The Value of Production Flexibility in Bad Times: Evidence from Covid Crisis Work-from-Home Announcements

Adlai Fisher, Jiri Knesl, and Ryan C.Y. Lee*

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ABSTRACT

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*Fisher: adlai.fisher@sauder.ubc.ca. Sauder School of Business, University of British Columbia, 2053 Main Mall, Vancouver, BC, V6T 1Z2. Knesl and Lee: jiri.knesl@sbs.ox.ac.uk; ryan.lee@sbs.ox.ac.uk. Said Business School, University of Oxford, Park End Street, OX1 1HP, Oxford, United Kingdom. We thank for helpful comments seminar participants at University of Oxford, the Vienna University of Economics and Business and Vrije universiteit Amsterdam. We also thank the Risk Management Institute (RMI) of the National University of Singapore for sharing their data, and the Natural Sciences and Engineering Research Council of Canada for financial support.

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Abstract

Financial markets significantly valued observable work-from-home adoption during the Covid-19 crisis. To show this, we develop a novel dataset of voluntary work-from-home announcements. In the five days after an announcement, cumulative abnormal stock returns reached five percent, and abnormal default probabilities declined by ten basis points, with stronger effects in non-essential businesses. Non-announcers with similar characteristics experienced up to half the short-run valuation gains, consistent with information spillovers. We validate prior measures of work-from-home suitability by showing they predict actual work-from-home decisions. Our study provides unique identification of the value of operating flexibility in bad times through information shocks.

1. Introduction

Production flexibility increases firm value, according to real options theory (e.g. Brennan and Schwartz, 1985, McDonald and Siegel, 1985). Such flexibility can take many forms, including ease of capital investment and disinvestment, labor hiring and firing, entry and exit, and changes in input mix, product mix, or production location.[1] Production flexibility also impacts diverse economic phenomena, for example in asset pricing (firm risk and return), macroeconomics and macro-finance (shock propogation and aggregate risk premia), corporate finance (interactions with capital structure and risk management), and industrial organization (strategic and competitive interactions).[2] Empirical measurement of production flexibility is nonetheless challenging. Firm-level estimates can be based on time-series regressions of accounting data, instruments such as unionization, or structural estimation.[3] Observable shocks to production flexibility, and their impact on firm value, are more difficult to estimate. Thus, circumstantial evidence for the value of production flexibility abounds, but direct evidence that positive shocks to flexibility increase firm value is elusive.

In this paper, we use a unique identification strategy based on information shocks to show that the financial markets attached a large positive value to production flexibility at the height of the Covid-19 crisis. To accomplish this we develop a novel hand-collected dataset of firms' voluntary work-from-home announcements, after the Covid crisis began, but before government-enforced lockdowns mandated work-from-home for

[1]See Triantis and Hodder (1990), Mauer and Triantis (1994), Hanka (1998), Carlson et al. (2004), Chen et al. (2011), and Fillat and Garetto (2015).

[2]Examples include Cooper (2006), Carlson et al. (2014), Reinartz and Schmid (2016), Donangelo et al. (2019), Clementi and Palazzo (2019), and Chen et al. (2019).

[3]See, for example, Lev (1974), Cooper and Haltiwanger (2006), Garcia-Feijoo and Jorgensen (2010), Chen et al. (2011), and Novy-Marx (2011).

non-essential businesses. Cumulative abnormal returns in the five days following announcement reached approximately five percent of firm value, and in the same window abnormal default probabilities of announcers fell by ten basis points.

The Covid crisis is particularly well-suited to study the value of production flexibility. Theoretically, flexibility is especially valuable when it can be achieved in times of aggregate economic stress.[4] Recent research proposes new measures of work-from-home suitability, and relates these measures cross-sectionally to firms' resilience in the face of the Covid-19 pandemic (Dingel and Neiman, 2020, Papanikolaou and Schmidt, 2020, Pagano et al., 2020).[5]

We add to this literature in two ways. First, existing identification is primarily cross-sectional, relating firm performance to measures of work-from-home suitability or risk exposures, whereas our identification is based on an information shock, the work-from-home announcement itself. While many characteristics, both *ex ante* and *ex post*, may be associated with work-from-home suitability, a work-from-home announcement is a direct shock to financial-market information about work-from-home suitability. An announcer goes from being a work-from-home candidate to verifiably committing to work-from-home. In the real options framework, this is an optimizing decision. Under incomplete information, markets may have an idea which firms might switch, but this knowledge is imperfect. The voluntary announcement to work-from-home is good news: It confirms that the firm has an option to switch and that it is sufficiently low cost or

[4]This point is emphasized by Zhang (2005), who focuses on the classical case of flexibility in capital investment.

[5]For additional discussion of work-from-home and resilience in the face of the Covid-19 pandemic, see, for example, Acharya and Steffen (2020), Albuquerque et al. (2020), Barrero et al. (2020), Bretscher et al. (2020), Brynjolfsson et al. (2020), Fahlenbrach et al. (2020), Ramelli and Wagner (2020), and Ding et al. (2021).

high productivity to be exercised. The information shock is positive because the option itself is positive and because financial markets have incomplete information about which firms have the most valuable work-from-home options. This mode of identification of the value of production flexibility is different from cross-sectional comparisons of suitability for work-from-home with value, risk, or returns.

Our second contribution is that by directly measuring voluntary work-from-home decisions, our data allows us to estimate the explanatory power of various proposed measures of work-from-home suitability. We show that controlling for other characteristics, the sector and industry labor-suitability measures of Dingel and Neiman (2020) and Papanikolaou and Schmidt (2020) both significantly predict actual work-from-home decisions. Our study thus validates the key measures of remote-work capability used in existing literature, and also establishes a positive and economically significant value attached to work-from-home flexibility by financial markets.

We develop our data by crawling the official websites of firms from the 2019 Compustat database with active company URLs.[6] We search for keywords related to work-from-home using natural language processing to parse the text. We focus on the period January 20, 2020 - March 19, 2020, closely corresponding to the Ramelli and Wagner (2020) "outbreak" and "fever period" of growing global awareness of the pandemic, but prior to large-scale U.S. lockdowns. Corporate work-from-home policies in this period can unambiguously be categorized as voluntary since no states had yet declared lock-

[6]Our initial web-crawling was done in mid-2020. In the second quarter of 2021 we used Google's archived search capability to confirm the dates and web-site postings where possible, and when the announcements could not be confirmed emailed the companies to ask for confirmation of a public posting on the initially determined date. Events that could not be confirmed by either method were removed from our sample of announcers.

downs. During this period, we find that 282 firms, or approximately 11% of the sample, institute voluntary work-from-home policies.

We first consider the characteristics that predicted work-from-home adoption. We choose four primary variables from the prior literature that have potential to predict work-from-home flexibility. First, Dingel and Neiman (2020) develop a sectoral (2-digit NAICS industry) level measure ("DN") of work-from-home suitability based on sectoral occupation mix according to BLS occupational classifications and subjectively-coded assessments of suitability of each occupation to remote work. Second, Papanikolaou and Schmidt (2020) ("PS") develop a similar variable at the more refined 4-digit-NAICS level. These are unambiguously measures of labor flexibility. We also consider two additional firm-level variables that may relate to either technology or organizational investments relevant to work-from-home capability. The intangible capital ("IK") measure of Peters and Taylor (2017) capitalizes prior SG&A and R&D expenditures. The organizational capital ("OK") measure of Eisfeldt and Papanikolaou (2013) capitalizes SG&A only. We also include as controls standard firm characteristics such as size, book-to-market ratio, profitability, and investment.

Several of these variables have strong univariate relationships with the work-from-home decision. In multivariate regressions, the variables that most stand out are the PS measure of labor-suitability to work-from-home and firm size as a control. The marginal effects of the PS measure are noteworthy. Moving from the 10th to 90th percentile of the distribution of the PS measure shifts the marginal likelihood of observable work-from-home adoption by fifteen percentage points, from six percent to twenty-one percent likelihood. The t-statistic for the one-tailed test that the PS measure does not positively predict work-from-home adoption exceeds ten.[7] Armed with this evidence from logit regressions, we develop several matched samples of firms that are like the sample of work-from-home ("WFH") announcers in their prior measurable characteristics, but did not announce work-from-home policies. These matched samples are formed on the bivariate matches industry-size, industry-PS, size-PS, and on the propensity score obtained from the logit regression that uses all three predictor variables.

Announcement effects, from both stock returns and default probabilities, are economically and statistically significant. We first use the standard event-study methodology of choosing the market and industry returns as benchmarks. In the five days following announcement of work-from-home adoption, firms experience cumulative abnormal returns in their stock market valuation of five percent, and abnormal default probability falls by ten basis points, both statistically significant. Both effects are considerably stronger, both economically and statistically, for firms categorized as "non-essential" versus "essential." For essential businesses, work-from-home ability may be less important because the nature of their business ensures the importance of their continued operation even if work cannot be performed remotely. Non-essential businesses are more likely to suffer if they cannot adapt to remote work. The announcement effects are consistent with this interpretation.

We next use additional characteristics of the WFH sample – their PS ranking, size, and propensity score – to further refine the announcement return benchmarks. These results show that controlling for observable characteristics, the announcement effects are still statistically and economically significant, but smaller. Non-announcers with

[7] The one-tailed test is appropriate here because prior literature explicitly proposes this measure as a positive measure of work-from-home ability.

similar observable characteristics to the announcers experienced up to half of the short-term valuation gains of the announcers. This is consistent with the market rewarding characteristics associated with work-from-home capability, even for firms that have not yet announced a work-from-home policy.

We finally consider operating performance. Both the WFH firms and their matches performed similarly by quarterly year-over-year measures of growth in revenues, profits, and employment. Both groups showed stronger operating performance than typical firms (i.e., non-matches) through the majority of the Covid period, with reversal becoming apparent in the second quarter of 2021. Thus, operating performance shows mitigation of the risks associated with the Covid contraction, and relates more strongly to the variables such as PS that predict work-from-home announcement, rather than the announcement itself.

Our paper adds to the literature in several ways. First, we validate prior measures of work-from-home suitability as predicting actual work-from-home decisions at the firm level. Second, we show that financial markets attached significant value to observable work-from-home adoption in the midst of the Covid crisis. This contributes to the broader literature emphasizing the value of various forms of production flexibility, especially during bad times, as well as the more recent literature emphasizing resilience in the face of the Covid crisis (e.g., Mauer and Triantis, 1994, Papanikolaou and Schmidt, 2020, Pagano et al., 2020). Finally, the new data we develop on voluntary work-from-home announcements in the midst of the Covid crisis should be useful to future research.

2. Data and Measurements

Our sample begins with the universe of firms from CRSP database with a listed common stock on NYSE, Amex (NYSE MKT), or NASDAQ traded at a price equal to or higher than 2 USD per share as of the beginning of 2020. Since our approach makes use of firms' voluntary announcements on official websites, we require the firms to have a non-missing URL in the 2019 COMPUSTAT database. This requirement corresponds to, for example, 75 percent coverage of firms in Russell 1000. After crawling the websites, we keep the firms that have active URLs. The final sample includes 2545 unique firms. For stock return data, we use the CRSP database for years 2019 and 2020 and supplement with 2021 data from Compustat and yahoo.com/finance. For default probabilities, we use the data from the Risk Management Institute (RMI) of the National University of Singapore, which have been successfully used in previous studies (e.g., Gallagher et al. (2020)). The RMI database contains forward looking default probabilities estimated from the model of Duan et al. (2012) for various maturities updated on a daily basis. We use default probabilities for maturity of 12 months.

2.1. Work-from-home

Our aim is to identify individual U.S. firms that announced work-from-home in the early Covid-19 outbreak period. We focus on work-from-home announcements in the period from January 20, 2020 - March 19, 2020, which corresponds to the Ramelli and Wagner (2020) "outbreak" and "fever period" of growing global awareness of the pandemic, but prior to large-scale U.S. lockdowns. Corporate work-from-home policies in this period can unambiguously be categorized as voluntary since no U.S. state had yet declared a lockdown.

Ramelli and Wagner (2020) document the growing awareness of Covid-19 risks at the onset of the Covid-19 pandemic and provide a timeline of important events. They recognize January 20 as the beginning of the outbreak, when Chinese health authorities confirmed human-to-human transmission. The first conference call that explicitly discussed the coronavirus was on January 22. The Chinese city Wuhan was placed under lockdown on January 23.[8] The severity of the risk associated with Covid-19 became even more apparent one month later when Italy imposed a local lockdown on February 23. Specifically, Google search on Covid-19 significantly rose and the earnings conference calls that mentioned Covid-19 increased from 30 percent to around 50 percent after the Italy lockdown. Hence, Ramelli and Wagner set the Covid-19 "fever period" starting from Monday February 24 and ending on Friday March 20. While they highlight Friday, March 20, as the end of the fever period because the Federal Reserve announced major interventions in corporate credit market on March 23, we emphasize that March 20 broadly captures the timing when U.S. states began imposing official lockdown policies. The first U.S. state to announce a shelter-in-place measure was California in the evening of March 19.[9][10] Illinois and New Jersey, as the second and third respectively, followed to issue shelter-in-place orders on Saturday March 21. By the end of March, a majority of US states (35) have issued their shelter-in-place measures.

[8]We use the terms lockdown, stay-at-home, and shelter-in-place interchangeably.

[9]Except for Puerto Rico (U.S. territory) that announced a shelter-in-place measure on March 15.

[10]Although Ramelli and Wagner (2020) define the "fever period" January 23-March 20, we cut it shorter by one day, January 23-March 19 since California, as the first U.S. state, announced a lockdown on March 19, 2020.

Beginning with the outbreak of Covid-19, firms were actively revealing their corporate responses to Covid-19 on their official web pages through channels such as press releases, Covid pages, or official corporate forum posts. We fetch the firms' announcements and date stamp data by crawling their websites through the Google API. We then use natural language processing to parse and analyze the text and manually confirm the messages and date stamps of work-from-home (WFH) announcements.

We use the Google API to access the information gathered by Google's web crawlers. To begin the process, crawlers visit the web pages based on our list of URLs to discover publicly available content, follow sitemaps to continue the searching activities, and bring the data back to servers. According to Google, their crawlers would pay "special attention" to the changes in existing sites, a feature that is useful to detect the announcements of corporate responses to Covid-19.

We accessed Google's search data in early June 2020 and fetched companies' voluntary WFH announcements made over the period from January 20 to March 19. Following Loughran and McDonald (2011) among other textual analysis studies in finance, we use a bag of words method to parse the web content regarding 'work from home'. Our bag of WFH words includes "work from home", "wfh", "working from home", "work-from-home", "home working", "remote work", "remote working", "work remotely", "work from anywhere", "working from anywhere", and "work anywhere". Further, we manually verify the WFH text to ensure that the content is directly relevant to WFH policy of the company. If a firm has expressed any policy or discussion about implementing WFH, we record the first date stamp of each firm regarding the changes in the WFH text on their websites.

To increase the precision and remove false negatives, we further took the sample of firms that have not been recognized as having made an announcement yet and manually searched for the bag of words described above together with the companies' names on Google search interface for the period from January 20 to March19, 2020. We again recorded the date stamp of the firm's first relevant announcement.

For 27 companies, the announcement on their websites regarding remote-work policy was insufficiently clear that we emailed these companies (up to three times) to clarify that their announcement reflected adoption of a work-from-home policy. We received 7 positive responses to these requests for clarification and denoted the remaining as not having made an announcement. We of course acknowledge that despite our best efforts, our data is an imperfect reflection of adoption of work-from-home policy. In particular, while all of our WFH firms did in fact publicly announce work-from-home adoption on the specified dates, other firms will surely have adopted work-from-home policies without making announcements on their official public websites (e.g., alternatively through internal communications). Nonetheless, our efforts reflect well the information available to markets, and in particular the effort a thorough investor might make gathering information related to companies' work-from-home policies by utilizing company websites and the Google search engine.

Figure 1 shows typical WFH announcements. For example, on March 2 Twitter started "strongly encouraging employees to work from home" and, later on March 11, required that all employees "must work from home" in another announcement.[11] In Twitter's case, we record Twitter as a WFH firm starting from March 2. By March

[11] See https://blog.twitter.com/en_us/topics/company/2020/keeping-our-employees-and-partners-safe-during-coronavirus.html.

19 when the first state-wide lockdown was implemented in California, 282 firms had announced adopting work-from-home. Our simplest dummy variable, WFH_i, as an indicator for announcing a work-from-home policy within our search window.

Firms' operations during Covid-19 were affected not only by work-from-home but also by governments' measures ordering closure of on-site operations of non-essential businesses. Only businesses classified as essential (sometimes referred to as life-sustaining) were allowed to remain open and maintain in-person operations. The list of these critical business categories was originally guided by the Department of Homeland Security's Cybersecurity and Infrastructure Security Agency and included, for example, medical supply chains, energy, food, industrial manufacturing and emergency services. We follow the list of life-sustaining business classifications issued by the state government of Pennsylvania. We classify firms as essential if they belong to the life-sustaining industries according to this list, and as non-essential otherwise. Although we acknowledge that the criteria for essential classifications vary somewhat across states (liquor retailers are examples of these), the core of essential industry classification is relatively consist across states (Song et al. (2021)). The Pennsylvania classification is advantageous as Pennsylvania is one of a few states that provided a list of systematic categorizations for essential businesses based on the NAICS codes while many other states gave only descriptive guidance.[12] Second, Pennsylvania called for the closure of non-essential businesses at an early stage of the Covid-19 crisis, and their list of NAICS codes for essential businesses was available to the public.[13]

[12]For example, California. See, https://covid19.ca.gov/essential-workforce. Compare with https://dced.pa.gov/covid-19-exempt-businesses/ or https://siccode.com/page/coronavirus-essential-businesses-by-naics-code.

[13]This announcement was released on the Governors' of Pennsylvania website with date of March 19,

2.2. Types of Labor and Capital

We use four primary variables to measure the differences in firm's type of labor and capital that might affect the firm's ability to effectively work from home and hence the likelihood to announce such corporate policy voluntarily before it is required by governments' lockdown policies. To differentiate between labor that is suitable for work from home and that is not, we use the variables defined by Dingel and Neiman (2020) and Papanikolaou and Schmidt (2020). Dingel and Neiman use comprehensive occupation characteristics from the O*NET database to identify occupations suitable for remote work. Using this classifications they calculate the percentage share of these occupations for 2-digit NAICS industries. We denote this percentage share as DN. Papanikolaou and Schmidt use the American Time Use Survey (ATUS) to identify occupations that had demonstrated the capability for "telecommuting" in years prior to 2020. Using this, they calculate the percentage of such occupations for 4-digit NAICS industries. We denote this variable as PS.[14]

To differentiate between different types of firms' capital possibly relevant to remote work, we consider intangible capital (IK) and organization capital (OK). We follow the methodology in Peters and Taylor (2017) and construct intangible capital by capitalizing a fraction of selling, general and administrative expenses and R&D expenses. The organizational capital measure follows from Eisfeldt and Papanikolaou (2013, 2012) and capitalizes a fraction of selling, general and administrative expenses only. We scale

2020, see, https://www.governor.pa.gov/newsroom/all-non-life-sustaining-businesses-in-pennsylvania-to-close-physical-locations-as-of-8-pm-today-to-slow-spread-of-covid-19/.

[14]Please note that Papanikolaou and Schmidt (2020) are interested in identifying industries that are more likely to be disrupted (i.e., opposite to industries we are interested in) and hence further transform the equivalent of the PS measure as $1 - PS$. To keep simplicity and consistency with other variables, we don't apply this transformation.

intangible capital and organization capital by total assets.

We provide summary statistics of all variables in table 1. Panel A shows the statistical properties of these variables in the cross-section of firms in our sample. Since WFH is a dummy indicator, its mean indicates that 11 percent of firms in the sample announced voluntary WFH. Firms' share of labor suitable for telecommuting PS is 27 percent, on average, and varies considerably in the cross section from 5 percent at 10^{th} percentile to 55 percent at 90^{th} percentile. Firms' share of labor suitable for remote work DN also shows large differences in the cross section with a higher mean of 44 percent. The ratios of intangible and organizational capital to total assets, IK and OK, vary strongly in the cross-section from close to zero at 10^{th} percentile to above one at 90^{th} percentile. The remaining variables are standard control variables.

Panel B shows the correlation matrix between WFH and the labor- and capital-type related variables. We point out that WFH is positively correlated with both PS and DN and these two variables correlate with each other with coefficient of 0.42. IK and OK are correlated with each other although not strongly with WFH.

Panel C characterizes the WFH and non-WFH firms using these variables. WFH firms tend to have higher PS and DN values (consistent with panel B) and the difference relative to non-WFH firms is statistically and economically significant. At the same time, WFH firms seem to be relatively similar to non-WFH firms in terms of both types of capital, IK and OK. The WFH firms tend to be also larger in size and number of employees and have lower book-to-market ratio BM. On average, they are also more profitable and have higher average investment rate.

3. Work-from-home Predictors and Announcement Effects

Remote work has been a key tool by which firms have adapted to the Covid economy. Previous measures of work-from-home suitability have been proposed, and our study is the first to validate these measures using actual work-from-home decisions at the firm level. In this section, we investigate the observable characteristics that predict corporate work-from-home decisisions. We also use these predictors to construct characteristic-matched samples for work-from-home announcers, and investigate announcement effects.

3.1. Work-from-home Logit Regressions

As predictors of observable work-from-home adoption, we consider the four previously described variables from prior literature that might relate to work-from-home capability: DN, PS, IK, and OK. We also consider as control variables log market equity, book-to-market ratio, profitability and investment, which are known to be associated with stock and operating performance. We do not offer a direct hypotheses for how these should affect firms' work-from-home capabilities, but they are common controls and natural to include. We also use the log number of firm employees as a control since remote work would seem to focus on labor as an input rather than capital.

We estimate a logit model as described in equation 1 with the likelihood of voluntary work-from-home decision ($WFH = 1$) as the dependent variable and the characteristics above as explanatory variables:

$$p\left(WFH_i = 1\right) \;=\; \frac{1}{1+e^{x_i+v_i}}, \tag{1}$$

where x_i is one (or all) of these variables: PS, DN, IK and OK. v_i is a vector of control variables consisting of log size $LnME$, log number of employees $LnEmp$, book-to-market ratio BM, profitability and investment. To allow easier comparison, we standardize all explanatory variables to standard deviation of one.

In the first column, we use the controlling variables only. Among these, $LnME$, profitability and investment appear to predict firm's voluntary WFH decisions. In the remaining columns, we investigate the effect of variables we hypothesize to be instrumental for firms' work-from-home decisions. First, we use one of these variables at a time, then we use all together both with and without industry fixed effects. The second column shows that the industry shares of labor suitable for telecommuting, PS, is a very strong predictor of firms' voluntary work-from-home announcements. The fitted likelihoods in the lower part of the table indicate that increasing this variable from 10th percentile to 90th percentile would increase firm's likelihood to voluntarily announce work-from-home from 6 to 21 percent, which we recognize as a significant impact. Column 3 reveals a similar role for the fraction of labor suitable for remote work, DN, with very similar coefficient and the impact on the likelihood to announce work-from-home. In the next two columns we turn to variables characterizing firm's capital, IK and OK. Among these two, intangible capital IK has marginally significant effect on WFH announcements.

When we include all variables together in column 6, PS, DN and $LnME$ retain their strong predictive power and other variables turn out insignificant ($lnEmp$ being at the margin). Estimations in columns 7-10 include industry fixed effects at the level of 2-digit NAICS industries. As DN is defined at the same level of industry classification, we exclude it from this part of the analysis and its predictive power is subsumed by the industry fixed effects. The share of labor suitable for telecommuting PS, is again a strong predictor of voluntary work-from-home announcements in column seven. IK and OK are both insignificant in columns 8 and 9. In column 10, we use all variables together with industry fixed effects. Among these, PS and $LnME$ are the strongest predictors of firm's voluntary work-from-home announcements ($lnEmp$ is again marginal). The effect of PS on the likelihood of the announcement remains unchanged (6-21 percent). The effect of the DN variable documented in columns 3 and 6 is captured by including industry fixed effects in column 10. In column 11, we use PS and LnME together with industry fixed effects only. The coefficients of PS and LnME are relatively unchanged and the pseudo R^2 stays comparable with column 10, highlighting that these variables alone are the main source of the predictive power.

These results are interesting for two reasons. On their own, they allow to verify whether firms that possess specific characteristics assumed to be indicative of firms' ability to work from home indeed announced work-from-home policy. Our results show that the labor-related variables such as PS and DN, which are widely used in a number of studies (Barry et al. (2021), Pagano et al. (2020), Mertens et al. (2021), Hensvik et al. (2020), and Bai et al. (2021)), are indeed informative about which firm truly worked from home. Second, these results inform us how to construct a sample of "matched" firms which possess the characteristics instrumental for work-from-home ability, but don't appear to have made an announcement. This is the exercise we turn to next.

3.2. Matching

The last column in table 2 indicates that PS and lnME are the most significant predictors of work from home and the DN importance is captured by industry fixed effects. Now we utilize this result and build samples of firms that do not have a record of voluntary WFH announcement but are along these dimensions closely comparable to firms with voluntary WFH announcements. Our first three matching techniques use pair combinations of these variables. In our first approach, for each firm that made a voluntary WFH announcement, we search for three closest matches by distance in firm's size in the same 2-digit industry (industry-size matching). In our second approach, we search for three closest matches by distance in the PS variable in the same 2-digit industry (industry-PS matching). In our third approach, we search by distance in PS within the same size quintile (size-PS matching). In our fourth approach, we use all these variables together. We estimate the propensity score using model 1 based on PS, $LnME$ and industry fixed effects and search for three closest matches by distance in propensity score.

We approach this matching exercise in chronological order in which firms made the WFH announcements. Our matching is without replacement in the sense that a firm can be used as a match only once. At the same time, if a firm used as a match at an earlier date announces itself a voluntary WFH at a later date, we replace it with a new match. We describe the details of the matching algorithm in appendix 6.1. Table 11 shows the summary statistics for these four matching techniques. In the first approach by industry and size, we are able to find matches for all WFH firms. In the remaining three approaches, the matching is limited to a slightly smaller set of WFH firms (236 instead of 282) since the PS variable is not available for some industries. The matched firms are, on average, very close to the true WFH firms in terms of the matching variables.

Defining the set of closest matches allows us to compare the true WFH firms not only with firms without a record of voluntary WFH announcement in general, but particularly with firms without such record but otherwise very similar characteristics related to firm's ability to work-from-home.

3.3. Announcement Effects

We begin our analysis of announcement effects using market returns $R_{mkt,t}$ and industry returns $R_{industry,t}$ as benchmarks. We run panel regressions of the form:

$$R_{it} = \alpha + \beta_{mkt} R_{mkt,t} + \beta_{industry} R_{industry,t} + WFH_{i,0,4} + WFH_{i,5,9} + \epsilon_{i,t}, \qquad (2)$$

where $WFH_{i,0,4}$ and $WFH_{i,5,9}$ are dummy variables equal to one when firm i has announced a work-from-home policy in the past zero to four, or five to nine days, respectively.

Results are shown in Table 3. Panel A shows results for all firms. Using either market returns, industry returns, or both as a benchmark, announcement effects are approximately one percent per day in the five days beginning with the announcement day, or about five percent cumulatively. The coefficient is statistically significant at the one percent level with a t-statistic of almost four. The abnormal returns are positive but not significantly different from zero in the following five days. Panels B and C show that the announcement effects concentrate more heavily in non-essential businesses versus essential businesses. Abnormal returns for non-essential firms are about 50 percent larger for non-essential firms vs. essential firms, respectively about six and four percent of value cumulatively over the five day period. In both subgroups the announcement effects are statistically significant at the one percent level.

Table 4 shows results of additional benchmarking using observable firm characteristics. We use regressions of the form:

$$R_{it} - R^{benchmark_{i,t}} = \alpha + \beta_{mkt} R_{mkt,t} + WFH_{i,0,4} + WFH_{i,5,9} + \epsilon_{i,t}, \tag{3}$$

where $R_{i,t}^{benchmark}$ is the market return in column 1, and in columns 2 through 5 is one of the four benchmarks established in Section 3: bivariate matching on industry-size, industry-PS, or size-PS, or propensity score matching. Benchmarking to the market in column (1) gives very similar announcement effects to Table 3, as expected. Benchmarking using observable characteristics in columns (2)-(5) reduces the observed announcement effects to varying degrees, to a range of forty to ninety basis points per day, or 2-4.5% cumulatively, in all cases still statistically significant at the one percent level. Despite the somewhat smaller magnitudes of the announcement effects in columns (2)-(5), t-statistics increase substantially, ranging from five to more than ten standard deviations from zero. Benchmarking with observable characteristics naturally reduces the size of the residuals, improving inference. The lower announcement effects in columns (2)-(5) reflect the returns of characteristic-matched peers in the announcement windows. Non-announcers with characteristics similar to announcers experience modest gains in the announcement windows, explaining the somewhat smaller benchmark adjusted returns. Panels B and C once again show that the announcement effects are considerably larger for non-essential versus essential firms.

If work-from-home ability reflects a form of production flexibility that is particularly important during the Covid-19 pandemic, we expect it to both increase firm value and reduce firm risk. Both of these suggest a reduction in default probabilities when a public announcement reveals a firm's remote work capability. We use the 12-month forward-looking default probabilities at the firm level and calculate daily changes during the Covid period. To investigate announcement effects on default probabilities, we repeat the regressions 2 and 3 using changes in firm default probabilities on the left-hand-side. On the right-hand-side we use as controls the equal-weighted average change in default probabilities across all firms in our sample including non-announcers, and similar equal-weighted average changes in default probabilities by industry.

Table 5 shows results using only average and industry-average changes in default probabilities as controls. In the sample of all firms shown in Panel A, the average announcement effect is 2 basis points per day, significant at the 1% level. The cumulative economic magnitude of 10 basis points over a five day period may seem small, but keep in mind the average default probability of all firms in our sample is typically in the range of 1%, so a change of ten basis points is economically meaningful. Panels B and C show that the effects concentrate heavily in non-essential firms, both economically and statistically. Many of the results for essential firms are not statistically significant, and the economic magnitude for non-essential firms is about three times larger than for essential firms.

We use additional benchmarking in Table 6 to further understand the default probability announcement effects. Benchmarking by firm characteristics in columns 2-4 reduces the economic and statistical significance of the announcement effects, in two of the four cases resulting in no statistically significant reduction in default probabilities. The results in Panels B and C again show the concentration of announcement effects in non-essential firms. For essential firms in Panel B there are no statistically significant reductions in default probabilities, whereas for non-essential firms in Panel C all benchmarks show statistically significant reductions in default probabilities, with cumulative magnitudes ranging from 2.5-7.5 basis points over the five day announcement window. From these results, we infer that firms with characteristics similar to announcing firms also experience reductions in default probabilities, albeit smaller, in the announcement windows.

4. Additional Results

In order to better understand our sample, we compare the operating performance of the work-from-home announcers, their characteristic-based matches, and other firms. Since work-from-home firms and their matches both tend to have high PS scores, we anticipate their differences relative to other firms to complement the findings of Papanikolaou and Schmidt (2020) on high versus low PS score firms. They find that in non-critical industries presumably more flexible high PS-score firms have higher cumulative returns than low PS-score firms through most of 2020, with some reversal appearing by the end of their sample at the end of 2020. We assess operating performance in quarterly data until the second quarter of 2021.

For each firm in our sample, beginning in 2019Q1 we calculate for each quarter the year-over-year rate of growth in sales, operating profits, total assets, and R&D expenses. Each year we calculate year-over-year growth in employees. For i denoting the accounting growth rate of interest and t denoting quarters or years as appropriate, we run regressions of the form:

$$\begin{aligned} Y_{i,t} =& \alpha + \beta_0 \times WFH_i + \beta_1 \times CovidPeriod_t + \beta_2 \times WFH_i \times CovidPeriod_t \\ & + LnME_{i,t} + FE^{ind} + FE^t + \epsilon_{i,t}. \end{aligned} \tag{4}$$

The variable WFH_i is a (time-constant) dummy variable for our work-from-home announcers, $CovidPeriod_t$ is a dummy variable indicating whether the firm's fiscal quarter end (fiscal year end for the number of employees) falls into the Covid-19 period, which we designate to be the year 2020. $LnME$ is log market capitalization. FE denotes fixed effects, by industry and by time.

Table 7 shows results, which are striking. Panel A shows results for all firms. Unsurprisingly, the Covid period was bad for average firms by all metrics, with year over-year declines in the high single digit percentages for all variables, and statistical significance at the 1% level. The WFH dummy on its own is unremarkable, but the interaction with the Covid period show broad outperformance for WFH firms. All of the interaction terms are positive, with four of the five statistically significant at the ten percent level, three at five percent, and two at one percent. Decomposing these results in Panels B and C into essential versus non-essential firms provides further detail. The average effects for essential versus non-essential firms are comparable, and there is no appearance that either group experienced substantially different operating performance in any category. The WFH interactions with the Covid period are always positive in both panels. For essential firms, only the asset growth and R&D interactions are statistically significant. For non-essential firms, four of the five interactions are statistically significant. The operating performance results thus generally agree with the announcement effects, which are stronger for non-essential firms than essential firms.

In Table 8 we show the same analysis for the characteristic-matched samples. These show patterns very similar to the WFH firms, and we conclude that operating performance was largely driven by the characteristics associated with the WFH announcement, not the announcement itself. WFH firms and their characteristic-based matches had better operating performance than other firms during the Covid period, by similar amounts. In both cases the outperformance is stronger in non-essential than in essential industries.

To further demonstrate the dynamics of operating performance, Table 9 shows similar regressions removing the single Covid period dummy and replacing it with dummies for each quarter beginning in 2020Q1, and ending in 2021Q2. We also include interactions of the WFH dummy with each of the time dummies. Employment is no longer included since it is observed at annual frequency. The time dummies demonstrate well the dynamics of the Covid crisis. The worst quarter was 2020Q2, with an average decline of 18.9% in sales, 16.6% in profits, and 12.1% in R&D. Quarters 1 and 3 of 2020 show still large and significant negative effects. 2020Q4 and 2021Q1 appear to show a leveling off, with a rebound appearing in the first quarter of 2021 in gross profits only. The second quarter of 2022 shows a very strong rebound, aided of course by the low comparables from the prior year. The WFH interactions show a similar reversal. In the worst quarters of the Covid crisis, work-from-home firms outperformed other firms. By the second quarter of 2021, the WFH interaction shows a statistically significant reversal for sales growth. Panels B and C show that for non-essential firms, the reversal is stronger and extends to gross profit growth as well as sales growth. Table 10 shows the same results for matches. Once again, operating performance is similar for the WFH announcers and their characteristic-based matches. Operating performance is driven by the underlying characteristics, including the PS measure of work-from-home suitability, rather than the announcement itself.

5. Conclusion

A variety of forms of production flexibility are valuable to firms (e.g. Brennan and Schwartz, 1985), especially when effective in times of aggregate economic distress (Zhang, 2005). The Covid crisis has been one of the most severe economic shocks of the past century. At the depths of the crisis, considerable uncertainty existed regarding the severity of the pandemic, how firms would adapt, and which firms could adapt.

The existing literature proposes work-from-home capability as one of the key types of production flexibility by which firms adjusted to the pandemic (Papanikolaou and Schmidt, 2020, Pagano et al., 2020). We add to this literature by developing a unique dataset of firms' voluntary work-from-home announcements. We confirm the validity of prior proposed measures of remote-work capability by showing that sector (DN) and industry (PS) measures of work-from-home suitability significantly predicted voluntary work-from-home adoption. Further, announcement effects of work-from-home adoption are statistically and economically significant, both in stock returns and default probabilities. Firms with similar characteristics but that did not announce experienced positive but smaller valuation effects.

Operationally, the work-from-home announcers showed similar performance to their characteristic-based matches, with both displaying relatively strong sales growth, profit growth, and other operating metrics through the worst quarters of the crisis, and reversal appearing in the second quarter of 2020. Therefore, the characteristics associated with work-from-home, rather than the announcement itself, are what predict less operational sensitivity to the Covid contraction. Nonetheless, the work-from-home announcements are a useful instrument. Firms that announced work-from-home adoption provided useful information to markets, confirming an important aspect of their ability to adjust to even a protracted pandemic. Consistent with the value of operational flexibility, particularly against adverse aggregate shocks, the work-from-home firms received economically and statistically significant valuation increases following their announcements.

The importance of remote work will only increase going forward. We hope that our data on the first firms to publicly announce voluntary work-from-home adoptions will be useful to future researchers.

6. Appendix

6.1. Matching Methodology

We use four different approaches to find suitable matches for each WFH firm, based on the results in table. The first approach is based on matching by firm size within the same 2-digit naics industry. The second approach is based on matching by the PS variable within the same 2-digit industry. In the third approach, we sort firms into quintiles and match firms by PS within the same size-quintile. In the fourth approach, we combine all these variables together by estimating the propensity score based on PS, size and industry fixed effects, and match firms based on their propensity score.

We match firms chronologically in line with the occurrence of firms' WFH announcements. Our matching is without replacement in a sense that each potential matching candidate firm can be used as a match for only one WFH firm. At the same time if this match firm announces by itself at a later point in time, we replace it with a new matching candidate. Specifically, the matching algorithm works like this. On each announcement date t, there is a set of WFH firms without a match, N_t^{WFH}, and a set of WFH with a match, M_t^{WFH}, where the latter is an empty set at the very beginning. For each firm $i \in N_t^{WFH}$, we calculate the absolute distance in the matching variable, x, between the firm i and all potential matches $j \notin N_t^{WFH}$, $j \notin N_{\tau<t}^{WFH}$, $j \notin M_t^{WFH}$ and $j \notin M_{\tau<t}^{WFH}$, i.e., $|x_i - x_j|$. When matching by industry and size or industry and PS, the matching variable is size or PS, respectively, and we consider only firms in the same industry. When matching by size quintile and PS, the matching variable is PS and we consider firms in the same size quintile only. When matching by propensity score, the

matching variable is propensity score and we consider all firms.

The matching starts with the WFH firm i^* that has the smallest absolute distance from a potential match, i.e., $i^* = argmin_{i \in N_t^{WFH}} |x_i - x_j|$. The match for this firm is the closest candidate $j^* = argmin_j |x_{i^*} - x_j|$. This match j^* is then removed from the pool of potential candidates and the firm i^* is moved from set N_t^{WFH} to set M_t^{WFH}. The matching proceeds to the next WFH firm i^* to be matched that is determined again as $i^* = argmin_{i \in N_t^{WFH}} |x_i - x_j|$. If there is no potential match for a firm, we skip the firm and move to the next firm. This happens for firms in some industries for which the PS variable is not defined. After we try to find a match for all firms in N_t^{WFH}, we move to the next announcement date t' and define the sets of WFH firms with and without a match, $N_{t'}^{WFH}$ and $M_{t'}^{WFH}$, respectively, and search for matches again. The set $N_{t'}^{WFH}$ consists of firms announcing WFH at that time t', but may also include firms that had announced WFH at earlier time $t < t'$ and their match j^* is not eligible anymore because it announces WFH by itself at time t' and hence belongs to $N_{t'}^{WFH}$.

Since we are searching for up to three matches, we apply this algorithm three times. At each time t, we search for the first match for each firm in N_t^{WFH}. After we try to find the first match for each of the firms at this specific time t, we define N_t^{WFH} again (as it was at the beginning of the search at time t) and search for the second match for each firm and similarly for a third match. Given the fact that our matching algorithm is chronologically in line with the WFH announcements and we apply matching without replacement, searching for a higher number of matches affects the matching at later dates. For example, a firm that is assigned as a third match to a WFH firm at time t_1 might have been a first match to a different WFH at time $t_2 > t_1$, but it is removed from the set of potential matches early on at time t_1. The average quality of the matching procedure is high and the matches are, on average, very close the the announcers in terms of the matching variables as shown in table 11.

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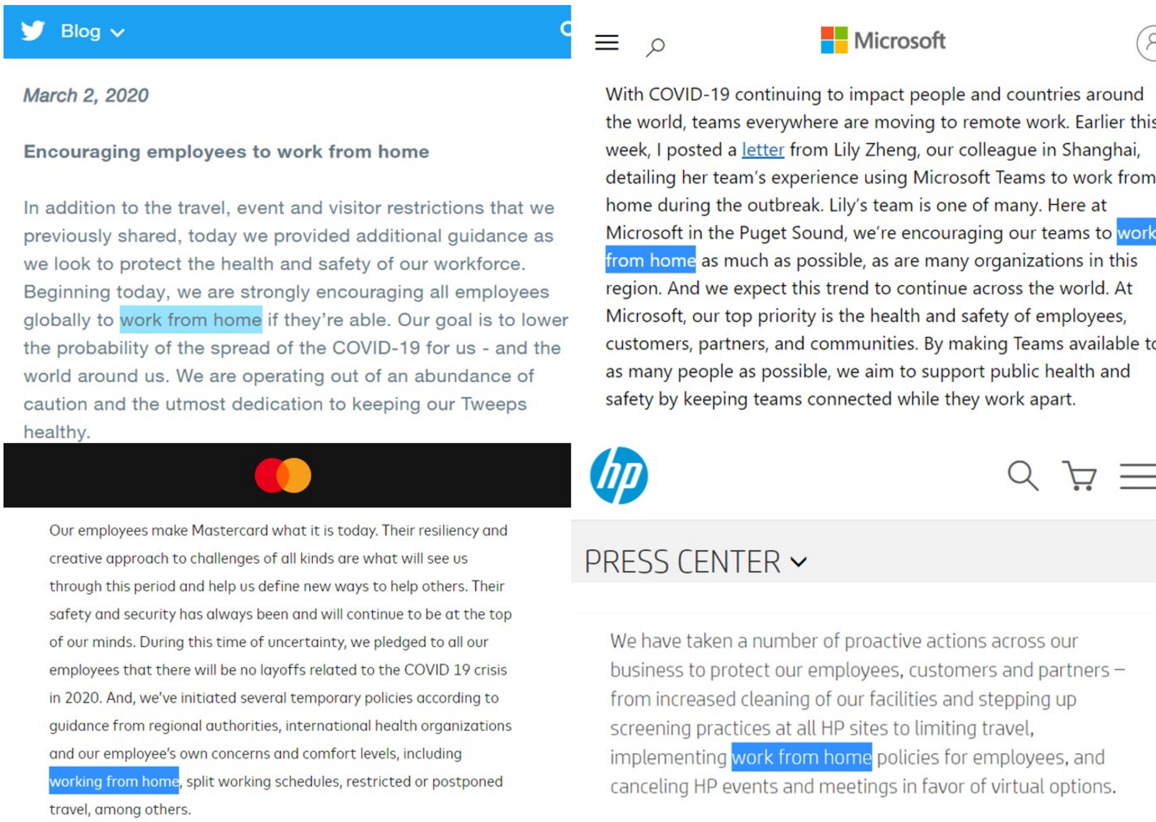
Figure 1: Typical Work-from-Home Announcements Exhibits of typical announcements of work-from-home from four large companies (Twitter Inc., Mastercard Inc., Microsoft Corporation, and Hewlett-Packard Company).



Blog

March 2, 2020

Encouraging employees to work from home

In addition to the travel, event and visitor restrictions that we previously shared, today we provided additional guidance as we look to protect the health and safety of our workforce. Beginning today, we are strongly encouraging all employees globally to work from home if they're able. Our goal is to lower the probability of the spread of the COVID-19 for us - and the world around us. We are operating out of an abundance of caution and the utmost dedication to keeping our Tweeps healthy.

Microsoft

With COVID-19 continuing to impact people and countries around the world, teams everywhere are moving to remote work. Earlier this week, I posted a letter from Lily Zheng, our colleague in Shanghai, detailing her team's experience using Microsoft Teams to work from home during the outbreak. Lily's team is one of many. Here at Microsoft in the Puget Sound, we're encouraging our teams to work from home as much as possible, as are many organizations in this region. And we expect this trend to continue across the world. At Microsoft, our top priority is the health and safety of employees, customers, partners, and communities. By making Teams available to as many people as possible, we aim to support public health and safety by keeping teams connected while they work apart.

Our employees make Mastercard what it is today. Their resiliency and creative approach to challenges of all kinds are what will see us through this period and help us define new ways to help others. Their safety and security has always been and will continue to be at the top of our minds. During this time of uncertainty, we pledged to all our employees that there will be no layoffs related to the COVID 19 crisis in 2020. And, we've initiated several temporary policies according to guidance from regional authorities, international health organizations and our employee's own concerns and comfort levels, including working from home, split working schedules, restricted or postponed travel, among others.

PRESS CENTER

We have taken a number of proactive actions across our business to protect our employees, customers and partners – from increased cleaning of our facilities and stepping up screening practices at all HP sites to limiting travel, implementing work from home policies for employees, and canceling HP events and meetings in favor of virtual options.

Table 1: Summary Statistics and Variable Properties. Panel A presents summary statistics of these variables: WFH (dummy variable indicating whether a firm made a voluntary WFH announcement), PS (industry's share of labor suitable for 'telecommuting' from Papanikolaou and Schmidt (2020)), DN (industry's share of labor suitable for work-from-home from Dingel and Neiman (2020)), IK (Intangible capital from Peters and Taylor (2017)), OK (organizational capital from Eisfeldt and Papanikolaou (2013)), LnME (log of firm's market capitalization at the end of 2018), LnEmp (log of firm's number of employees from 2018), BM (book-to-market ratio), Profitability (gross profitability defined as revenues minus cost of goods sold to total assets) and Investment (annual change in total assets to total assets). Panel B shows the correlation matrix between some of these variables. Panel C shows the average and median of these varibles among Non-WFH firms and WFH firms.

Panel A. Summary statistics

	Mean	St. Dev.	Min	P10	Median	P90	Max
WFH	0.11	0.31	0.00	0.00	0.00	1.00	1.00
PS	0.27	0.18	0.00	0.05	0.23	0.55	0.76
DN	0.44	0.27	0.04	0.19	0.25	0.80	0.83
IK	0.49	0.84	0.00	0.01	0.27	1.13	18.80
OK	0.81	1.17	0.00	0.00	0.45	2.03	16.75
LnME	20.89	1.92	14.68	18.49	20.87	23.43	27.38
LnEmp	7.56	2.13	1.39	4.77	7.65	10.25	14.60
BM	0.64	0.56	0.00	0.12	0.53	1.23	9.73
Profitability	0.26	0.33	-2.07	0.02	0.24	0.60	3.31
Investment	0.07	0.36	-12.29	-0.10	0.05	0.37	1.00

Panel B. Correlation coefficients

	WFH	PS	DN	IK	OK
WFH	1.00				
PS	0.15	1.00			
DN	0.08	0.42	1.00		
IK	-0.02	0.28	-0.05	1.00	
OK	0.01	0.05	-0.20	0.52	1.00

Panel C. Summary statistics for WFH and non-WFH firms

	Non-WFH firms		WFH firms		Difference WFH - Non-WFH	
	Mean	Median	Mean	Median	Diff.	t-stat
PS	0.262	0.234	0.348	0.336	0.086	[6.23]
DN	0.430	0.250	0.522	0.720	0.092	[5.50]
IK	0.496	0.260	0.445	0.378	-0.051	[-1.60]
OK	0.810	0.429	0.841	0.649	0.031	[0.51]
LnME	20.732	20.715	22.155	22.028	1.423	[11.60]
LnEmp	7.425	7.493	8.607	8.455	1.182	[10.12]
BM	0.657	0.547	0.497	0.355	-0.160	[-5.43]
Profitability	0.248	0.227	0.326	0.307	0.078	[4.79]
Investment	0.069	0.047	0.100	0.059	0.031	[1.78]

Table 2: Likelihood of Firms' Voluntary Work-from-home Decisions. This table shows the results of estimating the logit model $p\left(WFH_i = 1\right) = \frac{1}{1+e^{x_i+v_i}}$, where WFH_i is an indicator variable indicating firms that announced a voluntary work-from-home regime by March 19, 2020 and x_i is one or all of four explanatory variables: PS, DN, IK, and OK, except in column 1. Regressions include also a set of control variables v_i: $LnME$, $LnEmp$, BM, $Profitability$ and $Investment$. The logit model is estimated from cross section of firms with explanatory variables from year 2018. Second half of the table (Fitted likelihoods) reports the fitted likelihood of $WFH = 1$ for low and high value of the main explanatory variable. Fitted likelihoods in columns 6 and 10 are calculated for low and high of PS. Low and high values correspond to 10th and 90th percentile of the main explanatory variable, respectively. Industry fixed effects are at 2-digit NAICS. The DN variable is defined at the level of 2-digit NAICS industries and hence we omit it from regressions with industry fixed effects. ***, **, and * indicate 99%, 95%, and 90% significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
PS		0.56***				0.44***	0.61***			0.60***	0.57***
		[7.20]				[4.65]	[5.32]			[5.17]	[5.29]
DN			0.57***			0.27***					
			[7.59]			[2.91]					
IK				0.20*		0.02		0.22		0.16	
				[1.69]		[0.10]		[1.64]		[0.88]	
OK					0.04	0.03			0.05	-0.05	
					[0.33]	[0.21]			[0.36]	[-0.29]	
$LnME$	0.81***	0.60***	0.74***	0.83***	0.82***	0.63***	0.61***	0.74***	0.75***	0.60***	0.72***
	[6.88]	[4.34]	[5.97]	[6.98]	[6.66]	[4.31]	[3.91]	[5.35]	[5.26]	[3.71]	[9.38]
$LnEmp$	-0.02	0.29**	0.18	0.01	-0.02	0.29*	0.28*	0.21	0.17	0.32*	
	[-0.16]	[2.00]	[1.39]	[0.10]	[-0.18]	[1.94]	[1.71]	[1.42]	[1.11]	[1.86]	
BM	0.00	0.17*	0.01	0.03	0.00	0.15	0.11	0.04	0.03	0.12	
	[0.02]	[1.85]	[0.06]	[0.34]	[0.04]	[1.57]	[1.03]	[0.38]	[0.27]	[1.10]	
$Profitability$	0.23***	0.17*	0.34***	0.17*	0.20	0.19	0.21**	0.25**	0.28**	0.20	
	[2.78]	[1.93]	[4.02]	[1.89]	[1.49]	[1.34]	[2.05]	[2.51]	[2.00]	[1.32]	
$Investment$	0.23*	0.13	0.18	0.24**	0.23*	0.12	0.12	0.19	0.17	0.14	
	[1.82]	[1.01]	[1.45]	[1.98]	[1.84]	[0.95]	[0.93]	[1.48]	[1.31]	[1.05]	
Industry FE	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
N	2316	1970	2316	2314	2314	1968	1938	2298	2298	1936	2125
$Pseudo\ R^2$	0.091	0.124	0.127	0.092	0.091	0.130	0.142	0.138	0.137	0.143	0.127
Fitted likelihoods											
Low		0.06	0.07	0.10	0.11	0.07	0.06	0.10	0.11	0.06	0.06
High		0.21	0.20	0.13	0.12	0.18	0.22	0.13	0.12	0.21	0.21

Table 3: Announcement Effects: Stock Returns. The table shows the results of regressing a panel of daily stock returns on a constant, an indicator variable $WFHday_{0,4}$ indicating the window of five days from the firm's announcement to work from home (starting at day zero of the announcement), an indicator variable $WFHd_{5,9}$ indicating a subsequent window of five days, return on aggregate stock market R^{market} and the stock's industry return $R^{industry}$. Columns 4-6 include industry fixed effects at NAICS 2 digits level. The standard errors (Driscoll and Kraay (1998) with 20 lags) for market and industry returns are in parentheses and the equivalently calculated t-statistics for the indicator variables and constant in brackets. ***, **, and * indicate 99%, 95%, and 90% significance, respectively. Significance stars are omitted for market and industry returns. The panel is from July 1, 2019 to April 1, 2020 (i.e., end of fever period March 19 plus the necessary 10-day announcement window) and consists of 483484, 315714, and 167770 observations in panels A, B, and C, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All firms						
$WFH_{0,4}$	0.010***	0.009***	0.010***	0.010***	0.009***	0.010***
	[3.85]	[3.54]	[3.74]	[3.95]	[3.54]	[3.77]
$WFH_{5,9}$	0.004	0.003	0.003	0.004	0.003	0.003
	[1.28]	[1.45]	[1.20]	[1.29]	[1.46]	[1.21]
R_{market}	1.09		0.31	1.09		0.31
	(0.030)		(0.045)	(0.030)		(0.045)
$R_{industry}$		0.98	0.73		0.98	0.73
		(0.021)	(0.032)		(0.021)	(0.031)
$Constant$	-0.000	-0.000	-0.000			
	[-0.13]	[-0.14]	[-0.12]			
Industry FE	No	No	No	Yes	Yes	Yes
R^2	0.243	0.258	0.260	0.243	0.258	0.260
Panel B. Essential Firms						
$WFH_{0,4}$	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	[3.97]	[3.66]	[3.85]	[4.09]	[3.67]	[3.87]
$WFH_{5,9}$	0.002	0.001	0.001	0.002	0.001	0.001
	[0.96]	[0.69]	[0.59]	[0.98]	[0.67]	[0.58]
R_{market}	1.08		0.23	1.08		0.23
	(0.026)		(0.060)	(0.026)		(0.061)
$R_{industry}$		0.97	0.78		0.97	0.78
		(0.018)	(0.048)		(0.018)	(0.047)
$Constant$	-0.000	-0.000	-0.000			
	[-0.14]	[-0.15]	[-0.14]			
Industry FE	No	No	No	Yes	Yes	Yes
R^2	0.226	0.243	0.244	0.225	0.243	0.244
Panel C. Non-essential Firms						
$WFH_{0,4}$	0.013***	0.011***	0.012***	0.013***	0.011***	0.012***
	[3.53]	[3.30]	[3.57]	[3.64]	[3.34]	[3.65]
$WFH_{5,9}$	0.005	0.005*	0.005	0.005	0.006*	0.005
	[1.40]	[1.85]	[1.44]	[1.42]	[1.89]	[1.47]
R_{market}	1.11		0.44	1.11		0.44
	(0.038)		(0.050)	(0.038)		(0.049)
$R_{industry}$		1.00	0.63		1.00	0.63
		(0.031)	(0.052)		(0.031)	(0.051)
$Constant$	-0.006	-0.005	-0.005			
	[-1.63]	[-1.54]	[-1.59]			
Industry FE	No	No	No	Yes	Yes	Yes
R^2	0.284	0.292	0.298	0.284	0.292	0.297

Table 4: Announcement Effects: Stock Return Relative to Matched Firms. The table shows the results of regressing a panel of "abnormal" daily stock returns of firms that announced voluntary WFH on a constant, announcement-window indicator variables $WFHday_{0,4}$ and $WFHd_{5,9}$, defined in notes of table 3, and return on aggregate stock market R^{market}. "Abnormal" return is defined as return difference relative to return of aggregate stock market return in column 1 and relative to return of matched firms in columns 2-5. The matching method is indicated in columns. For each WFH firm we use up to three matched firms and average across their returns. The standard errors (Driscoll and Kraay (1998) with 20 lags) for market returns are in parentheses and the equivalently calculated t-statistics for the indicator variables and constant in brackets. ***, **, and * indicate 99%, 95%, and 90% significance, respectively. Significance stars are omitted for market returns. The panel is from July 1, 2019 to April 1, 2020 (i.e., end of fever period March 19 plus the necessary 10-day announcement window).

	(1) Market	(2) Industry-size	(3) Industry-PS	(4) Size-PS	(5) Propensity score
Panel A. All firms					
$Constant$	-0.001	0.000	-0.000	-0.000	-0.000
	[-1.46]	[0.10]	[-0.39]	[-0.43]	[-1.56]
$WFH_{0,4}$	0.010***	0.007***	0.004***	0.005***	0.009***
	[3.33]	[11.60]	[6.09]	[5.05]	[8.68]
$WFH_{5,9}$	0.004	0.001	0.004*	0.002	0.001
	[1.57]	[0.39]	[1.89]	[0.91]	[0.70]
R_{market}	0.04	-0.04	-0.02	-0.03	-0.01
	(0.023)	(0.008)	(0.013)	(0.007)	(0.005)
Industry FE	No	No	No	No	No
R^2	0.004	0.002	0.001	0.001	0.002
N	53579	53579	44839	44839	44839
Panel B. Essential Firms					
$Constant$	-0.001	0.000	0.000	0.000	-0.000
	[-1.47]	[0.08]	[0.20]	[0.09]	[-1.52]
$WFH_{0,4}$	0.007***	0.006***	-0.000	0.003***	0.007***
	[3.44]	[7.84]	[-0.00]	[5.07]	[9.05]
$WFH_{5,9}$	0.002	-0.001	0.003	0.001	0.001
	[1.11]	[-0.29]	[1.37]	[0.79]	[0.99]
R_{market}	0.05	-0.05	-0.01	-0.04	-0.02
	(0.026)	(0.014)	(0.012)	(0.010)	(0.007)
Industry FE	No	No	No	No	No
R^2	0.003	0.002	0.000	0.001	0.001
N	27359	27359	24509	24509	24509
Panel C. Non-essential Firms					
$Constant$	-0.001	0.000	-0.000	-0.000	-0.000
	[-1.15]	[0.04]	[-0.88]	[-0.65]	[-0.91]
$WFH_{0,4}$	0.012***	0.009***	0.008***	0.007***	0.012***
	[3.07]	[9.10]	[8.96]	[4.10]	[4.75]
$WFH_{5,9}$	0.006*	0.002	0.006**	0.003	0.001
	[1.89]	[0.98]	[2.15]	[0.95]	[0.44]
R_{market}	0.03	-0.02	-0.03	-0.03	-0.00
	(0.022)	(0.008)	(0.015)	(0.007)	(0.015)
Industry FE	No	No	No	No	No
R^2	0.005	0.002	0.002	0.001	0.003
N	26220	26220	20330	20330	20330

Table 5: Announcement Effects: Default Probabilities. The table shows the results of regressing a panel of daily changes in default probabilities on a constant, an indicator variable $WFHday_{0,4}$ indicating the window of five days from the firm's announcement to work from home (starting at day zero of the announcement), an indicator variable $WFHd_{5,9}$ indicating a subsequent window of five days, on average change in default probabilities across market $PrDef^{market}$ and average change in default probabilities across firms within industries $PrDef^{industry}$. Columns 4-6 include industry fixed effects at NAICS 2 digits level. The standard errors (Driscoll and Kraay (1998) with 20 lags) for market and industry changes in default probabilities are in parentheses and the equivalently calculated t-statistics for the indicator variables and constant in brackets. ***, **, and * indicate 99%, 95%, and 90% significance, respectively. Significance stars are omitted for market and industry returns. The panel is from July 1, 2019 to April 1, 2020 (i.e., end of fever period March 19 plus the necessary 10-day announcement window) and consists of 474083, 308634, and 165449 observations in panels A, B, and C, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All firms						
$WFH_{0,4}$	-0.020***	-0.014***	-0.021***	-0.021***	-0.014***	-0.021***
	[-3.28]	[-3.12]	[-4.13]	[-3.30]	[-3.12]	[-4.11]
$WFH_{5,9}$	0.004	-0.001	0.004	0.003	-0.001	0.003
	[0.84]	[-0.28]	[0.82]	[0.71]	[-0.28]	[0.79]
$PrDef_{market}$	0.66		0.36	0.66		0.35
	(0.029)		(0.023)	(0.029)		(0.023)
$PrDef_{industry}$		0.39	0.30		0.39	0.30
		(0.062)	(0.052)		(0.062)	(0.051)
$Constant$	-0.003	0.000	-0.002			
	[-1.31]	[1.21]	[-1.30]			
Industry FE	No	No	No	Yes	Yes	Yes
R^2	0.101	0.138	0.160	0.100	0.138	0.160
Panel B. Essential Firms						
$WFH_{0,4}$	-0.010	-0.006	-0.011*	-0.011	-0.006	-0.011*
	[-1.33]	[-1.61]	[-1.85]	[-1.40]	[-1.63]	[-1.86]
$WFH_{5,9}$	0.002	-0.003	0.001	0.002	-0.003	0.001
	[0.53]	[-0.97]	[0.23]	[0.36]	[-1.00]	[0.17]
$PrDef_{market}$	0.59		0.32	0.59		0.32
	(0.017)		(0.020)	(0.017)		(0.020)
$PrDef_{industry}$		0.34	0.27		0.34	0.27
		(0.056)	(0.046)		(0.055)	(0.045)
$Constant$	-0.003	0.000	-0.002			
	[-1.32]	[1.19]	[-1.28]			
Industry FE	No	No	No	Yes	Yes	Yes
R^2	0.090	0.136	0.156	0.088	0.136	0.156
Panel C. Non-essential Firms						
$WFH_{0,4}$	-0.034***	-0.028***	-0.035***	-0.035***	-0.029***	-0.036***
	[-5.28]	[-6.86]	[-5.91]	[-5.21]	[-6.85]	[-5.90]
$WFH_{5,9}$	0.007	0.005	0.009	0.007	0.005	0.009
	[1.23]	[1.05]	[1.62]	[1.08]	[0.96]	[1.52]
$PrDef_{market}$	0.79		0.34	0.79		0.34
	(0.052)		(0.037)	(0.052)		(0.037)
$PrDef_{industry}$		0.58	0.45		0.58	0.45
		(0.046)	(0.051)		(0.046)	(0.051)
$Constant$	-0.004	0.000	-0.001			
	[-1.32]	[0.14]	[-0.41]			
Industry FE	No	No	No	Yes	Yes	Yes
R^2	0.121	0.165	0.178	0.121	0.164	0.177

Table 6: Announcement Effects: Default Probabilities Relative to Matched Firms. The table shows the results of regressing a panel of relative changse in default probabilities of firms that announced voluntary WFH on a constant, announcement-window indicator variables $WFHday_{0,4}$ and $WFHd_{5,9}$, defined in notes of table 3, and average change in default probabilities across market $PrDef^{market}$. Relative change in default probabilities is defined as the daily change in default probability of WFH firm relative to daily average change in default probabilities across market in columns 1, and relative to daily change in default probabilities of matched firms in columns 2-5. The matching method is indicated in columns. For each WFH firm we use up to three matched firms and average across them. The standard errors (Driscoll and Kraay (1998) with 20 lags) for $PrDef_{market}$ are in parentheses and the equivalently calculated t-statistics for the indicator variables and constant in brackets. ***, **, and * indicate 99%, 95%, and 90% significance, respectively. Significance stars are omitted for $PrDef_{market}$. The panel is from July 1, 2019 to April 1, 2020 (i.e., end of fever period March 19 plus the necessary 10-day announcement window).

	(1)	(2)	(3)	(4)	(5)
	Market	Industry-size	Industry-PS	Size-PS	Propensity score
Panel A. All firms					
$Constant$	0.000	0.000	0.000	0.000	0.000
	[1.03]	[0.08]	[0.63]	[0.50]	[1.11]
$WFH_{0,4}$	-0.011***	0.001	-0.006***	-0.006***	-0.003
	[-3.73]	[0.31]	[-2.82]	[-2.99]	[-1.30]
$WFH_{5,9}$	-0.000	0.007	-0.007*	0.000	0.001
	[-0.09]	[1.47]	[-1.95]	[0.10]	[0.11]
$PrDef_{market}$	-0.63	-0.20	-0.14	-0.11	-0.09
	(0.015)	(0.016)	(0.013)	(0.013)	(0.016)
Industry FE	No	No	No	No	No
R^2	0.162	0.015	0.007	0.005	0.003
N	52912	52912	44465	44465	44465
Panel B. Essential Firms					
$Constant$	-0.000	-0.000	0.000	0.000	0.000
	[-0.81]	[-0.56]	[0.14]	[0.67]	[0.52]
$WFH_{0,4}$	-0.001	0.005*	-0.004	0.001	0.004
	[-0.42]	[1.77]	[-1.34]	[0.32]	[1.43]
$WFH_{5,9}$	-0.001	0.004	0.003**	0.005*	-0.002
	[-0.53]	[0.83]	[2.05]	[1.96]	[-0.71]
$PrDef_{market}$	-0.76	-0.25	-0.12	-0.15	-0.26
	(0.011)	(0.014)	(0.011)	(0.019)	(0.016)
Industry FE	No	No	No	No	No
R^2	0.340	0.027	0.008	0.013	0.026
N	27072	27072	24325	24325	24325
Panel C. Non-essential Firms					
$Constant$	0.001	0.000	0.000	0.000	0.001
	[1.30]	[0.53]	[0.81]	[0.19]	[1.45]
$WFH_{0,4}$	-0.024***	-0.005**	-0.008***	-0.014***	-0.015***
	[-6.52]	[-2.38]	[-2.65]	[-4.69]	[-4.63]
$WFH_{5,9}$	0.002	0.011*	-0.019***	-0.005	0.004
	[0.33]	[1.83]	[-2.81]	[-0.83]	[0.56]
$PrDef_{market}$	-0.49	-0.15	-0.16	-0.07	0.12
	(0.021)	(0.022)	(0.022)	(0.013)	(0.025)
Industry FE	No	No	No	No	No
R^2	0.078	0.008	0.007	0.002	0.005
N	25840	25840	20140	20140	20140

Table 7: Firm Operating Performance and Work-from-Home during Covid-19.

This table reports the results of estimating regression of the form: $Y_{i,t} = \alpha + \beta_0 \times WFH_i + \beta_1 \times CovidPeriod_t + \beta_2 \times WFH_i \times CovidPeriod_t + LnME_{i,t} + FE^{ind} + FE^{Q} + \epsilon_{i,t}$, where $Y_{i,t}$ is growth in one of these variables: sales, gross profit, total assets, R&D and number of employees. WFH_i is a (time-constant) dummy variable indicating whether a firm announced WFH regime by March 19, 2020. $CovidPeriod_t$ is a dummy variable indicating whether the firm's fiscal quarter end (fiscal year end for the number of employees) falls into the covid-19 period, i.e., year 2020. $LnME$ is log market capitalization. The data is at quarterly frequency except for the number of employees which is at annual frequency. To avoid a potential seasonality, we calculate the growth in the quarterly variables by comparing the same quarters in two consecutive years, e.g., $Y_{i,2019Q1} = \frac{Sales_{i,2019Q1} - Sales_{i,Q2018Q1}}{Sales_{i,2018Q1}}$. Regressions include quarter and industry (Naics 2- digits) fixed effects. Standard errors are clustered at 2-digit NAICS industries. The panel of firms spans the period from 2019 to Q1 2021. Panel A reports estimation for all firms in the sample, panel B for essential firms and panel C for non-essential firms.

	Growth in				
	Sales	Gross profits	Assets	R&D	Employees
Panel A. All firms					
WFH	0.000	0.007	0.010	-0.021	-0.002
	[0.04]	[0.60]	[0.52]	[-0.83]	[-0.20]
$CovidPeriod$	-0.095***	-0.086***	-0.041***	-0.066***	-0.059***
	[-9.07]	[-7.10]	[-2.97]	[-6.41]	[-7.10]
$WFH \times CovidPeriod$	0.033**	0.020	0.019*	0.043***	0.034***
	[2.52]	[1.17]	[1.75]	[6.86]	[4.05]
$LnME$	-0.002	-0.003**	-0.002	-0.001	0.002*
	[-1.03]	[-2.28]	[-1.26]	[-0.24]	[1.72]
Industry FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	No
R^2	0.095	0.073	0.038	0.042	0.090
N	21668	20060	22523	8545	4963

Table 7 continued

	Growth in				
	Sales	Gross profits	Assets	R&D	Employees
Panel B. Essential Firms					
WFH	0.005	0.014	0.002	-0.019	0.001
	[0.36]	[0.55]	[0.08]	[-0.38]	[0.04]
$CovidPeriod$	-0.096***	-0.087***	-0.030*	-0.072***	-0.056***
	[-6.85]	[-5.04]	[-1.96]	[-3.50]	[-5.37]
$WFH \times CovidPeriod$	0.019	0.003	0.031***	0.055***	0.017
	[1.26]	[0.15]	[2.84]	[2.67]	[1.42]
$LnME$	-0.004	-0.004**	-0.003	0.003	0.002
	[-1.41]	[-2.39]	[-1.62]	[0.72]	[1.53]
Industry FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	No
R^2	0.098	0.069	0.034	0.039	0.111
N	13860	12474	14693	5492	3230
Panel C. Non-essential Firms					
WFH	-0.001	0.001	0.008	0.002	-0.001
	[-0.09]	[0.04]	[0.39]	[0.08]	[-0.11]
$CovidPeriod$	-0.092***	-0.083***	-0.061***	-0.055***	-0.064***
	[-7.09]	[-5.03]	[-4.78]	[-4.08]	[-6.60]
$WFH \times CovidPeriod$	0.048***	0.035**	0.016*	0.026	0.053***
	[3.68]	[2.40]	[1.72]	[1.18]	[3.32]
$LnME$	0.002	-0.002	0.002	-0.005	0.004
	[0.55]	[-0.90]	[1.28]	[-0.79]	[1.42]
Industry FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	No
R^2	0.119	0.095	0.076	0.068	0.102
N	7808	7586	7830	3053	1733

Table 8: Firm Operating Performance of Matched Firms during Covid-19, All Firms. This table reports the results of estimating regression of the form: $Y_{i,t} = \alpha + \beta_0 \times Match_i + \beta_1 \times CovidPeriod_t + \beta_2 \times Match_i \times CovidPeriod_t + LnME_{i,t} + FE^{ind} + FE^{Q} + \epsilon_{i,t}$, where $Y_{i,t}$ is growth in one of these variables: sales, gross profit, total assets and R&D indicated in panels. $Match_i$ is a dummy variable indicating whether a firm is a close match to a firm that announced WFH regime by March 19, 2020 and the matching methods are indicated in columns. $CovidPeriod_t$ is a dummy variable indicating whether the firm's fiscal quarter end (fiscal year end for the number of employees) falls into the covid-19 period, i.e., year 2020 and $LnME$ is log market capitalization. The data is at quarterly frequency except for the number of employees which is at annual frequency. To avoid a potential seasonality, we calculate the growth in the quarterly variables by comparing the same quarters in two consecutive years, e.g., $Y_{i,2019Q1} = \frac{Sales_{i,2019Q1} - Sales_{i,Q2018Q1}}{Sales_{i,2018Q1}}$. Regressions include quarter and industry (Naics 2- digits) fixed effects. Standard errors are clustered at 2-digit NAICS industries. The panel of firms spans the period from 2019 to Q1 2021.

	Industry-size	Industry-PS	Size-PS	Propensity score
Panel A. Revenue growth				
$Match$	-0.001	-0.018	0.004	0.013
	[-0.12]	[-1.25]	[0.30]	[0.68]
$CovidPeriod$	-0.103***	-0.102***	-0.101***	-0.101***
	[-8.03]	[-7.84]	[-7.79]	[-7.60]
$Match \times CovidPeriod$	0.036**	0.037**	0.034*	0.035*
	[2.08]	[1.97]	[1.88]	[1.73]
$LnME$	-0.003	-0.001	-0.003	-0.004
	[-1.26]	[-0.74]	[-1.55]	[-1.56]
Industry FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
R^2	0.096	0.095	0.096	0.098
N	21668	21668	21668	21668
Panel B. Gross profit growth				
$Match$	-0.002	-0.006	0.007	0.024
	[-0.21]	[-0.39]	[0.45]	[1.40]
$CovidPeriod$	-0.091***	-0.092***	-0.091***	-0.089***
	[-6.51]	[-6.41]	[-6.50]	[-6.18]
$Match \times CovidPeriod$	0.024	0.030	0.027	0.019
	[1.03]	[1.62]	[1.35]	[0.81]
$LnME$	-0.003**	-0.003**	-0.004***	-0.005***
	[-2.17]	[-2.04]	[-2.92]	[-2.98]
Industry FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
R^2	0.073	0.073	0.074	0.075
N	20060	20060	20060	20060

Table 8 continued

	Industry-size	Industry-PS	Size-PS	Propensity score
Panel C. Total assets growth				
$Match$	0.013	-0.005	0.013	0.032
	[0.87]	[-0.29]	[0.60]	[1.47]
$CovidPeriod$	-0.040***	-0.042***	-0.040***	-0.043***
	[-2.68]	[-2.65]	[-2.72]	[-2.64]
$Match \times CovidPeriod$	0.005	0.012	0.007	0.016
	[0.30]	[1.32]	[0.66]	[1.08]
$LnME$	-0.003*	-0.001	-0.003*	-0.004***
	[-1.70]	[-0.87]	[-1.81]	[-2.73]
Industry FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
R^2	0.038	0.038	0.038	0.042
N	22523	22523	22523	22523
Panel D. R&D growth				
$Match$	0.031	-0.054**	-0.006	0.020
	[1.52]	[-2.15]	[-0.27]	[1.02]
$CovidPeriod$	-0.055***	-0.073***	-0.057***	-0.067***
	[-5.01]	[-5.80]	[-5.77]	[-4.64]
$Match \times CovidPeriod$	-0.015*	0.038***	-0.010	0.019
	[-1.72]	[3.52]	[-0.83]	[1.22]
$LnME$	-0.003	0.001	0.000	-0.004
	[-1.60]	[0.31]	[0.11]	[-1.52]
Industry FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
R^2	0.043	0.046	0.042	0.043
N	8545	8545	8545	8545
Panel E. Employees growth				
$Match$	0.012	-0.016	0.010	0.025**
	[1.34]	[-1.09]	[0.80]	[2.03]
$CovidPeriod$	-0.054***	-0.061***	-0.055***	-0.057***
	[-6.37]	[-5.88]	[-6.01]	[-5.47]
$Match \times CovidPeriod$	-0.002	0.023**	0.001	0.007
	[-0.21]	[2.06]	[0.09]	[0.63]
$LnME$	0.002	0.003**	0.002	0.000
	[0.95]	[2.11]	[1.14]	[0.19]
Industry FE	Yes	Yes	Yes	Yes
Quarter FE	No	No	No	No
R^2	0.089	0.090	0.089	0.093
N	4963	4963	4963	4963

Table 9: Firm Operating Performance and Work-from-Home during Covid-19, Quarter by Quarter. This table reports the results of estimating regression of the form: $Y_{i,t} = \alpha + \beta_0 \times WFH_i + \sum_{q=20Q1}^{21Q2} \beta_{1,q} \times CovidQuarter_q + \sum_{q=20Q1}^{21Q2} \beta_{2,q} \times WFH_i \times Covidquarter_q + FE^{ind} + FE^Q + \epsilon_{i,t}$, where $Y_{i,t}$ is growth in one of these variables: sales, gross profit, total assets and R&D. WFH_i is a (time-constant) dummy variable indicating whether a firm announced WFH regime by March 19. $CovidQuarter_q$ are dummy variables indicating the individual quarters from the outbreak of covid-19, 2020 Q1-2021 Q2. The data is at quarterly frequency. To avoid a potential seasonality, we calculate the growth in the quarterly variables by comparing the same quarters in two consecutive years, e.g., $Y_{i,2019Q1} = \frac{Sales_{i,2019Q1} - Sales_{i,Q2018Q1}}{Sales_{i,2018Q1}}$. Regressions include quarter and industry (Naics 2- digits) fixed effects. Standard errors are clustered at 2-digit NAICS industries. The panel of firms spans the period from 2019 Q1 to 2021 Q2. Panel A reports estimation for all firms in the sample, panel B for essential firms and panel C for non-essential firms.

	Growth in			
	Sales	Gross profits	Assets	R&D
Panel A. All firms				
WFH	0.004	0.020**	0.011	-0.027
	[0.48]	[2.17]	[0.58]	[-1.12]
$20Q1$	-0.071***	-0.065***	-0.061***	-0.070***
	[-7.34]	[-3.25]	[-3.39]	[-7.14]
$20Q2$	-0.189***	-0.166***	-0.042*	-0.121***
	[-7.75]	[-6.78]	[-1.92]	[-6.96]
$20Q3$	-0.083***	-0.034**	-0.032	-0.082***
	[-5.28]	[-2.41]	[-1.55]	[-3.58]
$20Q4$	-0.037**	0.017	-0.027	-0.046***
	[-2.42]	[1.23]	[-1.32]	[-2.67]
$21Q1$	0.012	0.145***	-0.011	-0.076***
	[0.50]	[4.29]	[-0.54]	[-3.13]
$21Q2$	0.311***	0.473***	-0.022	0.056*
	[3.74]	[7.20]	[-1.39]	[1.87]
$WFH \times 20Q1$	0.018**	0.005	0.025*	0.040***
	[2.16]	[0.31]	[1.82]	[3.78]
$WFH \times 20Q2$	0.061***	0.049*	0.014	0.053***
	[2.75]	[1.94]	[1.09]	[4.81]
$WFH \times 20Q3$	0.035**	0.009	0.027*	0.061***
	[2.07]	[0.53]	[1.93]	[3.82]
$WFH \times 20Q4$	0.034**	0.011	0.012	0.066***
	[2.40]	[0.81]	[0.51]	[8.73]
$WFH \times 21Q1$	0.017	-0.007	0.001	0.063***
	[0.78]	[-0.20]	[0.03]	[6.08]
$WFH \times 21Q2$	-0.130**	-0.140	-0.004	0.047**
	[-2.10]	[-1.49]	[-0.22]	[2.47]
$LnME$	-0.004**	-0.004***	-0.003*	-0.002
	[-2.01]	[-3.25]	[-1.85]	[-0.65]
Industry FE	Yes	Yes	Yes	Yes
R^2	0.161	0.166	0.037	0.050
N	23987	22174	24929	9438

Table 9 continued

	Panel B. Essential firms Growth in				Panel C. Non-essential firms Growth in			
	Sales	Gross profits	Assets	R&D	Sales	Gross profits	Assets	R&D
WFH	0.008	0.022	0.004	-0.028	0.009	0.017	0.003	-0.001
	[0.53]	[1.03]	[0.21]	[-0.59]	[0.63]	[1.24]	[0.16]	[-0.07]
$20Q1$	-0.083***	-0.086***	-0.074***	-0.092***	-0.047**	-0.030**	-0.037	-0.029
	[-5.26]	[-2.81]	[-3.45]	[-4.66]	[-2.53]	[-2.10]	[-1.29]	[-1.32]
$20Q2$	-0.184***	-0.150***	-0.023	-0.129***	-0.198***	-0.194***	-0.081***	-0.103***
	[-6.02]	[-5.18]	[-0.96]	[-3.64]	[-7.38]	[-6.33]	[-3.72]	[-4.07]
$20Q3$	-0.084***	-0.022	-0.008	-0.087***	-0.082***	-0.056***	-0.079***	-0.070***
	[-3.83]	[-1.29]	[-0.34]	[-2.59]	[-7.13]	[-3.40]	[-3.31]	[-8.05]
$20Q4$	-0.040**	0.020	0.005	-0.044	-0.032	0.013	-0.092***	-0.046***
	[-2.13]	[1.58]	[0.27]	[-1.58]	[-1.55]	[0.56]	[-3.10]	[-3.88]
$21Q1$	0.001	0.159***	0.009	-0.100***	0.033	0.118***	-0.053**	-0.026*
	[0.03]	[3.86]	[0.44]	[-3.35]	[1.54]	[4.79]	[-2.19]	[-1.81]
$21Q2$	0.275**	0.420***	-0.007	0.048	0.381***	0.567***	-0.052	0.074**
	[2.38]	[5.28]	[-0.47]	[1.34]	[6.40]	[5.64]	[-1.44]	[2.48]
$WFH \times 20Q1$	0.003	-0.021	0.035***	0.051***	0.026**	0.019	0.012	0.021
	[0.26]	[-0.79]	[3.31]	[4.07]	[2.20]	[1.63]	[0.65]	[0.80]
$WFH \times 20Q2$	0.043*	0.033	0.030*	0.062*	0.086***	0.079***	0.016	0.033
	[1.74]	[1.03]	[1.79]	[1.92]	[3.55]	[3.43]	[1.63]	[1.05]
$WFH \times 20Q3$	0.021	-0.004	0.040**	0.079*	0.048***	0.028**	0.032***	0.040
	[1.00]	[-0.14]	[2.26]	[1.93]	[2.75]	[1.99]	[3.15]	[1.57]
$WFH \times 20Q4$	0.030	0.019	0.014	0.092***	0.032**	0.004	0.034**	0.034
	[1.53]	[1.06]	[0.43]	[2.83]	[2.47]	[0.31]	[2.27]	[1.18]
$WFH \times 21Q1$	0.025	0.020	-0.006	0.094***	0.004	-0.016	0.037*	0.026
	[0.97]	[0.58]	[-0.16]	[2.96]	[0.21]	[-0.44]	[1.77]	[1.11]
$WFH \times 21Q2$	-0.112	-0.064	-0.008	0.124**	-0.178***	-0.256***	0.016	-0.013
	[-1.54]	[-0.66]	[-0.33]	[2.52]	[-3.29]	[-3.26]	[0.88]	[-0.42]
$LnME$	-0.005*	-0.005**	-0.004**	0.001	-0.001	-0.003*	0.001	-0.004
	[-1.83]	[-2.40]	[-2.17]	[0.31]	[-0.29]	[-1.78]	[0.80]	[-0.75]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.145	0.151	0.040	0.049	0.220	0.207	0.072	0.072
N	15343	13796	16262	6068	8644	8378	8667	3370

Table 10: Firm Operating Performance of Matched Firms during Covid-19, Quarter by Quarter. This table reports the results of estimating regression of the form: $Y_{i,t} = \alpha + \beta_0 \times Match_i + \sum_{q=20Q1}^{21Q2} \beta_{1,q} \times CovidQuarter_q + \sum_{q=20Q1}^{21Q2} \beta_{2,q} \times Match_i \times Covidquarter_q + FE^{ind} + FE^{Q} + \epsilon_{i,t}$, where $Y_{i,t}$ is growth in one of these variables: sales, gross profit, total assets and R&D indicated in panels. $Match_i$ is a (time-constant) dummy variable indicating whether a firm is a close match to a firm that announced WFH regime by March 19, and the matching methods are indicated in columns. $CovidQuarter_q$ are dummy variables indicating the individual quarters from the outbreak of covid-19, 2020 Q1-2021 Q2. The data is at quarterly frequency. To avoid a potential seasonality, we calculate the growth in the quarterly variables by comparing the same quarters in two consecutive years, e.g., $Y_{i,2019Q1} = \frac{Sales_{i,2019Q1} - Sales_{i,Q2018Q1}}{Sales_{i,2018Q1}}$. Regressions include quarter and industry (Naics 2- digits) fixed effects. Standard errors are clustered at 2-digit NAICS industries. The panel of firms spans the period from 2019 Q1 to 2021 Q2.

	Growth in revenues				Growth in gross profit			
	Industry-size	Industry-PS	Size-PS	Propensity score	Industry-size	Industry-PS	Size-PS	Propensity score
$Match$	0.011	-0.009	0.013	0.023	0.019**	0.015	0.027	0.047***
	[0.99]	[-0.67]	[0.79]	[1.22]	[2.16]	[0.95]	[1.34]	[2.76]
$20Q1$	-0.075***	-0.073***	-0.072***	-0.071***	-0.068***	-0.066***	-0.065***	-0.066***
	[-8.11]	[-9.26]	[-8.30]	[-7.80]	[-3.91]	[-3.67]	[-3.75]	[-3.81]
$20Q2$	-0.203***	-0.200***	-0.201***	-0.200***	-0.177***	-0.175***	-0.176***	-0.175***
	[-6.94]	[-7.03]	[-6.98]	[-6.90]	[-5.62]	[-6.27]	[-6.00]	[-5.76]
$20Q3$	-0.093***	-0.089***	-0.090***	-0.087***	-0.041**	-0.039**	-0.042**	-0.032*
	[-5.14]	[-4.65]	[-5.48]	[-5.22]	[-2.22]	[-2.15]	[-2.38]	[-1.69]
$20Q4$	-0.038**	-0.041**	-0.039**	-0.042**	0.024	0.018	0.020	0.022
	[-2.20]	[-2.41]	[-2.54]	[-2.52]	[1.24]	[1.00]	[1.09]	[1.13]
$21Q1$	0.018	0.016	0.015	0.015	0.157***	0.159***	0.155***	0.157***
	[0.84]	[0.67]	[0.75]	[0.81]	[5.09]	[4.54]	[4.09]	[4.22]
$21Q2$	0.337***	0.341***	0.339***	0.341***	0.521***	0.515***	0.516***	0.515***
	[4.01]	[3.96]	[3.90]	[4.00]	[6.95]	[7.25]	[7.39]	[6.96]
$Match \times 20Q1$	0.020*	0.017	0.012	0.010	0.008	0.005	-0.000	0.002
	[1.86]	[1.01]	[0.98]	[0.84]	[0.49]	[0.23]	[-0.02]	[0.11]
$Match \times 20Q2$	0.063**	0.065**	0.067**	0.066**	0.049	0.051**	0.054*	0.053
	[2.20]	[2.32]	[2.31]	[2.16]	[1.42]	[2.04]	[1.82]	[1.58]
$Match \times 20Q3$	0.040*	0.035	0.035*	0.027	0.023	0.019	0.029	-0.003
	[1.68]	[1.43]	[1.72]	[1.22]	[1.19]	[0.80]	[1.42]	[-0.13]
$Match \times 20Q4$	0.014	0.026	0.020	0.031	-0.014	0.003	-0.006	-0.013
	[0.69]	[1.38]	[0.98]	[1.12]	[-0.83]	[0.13]	[-0.26]	[-0.52]
$Match \times 21Q1$	-0.011	-0.007	-0.003	-0.005	-0.037	-0.050***	-0.038	-0.045**
	[-0.68]	[-0.48]	[-0.24]	[-0.28]	[-1.35]	[-2.69]	[-1.41]	[-2.07]
$Match \times 21Q2$	-0.121***	-0.158***	-0.149***	-0.158***	-0.186**	-0.201**	-0.198**	-0.203**
	[-3.28]	[-3.08]	[-2.60]	[-2.72]	[-2.17]	[-2.48]	[-2.47]	[-2.41]
$LnME$	-0.004*	-0.003*	-0.004**	-0.005**	-0.004**	-0.003**	-0.004**	-0.006***
	[-1.87]	[-1.69]	[-2.28]	[-1.99]	[-2.18]	[-2.36]	[-2.27]	[-2.99]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.163	0.165	0.164	0.166	0.170	0.171	0.171	0.171
N	23987	23987	23987	23987	22174	22174	22174	22174

Table 10

	Growth in assets				Growth in R&D			
	Industry-size	Industry-PS	Size-PS	Propensity score	Industry-size	Industry-PS	Size-PS	Propensity score
Match	0.018	-0.003	0.016	0.031	0.035	-0.062**	-0.007	0.018
	[0.97]	[-0.20]	[0.66]	[1.36]	[1.59]	[-2.22]	[-0.31]	[0.87]
$20Q1$	-0.059***	-0.064***	-0.059***	-0.061***	-0.059***	-0.071***	-0.055***	-0.067***
	[-3.43]	[-3.31]	[-3.33]	[-3.43]	[-5.81]	[-5.99]	[-6.79]	[-4.42]
$20Q2$	-0.043*	-0.043*	-0.043*	-0.046*	-0.112***	-0.134***	-0.116***	-0.131***
	[-1.76]	[-1.77]	[-1.79]	[-1.84]	[-6.47]	[-6.38]	[-7.67]	[-5.50]
$20Q3$	-0.030	-0.032	-0.032	-0.035	-0.066***	-0.090***	-0.072***	-0.085***
	[-1.28]	[-1.38]	[-1.40]	[-1.44]	[-3.07]	[-3.24]	[-3.30]	[-2.79]
$20Q4$	-0.024	-0.027	-0.026	-0.031	-0.031*	-0.056***	-0.037*	-0.044**
	[-1.06]	[-1.14]	[-1.13]	[-1.25]	[-1.77]	[-2.87]	[-1.89]	[-2.10]
$21Q1$	-0.005	-0.008	-0.008	-0.013	-0.065***	-0.085***	-0.074***	-0.078***
	[-0.23]	[-0.34]	[-0.34]	[-0.54]	[-3.63]	[-2.81]	[-3.33]	[-2.62]
$21Q2$	-0.018	-0.018	-0.018	-0.021	0.080***	0.053	0.073***	0.061*
	[-0.94]	[-1.02]	[-1.01]	[-1.10]	[5.04]	[1.40]	[3.18]	[1.88]
$Match \times 20Q1$	0.000	0.018	0.002	0.009	-0.018	0.019	-0.029*	0.004
	[0.02]	[1.46]	[0.24]	[0.56]	[-1.41]	[1.09]	[-1.89]	[0.19]
$Match \times 20Q2$	0.007	0.009	0.008	0.020	-0.005	0.063***	0.006	0.048**
	[0.35]	[0.77]	[0.50]	[1.18]	[-0.39]	[3.60]	[0.57]	[2.04]
$Match \times 20Q3$	0.003	0.010	0.011	0.023	-0.023*	0.051***	-0.003	0.031
	[0.16]	[0.72]	[0.64]	[1.17]	[-1.95]	[2.63]	[-0.16]	[1.17]
$Match \times 20Q4$	-0.004	0.003	-0.000	0.017	-0.018	0.062***	0.001	0.020
	[-0.17]	[0.19]	[-0.00]	[0.83]	[-0.98]	[4.17]	[0.06]	[1.29]
$Match \times 21Q1$	-0.016	-0.010	-0.010	0.009	-0.005	0.054**	0.020	0.031
	[-0.67]	[-0.49]	[-0.41]	[0.43]	[-0.27]	[2.46]	[1.62]	[1.58]
$Match \times 21Q2$	-0.014	-0.014	-0.015	-0.005	-0.050	0.029	-0.030	0.004
	[-0.69]	[-0.93]	[-0.69]	[-0.31]	[-1.31]	[0.94]	[-0.85]	[0.20]
$LnME$	-0.004**	-0.002	-0.003**	-0.005***	-0.004*	0.000	-0.000	-0.005**
	[-2.09]	[-1.45]	[-2.43]	[-3.00]	[-1.76]	[0.07]	[-0.09]	[-1.97]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.037	0.036	0.037	0.040	0.051	0.054	0.050	0.051
N	24929	24929	24929	24929	9438	9438	9438	9438

Table 11: Matching Statistics. This table summarizes the statistics and quality of matching work-from-home firms with their equivalents based on industry-size, industry-PS, size-PS and propensity score as indicated in columns. The panels show the number of firms for which a matching firm can be found, the average absolute distance in the matching variable between the WFH firm and its matches, and the maximum absolute distance. The matching algorithm is described in detail in appendix 6.1.

	Industry size	Industry PS	Size PS	Propensity score
Panel A. Number of firms with a match				
1^{st} *match*	282.0	236.0	236.0	236.0
2^{nd} *match*	282.0	236.0	236.0	236.0
3^{rd} *match*	282.0	236.0	236.0	236.0
Panel B. Average absolute distance				
1^{st} *match*	0.149	0.003	0.007	0.008
2^{nd} *match*	0.249	0.004	0.009	0.011
3^{rd} *match*	0.329	0.005	0.012	0.013
Panel C. Maximum absolute distance				
1^{st} *match*	5.21	0.318	0.249	0.243
2^{nd} *match*	5.809	0.318	0.261	0.269
3^{rd} *match*	5.986	0.318	0.284	0.275