NBER WORKING PAPER SERIES

# DIGITAL RESILIENCE:
# HOW WORK-FROM-HOME FEASIBILITY AFFECTS FIRM PERFORMANCE

John (Jianqiu) Bai
Erik Brynjolfsson
Wang Jin
Sebastian Steffen
Chi Wan

Working Paper 28588
http://www.nber.org/papers/w28588

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2021

Erik Brynjolfsson thanks the Stanford Digital Economy Lab (https://digitaleconomy.stanford.edu/) for financial support for this research. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Digital Resilience: How Work-From-Home Feasibility Affects Firm Performance
John (Jianqiu) Bai, Erik Brynjolfsson, Wang Jin, Sebastian Steffen, and Chi Wan
NBER Working Paper No. 28588
March 2021
JEL No. D23,J21,L0,L25,O0,O33

**ABSTRACT**

Digital technologies may make some tasks, jobs and firms more resilient to unanticipated shocks. We extract data from over 200 million U.S. job postings to construct an index for firms' resilience to the Covid-19 pandemic by assessing the work-from-home (WFH) feasibility of their labor demand. Using a difference-in-differences framework, we find that public firms with high pre-pandemic WFH index values had significantly higher sales, net incomes, and stock returns than their peers during the pandemic. Our results indicate that firms with higher digital resilience, as measured through our pre-pandemic WFH index, performed significantly better in general, and in non-essential industries in particular, where WFH feasibility was necessary to continue operation. The ability to use digital technologies to work remotely also mattered more in non-high-tech industries than in high-tech ones. Lastly, we find evidence that firms with lower pre-pandemic WFH feasibility attempted to catch up to their more resilient competitors via greater software investment. This is consistent with a complementarity between digital technologies and WFH practices. Our study's results are robust to a variety of empirical specifications and provide a first look at how WFH practices improved resilience to a major, unanticipated social and economic shock.

John (Jianqiu) Bai
D’Amore-McKim School of Business
Northeastern University
j.bai@northeastern.edu

Erik Brynjolfsson
Stanford Digital Economy Laboratory
366 Galvez Street, Room 238
Stanford, CA 94305
and NBER
erik.brynjolfsson@gmail.com

Wang Jin
245 First Street, Room E94
MIT Initiative on the Digital Economy
Cambridge, MA 02142
jwangjin@mit.edu

Sebastian Steffen
Massachusetts Institute of Technology
ssteffen@mit.edu

Chi Wan
College of Management
University of Massachusetts
Boston, MA 02125
United States
chi.wan@umb.edu

# Digital Resilience: How Work-From-Home Feasibility Affects Firm Performance

*By* John (Jianqiu) Bai, Erik Brynjolfsson, Wang Jin, Sebastian Steffen, and Chi Wan*

*Digital technologies may make some tasks, jobs and firms more resilient to unanticipated shocks. We extract data from over 200 million U.S. job postings to construct an index for firms' resilience to the Covid-19 pandemic by assessing the work-from-home (WFH) feasibility of their labor demand. Using a difference-in-differences framework, we find that public firms with high pre-pandemic WFH index values had significantly higher sales, net incomes, and stock returns than their peers during the pandemic. Our results indicate that firms with higher digital resilience, as measured through our pre-pandemic WFH index, performed significantly better in general, and in non-essential industries in particular, where WFH feasibility was necessary to continue operation. The ability to use digital technologies to work remotely also mattered more in non-high-tech industries than in high-tech ones. Lastly, we find evidence that firms with lower pre-pandemic WFH feasibility attempted to catch up to their more resilient competitors via greater software investment. This is consistent with a complementarity between digital technologies and WFH practices. Our study's results are robust to a variety of empirical specifications and provide a first look at how WFH practices improved resilience to a major, unanticipated social and economic shock.*

*Keywords: Digital Resilience, Work-From-Home, IT Complementarity, Firm Performance, Covid-19*

"We are finding we can reorganize our companies electronically very rapidly and that's the only type of organization that can begin to keep pace with the changing business conditions."

- Steve Jobs, 1990

As digital technologies proliferate, work-from-home (WFH), sometimes referred to as telework, telecommuting, or remote work, has become an increasingly com-

* Bai: D'Amore-McKim School of Business (Northeastern University), Boston, MA 02115, j.bai@northeastern.edu. Brynjolfsson: Digital Economy Lab (Stanford University), Stanford, CA 94305, and NBER, Cambridge, MA 02138 erikb@stanford.edu. Jin: MIT Sloan School of Management, Cambridge, MA 02142, jwangjin@mit.edu. Steffen: MIT Sloan School of Management, Cambridge, MA 02142, ssteffen@mit.edu. Wan: College of Management (University of Massachusetts Boston) Boston, MA 02125, chi.wan@umb.edu.

mon practice and constitutes an important dimension in the future of work.[1] A recent survey by Gallup estimated that more than 43% of workers reported working remotely at least once a week in 2017, and this number rose sharply during April and May of 2020 (Erik Brynjolfsson, John J Horton, Adam Ozimek, Daniel Rock, Garima Sharma and Hong TuYe, 2020) and is expected to increase significantly in the coming decades.[2] While the unanticipated coronavirus outbreak highlights the importance of work flexibility and has forced many firms to shift to WFH practices as the new work norm, firms varied greatly in their adoption of WFH practices before the onset of the outbreak. In this paper, we study the impact of pre-Covid-19 WFH feasibility, as a measure of firms' resilience to the Covid-19 pandemic, on firms' performance and investments.

The Covid-19 pandemic, caused by the SARS-CoV-2 virus, is an ongoing outbreak. As of December 2020, the pandemic has infected more than 66.3 million people and claimed over 1.52 million lives worldwide.[3] In the United States, the pandemic has resulted in significant disruptions to social and economic activities, as lockdowns forced non-essential businesses to close and individuals to stay home.[4]

The limited number of studies regarding WFH adoption on firm performance have found a small, but positive effect (Brittany Harker Martin and Rhiannon MacDonnell, 2012; Nicholas Bloom, James Liang, John Roberts and Zhichun Jenny Ying, 2015) and as well as a contingency on complementary HR practices (Angel Martínez Sánchez, Manuela Pérez Pérez, Pilar de Luis Carnicer and Maria José Vela Jiménez, 2007; Angel Martínez-Sánchez, Manuela Pérez-Pérez, María José Vela-Jiménez and Pilar De-Luis-Carnicer, 2008).

In many cases, the implementation of WFH practices can enable firms to continue operation during the pandemic. However, some jobs cannot feasibly be shifted to work from home, rendering some firms less resilient and potentially unable to operate at all. Thus, while virtually all firms were incentivized to shift to WFH practices through the pandemic, it was more feasible for some to do so than others. The WFH feasibility of pre-pandemic hiring therefore serves as an exogenous shifter of the impact of the pandemic.

In addition, government-issued stay-at-home orders also forced many firms to reduce basic operations and others to cease operations entirely. This especially affected non-essential industries, leading to substantial, and potentially permanent, loss of sales, customers, and profits. Even where firms were allowed to continue their operations, the risk of Covid-19 often significantly reduced the efficiency of on-premise employees and operations compared to WFH employees. Thus, all else

[1] See U.S. Census report: https://www.census.gov/library/visualizations/2013/comm/home_based_workers.html.

[2] https://www.nytimes.com/2017/02/15/us/remote-workers-work-from-home.html.

[3] https://coronavirus.jhu.edu/map.html.

[4] As of April 4, 2020, most of the U.S. states have instituted some form of stay-at-home executive order. See https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html for details.

equal, the feasibility of shifting employees to WFH practices should have helped firms become more resilient during the pandemic.

To test our hypothesis, we merge the near-universe of U.S. job postings from Burning Glass Technologies (BGT) with a recently developed occupational WFH feasibility indicator by Dingel and Neiman (2020) to construct, for the first time, a firm-level measure of the percentage of its workforce that has the WFH option – a firm-level WFH feasibility index. We then estimate a difference-in-differences (DID) regression model to examine whether and how much a firm's WFH feasibility *prior to* the Covid-19 pandemic influences its financial and stock market performance during this crisis.

Our key finding is that firms with high pre-pandemic WFH feasibility, and thus higher resilience to the pandemic, fared significantly better – with roughly 15% higher net incomes, 4% higher sales, and better stock market performance (measured by stock returns and volatility) compared to firms with lower pre-pandemic WFH indices. In contrast, as a response to the pandemic, firms with lower pre-Covid-19 WFH indices retained a significantly higher percentage of software investment, as they attempt to catch up in IT to facilitate remote work and to continue operation during the pandemic.

We also find that pre-pandemic WFH feasibility is associated with better performance during the pandemic for all firms but especially those in non-essential industries. These are the ones whose operations were more likely to be adversely affected by Covid-19 and the associated government restrictions. In addition, we find that firms in non-essential industries with lower pre-pandemic WFH indices spent a significantly larger share on IT investments, while essential firms, which were legally guided to continue operation did not. Moreover, these results are stronger in non-high-tech industries as high WFH firms in these industries had the largest relative advantages over their competitors. Conversely, in high-tech industries, a higher percentage of firms were already able to support remote work, such that even the low WFH firms in high-tech industries did not fare much worse than their high WFH peers. Our findings provide further evidence that WFH practices and complementary digital technologies were critical to continue operation Rahul De', Neena Pandey and Abhipsa Pal (2020), especially for those non-essential businesses that were forced to adjust. These results are robust to empirical specifications that control for a host of firm-level characteristics and fixed effects.

Our identifying assumption for causal estimates is that firm's pre-pandemic WFH index is orthogonal to the timing of the Covid-19 pandemic. In other words, firms were unable to anticipate the pandemic and were unable to fully prepare for it by hiring for more WFH feasible jobs or preemptively altering their business operation in the short-term (Cosmin Ilut, Matthias Kehrig and Martin Schneider, 2018). We believe this to be a reasonable assumption, given the unanticipated nature of the public health crisis as well as the delayed governmental and state responses.

Our study contributes to two strands of literature. By studying the determinants of firm resilience during the Covid-19 pandemic, our paper joins a recent body of research that examines contributing factors to firms' differential performance during the crisis episodes. Rui Albuquerque, Yrjo Koskinen, Shuai Yang and Chendi Zhang (2020) and Karl V Lins, Henri Servaes and Ane Tamayo (2017) find that firms with high environmental and social ratings tend to perform better during the Covid-19 pandemic and the 2007-2008 financial crisis, respectively. Other studies find evidence that firms with access to liquidity (Viral V Acharya and Sascha Steffen, 2020), high cash holdings (Stefano Ramelli and Alexander F Wagner, 2020), or a strong balance sheet (Wenzhi Ding, Ross Levine, Chen Lin and Wensi Xie, 2020) tend to perform better in the first quarter of 2020. During crises, firms also tend to accelerate the restructuring of their production towards routine-biased technologies and their complementary workers (Brad Hershbein and Lisa B. Kahn, 2018). Our study expands the understanding of the determinants of firm resilience during a crisis period by taking a more labor-oriented focus. Specifically, our evidence suggests that digitally-enabled flexible work arrangements such as WFH can significantly reduce operational disruptions that firms experience in difficult times and help with their resurgence in the aftermath of the crisis.[5]

Second, our study contributes to the recent literature that studies the shift of workplace norms towards more flexible work settings, such as working from home. In particular, Brynjolfsson et al. (2020) survey a nationally-representative sample of the U.S. population. Their results suggest that over 30 percent of workers switched to remote work during the pandemic and also report that the switch to WFH can be predicted by the incidence of Covid-19. This further supports our use of WFH feasibility as a measure of pandemic resilience. By conditioning on firms' ex ante WFH indices we mitigate endogeneity concerns that may arise from heterogeneity in firms' shift towards WFH practices *during* the pandemic. Thus, by investigating how differences in resilience lead to differential performance during the pandemic, we also provide further evidence for the value created by digitally-enabled WFH practices.

The remainder of the paper proceeds as follows. Section I develops a set of testable hypotheses. Section II discusses the data and summary statistics. We present our empirical findings in Section III and conclude in Section IV.

[5]Several other papers that examine the labor aspects during the Covid-19 crisis include the following: Seth G Benzell, Avinash Collis and Christos Nicolaides (2020) compare the actual closures of commercial locations to their recommendation of what should be closed first, and generate implications for the optimal sequence of re-openings when policymakers revive the economy. Andrew G Atkeson (2020) analyzes the economic consequences of the Covid-19 pandemic and how they correlate with various assumptions about the ratio between the susceptible – infected – and recovered groups in the population. Eliza Forsythe, Lisa B Kahn, Fabian Lange and David Wiczer (2020) and Olivier Coibion, Yuriy Gorodnichenko and Michael Weber (2020) study the labor market implications of the Covid-19 pandemic.

## I. Hypothesis Development

A large body of prior literature explores the effect of WFH or remote work practices on work-related outcomes at the individual-level including higher job satisfaction (Timothy D Golden and John F Veiga, 2005; Timothy D Golden, 2006), prolonged work hours and higher work efficiency (Mary Madden and Sydney Jones, 2008; Bloom et al., 2015), lower worker stress (Ravi S Gajendran and David A Harrison, 2007), and potentially lower turnover (Phyllis Moen, Erin L Kelly and Rachelle Hill, 2011; Eleni T Stavrou, 2005). In contrast, relatively few studies focus on firm and organizational outcomes (Bloom et al. 2015; also see Tammy D Allen, Timothy D Golden and Kristen M Shockley (2015) for a review) possibly because large-scale firm-level data on the adoption of WFH practices is hard to come by. Among limited firm-level studies, the effect of WFH on firm performance is found to be positive (Christine Siegwarth Meyer, Swati Mukerjee and Ann Sestero, 2001), but the magnitude tends to be small (Martin and MacDonnell, 2012) and contingent on complementary human resource management practices (Sánchez et al., 2007; Martínez-Sánchez et al., 2008).

Higher Resilience Through WFH during the Pandemic. — Although the digital technologies that make WFH practices were known and implemented long before 2020, the global pandemic has drastically accelerated their adoption (Brynjolfsson et al., 2020). The pandemic led the government, states, and local authorities to impose strict rules that limited mobility of employees through March and April (through stay-at-home orders). In addition, many workers voluntarily stayed home to minimize the risk of infection. In combination, firms had to aggressively apply digital tools and adjust towards WFH practices. These enabled many firms to continue operation during the pandemic. For instance, digital tools allowed firms' employees to maintain continuous communication with customers and suppliers while working remotely, thereby ensuring a less disrupted operation during the period of a lockdown. Digital tools and the WFH practices they enabled were therefore critical components of firm resilience against the pandemic.

However, the feasibility of remote work was more feasible for some firms and workers than others. While some industries, such as the information-services-providing industries, naturally had higher feasibility for WFH practices, there are still important within-industry differences between firms' adoption of these practices. Firms rely on different production methods, management, levels of automation, or logistics and may thus have workforces that consist of very different occupations with varying degrees of WFH feasibility.

Essential vs. Non-Essential Industries. — Although the aforementioned resilience-improving effect of WFH is dispersed widely across industries, the extent to how much firms benefit from WFH feasibility will be conditional on how much of their operations were disrupted by the pandemic. For instance, stay-at-home orders affected some firms and industries more than others. A natural way to think about the level of constraints that the government order has put on different industries is through the definition of *essential industries*. If an industry was deemed essential, such as the food retail or health care industries, it was allowed to continue operation on premise during the pandemic. Thus, firms in these industries are less likely to depend on the WFH feasibility of their employees. In contrast, many firms in *non-essential industries* were forced to cease or modify their operation due to the risk of Covid-19. Therefore, firms' feasibility to have their workers work remotely becomes crucial in these industries. Digital resilience, as measured by ability to work remotely, is likely to be a greater determinant of success or even survival during the pandemic in non-essential compared to essential industries.

WFH and Complementary IT Investment. — Digital technologies create the potential for increased resilience in firms' work arrangements. As early as the 1980s, Mancur Olson (1982) pointed out that the prospect of telecommuting work originated from the advancement of information and communication technology (ICT). Further development on storage, communication, and other transformational technologies in IT unleashed the power of storage, transmission, and sharing of knowledge and information across time and space, facilitated coordination among geographically dispersed workers, and significantly transformed workplace practices (Paul M Leonardi and Diane E Bailey, 2008). With the rise of the digital economy (Erik Brynjolfsson and Andrew McAfee, 2014), a significantly higher percentage of jobs became suitable for WFH or remote work (Joseph Migga Kizza, 2017). Meanwhile, complementary ICT investment on both infrastructure and software (e.g. high-speed internet and Zoom) were on the rise despite the drastically falling unit cost, corroborated with the argument that IT enables WFH. Such evidence has been found in both case studies (Michael Collins, 2005) and large-scale research (Gerald S Oettinger, 2011). As pandemic forced firms to adopt WFH (Brynjolfsson et al., 2020), the laggards (those firms with low pre-pandemic WFH feasibility) might suffer from a lack of proper ICT infrastructure and/or software to support such change in operation and hence are likely to (sustain or increase) investment in ICT during the pandemic.

## II. Variable Construction and Summary Statistics

### A. Data

WFH Index. — To construct a firm-level WFH index, we proceed in several steps: First, we obtain detailed job postings data from Burning Glass Technologies (BGT) - a high-quality data source with comprehensive coverage of job posting portals beginning in 2010 and with increasing popularity in recent economic research (Hershbein and Kahn, 2018; David Deming and Lisa B Kahn, 2018; José Azar, Ioana Marinescu, Marshall Steinbaum and Bledi Taska, 2020; Subhro Das, Sebastian Steffen, Wyatt Clarke, Prabhat Reddy, Erik Brynjolfsson and Martin Fleming, 2020; Daron Acemoglu, David Autor, Jonathon Hazell and Pascual Restrepo, 2020).[6] BGT annotates each job posting with an occupational title (6-digit SOC code), industry code, employer information, job posting date, and more. We aggregate this data to the employer-SOC (6-digit) level to obtain a measure of how many job postings the employer posts in each month, quarter, and year for each SOC occupation.

Second, we merge this data with the WFH feasibility data from Jonathan Dingel and Brent Neiman (2020). They provide a binary index at the 8-digit Occupational Information Network (O*NET) code level,[7] as well as a continuous, aggregated index at the 6-digit Standard Occupational Classification (SOC) level, which takes employment shares into account.[8]

Finally, we take the weighted average over each firm's occupational WFH indices, weighted by its number of job postings for each occupation. This procedure enables us to construct, for each firm, the percentage of its labor demand that has WFH feasibility. Ideally, one would like to have such a measure constructed over all existing employees, which would capture the actual prevalence of WFH feasibility within an organization. Since such data is not available, we take the next best alternative and use the average value of each firm's quarterly WFH index over the 2010-2019 period.

Notably, our measure is a forward-looking demand measure and we do not observe whether firms manage to fill these positions. In principle, it could bias our results if employers (job seekers) were able to anticipate the pandemic and adjust the job postings (offers) and hire (accept) towards occupations with higher WFH feasibility. However, due to the unanticipated nature of the pandemic, this seems highly unlikely. In fact, while we observed significant changes in average quarterly WFH indices during the pandemic (relative to the average indices in the first quarter of 2019), there are *no* significant differences among the quarters prior to the pandemic in 2019 regardless of whether firms had high or low pre-pandemic WFH indices as can be seen in Figure 1.

A more serious concern might be that we do not observe the large number of

[6]BGT provides partial coverage for 2007, but does not provide any coverage of job postings in 2008 or 2009. We therefore use BGT data starting from 2010.

[7]O*Net is a free online database that contains hundreds of occupational definitions to help students, job seekers, businesses and workforce development professionals to understand today's world of work in the United States. It was developed under the sponsorship of the US Department of Labor/Employment and Training Administration (USDOL/ETA) through a grant to the North Carolina Employment Security Commission (now part of the NC Commerce Department) during the 1990s.

[8]Technically, their measure is at the 6-digit SOC hybrid level defined by the Bureau of Labor Statistics for the Occupational Employment Survey (OES). The BLS implemented this slightly altered taxonomy as an interim solution between the switch from the 2010 SOC system to the 2018 SOC system, which will be fully used for the 2020 OES. The BGT data uses the 6-digit 2010 SOC system, for which a crosswalk to the 6-digit hybrid system is readily available on the BLS website: `https://www.bls.gov/oes/soc_2018.htm`.

layoffs and furloughs during the pandemic. Again, for our main question in which we are interested in the effect of pre-pandemic WFH feasibility (firm resilience), this is not a concern.[9] Therefore, in the subsequent sections, high WFH index always refers to a high *pre-pandemic* WFH index, unless otherwise specified.

Accounting Fundamentals and Stock Return Data. — We obtain quarterly accounting information from 2019 Q1 to 2020 Q3 from Compustat and stock return data from the Center for Research in Security Prices (CRSP). This data provides us key outcome and explanatory variables including sales, net income, capital expenditures, stock returns, and total assets.

Merging Data from Compustat and Burning Glass Technologies. — Since Compustat and BGT do not share a common firm identifier, we take a multi-step approach to merge the two databases. Specifically, we use a combination of name and address fuzzy matching to construct a bridge between Compustat and BGT data. We use several methods including Soundex and Levenshtein distance to ensure match quality.

In some cases, an employer name in the BGT data is a subsidiary of a Compustat firm but its name is distinct from its parent, thus the existing algorithm cannot recognize their connection. To resolve this problem, we follow M. Campello, J. Gao and Q. Xu (2019) and match the remaining employers to the subsidiaries of Compustat firms using information extracted from historical Orbis data provided by Bureau van Dijk (BvD). Orbis traces the evolution of firms' organizational structure through time, maintaining the parent-subsidiary correspondence. This historical information is robust to subsidiary opening, closing, and ownership changes, which is crucial for accurate matching.[10] We manually check the links identified to ensure the accuracy of our matching.

### B. *Summary Statistics*

Following the procedure in section II.A, we are able to match over 3,800 unique firms in Compustat. For instances where a Compustat firm has multiple sub-

[9]However, this does matter for studying how firms dynamically adjust their hiring during the pandemic. Firms with low pre-pandemic WFH indices, particularly in non-essential industries, likely had stronger pressure to fire workers in occupations that were not WFH feasible or hire more workers in occupations that permit remote work to continue operation. Many firms were forced to alter their business operations entirely towards higher work-from-home feasibility as can be seen in schools or management consulting. Since we do not observe the number of layoffs or reductions in hours, our WFH index during the pandemic is a noisy signal of resilience. A decline in a firm's WFH index during the pandemic may even be a sign of recovery as the firm begins to rehire previously fired workers in non-WFH occupations. Indeed, we do observe these trends and further analyze the recovery dynamics in a parallel study. Despite the potential endogeneity of the WFH indices *during the pandemic*, the *pre-pandemic* WFH indices are still an exogenous shifter of firms' pandemic performance, because the pandemic was unanticipated and significant change in WFH feasibility for large public firms through hiring is highly unlikely in the short-term (Ilut, Kehrig and Schneider, 2018).

[10]We refer interested readers to Campello, Gao and Xu (2019) for a more detailed description of this part of the matching exercise.

sidiaries, our firm-level WFH index uses a weighted average of all the subsidiaries' WFH indices, where the weight is each subsidiary's number of job postings. After the cleaning process,[11] our final analytical sample includes 9,550 observations corresponding to 2,176 unique public firms. The average WFH index by sectors based on firms in our sample is presented in Figure 2. Information, finance, education, and professional services are among the sectors with the highest WFH indices while retail, health care, and accommodation sectors have the lowest average WFH indices for both 2019 and 2020, consistent with the general presumption.

Table 1 Panel A shows that the mean value of the WFH index is 0.575 with a standard deviation of 0.286, which indicates a sizeable amount of variation in the cross section. Panel B further breaks down the key variables into pre- and post-Covid-19 periods and contrasts their values between subsamples of firms in the top quarter pre-Covid-19 WFH index (HighWFH=1) and the rest (HighWFH=0). We observe a differential impact of Covid-19 on high- and low-WFH firms. For instance, while the two groups of firms have similar average quarterly stock returns before the pandemic (7.0% vs. 6.9%), the high-WFH firms experience a relatively higher cumulative return during the period after the breakout of the disease than low-WFH firms (4.3% vs. -1.5%). Similarly, while the average net income of high-WFH firms increased modestly from $281.7 million in 2019 to $316.8 million in 2020, the measure for low-WFH firms has only increased from $199.3 million to $212.5 million over the same period. This indicates a significantly higher growth of net income (12.5% vs. 6.6%) between the high-WFH firms and the rest of the firms during the same period. Although large in magnitude, these differences in means could be driven by the distribution of WFH indices within and/or across industry and therefore demand multivariate analyses, which we turn to in the next section.

## III. Empirical Methodology & Results

### *A. Empirical Methodology*

To test our hypothesis, we employ a difference-in-differences (DID) research design. Specifically, we estimate the following multi-variate fixed effects regression:

$$Y_{it} = \beta(\text{HighWFH}_i \times \text{Covid-19}_t) + \gamma X_{i,t-1} + \upsilon_i + \tau_t + \epsilon_{i,t} \tag{1}$$

where subscript $i$ and $t$ index firm and time (i.e., quarter), respectively.[12] $Y_{it}$ specifies the firm-level outcome variables for both financial and stock market performance. In particular, we examine sales, net income, total capital investment,

[11] We require all observations to have non-missing information for key variables for our empirical exercise and hence have less unique firms in our analytic sample than in the matched sample.

[12] In particular, by including firm and time fixed effects, we already control for individual firms' indicators for belonging to the top WFH quartile ($HighWFH_i$) as well as for the indicators for time periods during the pandemic ($Covid_t$).

software capital investment, stock returns, and return volatility. $HighWFH_i$ is an indicator variable, which takes the value of one if firm $i$'s average WFH index calculated based on its annual job posting data during the pre-Covid-19 period (2010-2019) falls into the top quartile of the sample distribution and zero otherwise. $Covid-19_t$ is an indicator variable that is set equal to one for 2020 Q1-Q3 and zero otherwise. The parameter of interest is $\beta$, which captures the differential impact of Covid-19 on firms with high versus the rest of the firms (with lower pre-pandemic WFH indices). X is an array of time-varying firm-level controls including firm size (total asset), cash holdings, leverage ratio, R&D indicator, and the dividend payout indicator. $\upsilon_i$ specifies firm-fixed effects, which controls for time-invariant firm-level characteristics. $\tau_t$ specifies the time-fixed effects. Note that the inclusion of both firm-fixed effects and time-fixed effects absorbs the main effect of *HighWFH* and *Covid-19*. Throughout our empirical analyses, robust standard errors are clustered at the firm level.[13]

### *B. Empirical Results*

In this section, we present regression results on the impact of pre-Covid-19 WFH on firm performance through the first three quarters of 2020. We focus our attention primarily on firms' financial and stock market outcomes.

Financial Performance. — We first investigate whether WFH drives better financial performance during the first three quarters of 2020 (Table 2). After controlling for time and firm fixed effects as well as time-varying firm-level characteristics such as firm size, cash holdings, leverage ratio, and R&D, firms that had high WFH indices prior to the Covid-19 pandemic earned 15.5% higher net income and 3.8% higher sales relative to their low-WFH peers (Columns 1 and 2, respectively) during the pandemic - both coefficients are significant at the 1% level. Interestingly, these firms also retained a higher level of overall capital investment but allocated a smaller share towards software capital investment. The finding that high-WFH firms had a lower software capital investment rate than their low-WFH peers during the pandemic shows that IT investments are complementary to WFH practices. Firms with lower pre-Covid-19 WFH indices had to retain IT investment as well as shift hiring towards more WFH feasible jobs to continue their operation, while firms with high pre-Covid-19 WFH indices already happened to have these very valuable elements in place before the unprecedented pandemic.[14]

[13]In an alternative specification, we augment the time-fixed effect with state-quarter fixed effects, which is motivated by the recent findings in Brynjolfsson et al. (2020) that the Covid-19-induced switch to WFH is highly correlated with the incidence of the pandemic in each state. Our baseline results are fully retained after controlling for the interactions of time and state (based on firm headquarters) fixed effects.

[14]Note that there is a significant percentage of firms that reported missing capital investment on software in Compustat. We treat them as zeroes in the main analysis. However, our results are robust

Stock Market Performance. — Using a similar regression framework, we examine whether firms' stock market performance during the Covid-19 pandemic is correlated with their ex ante WFH feasibility. In March 2020, the Covid-19 pandemic and the oil price war between Russia and the Organization of the Petroleum Exporting Countries (OPEC) resulted in the most significant stock market crash in the last decade. In particular, between February 12, 2020 and March 23, 2020, all three major stock indices (i.e., the Dow Jones Industrial Average, the NASDAQ Composite, and S&P 500 Index) experienced larger than 20% declines.

Since reaching a bottom in March 2020, all three stock indices have not only rebounded, but have reached new heights by November 2020. This is due to a variety of reasons ranging from expectations of an effective vaccine, unprecedented liquidity injections by the Federal Reserve, to historic stimulus packages passed by Congress. At a micro-level, firms that were well-known to have high WFH feasibility (e.g. mainly firms in the Information sector) or that specialized in WFH-complementary technologies (e.g. Zoom and DocuSign) significantly outperformed the traditional firms.

We examine specifically firm-level WFH feasibility on outcome variables such as stock returns and volatility, and report the results in Table 3. We find that, compared to low-WFH firms, firms with high levels of WFH prior to the Covid-19-induced shutdown had significantly higher returns and abnormal returns, and meanwhile, lower volatility and idiosyncratic volatility.[15] Concretely, our estimates in Column 2 of Table 3 suggest that, ceteris paribus, firms in the top pre-pandemic WFH quartile (i.e., *HighWFH=1*) earned a 4.3% higher abnormal return than other firms during the pandemic. These results together suggest that high values of pre-pandemic WFH, as a proxy of firms' resilience to the pandemic, caused firms to perform significantly better.

Robustness Tests. — We conduct several robustness checks to address additional concerns and obtain similar results as in the main findings. First, we examine the effect of WFH feasibility before the Covid-19 pandemic to explore the existence of pre-trends. That is, the identified performance effect of high pre-Covid-19 WHF should only be evident in the first quarter of 2020 and not in the quarters preceding the pandemic (as merely a continuation of a potential pre-trend). To address this concern, we examine the timing of the treatment effects and report our results in Figure B1 Panels A and B. The specifications mirror our baseline models. The only modification is that we explore the differences between firms with high vs. lower pre-Covid-19 WFH indices by quarter. These figures show that firms with high pre-Covid-19 WFH indices had either similar or

and consistent using only firms with a history of reporting their capital investment in software. Results are available upon request.

[15]Return volatility and idiosyncratic volatility are calculated as the standard deviation of daily returns over a quarter and that of residuals obtained from fitting a CAPM using daily returns in a quarter. Our construction of idiosyncratic volatility is in line with Andrew Ang, Robert J Hodrick, Yuhang Xing and Xiaoyan Zhang (2006). Table 1 Panel A details the variable definitions.

somewhat worse performance prior to the pandemic with a sharp turning point between 2019 Q4 and 2020 Q1, which coincides with the timing of the pandemic and thus confirms the non-existence of pre-trends.

Second, our identification strategy exploits the fact that the pandemic was unanticipated and that some firms happened to be more resilient than their peers due to their pre-Covid hiring. There is still a possibility that performance differences during the pandemic are driven by other, unobserved firm-level characteristics that our resilience measure does not capture. We thus perform both propensity score matching and coarsened exact matching to construct samples that consist of similar firms (using pre-pandemic observables) with high and low WFH indices. More specifically, we matched the firms using return on asset and size prior to the pandemic within 2-digit NAICS level industries based on each outcome variable.[16] Within this matched subsample, we find consistent and robust results that are similar to our main findings.[17]

Lastly, we consider an alternative WFH proxy (WFH index) by using a continuous WFH index instead of an indicator as our key explanatory variable. We also test an alternative specification augmenting the time fixed effect with state-quarter fixed effects in Appendix E.

In all aforementioned robustness tests, we find that our baseline results are fully retained. These results can be found in the appendix.

### *C. Industry Heterogeneity*

So far, we reported the average effects of high WFH feasibility on firm performance using the entire analytic sample. In this section we explore specific groups of industries in more detail.

Essential vs. Non-Essential Industries. — In Table A1, we break down our sample and separately examine the impact of WFH in essential and non-essential industries based on 4-digit NAICS codes as in Dimitris Papanikolaou and Lawrence D W Schmidt (2020)).[18] We find that high WFH firms in non-essential industries had 18.3% and 5.9% higher sales and net incomes, respectively, than their peers with lower pre-Covid-19 WFH indices. In contrast, for firms in essential industries, these differentials are generally smaller and sometimes noisy. Meanwhile, we find more salient differences in results for stock market performance between the essential and non-essential industries. While high WFH firms in the non-essential industries seem to enjoy significantly higher returns and lower

[16]We match the treatment and control groups through propensity score matching using the nearest neighbor method imposing common support with 3 neighbors and 0.001 caliper.

[17]In order to rule out the possibility that our WFH indices are picking up random effects, we also perform a placebo test by constructing an alternative index using the rank of firms by firms' name in alphabetical order. The results are reported in Appendix G.

[18]For more details on the definition of the essential and non-essential industries (at 4-digit NAICS level), please see Papanikolaou and Schmidt (2020)

volatility than their peers, the effect of high WFH feasibility is more moderate in essential industries. This is consistent with the argument that pre-pandemic WFH suitability within non-essential industries played a crucial role for firms resilience and their ability to effectively continue their operation. In addition, our results indicate that the significant differences in capital investments on software primarily load on firms in non-essential industries where the continuation of operation hinges on such investments more strongly. This finding further corroborates the notion of complementarity between work-from-home practices and IT.[19]

High-Tech vs. Non-High-Tech. — We follow Ryan A Decker, John Haltiwanger, Ron S Jarmin and Javier Miranda (2017) to separate our sample into high-tech and non-high-tech industries and re-estimate our main regressions separately in these subsamples.[20] Conventional wisdom suggests that firms in high-tech industries are more able to adopt WFH due to the nature of their work, while firms in other industries generally do not have such flexibility. The results of this exercise are presented in Table A2.

Panels A and B of Table A2 present the financial performance results for the high-tech and non-high-tech industries, respectively. Overall, we find that our results are consistently smaller and mostly insignificant in the high-tech industries, but are more pronounced in the non-high-tech industries. Panels C and D display a similar pattern for firms' stock market performance. While these results may appear somewhat surprising at first glance, they are consistent with the notion in (Erik Brynjolfsson and Paul Milgrom, 2012): once WFH practices are adopted, which is likely the case in the high-tech industry,[21] further improving WFH adoption may not be feasible or may not generate additional comparative advantages in firm performance.

Although we find some industry variation in the effects of the pre-Covid-19 WFH index on firm resilience during the pandemic, we note that our sample is comprised of large public firms that are likely operating in multiple industries simultaneously, which could lead to measurement errors, especially when firms are relatively evenly split among multiple industries.

## IV. Conclusion

The digital tools and workforce capability to work from home have the potential to enable firms to maintain enterprise value despite the challenges of the Covid-

[19]We further explore the heterogeneous effects of the WFH on firm resilience during the Covid-19 pandemic by breaking down our sample by sectors. Using the baseline specification similar to those in Tables 2 and 3, we estimate the marginal effects of the interaction term between the high WFH indicator and the pandemic indicator and plot them in Appendix F Figure F1. We find that the identified effect of WFH loads primarily on manufacturing, finance, insurance and real estate, and service sectors. The definitions of sectors are reported in Appendix H1.

[20]The high-tech industry is defined as in Decker et al. (2017) and can be found in Appendix Table H2.

[21]The mean and median of WFH indices for high-tech industries are 0.71 and 0.78 respectively with a standard error of 0.25 while the mean and median of WFH indices for other industries are 0.55 and 0.56 with a larger standard error of 0.29.

19 pandemic. Firms with greater WFH opportunities can provide more safety for their workers, and thereby increase the resilience of the firm's operations. However, large-scale evidence on the actual effectiveness of WFH practices, is scarce.

In this paper, we exploit the near-universe of U.S. job postings from the BGT database to construct a novel firm-level WFH index to give us insight into the resilience this capability creates. We find that firms with high pre-pandemic WFH index values before the unanticipated crisis performed significantly better during the crisis compared to their peers on several dimensions ranging from financial performance, such as sales and net income, to stock returns and return volatility. The magnitude and significance of our results are robust to a range of robustness checks including tests for pre-trends, propensity score and coarsened exact matchings, continuous and dummy measures of WFH index, and the inclusion of state and quarter fixed effects. Moreover, we find evidence that non-essential industries, which were more vulnerable to government mandated restrictions on traditional work arrangements, benefited significantly more compared to essential industries. Non-high-tech industries also benefited more from high pre-Covid-19 WFH feasibility compared to high-tech industries during the pandemic. Our study provides some of the first evidence on how WFH practices helped firms cope with major adverse social and economic shocks and quantifies the magnitudes and significance of such effects within and across industries.

Our results imply that the pandemic further increased within-industry inequality. This is because larger firms (including "digital superstars") tend to be more IT-intensive (e.g. Amazon, Microsoft, Apple, IBM, Google, and Facebook to name a few) and are more likely to be in the high pre-pandemic WFH group. They therefore suffered significantly less than smaller firms. It thus seems likely that the pandemic further exacerbated the rising issue of market concentration.

Further investigation into the exact mechanisms through which WFH practices are linked to performance is a fruitful area for future research. A deep understanding of these underlying issues is particularly valuable to ensure a more efficient and smooth adoption of and transition into WFH as employers and employees alike embrace the new reality in the aftermath of the crisis. Striking the right balance between cost efficiency and supporting the firms and individuals who suffered the most from the pandemic will be critical to ensure a faster and equitable recovery.

## REFERENCES

**Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo.** 2020. "AI and Jobs: Evidence from Online Vacancies." *National Bureau of Economic Research Working Paper Series*, No. 28257.

**Acharya, Viral V, and Sascha Steffen.** 2020. "The Risk of Being a Fallen Angel and the Corporate Dash for Cash in the Midst of COVID." *The Review* *of Corporate Finance Studies*, 9(3): 430–471.

**Albuquerque, Rui, Yrjo Koskinen, Shuai Yang, and Chendi Zhang.** 2020. "Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash." *The Review of Corporate Finance Studies*, 9(3): 593–621.

**Allen, Tammy D, Timothy D Golden, and Kristen M Shockley.** 2015. "How Effective Is Telecommuting? Assessing the Status of Our Scientific Findings." *Psychological Science in the Public Interest*, 16(2): 40–68.

**Ang, Andrew, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang.** 2006. "The Cross-Section of Volatility and Expected Returns." *The Journal of Finance*, 61(1): 259–299.

**Atkeson, Andrew G.** 2020. "What Will be the Economic Impact of COVID-19 in the US? Rough Estimates of Disease Scenarios." *Research Department Staff Reports (Federal Reserve Bank of Minneapolis)*, 1–25.

**Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen.** 2020. "The Fall of the Labor Share and the Rise of Superstar Firms." *The Quarterly Journal of Economics*, 135(2): 645–709.

**Azar, José, Ioana Marinescu, Marshall Steinbaum, and Bledi Taska.** 2020. "Concentration in US labor markets: Evidence from online vacancy data." *Labour Economics*, 66.

**Benzell, Seth G, Avinash Collis, and Christos Nicolaides.** 2020. "Rationing social contact during the COVID-19 pandemic: Transmission risk and social benefits of US locations." *Proceedings of the National Academy of Sciences*, 117(26): 14642 LP – 14644.

**Bloom, Nicholas, James Liang, John Roberts, and Zhichun Jenny Ying.** 2015. "Does Working from Home Work? Evidence from a Chinese Experiment*." *Quarterly Journal of Economics*, 130(1): 165–218.

**Brynjolfsson, Erik, and Andrew McAfee.** 2014. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* WW Norton & Company.

**Brynjolfsson, Erik, and Paul Milgrom.** 2012. "Complementarity in Organizations." In *The Handbook of Organizational Economics.* , ed. ROBERT GIBBONS and JOHN ROBERTS, 11–55. Princeton University Press.

**Brynjolfsson, Erik, John J Horton, Adam Ozimek, Daniel Rock, Garima Sharma, and Hong TuYe.** 2020. "Covid-19 and Remote Work: an Early Look At Us Data." *NBER Working Paper*, , (June 220): 1–30.

**Campello, M., J. Gao, and Q. Xu.** 2019. "Personal Income Taxes and Labor Downskilling: Evidence from 27 Million Job Postings." *Kelley School of Business Research Paper.*

**Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber.** 2020. "Labor Markets During the COVID-19 Crisis: A Preliminary View." *NBER Working Paper 27017.*

**Collins, Michael.** 2005. "The (not so simple) case for teleworking: A study at Lloyd's of London." *New Technology, Work and Employment*, 20(2): 115–132.

**Das, Subhro, Sebastian Steffen, Wyatt Clarke, Prabhat Reddy, Erik Brynjolfsson, and Martin Fleming.** 2020. "Learning Occupational Task-Shares Dynamics for the Future of Work." *AIES '20*, 36–42. New York, NY, USA:Association for Computing Machinery.

**Decker, Ryan A, John Haltiwanger, Ron S Jarmin, and Javier Miranda.** 2017. "Declining Dynamism, Allocative Efficiency, and the Productivity Slowdown." *American Economic Review*, 107(5): 322–326.

**Deming, David, and Lisa B Kahn.** 2018. "Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals." *Journal of Labor Economics*, 36(S1): S337–S369.

**De', Rahul, Neena Pandey, and Abhipsa Pal.** 2020. "Impact of digital surge during Covid-19 pandemic: A viewpoint on research and practice." *International Journal of Information Management*, 55(Impact of COVID-19 Pandemic on Information Management Research and Practice: Editorial Perspectives).

**Dingel, Jonathan, and Brent Neiman.** 2020. "How Many Jobs Can be Done at Home?" *Becker Friedman Institute White Paper*, , (March): 16–24.

**Ding, Wenzhi, Ross Levine, Chen Lin, and Wensi Xie.** 2020. "Corporate Immunity to the COVID-19 Pandemic." *National Bureau of Economic Research.*

**Forsythe, Eliza, Lisa B Kahn, Fabian Lange, and David Wiczer.** 2020. "Labor demand in the time of COVID-19: Evidence from vacancy postings and UI claims." *Journal of public economics*, 189: 104238.

**Gajendran, Ravi S, and David A Harrison.** 2007. "The Good, the Bad, and the Unknown About Telecommuting: Meta-Analysis of Psychological Mediators and Individual Consequences." *Journal of Applied Psychology*, 92(6): 1524–1541.

**Golden, Timothy D.** 2006. "The role of relationships in understanding telecommuter satisfaction." *Journal of Organizational Behavior*, 27(3): 319–340.

**Golden, Timothy D, and John F Veiga.** 2005. "The Impact of Extent of Telecommuting on Job Satisfaction: Resolving Inconsistent Findings." *Journal of Management*, 31(2): 301–318.

**Hershbein, Brad, and Lisa B. Kahn.** 2018. "Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings." *American Economic Review*, 108(7): 1737–1772.

**Ilut, Cosmin, Matthias Kehrig, and Martin Schneider.** 2018. "Slow to Hire, Quick to Fire: Employment Dynamics with Asymmetric Responses to News." *Journal of Political Economy*, 126(5): 2011–2071.

**Kizza, Joseph Migga.** 2017. *Ethical and social issues in the information age. Texts in computer science*, Cham, Switzerland : Springer, 2017.

**Leonardi, Paul M, and Diane E Bailey.** 2008. "Transformational Technologies and the Creation of New Work Practices: Making Implicit Knowledge Explicit in Task-Based Offshoring." *MIS Quarterly*, 32(2): 411–436.

**Lins, Karl V, Henri Servaes, and Ane Tamayo.** 2017. "Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis." *The Journal of Finance*, 72(4): 1785–1824.

**Madden, Mary, and Sydney Jones.** 2008. "Networked Workers (PEW Report)."

**Martin, Brittany Harker, and Rhiannon MacDonnell.** 2012. "Is telework effective for organizations? A meta-analysis of empirical research on perceptions of telework and organizational outcomes." *Management Research Review*, 35(7): 602–616.

**Martínez-Sánchez, Angel, Manuela Pérez-Pérez, María José Vela-Jiménez, and Pilar De-Luis-Carnicer.** 2008. "Telework adoption, change management, and firm performance." *Journal of Organizational Change Management*, 21(1): 7–31.

**Meyer, Christine Siegwarth, Swati Mukerjee, and Ann Sestero.** 2001. "Work-Family Benefits: Which Ones Maximize Profits?" *Journal of Managerial Issues*, 13(1): 28–44.

**Moen, Phyllis, Erin L Kelly, and Rachelle Hill.** 2011. "Does Enhancing Work-Time Control and Flexibility Reduce Turnover? A Naturally Occurring Experiment." *Social Problems*, 58(1): 69–98.

**Oettinger, Gerald S.** 2011. "The Incidence and Wage Consequences of Home-Based Work in the United States, 1980-2000." *Journal of Human Resources*, 46(2): 237–260.

**Olson, Mancur.** 1982. *The Rise and Decline of Nations.* Yale University Press.

**Papanikolaou, Dimitris, and Lawrence D W Schmidt.** 2020. "Working Remotely and the Supply-side Impact of Covid-19." *National Bureau of Economic Research Working Paper Series*, No. 27330.

**Ramelli, Stefano, and Alexander F Wagner.** 2020. "Feverish Stock Price Reactions to Covid-19." *CEPR Working Paper No. DP14511.*

**Sánchez, Angel Martínez, Manuela Pérez Pérez, Pilar de Luis Carnicer, and Maria José Vela Jiménez.** 2007. "Teleworking and workplace flexibility: a study of impact on firm performance." *Personnel Review*, 36(1): 42–64.

**Stavrou, Eleni T.** 2005. "Flexible work bundles and organizational competitiveness: a cross-national study of the European work context." *Journal of Organizational Behavior*, 26(8): 923–947.

## V. Figures and Tables

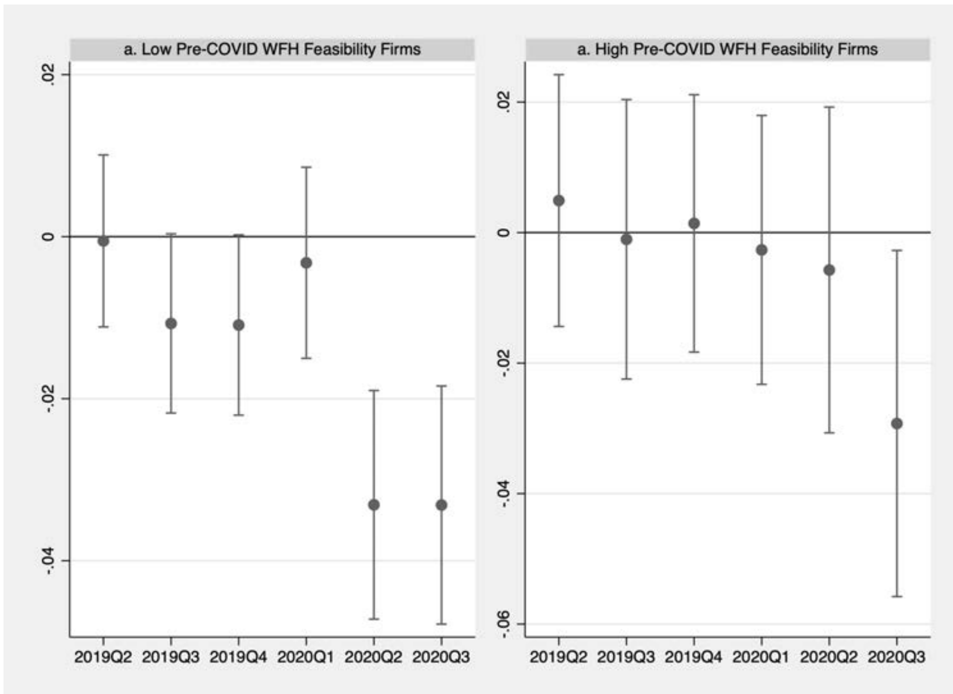



**Figure 1. : Quarterly WFH Index by Firms with High vs. Low Pre-Covid-19 WFH Feasibility**

*Notes:* This figure plots the average quarterly WFH index for firms with high vs. low pre-Covid-19 WFH feasibility index from 2019 Q2 to 2020 Q3. The values in 2019Q1 are used as the baseline group. Reported results are based on the specifications using average quarterly WFH index controlling for time-invariant firm unobservable and other firm controls. The WFH index is calculated based on our analysis sample. The source data comes from the Burning Glass Technologies (BGT) job vacancies data and the occupation level WFH feasibility indicator by Dingel and Neiman (2020).

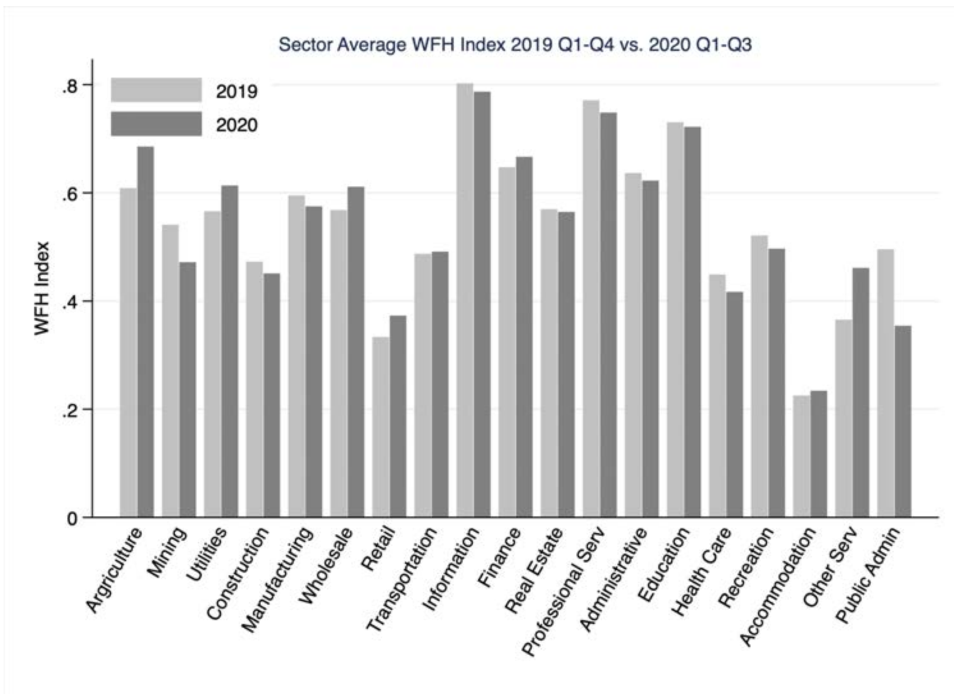



**Figure 2. : Sector Average WFH indices (2019 and 2020)**

*Notes:* This figure plots the average WFH index by sector in both 2019 Q1-Q4 and 2020 Q1-Q3. The average WFH index is calculated based on our analysis sample. The source data comes from the Burning Glass Technologies (BGT) job vacancies data and the occupation level WFH feasibility indicator by Dingel and Neiman (2020).

## Table 1—: Variable Definitions and Summary Statistics

### (A) Full Sample

| Variables | Definition | Mean (SD) |
|---|---|---|
| WFH index | Average pre-Covid-19 WFH feasibility index (based on BGT job postings). | 0.575 (0.286) |
| HighWFH | = 1 if firm's 2010-2019 WFH index is in top quartile of sample distribution (zero otherwise). | 0.250 (-) |
| Net Income | Firms' net income. | 220.5 (912.0) |
| Sales | Firms' total sales. | 2114 (7062) |
| Normalized Cap. Exp. | Firms' capital expenditure divided by total assets. | 0.018 (0.036) |
| Normalized Software Exp. | Firms' capital expenditure on software divided by total assets | 0.002 (0.013) |
| Return | Sum of monthly returns per quarter. | 0.045 (0.238) |
| Abn. Return | Sum of monthly abnormal returns per quarter. Monthly is the difference between excess return and the CAPM beta times market excess return. CAPM beta is estimated using past 36 monthly returns. | -0.018 (0.181) |
| Return Volatility | Standard deviation of daily returns per quarter multiplied by 2 [i.e. $\sqrt{4}$ quarters] to convert to annual basis. | 0.057 (0.045) |
| Idio. Volatility | Standard deviation of the residuals obtained from fitting daily CAPM for every month for each firm and converted to annual basis. | 0.044 (0.030) |
| Total Asset | Logarithm of total assets. | 29,230 (3,285) |

### (B) Key variables in subsamples by pre-Covid-19 WFH Index and Time

| pre-Covid-19 WFH Feasibility | High (HighWFH = 1) | | Low (HighWFH = 0) | |
|---|---|---|---|---|
| Variables | Before Covid-19 | After Covid-19 | Before Covid-19 | After Covid-19 |
| WFH index | 0.887 | 0.874 | 0.503 | 0.504 |
| | (0.114) | (0.143) | (0.268) | (0.259) |
| Net Income | 281.7 | 316.8 | 199.3 | 212.5 |
| | (943.2) | (972.9) | (847.0) | (1001) |
| Sales | 1,913 | 2,305 | 2,083 | 2,217 |
| | (5,958) | (7,465) | (6,970) | (7,571) |
| Normalized Cap. Exp. | 0.014 | 0.009 | 0.021 | 0.013 |
| | (0.024) | (0.014) | (0.046) | (0.019) |
| Normalized Software Exp. | 0.006 | 0.005 | 0.001 | 0.001 |
| | (0.025) | (0.020) | (0.008) | (0.009) |
| Return | 0.070 | 0.043 | 0.069 | -0.015 |
| | (0.189) | (0.331) | (0.166) | (0.326) |
| Abn. Return | -0.0004 | -0.001 | -0.005 | -0.054 |
| | (0.173) | (0.231) | (0.152) | (0.215) |
| Return Volatility | 0.045 | 0.082 | 0.043 | 0.084 |
| | (0.037) | (0.044) | (0.037) | (0.047) |
| Idio. Volatility | 0.037 | 0.058 | 0.036 | 0.060 |
| | (0.027) | (0.033) | (0.026) | (0.030) |
| Total Asset | 42,327 | 58,784 | 22,953 | 28,810 |
| | (235,800) | (294,900) | (136,000) | (175,700) |

*Notes:* Panel A reports variable definitions, data sources, and sample means. The sample period is 2019Q1-2020Q3. Panel B contrasts the means of key variables in pre- and post- Covid-19 subsamples (i.e., 2019 Q1-Q4 and 2020 Q1-Q3, respectively) and in the high and low pre-Covid-19 WFH subsamples. All continuous variables are winsorized at the 1st and 99th percentiles.

## Table 2—: WFH Feasibility and Financial Performance

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Log Net Income | Log Sales | Norm. Cap. Exp. | Norm. Software Exp. |
| HighWFH × COVID | 0.155 | 0.038 | 0.004 | -0.001 |
| | (3.32) | (3.50) | (2.36) | (-2.14) |
| Size | 0.310 | 0.532 | -0.026 | -0.003 |
| | (2.56) | (15.53) | (-1.19) | (-1.98) |
| Cash | -0.659 | -0.379 | -0.001 | -0.002 |
| | (-2.23) | (-4.92) | (-0.08) | (-0.99) |
| Leverage | 0.590 | -0.312 | 0.042 | 0.001 |
| | (2.29) | (-4.74) | (1.52) | (0.49) |
| R&D | 0.449 | 0.059 | -0.011 | -0.001 |
| | (1.76) | (1.43) | (-1.08) | (-0.45) |
| Dividend | -6.209 | -2.318 | 0.111 | 0.010 |
| | (-1.99) | (-2.42) | (1.29) | (1.13) |
| Tobin's q | 0.184 | 0.040 | 0.003 | -0.001 |
| | (5.91) | (5.24) | (2.55) | (-0.76) |
| ROE | 0.038 | 0.013 | 0.007 | -0.000 |
| | (0.45) | (0.63) | (1.65) | (-0.36) |
| Firm FE | Y | Y | Y | Y |
| Quarter FE | Y | Y | Y | Y |
| Observations | 9568 | 9568 | 9568 | 9568 |
| Adj. $R^2$ | 0.886 | 0.996 | 0.521 | 0.844 |

*Notes:* This table implements a difference-in-differences (DID) research design to examine the differential impact of Covid-19 on various performance metrics between firms with high and low WFH feasibility. The dependent variables across columns 1 to 4 are the logarithm of net income, logarithm of sales, total capital expenditure over total asset, and software expenditure over total asset, respectively. The regression model is specified in Equation 1, and all variables are defined in Table 1 Panel A. Omitting Tobin's q and ROE in the specification provide similar results (available upon request). Firm and time fixed effects are also included in the estimation. Standard errors are clustered at the firm level.

**Table 3—: WFH Feasibility and Stock Market Reactions**

| Models<br>Dependent Variable | (1)<br>Return | (2)<br>Abn Return | (3)<br>Volatility | (4)<br>Idio. Volatility |
|---|---|---|---|---|
| HighWFH × COVID | 0.051 | 0.043 | -0.006 | -0.004 |
| | (4.02) | (3.46) | (-3.47) | (-2.88) |
| Size | -0.120 | -0.074 | -0.003 | -0.005 |
| | (-3.87) | (-2.46) | (-0.76) | (-1.97) |
| Cash | 0.180 | 0.112 | -0.005 | -0.002 |
| | (2.27) | (1.58) | (-0.52) | (-0.27) |
| Leverage | 0.105 | 0.031 | 0.022 | 0.018 |
| | (1.54) | (0.46) | (3.03) | (3.72) |
| R&D | 0.013 | -0.058 | 0.058 | 0.014 |
| | (0.08) | (-0.61) | (4.19) | (1.26) |
| Dividend | 0.048 | -0.948 | 0.341 | 0.351 |
| | (0.05) | (-1.04) | (2.66) | (4.22) |
| Tobin's q | -0.110 | -0.091 | 0.002 | 0.001 |
| | (-10.14) | (-9.04) | (1.76) | (1.06) |
| ROE | 0.037 | 0.033 | -0.004 | -0.005 |
| | (1.26) | (1.25) | (-1.24) | (-2.32) |
| Firm FE | Y | Y | Y | Y |
| Quarter FE | Y | Y | Y | Y |
| Observations | 9550 | 9550 | 9550 | 9507 |
| Adj. $R^2$ | 0.449 | 0.147 | 0.713 | 0.750 |

*Notes:* This table implements a difference-in-differences (DID) research design to examine the differential impact of Covid-19 on stock market reactions between firms with high and low WFH feasibility. The dependent variables are total return and abnormal return in Columns (1) and (2); and return volatility and idiosyncratic volatility in Columns (3) and (4), respectively. The regression specification is specified in Equation 1, and all variables are defined in Table 1 Panel A. We further include Tobin's Q and return on equity (ROE) in the regression analysis. Firm and time fixed effects are also included in the estimation. Standard errors are clustered at the firm level.

## Appendix A

### Table A1—: WFH Feasibility and Firm Performance: Essential vs. Non-Essential

#### (A) Essential Industries (Financial performance)

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Log Net Income | Log Sales | Norm. Cap. Exp. | Norm. Software Exp. |
| HighWFH × COVID | 0.158 | 0.022 | 0.002 | -0.000 |
| | (2.27) | (1.24) | (1.72) | (-0.66) |
| Observations | 4336 | 4336 | 4336 | 4336 |
| Adj. $R^2$ | 0.924 | 0.997 | 0.750 | 0.970 |

#### (B) Non-Essential Industries (Financial performance)

| Models | (5) | (6) | (7) | (8) |
|---|---|---|---|---|
| Dependent Variable | Log Net Income | Log Sales | Norm. Cap. Exp. | Norm. Software Exp. |
| HighWFH × COVID | 0.183 | 0.059 | 0.007 | -0.001 |
| | (2.87) | (4.19) | (1.91) | (-1.70) |
| Observations | 5232 | 5232 | 5232 | 5232 |
| Adj. $R^2$ | 0.853 | 0.995 | 0.451 | 0.812 |

#### (C) Essential Industries (Stock market performance)

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Return | Abn Return | Volatility | Idio. Volatility |
| HighWFH × COVID | 0.028 | 0.028 | 0.001 | -0.001 |
| | (1.52) | (1.54) | (0.44) | (-0.51) |
| Observations | 4330 | 4330 | 4330 | 4323 |
| Adj. $R^2$ | 0.444 | 0.175 | 0.682 | 0.703 |

#### (D) Non-Essential Industries (Stock market performance)

| Models | (5) | (6) | (7) | (8) |
|---|---|---|---|---|
| Dependent Variable | Return | Abn Return | Volatility | Idio. Volatility |
| HighWFH × COVID | 0.062 | 0.043 | -0.010 | -0.004 |
| | (3.63) | (2.65) | (-4.65) | (-2.74) |
| Observations | 5220 | 5220 | 5220 | 5184 |
| Adj. $R^2$ | 0.459 | 0.131 | 0.727 | 0.775 |

*Notes:* This table re-assesses the results reported in Tables 2 and 3 in two subsamples: essential vs. non-essential industries. The definitions of essential and non-essential industries are based on (Papanikolaou and Schmidt, 2020) and can be found in Appendix Table H3. Panels A and B report the results using financial performance proxies as the dependent variables. Panels C and D repeat the exercise with return and volatility as the dependent variables. The specifications in these panels are identical to those in Tables 2 and 3. Firm and time fixed effects are also included in the estimation. Standard errors are clustered at the firm level.

**Table A2—: WFH Feasibility and Firm Performance: High-tech vs. Other Industries**

**(A)** High-tech Industries (Financial performance)

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Log Net Income | Log Sales | Norm. Cap. Exp. | Norm. Software Exp. |
| HighWFH × COVID | 0.095 | 0.030 | 0.000 | -0.002 |
| | (1.04) | (1.81) | (0.26) | (-1.34) |
| Observations | 1395 | 1395 | 1395 | 1395 |
| Adj. $R^2$ | 0.917 | 0.997 | 0.717 | 0.801 |

**(B)** Other Industries (Financial performance)

| Models | (5) | (6) | (7) | (8) |
|---|---|---|---|---|
| Dependent Variable | Log Net Income | Log Sales | Norm. Cap. Exp. | Norm. Software Exp. |
| HighWFH × COVID | 0.155 | 0.036 | 0.004 | -0.000 |
| | (2.70) | (2.61) | (2.15) | (-1.30) |
| Observations | 8173 | 8173 | 8173 | 8173 |
| Adj. $R^2$ | 0.878 | 0.996 | 0.517 | 0.892 |

**(C)** High-tech Industries (Stock market performance)

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Return | Abn Return | Volatility | Idio. Volatility |
| HighWFH × COVID | 0.041 | 0.019 | 0.001 | 0.001 |
| | (1.63) | (0.78) | (0.23) | (0.34) |
| Observations | 1395 | 1395 | 1395 | 1395 |
| Adj. $R^2$ | 0.380 | 0.156 | 0.695 | 0.776 |

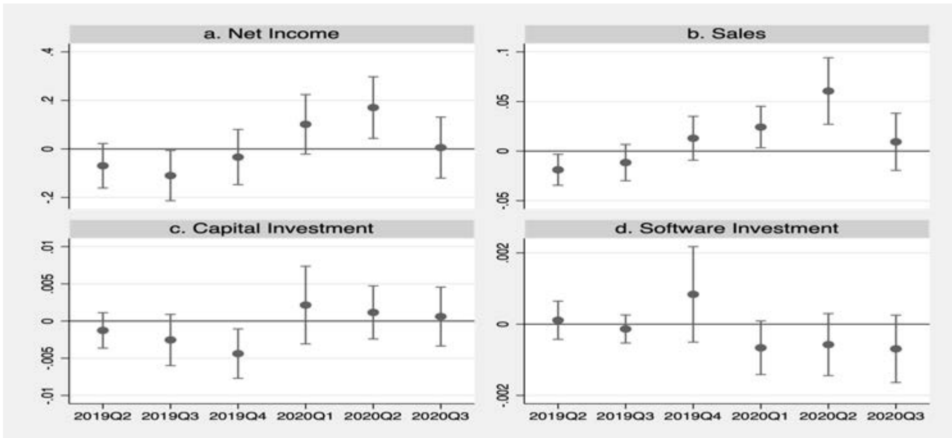
**(D)** Other Industries (Stock market performance)

| Models | (5) | (6) | (7) | (8) |
|---|---|---|---|---|
| Dependent Variable | Return | Abn Return | Volatility | Idio. Volatility |
| HighWFH × COVID | 0.041 | 0.031 | -0.004 | -0.002 |
| | (2.59) | (2.04) | (-1.90) | (-1.23) |
| Observations | 8155 | 8155 | 8155 | 8112 |
| Adj. $R^2$ | 0.469 | 0.151 | 0.722 | 0.750 |

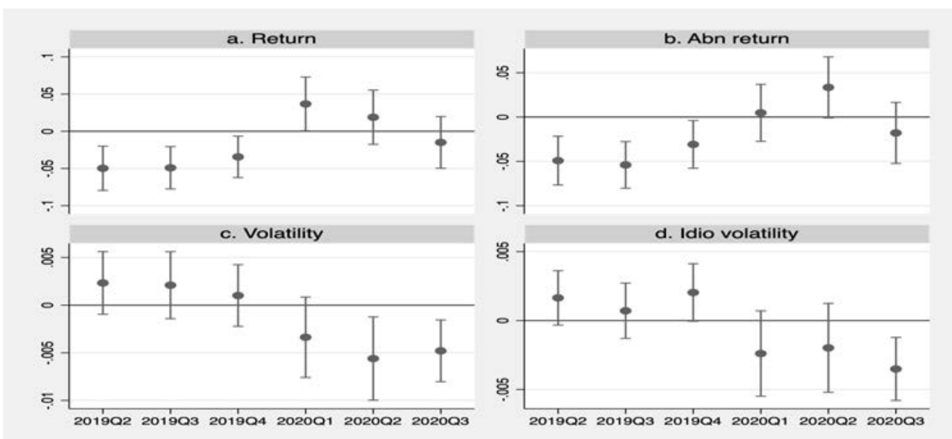
*Notes:* This table re-assesses the results reported in Tables 2 and 3 in two subsamples: high tech vs. other industries. The specifications in these panels are identical to those in Tables 2 and 3. The high-tech industries are defined as in Decker et al. (2017) and can be reviewed in Appendix Table H2. Panels A and B report the results with financial performance proxies as the dependent variables. Panels C and D repeat the exercise with return and volatility as the dependent variables. Firm and time fixed effects are also included in the estimation. Standard errors are clustered at the firm level.

## Appendix B

**Figure B1. : Dynamics of the treatment effect in the DID setting**




**(A)** Dynamics of the treatment effects in the DID setting on stock returns and volatility




**(B)** Dynamics of the treatment effects in the DID setting on financial performance

*Notes:* Panels A and B plot the impact of HighWFH on firm outcome variables (A: financial performance; B: stock returns and volatility) in the period of 2019Q2-2020Q3 with the 90% confidence interval attached. Results are based on specifications similar to the baseline models: we regress each outcome variable on the interaction of HighWFH and the quarter dummy alone with other firm controls. The values in 2019Q1 are used as the baseline for comparison.

## Appendix C

### Table C1—: WFH and firm performance: matched sample analyses

#### (A) Financial performance: matched sample analysis using PSM procedure

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Log Net Income | Log Sales | Norm. Cap. Exp. | Norm. Software Exp. |
| HighWFH × COVID | 0.150 | 0.030 | 0.001 | -0.002 |
| | (2.70) | (2.29) | (0.61) | (-1.46) |
| Observations | 4215 | 3979 | 3439 | 3907 |
| Adj. $R^2$ | 0.896 | 0.996 | 0.763 | 0.849 |

#### (B) Financial performance: matched sample analysis using CEM procedure

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Log Net Income | Log Sales | Norm. Cap. Exp. | Norm. Software Exp. |
| HighWFH × COVID | 0.199 | 0.029 | 0.001 | -0.001 |
| | (3.91) | (2.60) | (1.32) | (-1.72) |
| Observations | 6872 | 6872 | 6872 | 6872 |
| Adj. $R^2$ | 0.888 | 0.996 | 0.766 | 0.823 |

#### (C) Stock market performance: matched sample analysis using PSM procedure

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Return | Abn Return | Volatility | Idio. Volatility |
| HighWFH × COVID | 0.063 | 0.051 | -0.006 | -0.004 |
| | (4.59) | (3.73) | (-2.68) | (-2.47) |
| Observations | 5197 | 5197 | 5279 | 5172 |
| Adj. $R^2$ | 0.447 | 0.132 | 0.702 | 0.739 |

#### (D) Stock market performance: matched sample analysis using CEM procedure

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Return | Abn Return | Volatility | Idio. Volatility |
| HighWFH × COVID | 0.075 | 0.065 | -0.005 | -0.003 |
| | (5.51) | (4.87) | (-2.61) | (-2.29) |
| Observations | 6863 | 6863 | 6862 | 6837 |
| Adj. $R^2$ | 0.475 | 0.155 | 0.708 | 0.717 |

*Notes:* Panels A and B report the matched sample results for financial performance proxies where the matching procedure is the propensity score matching (PSM) and coarsened exact matching (CEM), respectively. For results in Panel A, we estimate a probit model where the dependent variable is HighWFH and the controls include pre-Covid-19 return on asset (operating income / total asset), employment, and industry (2-digit NAICS) fixed effects using the pre-Covid-19 sample. We further implement a K2K nearest neighbor matching with no replacement and common support for each of the outcome variables. The results in Panel B are based on the coarsened exact matching approach using the same set of pre–19 variables. Panels C and D conduct the same matched sample analysis for stock performance. Standard errors are clustered at the firm level.

## Appendix D

### Table D1—: WFH Feasibility and firm performance: Continuous WFH proxy

#### (A) Financial performance

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Log Net Income | Log Sales | Norm. Cap. Exp. | Norm. Software Exp. |
| HighWFH × COVID | 0.165 | 0.064 | 0.013 | -0.001 |
| | (1.83) | (3.02) | (3.59) | (-1.77) |
| Other Controls | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y |
| Quarter FE | Y | Y | Y | Y |
| Observations | 9568 | 9568 | 9568 | 9568 |
| Adj. $R^2$ | 0.886 | 0.996 | 0.522 | 0.844 |

#### (B) Stock Market performance

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Return | Abn Return | Volatility | Idio. Volatility |
| HighWFH × COVID | 0.042 | 0.051 | -0.008 | -0.009 |
| | (1.66) | (2.06) | (-2.48) | (-3.55) |
| Other Controls | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y |
| Quarter FE | Y | Y | Y | Y |
| Observations | 9550 | 9550 | 9550 | 9507 |
| Adj. $R^2$ | 0.448 | 0.145 | 0.713 | 0.750 |

*Notes:* Our baseline analysis is based on HighWFH, which takes the value of one if a firm's average WFH index calculated based on its annual job posting data during the pre-Covid-19 period (2010-2019) falls into the top quartile of the sample distribution and zero otherwise. In Panels A and B, we repeat the analysis using the raw, continuous WFH index. Firm and time fixed effects are also included in the estimation. Standard errors are clustered at the firm level.

## Appendix E

### Table E1—: WFH Feasibility and Firm Performance: State-Quarter Fixed Effects

#### (A) Financial performance

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Log Net Income | Log Sales | Norm. Cap. Exp. | Norm. Software Exp. |
| HighWFH × COVID | 0.151 | 0.033 | 0.002 | -0.001 |
| | (3.13) | (3.06) | (1.95) | (-1.91) |
| Other Controls | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y |
| State-Quarter FE | Y | Y | Y | Y |
| Observations | 9550 | 9550 | 9550 | 9550 |
| Adj. $R^2$ | 0.886 | 0.996 | 0.538 | 0.837 |

#### (B) Stock Market performance

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Return | Abn Return | Volatility | Idio. Volatility |
| HighWFH × COVID | 0.046 | 0.038 | -0.005 | -0.003 |
| | (3.51) | (2.98) | (-2.66) | (-2.28) |
| Other Controls | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y |
| State-Quarter FE | Y | Y | Y | Y |
| Observations | 9538 | 9538 | 9538 | 9495 |
| Adj. $R^2$ | 0.451 | 0.147 | 0.716 | 0.751 |

*Notes:* In Panels A and B, we repeat the analysis in Tables 2 and 3 using similar specifications but control for state-quarter fixed effects instead of quarter fixed effects to address the potential concern of geographic differences. Firm fixed effects are also included in the estimation. Standard errors are clustered at the firm level.

# Appendix F

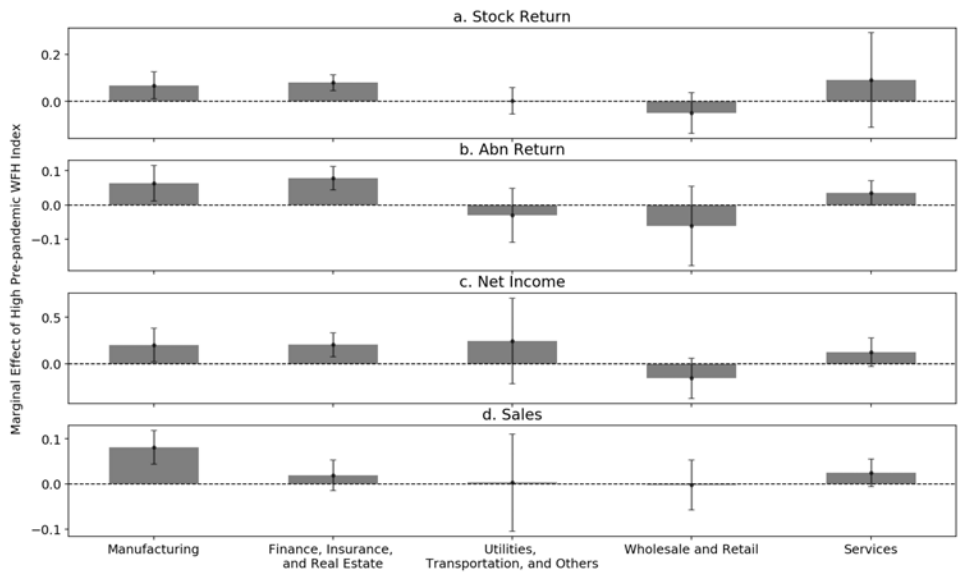



**Figure F1. : WFH Feasibility and Firm Performance across Sectors**

*Notes:* This figure plots the impact of HighWFH on firm outcome variables including financial performance and stock returns by sector with the 90% confidence interval attached. Reported results are based on the specifications similar to the baseline models: we regress each outcome variable on the interaction of HighWFH and the COVID dummy alone with other firm controls controlling for firm and quarter fixed-effects. We aggregate industry sectors following (David Autor, David Dorn, Lawrence F Katz, Christina Patterson and John Van Reenen, 2020), which can also be found in Appendix H4. Please see the U.S. Census for the definition of 2-digit NAICS industries in Appendix H1.

## Appendix G

### Table G1—: Falsification Test (by Position of Firm Name by Alphabetic Order)

**(A)** Financial performance

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Log Net Income | Log Sales | Norm. Cap. Exp. | Norm. Software Exp. |
| HighWFH × COVID | 0.005 | 0.009 | -0.001 | -0 |
| | (0.13) | (0.94) | (-0.68) | (-1.35) |
| Other Controls | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y |
| Quarter FE | Y | Y | Y | Y |
| Observations | 9568 | 9568 | 9568 | 9568 |
| Adj. $R^2$ | 0.886 | 0.996 | 0.521 | 0.844 |

**(B)** Stock Market performance

| Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable | Return | Abn Return | Volatility | Idio. Volatility |
| HighWFH × COVID | 0.016 | 0.010 | 0.002 | 0.002 |
| | (1.43) | (0.95) | (0.99) | (2.01) |
| Other Controls | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y |
| Quarter FE | Y | Y | Y | Y |
| Observations | 9550 | 9550 | 9550 | 9507 |
| Adj. $R^2$ | 0.447 | 0.145 | 0.712 | 0.750 |

*Notes:* In Panels A and B, we repeat the analyses from Tables 2 and 3 to run a placebo test, in which instead of using the WFH index, we construct a firm index based on the firm names in the alphabetical order prior to Covid-19 pandemic. All specifications here are identical to the baseline specifications in Tables 2 and 3. Robust standard errors are clustered at the firm level.

## Appendix H

**Table H1—: Industry definition at 2-digit NAICS Level.**

| Sector (2-Digit NAICS) | Description |
|---|---|
| 11 | Agriculture, Forestry, Fishing and Hunting |
| 21 | Mining, Quarrying, and Oil and Gas Extraction |
| 22 | Utilities |
| 23 | Construction |
| 31-33 | Manufacturing |
| 42 | Wholesale Trade |
| 44-45 | Retail Trade |
| 48-49 | Transportation and Warehousing |
| 51 | Information |
| 52 | Finance and Insurance |
| 53 | Real Estate and Rental and Leasing |
| 54 | Professional, Scientific, and Technical Services |
| 55 | Management of Companies and Enterprises |
| 56 | Administrative and Support and Waste Management and Remediation Services |
| 61 | Educational Services |
| 62 | Health Care and Social Assistance |
| 71 | Arts, Entertainment, and Recreation |
| 72 | Accommodation and Food Services |
| 81 | Other Services (except Public Administration) |
| 92 | Public Administration |

**Table H2—: High-Tech Industry definition at 4-digit NAICS Level according to Decker et al. (2017).**

| 4-Digit NAICS | Description |
|---|---|
| 3341 | Computer and peripheral equipment manufacturing |
| 3342 | Communications equipment manufacturing |
| 3344 | Semiconductor and other electronic component manufacturing |
| 3345 | Navigational, measuring, electromedical, and control instruments manufacturing |
| 3254 | Pharmaceutical and medicine manufacturing |
| 3364 | Aerospace product and parts manufacturing |
| 5112 | Software publishers; 5161 Internet publishing and broadcasting |
| 5179 | Other telecommunications |
| 5181 | Internet service providers and Web search portals |
| 5182 | Data processing, hosting, and related services |
| 5413 | Architectural, engineering, and related services |
| 5415 | Computer systems design and related services |
| 5417 | Scientific research-and-development services |

**Table H3—: Essential Industry definition at 4-digit NAICS Level according to Papanikolaou and Schmidt (2020).**

| 4-Digit NAICS | Description |
|---|---|
| 1111 | Oilseed and Grain Farming |
| 1112 | Vegetable and Melon Farming |
| 1113 | Fruit and Tree Nut Farming |
| 1119 | Other Crop Farming |
| 1121 | Cattle Ranching and Farming |
| 1122 | Hog and Pig Farming |
| 1123 | Poultry and Egg Production |
| 1124 | Sheep and Goat Farming |
| 1129 | Other Animal Production |
| 1141 | Fishing |
| 1142 | Hunting and Trapping |
| 1151 | Support Activities for Crop Production |
| 1152 | Support Activities for Animal Production |
| 2121 | Coal Mining |
| 2122 | Metal Ore Mining |
| 2123 | Nonmetallic Mineral Mining and Quarrying |
| 2131 | Support Activities for Mining |
| 2211 | Electric Power Generation, Transmission and Distribution |
| 2212 | Natural Gas Distribution |
| 2213 | Water, Sewage and Other Systems |
| 2373 | Highway, Street, and Bridge Construction |
| 3111 | Animal Food Manufacturing |
| 3112 | Grain and Oilseed Milling |
| 3113 | Sugar and Confectionery Product Manufacturing |
| 3114 | Fruit and Vegetable Preserving and Specialty Food Manufacturing |
| 3115 | Dairy Product Manufacturing |
| 3116 | Animal Slaughtering and Processing |
| 3117 | Seafood Product Preparation and Packaging |
| 3118 | Bakeries and Tortilla Manufacturing |
| 3119 | Other Food Manufacturing |
| 3121 | Beverage Manufacturing |
| 3254 | Pharmaceutical and Medicine Manufacturing |
| 3256 | Soap, Cleaning Compound, and Toilet Preparation Manufacturing |
| 3261 | Plastics Product Manufacturing |
| 3312 | Steel Product Manufacturing from Purchased Steel |
| 3313 | Alumina and Aluminum Production and Processing |
| 3331 | Agriculture, Construction, and Mining Machinery Manufacturing |

**Table H3—: Essential Industry definition at 4-digit NAICS Level (Continued).**

| 4-Digit NAICS | Description |
|---|---|
| 3391 | Medical Equipment and Supplies Manufacturing |
| 4242 | Drugs and Druggists' Sundries Merchant Wholesalers |
| 4245 | Farm Product Raw Material Wholesalers |
| 4413 | Automotive Parts, Accessories, and Tire Stores |
| 4441 | Building Material and Supplies Dealers |
| 4451 | Grocery Stores |
| 4452 | Specialty Food Stores |
| 4453 | Beer, Wine, and Liquor Stores |
| 4461 | Health and Personal Care Stores |
| 4471 | Gasoline Stations |
| 4523 | General Merchandise Stores, including Warehouse Clubs and Supercenters |
| 4539 | Other Miscellaneous Store Retailers |
| 4541 | Electronic Shopping and Mail-Order Houses |
| 4812 | Nonscheduled Air Transportation |
| 4841 | General Freight Trucking |
| 4842 | Specialized Freight Trucking |
| 4851 | Urban Transit Systems |
| 4852 | Interurban and Rural Bus Transportation |
| 4853 | Taxi and Limousine Service |
| 4859 | Other Transit and Ground Passenger Transportation |
| 4861 | Pipeline Transportation of Crude Oil |
| 4862 | Pipeline Transportation of Natural Gas |
| 4885 | Freight Transportation Arrangement |
| 4911 | Postal Service |
| 4921 | Couriers and Express Delivery Services |
| 4922 | Local Messengers and Local Delivery |
| 4931 | Warehousing and Storage |
| 5173 | Telecommunications Resellers |
| 5179 | Other Telecommunications |
| 5211 | Monetary Authorities-Central Bank |
| 5221 | Depository Credit Intermediation |
| 5222 | Nondepository Credit Intermediation |
| 5223 | Activities Related to Credit Intermediation |
| 5231 | Securities and Commodity Contracts Intermediation and Brokerage |
| 5232 | Securities and Commodity Exchanges |
| 5239 | Other Financial Investment Activities |
| 5241 | Insurance Carriers |
| 5242 | Agencies, Brokerages, and Other Insurance Related Activities |
| 5251 | Insurance and Employee Benefit Funds |

**Table H3—: Essential Industry definition at 4-digit NAICS Level (Continued).**

| 4-Digit NAICS | Description |
|---|---|
| 5259 | Other Investment Pools and Funds |
| 5411 | Legal Services |
| 5412 | Accounting, Tax Preparation, Bookkeeping, and Payroll Services |
| 5621 | Waste Collection |
| 5622 | Waste Treatment and Disposal |
| 5629 | Remediation and Other Waste Management Services |
| 6111 | Elementary and Secondary Schools |
| 6211 | Offices of Physicians |
| 6214 | Outpatient Care Centers |
| 6215 | Medical and Diagnostic Laboratories |
| 6216 | Home Health Care Services |
| 6219 | Other Ambulatory Health Care Services |
| 6221 | General Medical and Surgical Hospitals |
| 6223 | Specialty (except Psychiatric and Substance Abuse) Hospitals |
| 6231 | Nursing Care Facilities (Skilled Nursing Facilities) |
| 6233 | Continuing Care Retirement Communities and Assisted Living Facilities for the Elderly |
| 9211 | Executive, Legislative, and Other General Government Support |
| 9221 | Justice, Public Order, and Safety Activities |
| 9231 | Administration of Human Resource Programs |
| 9241 | Administration of Environmental Quality Programs |
| 9251 | Administration of Housing Programs, Urban Planning, and Community Development |
| 9261 | Administration of Economic Programs |
| 9271 | Space Research and Technology |
| 9281 | National Security and International Affairs |

**Table H4—: Aggregated Industry definition following Autor et al. (2020).**

| Aggregated Industry Sector | 2-Digit NAICS Code |
|---|---|
| Manufacturing | 31, 32, 33 |
| Finance, Insurance, & Real Estate | 52, 53 |
| Utilities, Transportation, and Others | 11, 21, 22, 23, 48, 49, 99 |
| Wholesale and Retail trade | 42, 44, 45 |
| Services | 51, 54, 55, 56, 61, 62, 71, 72, 81 |