and teleworkability occupations, respectively. The unreported control variables include the log of the number of infection cases (*Infection*), firm size (*Firm Size*), return-on-assets ratio (*ROA*), book-to-market ratio (*BM*), previous-quarter stock return (*Past Return*), return volatility (*Volatility*), and financial leverage (*Leverage*). All control variables are winsorized at the top and bottom 1% of the sample distribution and defined in Appendix Table 1. The regression model also includes firm-cohort and quarter-cohort fixed effects (FE). The t-statistics reported in parentheses are based on heteroskedasticity-consistent and county-level clustered standard errors. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. NObs is the number of observations.

			Dispersed Firms	Teleworkable Jobs
[-1.8ex]	(1)	(2)	(3)	(4)
Stay@Home	-0.229^{***}		-0.219^{***}	-0.269^{***}
	(-4.73)		(-3.12)	(-4.20)
Stay@Home Month -3		-0.086		
		(-0.63)		
Stay@Home Month -2		-0.044		
		(-0.58)		
Stay@Home Month -1		-0.046		
		(-0.63)		
Stay@Home Month +1		-0.213^{***}		
		(-3.22)		
Stay@Home Month +2		-0.205^{***}		
		(-4.27)		
Stay@Home Month +3		-0.076^{*}		
		(-1.77)		
Firm-cohort FE	Yes	Yes	Yes	Yes
Quarter-cohort FE	Yes	Yes	Yes	Yes
NObs	8,444	8,444	4,491	4,383
Adj. R^2	0.387	0.395	0.345	0.376

Table 6
The Channels

This table presents regression results of managerial sentiment on WFH_C by augmenting the baseline Model (1) with the interactions between WFH_C and various measures of psychological channels. The dependent variable is *Managerial Sentiment*, and the key explanatory variable is WFH_C, which is computed by the county-level work-from-home ratio in the [-30, -1] window prior to an earnings call day. Two measures for the social isolation channel are: *CEO Age* (defined as a dummy variable that equals one if the CEO age is below the sample median and zero otherwise) and *Teamwork* (defined as a dummy variable that equals one if the firm belongs to the Top 5 teamwork-intensive industries identified by Koren and Petö (2020)). The measures used to capture work stress under the pandemic include *CEO Tenure* (defined as the time difference between the 2020 year end and her appointment date) and *Teleworkability* (defined as the share of jobs that can be done at home weighted by the wage at the 2-digit NAICS level taken from Dingel and Neiman (2020)). The unreported control variables include the log of the number of infection cases (*Infection*), firm size (*Firm Size*), return-on-assets ratio (*ROA*), book-to-market ratio (*BM*), previous-quarter stock return (*Past Return*), return volatility (*Volatility*), and financial leverage (*Leverage*). All control variables are winsorized at the top and bottom 1% of the sample distribution and defined in Appendix Table 1. The regression models also include firm and calendar-quarter fixed effects (FE). The t-statistics reported in parentheses are based on heteroskedasticity-consistent and county-level clustered standard errors. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. NObs is the number of observations.

	The Social Isolation Channel		The Work Stress Channel	
	(1)	(2)	(3)	(4)
$WFH_C \times$ CEO Age	-0.344^{**}			
	(-1.99)			
$WFH_C \times$ Teamwork		-0.873^{***}		
		(-3.68)		
$WFH_C \times$ CEO Tenure			0.032^{***}	
			(2.82)	
$WFH_C \times$ Teleworkability				0.574^{*}
				(1.78)
WFH_C	-0.924^{***}	-1.013^{***}	-1.035^{***}	-1.453^{***}
	(-3.21)	(-4.77)	(-3.58)	(-5.56)
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
NObs	4,332	8,444	4,332	8,433
Adj. R^2	0.662	0.631	0.663	0.631

Table 7
WFH-Induced Managerial Sentiment, Corporate Cash Holdings, and Source of Cash

This table presents the regression results of the impact of the work-from-home-(WFH-) induced managerial sentiment ($\widehat{Sentiment}$) on corporate cash holdings in Column (1) and different sources of cash holdings in Columns (2)-(8). $\widehat{Sentiment}$ is the predicted *Managerial Sentiment* obtained from estimating Model (1) in Column (3) of Table 4. *Cash Holdings* denotes the total amount of cash and cash equivalents scaled by the previous year total assets. To test the $\widehat{Sentiment}$ effect on cash holdings observed during the COVID-19 pandemic, we follow Dessaint and Matray (2017) and estimate the $\widehat{Sentiment}$ effect on a number of sources of raising cash: a change in revenues (*Sales Growth*), operating profits (*Operating Margin*), net working capital requirements (*Net Working Capital*), investment (*Investment*), dividend payment (*Dividend*), repurchases (*Repurchases*), or new financing (debt or equity) (*New Financing*). The control variables include the log of the number of infection cases (*Infection*), firm size (*Firm Size*), return-on-assets ratio (*ROA*), book-to-market ratio (*BM*), previous-quarter stock return (*Past Return*), return volatility (*Volatility*), and financial leverage (*Leverage*). All control variables are winsorized at the top and bottom 1% of the sample distribution and defined in Appendix Table 1. The regression model also includes calendar-quarter and firm fixed effects (FE). The t-statistics reported in parentheses are based on heteroskedasticity-consistent and county-level clustered standard errors. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. NObs is the number of observations.

		Different Sources of Cash						
	Cash Holdings	Sales Growth	Operating Margin	Net Working Capital	Investment	Dividend	Repurchases	New Financing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Sentiment}$	-0.128^{***}	0.070	-0.140	-1.349	-0.015	-0.013	-0.003	-0.471^{***}
	(-2.48)	(0.28)	(-1.52)	(-1.06)	(-0.81)	(-0.34)	(-0.74)	(-2.71)
Infection	-0.002^{**}	-0.008	-0.0002	0.001	-0.001	-0.0001	-0.0001	0.012^{***}
	(-2.43)	(-1.35)	(-0.07)	(0.06)	(-1.00)	(-0.17)	(-1.29)	(2.72)
Firm Size	0.069^{***}	-0.017	-0.064^{***}	-0.031	0.018^{***}	0.005^{**}	-0.0001	0.146^{***}
	(7.04)	(-0.47)	(-2.91)	(-0.35)	(4.67)	(2.24)	(-0.45)	(3.33)
ROA	0.074	-1.360^{***}	-0.167^{*}	0.560	0.021	0.009	0.003^{*}	-0.284^{*}
	(1.56)	(-3.06)	(-1.94)	(1.23)	(1.14)	(1.04)	(1.76)	(-1.90)
BM	0.011^{***}	-0.064^{**}	-0.054^{***}	-0.037	0.005^{***}	0.0001	-0.0003	0.044
	(2.71)	(-2.59)	(-3.44)	(-0.81)	(3.12)	(0.04)	(-1.00)	(1.43)
Past Return	-0.004	0.090^{***}	0.033^{**}	-0.294	-0.004^{**}	0.002	0.0003^{**}	-0.113^{***}
	(-0.88)	(3.03)	(2.02)	(-1.42)	(-2.36)	(1.00)	(2.19)	(-8.08)
Volatility	0.126	-2.068^{***}	-0.236	-10.561	-0.053	-0.055	-0.012	-2.094^{***}
	(1.17)	(-2.71)	(-0.69)	(-1.04)	(-1.02)	(-1.19)	(-1.58)	(-4.93)
Leverage	0.044	0.640^{**}	0.255^{***}	-0.293	-0.009	-0.011	0.0005	-0.285^{*}
	(0.95)	(2.44)	(2.88)	(-0.78)	(-0.56)	(-0.95)	(0.29)	(-1.78)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NObs	8,337	8,138	6,802	6,629	6,821	6,840	6,840	8,323
Adj. R^2	0.842	0.143	0.973	0.603	0.674	0.820	0.244	0.690

Table 8
WFH-Induced Managerial Sentiment and Value of Cash

This table presents the work-from-home-(WFH-)induced managerial sentiment ($\widehat{Sentiment}$) on the marginal value of corporate cash holdings. $\widehat{Sentiment}$ is the predicted *Managerial Sentiment* obtained from estimating Model (1) in Column (3) of Table 4. We follow Faulkender and Wang (2006) and employ the change in a firm's equity market value over the quarter scaled by equity market value at the beginning of the quarter as the dependent variable. Similarly, ΔCash is the change in corporate cash holdings over the quarter scaled by equity market value at the beginning of the quarter. Following Faulkender and Wang's (2006) specification, Column (1) estimates the marginal value of cash, while controlling for change in earnings (Δ *Earnings*), change in net assets (Δ*Net Assets*), change in R&D (Δ*R&D*), change in dividends (Δ*Dividend*), market leverage (*Market Leverage*), new financing (*New Financing*), and lagged Cash (*Lagged Cash*). Column (2) estimates how the marginal value of cash changes for firms with low WFH-induced managerial sentiment (i.e., low $\widehat{Sentiment}$). All variables are defined in Appendix Table 1. The regression model also includes calendar-quarter and firm fixed effects (FE). The *t*-statistics reported in parentheses are based on heteroskedasticity-consistent and county-level clustered standard errors. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. NObs is the number of observations.

	(1)	(2)
ΔCash	0.527***	0.311**
	(4.48)	(1.96)
ΔCash × $\widehat{Sentiment}$		0.370***
		(2.46)
$\widehat{Sentiment}$		0.164
		(0.69)
ΔEarnings	0.112	0.117
	(1.57)	(1.64)
ΔNet Assets	−0.058	−0.060
	(−0.76)	(−0.78)
ΔR&D	1.996	2.094
	(1.43)	(1.51)
ΔDividend	1.345	1.338
	(0.47)	(0.48)
Market Leverage	0.0004	0.001
	(0.22)	(0.42)
New Financing	0.051	0.055
	(1.04)	(1.12)
Lagged Cash	1.328***	1.331***
	(11.04)	(11.32)
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
NObs	7,182	7,182
Adj. R^2	0.355	0.356

Table 9

Work from Home and Managerial Sentiment by Firm Pandemic-Vulnerability

This table presents regression results of managerial sentiment on WFH_C based on subsamples formed by firm vulnerability to the pandemic. Our sample is partitioned into two subsamples according to the sample median of industry-level disaster resilence from Pagano, Wagner, and Zechner (2020) in Columns (1)-(2) and whether the firm operates in a critical or non-critical industry during the pandemic based on the list of critical industries compiled by Papanikolaou and Schmidt (2020) in Columns (3)-(4). The dependent variable is *Managerial Sentiment*, and the key explanatory variable is the county-level work-from-home ratio (WFH_C) in the [-30, -1] window prior to an earnings call day. The control variables include the log of the number of infection cases (*Infection*), firm size (*Firm Size*), return-on-assets ratio (*ROA*), book-to-market ratio (*BM*), previous-quarter stock return (*Past Return*), return volatility (*Volatility*), and financial leverage (*Leverage*). All control variables are winsorized at the top and bottom 1% of the sample distribution and defined in Appendix Table 1. The regression model also includes firm and calendar-quarter fixed effects (FE). The t-statistics reported in parentheses are based on heteroskedasticity-consistent and county-level clustered standard errors. The p-values of the Chi-square tests on the statistical difference in the WFH_C coefficient estimates across subsamples are reported in the bottom row. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. NObs is the number of observations.

	High Resilience	Low Resilience	Critical Industries	Non-Critical Industries
	(1)	(2)	(3)	(4)
WFH_C	-1.242^{***}	-1.469^{***}	-0.681^{*}	-1.316^{***}
	(-3.96)	(-3.29)	(-1.90)	(-4.70)
Test for the Difference in the WFH_C Coefficients	0.227 (p-value=0.596)		0.635^{*} (p-value=0.072)	
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
NObs	3,879	1,983	2,588	5,856
Adj. R^2	0.605	0.651	0.619	0.638

Table 10
Work from Home and Insider Trading Activity

This table presents regression results of insider trading activity on WFH_C. The dependent variable is alternatively insider buys ($InsiderBuys$), insider sells ($InsiderSales$), and insider net trades ($NetTrades$), aggregated over the quarter post the earnings call day. WFH_C is the county-level work-from-home ratio in the [-30, -1] window prior to an earnings call day. The control variables include the log of the number of infection cases (*Infection*), firm size (*Firm Size*), return-on-assets ratio (*ROA*), book-to-market ratio (*BM*), previous-quarter stock return (*Past Return*), return volatility (*Volatility*), and financial leverage (*Leverage*). All control variables are winsorized at the top and bottom 1% of the sample distribution and defined in Appendix Table 1. The regression model also includes firm and calendar-quarter fixed effects (FE). The t-statistics reported in parentheses are based on heteroskedasticity-consistent and county-level clustered standard errors. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. NObs is the number of observations.

	InsiderBuys	InsiderSales	NetTrades
	(1)	(2)	(3)
WFH_C	-0.690^{***}	-0.076	-0.614^{*}
	(-2.69)	(-0.44)	(-1.94)
Infection	-0.076	0.033	-0.109
	(-0.76)	(0.73)	(-0.98)
Firm Size	-1.090	-0.085	-1.005
	(-1.04)	(-0.21)	(-0.91)
ROA	0.706	1.936	-1.230
	(0.17)	(0.59)	(-0.23)
BM	0.521	0.185	0.336
	(0.20)	(0.91)	(0.13)
Past Return	-0.216	0.701^{***}	-0.917^{**}
	(-0.62)	(2.76)	(-2.17)
Volatility	1.321	-8.452	9.773
	(0.11)	(-1.11)	(0.70)
Leverage	-0.854	-0.753	-0.100
	(-0.29)	(-0.41)	(-0.03)
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
NObs	2,091	2,091	2,091
Adjusted R^2	0.670	0.538	0.620

Table 11
Additional Robustness Tests

This table presents results from a host of robustness tests. Columns (1)-(6) replicate the baseline Model (1) using alternative *Managerial Sentiment* measures and different sentiment constructs on WFH_C, whereas Columns (7)-(8) expand the model specification in Column (3) of Table 4 to control for county-specific economic conditions (i.e., the unemployment rate (*Unemployment*) and log of median household income (*Household Income*)) and supply chain exposure to the COVID-19 crisis (i.e., *Major Customer*), which takes the value of one if the firm's major customer is headquartered in a county where the monthly COVID-19 infection cases exceeds the sample median and zero if otherwise). In Columns (1)-(5), we replace *Managerial Sentiment* with I/B/E/S managerial earnings forecasts, namely, the managerial earnings forecast bias ($MFBias$), pessimistic/optimistic forecast bias (*MFPessimism; MFOptimism*), forecast range (*MFRange*) and horizon (*MFHorizon*). In Column (6), managerial sentiment is measured by *Orthogonalized Sentiment*. WFH_C is the county-level work-from-home ratio in the [-30, -1] window prior to an earnings call day. We conduct probit regression estimations in Columns (2)-(3) and OLS estimations in other columns. Unreported control variables include the log of the number of infection cases (*Infection*), firm size (*Firm Size*), return-on-assets ratio (*ROA*), book-to-market ratio (*BM*), previous-quarter stock return (*Past Return*), return volatility (*Volatility*), and financial leverage (*Leverage*). All firm-level control variables are winsorized at the top and bottom 1% of the sample distribution and defined in Appendix Table 1. The regression models also include different combinations of calendar-quarter, firm, and industry fixed effects (FE). The t-statistics reported in parentheses are based on heteroskedasticity-consistent and county-level clustered standard errors. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. NObs is the number of observations.

	Alternative Measures of Managerial Sentiment					Orthogonalized		
	MFBias	MFPessimism	MFOptimism	MFRange	MFHorizon	Sentiment	Managerial Sentiment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WFH_C	-0.032^{***}	1.329^{***}	-1.340^{**}	-0.001	-1.074^{*}	-1.132^{***}	-0.575^{**}	-1.091^{***}
	(-2.56)	(2.75)	(-2.58)	(-0.26)	(-1.76)	(-5.30)	(-2.05)	(-2.73)
Unemployment							-0.050^{***}	
							(-3.08)	
Household Income							0.032	
							(0.65)	
Major Customer								-0.054^{***}
								(-3.60)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	-	Yes
Industry FE	-	-	-	-	-	-	Yes	-
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	603	603	603	603	603	8,444	8,444	3,491
Adj. (Pseudo) R^2	0.868	0.599	0.641	0.912	0.440	-0.358	0.266	0.687

Appendix Table 1

Variable Definition and Data Source

Variable	Definition (Data Source)
Measures of Work-from-Home Duration	
WFH_C	Daily stay-at-home ratios averaged across census blocks in a county in the [-30, -1] window before an earnings conference call, where the stay-at-home ratio is computed as the time spent at home scaled by the sum of stay-at-home time and non-stay-at-home time in a U.S. census block (SafeGraph)
WFH_S	Weighted average of county-level WFH_C ratios in a given state using the county-specific number of mobile devices as weights. (SafeGraph)
Measures of Managerial Sentiment	
Managerial Sentiment	Number of positive words minus the number of negative words, divided by the total number of words in the earnings call transcript multiplied by 1000. (Hassan et al. 2020)
$\widehat{Sentiment}$	Predicted value of managerial sentiment from regressing *Managerial Sentiment* on WFH_C and a host of control variables and fixed effects. (Column (3) of Table 4)
MFBias	Difference between management forecast using point estimates or midpoint of range estimates and actual earnings per share, scaled by the previous quarter stock price. (I/B/E/S)
MFPessimism	A dummy variable which takes a value of one if $MFBias$ is negative, and zero if otherwise. (I/B/E/S)
MFOptimism	A dummy variable which takes a value of one if $MFBias$ is positive, and zero if otherwise. (I/B/E/S)
MFRange	Difference between the upper and lower ends of range estimates scaled by previous quarter stock price, assuming zero for point estimates. (I/B/E/S)
MFHorizon	Natural logarithm of one plus the managerial forecast horizon. For each forecast, the horizon is computed as the number of calendar days between the forecast announcement date and the forecast period end date. (I/B/E/S)
Measures of Internet Search Attention	
Google SVI (Coronavirus)	Daily state-level Google search volume index for the "Coronavirus" topic on a scale of 1 to 100. (Google Trends)
Google SVI (Lockdown)	Daily state-level Google search volume index for the "Lockdown" topic on a scale of 1 to 100. (Google Trends)
Google SVI (Recession)	Daily state-level Google search volume index for the "Recession" topic on a scale of 1 to 100. (Google Trends)
Measures of Employee Online Reviews	
Negative Reviews	Adjusted probability of an employee's negative review in association with workplace communications (Glassdoor)
Positive Reviews	Adjusted probability of an employee's positive review in association with workplace communications (Glassdoor)
Net Reviews	Difference between Positive Reviews and Negatice Reviews (Glassdoor)
Cash and Sources of Cash Variables	
Cash Holdings	Cash and cash equivalents scaled by total assets at the beginning of 2020. (Compustat)
Sales Growth	Change in revenues scaled by previous quarter's revenues. (Compustat)
Operating Margin	Operating income after depreciation scaled by previous year's revenues. (Compustat)

Appendix Table 1 - Continued

Variable	**Definition (Data Source)**
Net Working Capital	Net working capital scaled by previous year's revenues. (Compustat)
Investment	Capital expenditure scaled by previous year's property, plant and equipment. (Compustat)
Dividend	Dividend payment scaled by the previous year's net income. (Compustat)
Repurchases	Purchases of common and preferred stocks scaled by the previous year's net income. (Compustat)
New Financing	Issuance of long-term debt and sale of new equity scaled by the previous quarter's market value of equity. (Compustat)
ΔCash	Change in cash scaled by the previous quarter's market value of equity. (Compustat)
ΔEarnings	Change in net income before extraordinary items scaled by the previous quarter's market value of equity. (Compustat)
ΔNet Assets	Change in total assets minus cash holdings scaled by the previous quarter's market value of equity. (Compustat)
ΔR&D	R&D expenses scaled by the previous quarter's market value of equity. (Compustat)
ΔDividend	Change in dividend payment scaled by the previous quarter's market value of equity. (Compustat)
Market Leverage	Total debt divided by the sum of total debt and market value of equity. (Compustat)
Other Variables	
Infection	Natural logarithm of the number of COVID-19 infection cases in a given county at the previous month end prior to an earnings call. (USAFacts)
Firm Size	Natural log of stock market capitalization. (Compustat)
ROA	Net income scaled by total assets. (Compustat)
BM	Book equity scaled by market value of equity. (Compustat, CRSP)
Past Return	Buy-and-hold daily stock returns in the previous quarter. (CRSP)
Volatility	Standard deviation of daily stock returns in the previous quarter. (CRSP)
Leverage	Total liabilities scaled by total assets. (Compustat)
CEO Age	A dummy variable which equals one if the CEO is below the median CEO age and zero otherwise. (ExecuComp)
CEO Tenure	Time difference between the 2020 year end date and the CEO appointment date. (ExecuComp)
InsiderBuys	Dollar value of company shares bought by corporate insiders scaled by market value of equity in thousands in the previous quarter. (Thomson/Refinitiv Insiders Data, Compustat)
InsiderSales	Dollar value of company shares sold by corporate insiders scaled by market value of equity in thousands in the previous quarter. (Thomson/Refinitiv Insiders Data, Compustat)
NetTrades	Dollar value of company shares bought by corporate insiders minus those sold by insiders scaled by market value of equity in thousands in the previous quarter. (Thomson/Refinitiv Insiders Data, Compustat)
Unemployment	A county's percent unemployment rate in 2019 (Bureau of Labor Statistics)
Household Income	Natural logarithm of a county's median household income in 2019 (Bureau of Labor Statistics)
Major Customer	A binary indicator that equals one if a firm's major customer is headquartered in the COVID-19 hotspot and zero if otherwise. For a given month, a county is classified as a hotspot if the number of its month-end infection cases is above the county-level median number of infection cases in the U.S. (Compustat's Supplier Chain Linking Suite; USAFacts)

Appendix Table 2
Stay-at-home Order Enforcement Dates by State

This table lists the enforcement dates of the stay-at-home orders in the U.S. states in 2020. NA indicates that a given state did not mandate the stay-at-home order in our sample period.

State	Enforcement Date	State	Enforcement Date
Alabama	2020-04-04	Montana	2020-03-28
Alaska	2020-03-28	Nebraska	NA
Arizona	2020-03-31	Nevada	2020-03-31
Arkansas	NA	New Hampshire	2020-03-28
California	2020-03-19	New Jersey	2020-03-21
Colorado	2020-03-26	New Mexico	2020-03-24
Connecticut	2020-03-23	New York	2020-03-22
Delaware	2020-03-24	North Carolina	2020-03-30
District of Columbia	2020-04-01	North Dakota	NA
Florida	2020-04-03	Ohio	2020-03-24
Georgia	2020-04-03	Oklahoma	2020-04-01
Hawaii	2020-03-25	Oregon	2020-03-23
Idaho	2020-03-25	Pennsylvania	2020-04-01
Illinois	2020-03-21	Rhode Island	2020-03-28
Indiana	2020-03-25	South Carolina	2020-04-07
Iowa	NA	South Dakota	NA
Kansas	2020-03-30	Tennessee	2020-04-02
Kentucky	2020-03-26	Texas	2020-04-02
Louisiana	2020-03-23	Utah	2020-03-27
Maine	2020-04-02	Vermont	2020-03-24
Maryland	2020-03-30	Virginia	2020-03-30
Massachusetts	2020-03-24	Washington	2020-03-23
Michigan	2020-03-24	West Virginia	2020-03-24
Minnesota	2020-03-28	Wisconsin	2020-03-25
Mississippi	2020-04-03	Wyoming	2020-03-28
Missouri	2020-04-06		

Internet Appendix

to Accompany

Work from Home, Managerial Sentiment, and Corporate Liquidity Management under COVID-19

Online Appendix OA1
Analyzing Communication-Related Online Employee Reviews using the Latent Dirichlet Allocation (LDA) Algorithm

This section describes technical details on how we construct our communication-related variables based on online employee reviews of companies in Glassdoor.com between 2019 and the first quarter of 2021.

The LDA topic modeling algorithm, developed by Blei, Ng, and Jordan (2003), is one of the prominent latent topic models and has been applied in several contexts, including financial economics (Bandiera et al. 2020). LDA employs the hierarchical Bayesian analysis to uncover the semantic structure of textual documents, assuming each document represents combinations of latent topics. We apply the LDA algorithm to analyze a collection of Glassdoor's free text online employee reviews. To remove the unnecessary noise caused by uninformative reviews, we manually collect a maximum of 50 top-rated employee reviews for each of our sample firms using a fuzzy-match process. We then match Glassdoor company names with Compustat names of our sample firms for accuracy and obtain 61,512 reviews. By treating free-text responses in *Pros* and *Cons* sections of Glassdoor separately, we end up with 123,024 employee reviews over two years.[40]

The LDA algorithm involves two steps. In the first step, a researcher needs to decide on the number of topics N based on the corpus of employee reviews. To minimize subjectivity when choosing the number of topics, we employ a topic coherence score matrix of the LDA model computed for every given number of topics with the number ranging from 3 to 20 (i.e., 18 topic coherence score matrices in total). The topic coherence score matrix indicates how well the LDA model fits the data for the particular number of topics. Based on these score matrices, we set N equal to nine for the goodness of fit. Next, for each r employee review, one chooses the topic distribution $\theta \sim \text{Dirichlet}(\alpha)$. For each w_M word, one picks a topic $z \sim$ Multinomial(θ) and a word $w_m \sim \text{Multinomial}(\beta_z)$, where each topic has a different parameter vector β for the words. Using a corpus of documents (i.e., employee reviews) between 2019 and the first quarter of 2021, we estimate the parameters α and β that maximize the likelihood of the observed data (words in reviews),

[40]We employ a two-year period of observations to facilitate the training of the LDA model.

marginalizing over the hidden variables, θ and z. Figure OA1 displays the set of words that appear more often in employee reviews over the two-year sample period. While words such as "people", "management", "employee", and "time" appear the most frequently, the word "communication" is also often mentioned in the employee reviews, confirming the validity of using this keyword in deciding the topic model.

We then apply the trained LDA topic model to a sample of 26,182 online employee reviews posted in the year 2020. The first set of LDA output includes the top keywords and their distributions in each topic. For each topic z, there is a set of vectors $\hat{\beta}_z = [\hat{\beta}_{z,1} \dots \hat{\beta}_{z,W}]'$, where $\hat{\beta}_{z,w}$ is the probability that the word w defines topic z. The second set of LDA output contains the probabilities of each employee review in relation to the nine latent topics. In particular, for each review r, there is a set of vectors $\hat{\theta}_r = [\hat{\theta}_{r,1}, \dots \hat{\theta}_{r,9}]'$, where $\hat{\theta}_r$ is the probability of review r that is in association with topic z, where $z = 1, ..., 9$. Among the nine latent topics, we label topic 5 as the "communication" topic as "communication" appears most frequently in this topic but not in any other topics. Figure OA2 shows the marginal distribution of each topic, denoted by the size of a circle shown on the left-hand-side of the figure, with the right-hand-side listing the frequency of the top 30 keywords for topic 5 (in red color) and in the training sample (in blue color).

To focus on communication-related reviews, we require the probability of a reviewer's *Pros* or *Cons* review (Probability) associated with the communication topic to rank the highest among the nine topics. This filtering leads to 1,067 reviewers from 718 companies in our sample. Due to the bounded nature of these probability variables, we apply a log transformation to these variables as follows:

$$\text{Adjusted Probability Value} = Log\left(\frac{\text{Probability}}{1 - \text{Probability}}\right), \tag{OA1}$$

where the adjusted *Cons* and *Pros* probability values are denoted as *Negative Reviews* and *Positive Reviews*, respectively. *Net Reviews* is equal to the difference between *Positive Reviews* and *Negative Reviews*.

Table OA1
Google Search Terms by Topic

This table lists the top 25 queried terms used in search of the following three Google search topics: coronavirus, lockdown, and recession in the year 2020.

Coronavirus	**Lockdown**	**Recession**
coronavirus cases	coronavirus lockdown	the recession
coronavirus update	lockdown California	what is recession
coronavirus update	California	great recession
coronavirus symptoms	COVID lockdown	what is a recession
thank you coronavirus helpers	lockdown browser	recession 2020
USA coronavirus	US lockdown	recession 2008
coronavirus map	lockdown states	2008
coronavirus tips	states lockdown	US recession
coronavirus news	lockdown news	depression
corona	Italy	coronavirus recession
Florida coronavirus	Michigan lockdown	what is the recession
coronavirus deaths	New York lockdown	recession definition
what is coronavirus	Italy lockdown	economy
coronavirus in us	Florida lockdown	the great recession
coronavirus california	states on lockdown	economy recession
corona virus	lockdown NYC	economic recession
New York coronavirus	USA lockdown	gum recession
New York coronavirus	Illinois lockdown	recession in US
Trump coronavirus	respondus lockdown browser	stocks
coronavirus michigan	lockdown Texas	stock market recession
symptoms of coronavirus	China lockdown	recession stocks
coronavirus Texas	lockdown Los Angeles	stock market
China coronavirus	Ohio lockdown	recession proof
US coronavirus cases	lockdown Ohio	GDP
CDC coronavirus	lock down	last recession

Figure OA1
WordCloud Analysis of Glassdoor's Employee Online Reviews

This figure depicts the wordcloud of the most relevant words in the entire set of employee reviews from Glassdoor from January 2019 to the first quarter of 2021. The font size of the word indicates its frequency in the corpus with a larger size indicating a higher frequency of the word appearing in the reviews.

Figure OA2
LDA Topic Models for Glassdoor's Online Employee Reviews

This figure reports the LDA output of topic models for Glassdoor's employee reviews. The panel on the left-hand-side illustrates the relative importance of the nine latent topics, with each circle area representing the importance of each topic over the entire corpus, and the distance between the centers of circles indicating their degree of similarity. The right-hand-side histogram reports the top 30 most relevant terms in Topic 5, labeled as "communication".