How Valuable is Corporate Adaptation to Crisis? Estimates from Covid-19 Work-from-Home Announcements

Abstract

This article estimates value and risk impacts of corporate adaptation to crisis using a unique sample of work-from-home announcements scraped from company websites during Covid-19. We find a 3-5% valuation increase compared to event-studies benchmarks, with significant reductions in market and labor-inflexibility risk exposures. The study infers adaptation benefits from corporate *action*, expanding on previous studies of flexibility and resilience emphasizing corporate characteristics. We estimate the characteristics that predicted work-from-home adoption, develop methodological extensions for clustered events, and show faster price response following Bloomberg coverage. Corporate adaptation to crisis adds value and reduces risk, beyond information in firm characteristics.

The deadly disease has arrived . . . , and employers are figuring out how to adapt.

—*The New York Times*, March 6, 2020

A corporation's ability to adapt to new circumstances, also called flexibility or resilience, depends on its assets, employees, financing, and strategy, and has long been viewed as a source of value and risk-mitigation (Stigler, 1939, Pindyck, 1982, Trigeorgis, 1996, Graham and Harvey, 2001).[1] Because both risk and the market price of risk increase in bad times, adaptation to crisis is particularly important.[2] The Covid-19 pandemic crystallized focus on corporate flexibility and resilience, especially work-from-home capability (Barry et al., 2022, Pagano et al., 2023).[3]

This article estimates value and risk impacts of corporate adaptation to Covid-19 using a unique sample of remote-work announcements. Early in the pandemic, we scraped company websites for statements of voluntary transitions to work-from-home, before required by mandatory lockdowns. Using event study methods, cumulative abnormal returns in the five days following announcement reached three-to-five percent of firm value. Further, announcer risk fell substantially relative to comparable firms, measured by declines in market beta, labor-inflexibility risk (Papanikolaou and Schmidt, 2022), and abnormal default probabilities. We conclude that adaptation to Covid-19 by voluntary transition to remote work increased the market's assessment of firm value and decreased perceived firm risk.

[1]See also Brennan and Schwartz (1985), McDonald and Siegel (1985), Triantis and Hodder (1990), Chen et al. (2011), Carlson et al. (2014), Reinartz and Schmid (2016), Gu et al. (2018), and Zhang (2019).

[2]Campbell and Cochrane (1999) discuss countercyclical risk premia and volatility. See Gabaix (2012) and Wachter (2013) for disaster risk premia.

[3]See also Acharya and Steffen (2020), Albuquerque et al. (2020), Au et al. (2021), Barrero et al. (2021), Bretscher et al. (2020), Brynjolfsson et al. (2020), Ding et al. (2021), Dingel and Neiman (2020), Fahlenbrach et al. (2021), Li et al. (2021), and Ramelli and Wagner (2020).

Our empirical identification strategy and quantitative findings are new to the literature on Covid-19 resilience specifically and corporate flexibility more generally. Prior studies compare firms with different *ex ante* characteristics. For example, in the Covid-19 literature, Dingel and Neiman (2020) ("DN") and Papanikolaou and Schmidt (2022) ("PS") create measures of labor suitability to the work-from-home transition from surveys and job types. PS further compare the stock returns of high- versus low-suitability firms. Similarly, the broader literature on corporate flexibility compares firms with high versus low operating leverage (Novy-Marx, 2011), labor leverage (Chen et al., 2011), and financial constraints (Campello et al., 2010). Prior literature on corporate flexibility thus emphasizes cross-sectional comparison of firms with different characteristics.

We add to cross-sectional comparisons using event studies, which employ matching and other control methods to compare firms with *similar* characteristics, but *different actions*.[4] In our case, the observable action is the voluntary announcement of a work-from-home policy. In short windows following announcement, the value of announcers increased, and risk decreased, relative to benchmarks. We thus add to prior literature investigating corporate flexibility or resilience as a firm characteristic by showing positive market reaction both statistically and economically to an observable corporate action – adaptation to work-from-home.

Our analysis begins by first investigating the corporate characteristics that predicted action, specifically the voluntary transition to remote work. Of the more than 2500 public firms with valid URLs whose websites we scraped, 273 had announced new remote-work policies before the first U.S. state-imposed lockdown on the evening of

[4]MacKinlay (1997) and Kothari and Warner (2007) survey event studies.

March 19. We use logistic regressions to determine the corporate characteristics that best predicted these work-from-home announcements. We consider the labor-suitability measures of DN and PS, intangible capital (Peters and Taylor, 2017), organizational capital (Eisfeldt and Papanikolaou, 2012, 2013), and other controls. Among these, the labor-suitability measures of DN and PS along with proxies for firm size are robustly the strongest predictors of work-from-home announcement. Using the BIC criteria for model selection, of the 1534 possible models combining different variables, the most informative model is parsimonious, combining the PS measure and log market capitalization. This result is important for two reasons. First, it validates that a widely used employment-flexibility characteristic (the PS measure) relates to action (work-from-home adoption). The statistically strong relationship mutually reinforces the validity of both the employment-flexibility measure and our new announcement data. Second, identifying the characteristics most closely associated with work-from-home announcement allows us to create matched samples of firms with similar characteristics that did not announce. These benchmarks are useful for event studies.

We next move on to analyzing announcement effects, in both value and risk. Our base results consider a five-day window beginning on the announcement day. We use panel regressions with event-window dummies, panel regressions of return differences relative to benchmarks, and scaled abnormal returns following methods developed by Brown and Warner (1980), Patell (1976), and extended by Kolari and Pynnönen (2010) to account for clustering of events in calendar time. We further account for the cross-serial correlations that arise in the test statistic with imperfectly clustered multi-day event windows. All of the methods lead to similar conclusions. Announcers experienced statistically significant abnormal returns in the days immediately following announcement, but not in windows before or after. Economically, the total amounts range from 3-5% of firm value. Magnitudes are at the lower end of the range with stronger benchmarking using characteristic matches and additional return factors, but stronger benchmarking does not diminish statistical significance because it also reduces noise. Announcement effects are smaller for firms in "essential" industries, but still statistically significant. Announcement effects also extend to risk. Comparing portfolios formed of announcers, characteristic-based matches, and other firms, the announcers experienced the strongest event-window declines in exposure to both market risk and the PS factor of supply-side Covid risk. From before to after the event window, announcer-portfolio PS exposure falls by 0.23 with a t-statistic below -5, while the characteristic-matched portfolio of non-announcers experienced essentially no change in exposure to PS risk. We find similar results of event-window reductions in default-probabilities using the measure of Duan et al. (2012). We conclude that work-from-home announcements informed markets about both firm value and risk.

We briefly comment on interpretation of these results. We do not claim that the announcement effects isolate purely operational effects of remote-work transitions. As is true of all imperfectly anticipated firm decisions, announcements are important both for the action itself, and also what the action reveals about underlying firm type (Lucas and McDonald, 1990, Carlson et al., 2006). Our work-from-home announcements communicated policy change, but also demonstrated adaptability in a concrete way that would have been difficult for markets to ascertain beforehand. Given this perspective, it would be surprising if work-from-home announcements did *not* positively impact market perceptions of firms. Corporate flexibility and resilience are widely believed to be important, but these characteristics must ultimately impact actions to be meaningful. Responding appropriately to crisis is the ultimate test of corporate resilience, and our work-from-home announcers demonstrated observable plans in this direction that markets positively reacted to.

Additional results confirm the validity and interpretation of our results. First, work-from-home announcements covered by Bloomberg realized abnormal returns more quickly, consistent with prominent news dissemination increasing the speed of price adjustment (Fedyk, 2022). Second, company ESG score (Albuquerque et al., 2020, Ding et al., 2021) helps to predict work-from-home announcement beyond labor-suitability, but does not alter inference about announcement effects. Finally, announcers and their characteristic-based matches experienced better operating performance than other firms during the pandemic, and announcers show significantly lower declines in employment and R&D relative to the matches. These results corroborate information transmission as an important channel of our announcement effects, show robustness to additional controls, and document ultimate effects on operating performance.

Beyond the broad literatures on corporate flexibility, resilience, and Covid risk, we emphasize relation to several papers. Pagano et al. (2023) ("PWZ") use Covid-19 to show how learning about a disaster and the eventual unfolding of events drive time-variation in the price of disaster risk. PWZ thus emphasize learning about aggregate disaster risk, while we show that markets learned from individual firms' announcements about adaptation to work-from-home. Barry et al. (2022) survey CFOs and find that corporate flexibility, particularly in the workplace, affects business plans and is important. Their perspective emphasizes looking inside the corporation at corporate plans to understand flexibility. We complement this look inside the corporation by documenting how markets observing from outside responded to a corporate action aimed at adapting to the crisis. Recent literature relies on survey- and experience-based measures of labor-suitability to remote work including the DN and PS estimates. We provide direct evidence of the validity of such measures for predicting actual work-from-home policies. Methodologically, we extend the single-day clustered event-study approach of Kolari and Pynnönen (2010) to imperfect clustering and multi-day event windows, accounting for cross-serial correlations. Finally, prior research addresses the pre-existing characteristics that made some firms more or less "immune" to the effects of Covid-19 (e.g., Ding et al., 2021). We add to this literature by showing market response to announcements of corporate *actions*. Distinct from assessments of *ex ante* corporate susceptibility, work-from-home announcements demonstrate corporate efforts to respond to new circumstances. Markets highly valued these adaptations.

A critique of our findings and the entire Covid resiliency literature is that such studies lack external validity because the pandemic was unique and will not be repeated. We disagree with this critique. Disasters and the anticipation of disasters are widely understood to be key drivers of economies and financial markets (Barro, 2006, 2009, Gabaix, 2012, Wachter, 2013). By their very nature, disasters are difficult to predict and each is unique in some respect. Nonetheless, agents and organizations of all types, including corporations, respond to disasters with intention to mitigate impact. Our results show that corporate responses to the pandemic were understood by financial markets in real time as value-increasing and risk-reducing. Our findings thus present a call-to-arms for corporate managers. Corporate characteristics can be difficult to change, relating to line of business or industry. Our results are explicitly not about characteristics, but actions that were within the control of firms given their observable characteristics. Moreover, we give tangible estimates for the value of these actions, in terms of both value and risk. These value and risk impacts are large and entirely new to the literature. If financial economists view disasters as an important area of study, then understanding how corporations react to disasters and the value created by their responses is essential.

1. Work-from-Home Announcements

Our initial sample consists of all firms in the CRSP database at the beginning of 2020 with listed common stock on the NYSE, Amex (NYSE MKT), or NASDAQ, and a share price higher than two dollars. We also require a non-missing company URL in COMPUSTAT. After checking URL validity, we have 2549 potential sample firms.

We search for announcements from January 20, 2020 - March 19, 2020, which corresponds to the Ramelli and Wagner (2020) "outbreak" and "fever" periods 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.

In greater detail, Ramelli and Wagner (2020) give a timeline of key events. They recognize January 20 as the "outbreak" beginning, when Chinese authorities confirmed human-to-human transmission. The Wuhan lockdown followed soon after on January 23. The Ramelli and Wagner "fever" period starts on January 24, after Italy imposed a local lockdown on January 23. Google search for "Covid-19" began to rise significantly at this time. Ramelli and Wagner choose March 20 as the final day of their fever period because the Federal Reserve announced major interventions in the corporate credit market on March 23. We end our sample period for announcements one day earlier, on March 19, because California announced the first U.S. state-imposed lockdown on the evening of March 19.[5] During our sample period, work-from-home announcements were voluntary and provided potential new information to capital markets.

Firms disseminated corporate responses to Covid-19 on their websites, through press releases, dedicated Covid pages, and official corporate forum posts. We used the Google API to obtain potential work-from-home announcements, natural language processing to parse and analyze the text, and manual verification to confirm the validity of work-from-home (WFH) announcements and date stamps.

Google asserts that its web crawlers pay "special attention" to changes in existing sites, which helps to more accurately detect corporate responses to Covid-19. We accessed Google's search data in early June 2020 to compile our initial dataset of WFH announcements. Following a bag-of-words approach (Loughran and McDonald, 2011), we used the search terms "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". Manual verification involved checking for false negatives using the Google web interface, narrowing date ranges and confirming date-time stamps, and ensuring that content describes a new WFH policy.[6] A thorough investor could in real time gather similar information to our

[5] By the end of March, a majority of US states (35) had issued shelter-in-place measures.

[6] For 27 companies, a website announcement regarding remote work was insufficiently clear that we

work-from-home sample by utilizing company websites and Google search. By March 19 when the first state-wide lockdown was implemented in California, 273 firms had announced voluntary transition to work-from-home.

Figure 1 shows several WFH announcements. These examples make clear that remote work was often a central part of larger corporate efforts to respond to the Covid pandemic. The announcements commonly referenced broader ideas such as business continuity and safety of employees, customers, and the public. We do not claim that the announcements isolate strictly operational effects of transitioning to work-from-home. Rather, as in all event studies, the announcements communicate an action, but the choice of action can convey additional information. Voluntary transitions to work-from-home reveal firms that were prepared to adapt to the Covid-19 crisis, and the market response reveals how investors interpreted this information.

Consider the null hypothesis that markets did *not* react to announcements of Covid responses. If this null were not rejected, an advocate for the importance of corporate flexibility might claim that markets already knew which firms would adapt and which would not. Our analysis shows however that while employment flexibility proxies from prior literature are highly significant and useful predictors of work-from-home adoption, they are far from perfect. We conclude that it is very unlikely that markets perfectly anticipated work-from-home announcements. Absence of value or risk impact associated with our announcements would therefore suggest that markets did not care very much about corporate adaptation to work-from-home. Such a finding would be difficult to square with the prevalent view that corporate flexibility and resilience are

emailed the companies (up to three times) to clarify whether the posting reflected work-from-home adoption. We received seven positive responses and categorized the remaining as not announcements.

valuable. If market participants understand the importance of corporate flexibility as a characteristic, then the act of adaptation to an ongoing crisis should also be valuable.

The examples in Figure 1 also help us to understand why non-announcers could not simply imitate announcers to obtain similar favorable market reactions. The work-from-home policy announcements were not cheap talk, i.e., costless and unverifiable statements without direct payoff implications (Crawford and Sobel, 1982). Remote-work policies are real decisions with implications for the productivity of hundreds or thousands of employees. Further, the announcement texts commonly reference prior planning and preparation that facilitated transition to work-from-home. It would be reasonable to infer that non-announcers had invested less in such prior preparations. Firms announcing voluntary transition to work-from-home therefore credibly demonstrated an important adaptation to crisis, and other firms could not necessarily immediately replicate these policies.

Figure 2 shows a timeline of our remote-work announcements, the S&P 500 index, a Google search index for "work from home", and a news-article frequency index.[7] The news index uses the same remote-work keywords as our announcement sample, and is based on articles from *The New York Times* and *The Wall Street Journal*. Consistent with Ramelli and Wagner (2020), Google search for remote-work increased throughout the fever period, and newspaper articles follow a similar pattern. At the end of the fever period as the S&P 500 reverses, the intensity of interest in work-from-home also reverses. The majority of announcements occurred when apparent concern for remote-work was

[7]Google search intensity is a common measure of attention, as in Da et al. (2011). Newspaper counts are used to measure economic policy uncertainty in Baker et al. (2016), and as a measure of attention to different types of macro news in Fisher et al. (2022).

greatest.[8] Our event-studies methodology, which builds on the prior approach of Kolari and Pynnönen (2010) for events clustered in time, is designed for such circumstances.

This figure also helps to illustrate the difference between cross-sectional versus event-study identification. The simplest dummy variable that we construct, WFH_i, indicates announcing a work-from-home policy any time within our search window. This variable relates to a corporate action, but is a pure cross-sectional variable. We use this variable to investigate whether prior measures of labor flexibility predicted voluntary adoption of work-from-home. Event studies use additional information from the timing of announcements, and show the market response to different observable actions taken by otherwise similar firms.

Firms were also affected by government orders to close on-site operations of non-essential businesses. Only essential businesses (sometimes called life-sustaining) could maintain in-person operations. The list of critical businesses was originally guided by the Department of Homeland Security's Cybersecurity and Infrastructure Security Agency and included medical supply chains, energy, food, industrial manufacturing, and emergency services. We follow the list of life-sustaining business classifications issued by Pennsylvania, based on NAICS codes. We classify firms as essential if belonging to an industry on this list, and non-essential otherwise.[9]

[8] Heightened general concern about remote work should of course raise the value of firm-specific news about adaptation. Hirshleifer and Sheng (2022) make a different point about complementarity in information processing between macro news and not-directly-related firm-specific news.

[9] See https://siccode.com/page/coronavirus-essential-businesses-by-naics-code. Other states gave descriptive guidance. See for example California: https://covid19.ca.gov/essential-workforce. Song et al. (2021) further discuss essential worker classification.

1.1. Labor suitability and other measures

We use measures of labor-suitability to remote-work developed by Dingel and Neiman (2020)("DN") and Papanikolaou and Schmidt (2022)("PS"). DN use occupation characteristics from the O*NET database to identify occupations adaptable to remote work. They calculate the percentage share of suitable occupations for 2-digit NAICS industries. PS use the American Time Use Survey (ATUS) to identify occupations that had demonstrated the capability for "telecommuting" in years prior to 2020. Our PS measure is the percentage of such occupations for 4-digit NAICS industries.[10] The DN and PS measures of labor suitability capture the standard primary data sources, O*NET and ATUS, used in the literature. For example, Pagano et al. (2023) also use measures of labor suitability to work-from-home based on the O*NET and ATUS databases.[11]

To differentiate between different types of capital possibly relevant to remote work, we consider intangible capital (IK) and organization capital (OK). We follow 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 (2012, 2013) and capitalizes a fraction of selling, general and administrative expenses only. We scale intangible capital and organization capital by total assets.

Table 1 provides summary statistics. Panel A shows properties over the cross-section of firms in our sample. Since WFH is an indicator, its mean reflects that 11 percent of firms in the sample announced remote-work policies in our sample period.

[10]Our PS measure is one minus the value used in their paper, affecting only exposition.

[11]Pagano et al. (2023) report that their results are robust to using the DN measure as well as Koren and Pető (2020), Hensvik et al. (2020), and Bai et al. (2021), which also use the O*NET and ATUS databases.

The PS share of labor suitable for telecommuting averages 27 percent, varying from 5 percent at the 10^{th} percentile to 55 percent at the 90^{th} percentile. DN shows a higher mean of 44 percent also with large cross-sectional variation. Intangible capital IK and organizational capital OK range from close to zero at the 10^{th} percentile to above one at the 90^{th} percentile. The remaining variables are standard controls. Panel B shows correlations between WFH and the labor- and capital-related variables. WFH correlates positively with both PS and DN, and the latter two variables have correlation coefficient of 0.42. IK and OK correlate positively with each other but not strongly with WFH.

Panel C characterizes the WFH and non-WFH firms using these variables. Work-from-home announcers have higher PS and DN values consistent with panel B, and the difference relative to non-WFH firms is statistically significant. On average, work-from-home firms also have lower intangible capital IK. The difference in organizational capital OK is insignificant. Considering controls, WFH firms are larger in market capitalization and number of employees, more profitable, and have lower book-to-market ratio and market beta.

1.2. Predicting announcements

To predict observable work-from-home adoption, we estimate a logit model:

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

where x_i is one (or all) of PS, DN, IK and OK, and v_i is a vector of controls. To allow comparison, we standardize all explanatory variables.

Table 2 shows results. The first column includes only controls, and among these $LnME$ and market beta significantly predict the WFH decision. Larger, lower market risk firms were more likely to voluntarily adopt remote work. The remaining columns investigate PS, DN, IK, and OK individually, and all together, with and without industry fixed effects. PS is a strong positive predictor of work-from-home announcements (column 2). The fitted likelihoods in the lower part of the table indicate that increasing PS from the 10th percentile to the 90th percentile increases the likelihood of remote-work announcement from 6 to 19 percent. Column 3 shows similar results for DN. Neither IK nor OK significantly predicts WFH announcements (columns 4 and 5). Column 6 includes all variables together without industry fixed effects, showing PS, DN, $LnME$, and market beta to retain predictive power.

Estimations in columns 7-10 include industry fixed effects at the level of 2-digit NAICS. As DN is defined at the same level, we exclude it from analysis. PS is again a strong predictor of work-from-home announcements (column 7), while IK and OK are insignificant (columns 8 and 9). Column 10 uses all variables together, showing PS and $LnME$ to be the only significant predictors. The marginal effects of PS on announcement likelihood remain unchanged (6-19 percent).

We also report the Bayesian Information Criterion (BIC), commonly used in model selection. We compared the BIC for all possible combinations of explanatory variables. From the 1534 possibilities,[12] we select the model minimizing BIC, shown in column 11, which uses PS and $LnME$ without industry fixed effects. We use this model to calculate propensity score for one of our benchmarks in the following section.

[12]There are 1023 models from the ten explanatory variables without industry fixed effects and 511 models for the nine variables (excluding DN) with industry fixed effects.

2. Announcement Effects

This section shows that financial markets responded positively to announcements of voluntary adoption of work-from-home. In event windows immediately following announcements, work-from-home adopters increased in value relative to controls. Announcers also experienced declines in risk, measured by changes in market and Covid-19 risk loadings as well as abnormal default probabilities.

2.1. Event study methodology

We use three methodologies to assess the stock-market reaction to voluntary work-from-home announcements. First, we use panel regressions with market and/or industry returns as controls, and heteroskedasticity-robust standard errors clustered by calendar date and adjusted for autocorrelation as in Driscoll and Kraay (1998):

$$R_{it} = const + \beta_{mkt} R_{mkt,t} + \beta_{industry} R_{industry,t} + a_1 WFH_{i,0,4} + a_2 WFH_{i,5,9} + \epsilon_{i,t}, \quad (2)$$

where $R_{mkt,t}$ and $R_{industry,t}$ are market and industry returns, and $WFH_{i,0,4}$ and $WFH_{i,5,9}$ are indicator 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.

Section 1 showed that key drivers of work-from-home announcements are firm size and the PS measure of labor suitability to remote work. We control for these characteristics using panel regressions on the return differences:

$$R_{i,t} - R_{i,t}^{benchmark} = const + \beta_{mkt} R_{mkt,t} + a_1 WFH_{i,0,4} + a_2 WFH_{i,5,9} + \epsilon_{i,t}, \quad (3)$$

where $R_{i,t}^{benchmark}$ is one of several benchmarks, including quintile portfolios by size, industry-size, and PS-size, with independent sorts. We also use a propensity-score benchmark, derived from the work-from-home logit specification that minimizes the BIC criterion (Table 2, column 11). At the beginning of the sample period, for each work-from-home firm we rank the closest matches by propensity score for all firms belonging to the same industry-size quintile. The benchmark comprises the top five matches that have not themselves previously announced, equally weighted. We match with replacement, so a firm can be used as a benchmark more than once, which improves match accuracy. If a benchmark firm announces a work-from-home policy, it is dropped as a match for all sample firms and replaced with the next closest propensity-score match from the original ranking.

We also extend the scaled abnormal returns event-study methodology of Kolari and Pynnönen (2010), which itself builds on the classical methodologies of Brown and Warner (1980) and Patell (1976), but accounts for event clustering in time and possible cross-sectional correlation in event returns. Kolari and Pynnönen (2010) focus on the case where all events cluster on the same day. We extend their methodology by explicitly considering event windows that span multiple days, and event windows that cluster in time but need not be exactly identical across all observations. These generalizations are necessary for WFH announcements, which cluster in time, but are not all on the same day. Kolari and Pynnönen (2010) incorporate contemporaneous cross-correlations because these appear in the variance of the test-statistic when events occur all on a single day. For multi-day event windows or when events do not cluster on the same day, we show in the Appendix that additional moments in the variance of the test statistic are own- and cross-serial correlations. We provide standard errors for the scaled-abnormal-return test-statistic that account for these additional moments.

2.2. Valuation changes

Table 3 shows the panel regressions from equation (2). In Panel A (full sample), using market returns, industry returns, or both as benchmarks, announcement effects are up to one percent per day in the five days beginning with the announcement day, or five percent cumulatively. The coefficients are statistically significant at the one- or five-percent level in all cases. The abnormal returns are not significantly different from zero in the following five days. Panels B and C show that the announcement effects concentrate somewhat more heavily in non-essential versus essential businesses. Point estimates of cumulative abnormal returns over the announcement window range from 3.5-4 percent for essential firms, and from 4-6 percent for non-essential firms, in all cases again statistically significant at the one- or five-percent level.

Table 4 shows additional benchmarking using observable firm characteristics. Comparing to the market in column 1 gives similar announcement effects to Table 3. Benchmarking to additional characteristics in columns 2-5 reduces the observed announcement effects to varying degrees, to a range of sixty to eighty basis points per day, or 3-4% cumulatively. Despite the marginally smaller economic magnitudes of the announcement effects, t-statistics increase, in all cases significant at the 1% level. The improvement in power is natural, since improved benchmarking reduces noise. The marginally lower announcement effects in columns 2-5 allow us to infer that non-announcers with characteristics similar to announcers experienced returns more similar to announcers than the overall market. A dynamic theory might suggest information spillovers from announcers to similar firms, but the return similarity could also be explained by common exposures to exogenous shocks. We leave further consideration of such possibilities to future research. Panels B and C once again show that the announcement effect point estimates are somewhat larger for non-essential (3-5% cumulatively) versus essential firms (2-3.5%).

Table 5 shows results for scaled abnormal returns. We benchmark by size, industry-size, and PS-size quintiles as well as propensity score as indicated in panel titles, and further control for market and Fama-French 3- and 5-factors as indicated in column headers. We calculate the scaled abnormal returns during a pre-event window of 10 days prior to the WFH announcement, an event window of five days beginning on the announcement date, and a post-event window of the following five days. The first three columns with CAPM risk-adjustment show significantly positive scaled abnormal returns in the event window (second column), and returns indistinguishable from zero in the pre- and post-event windows (first and third columns) with the exception of one case at the ten percent level. The remaining columns with FF3 and FF5 risk-adjustment show similar results, with slightly smaller point estimates for the announcement-window scaled abnormal returns, but comparable *t*-statistics due to smaller standard errors.

Figure 3 displays the scaled abnormal returns in event time for benchmarks based on industry-size quintiles (Panels A-C) and propensity score (Panels D-F).[13] By row the panels show performance evaluation for the market-model, FF3, and FF5. The scaled abnormal returns spike following announcement, and slowly fade through the event window. The blue line, which averages daily abnormal returns within the three

[13]The Online Appendix shows similar results for benchmarks based on size and PS-size quintiles.

separate windows, visually displays positive average abnormal returns during the five-day event window with no pre- or post-trend.

The three above methodologies provide consistent results and robustly identify a significant positive stock-price reaction to voluntary work-from-home announcements. We conclude that the stock market positively valued firms' observed adaptations to remote work during the pandemic.

2.3. Changes in risk

Corporate adaptation should not only add value, but also mitigate risk.[14] We test whether voluntary announcements of work-from-home transitions reduced risk. We consider systematic risk exposure measured by market beta and the Covid-19 risk factor of PS, as well as abnormal default probabilities. PS form their factor from stocks in non-critical industries, long (short) those with low (high) share of labor suitable to work-from-home. PS propose that this factor captures exposure to supply-side disruptions associated with Covid-19.

To test for changes in systematic risk, we construct three portfolios composed of: 1) WFH sample firms with valid matches, 2) matches by the propensity-score method, and 3) other firms (non-WFH and non-matches). From the first trading day in 2020 until the end of July, we calculate daily value-weighted returns for each portfolio. These portfolios would not have been tradeable since the identities of the eventual WFH announcers was not known in January, but they are nonetheless valid for measuring

[14]High levels of risk and uncertainty during the pandemic are documented by Altig et al. (2020), Baker et al. (2020), and Ramelli and Wagner (2020).

changes in risk. For each portfolio we run regressions of the form:

$$\begin{aligned} R_t &= const + \beta_{mkt} R_{mkt,t} + \beta_{PS} R_{PS,t} \\ &\quad + post_t \left(\Delta const + \Delta\beta_{mkt} R_{mkt,t} + \Delta\beta_{PS} R_{PS,t} \right) + \epsilon_t, \end{aligned} \tag{4}$$

where $post_t$ is an indicator equal to one after the fever period (from March 20, 2020) and zero otherwise, and $R_{PS,t}$ are returns on the PS factor. To obtain a clean demarcation between the pre- and post-periods, we omit dates within the fever period (February 24 - March 19) from the regressions. The coefficients Δ_{const}, $\Delta\beta_{mkt}$, and $\Delta\beta_{PS}$ respectively measure the change in intercept and changes in market and PS loadings from the pre to post periods. We hypothesize that WFH announcers should see Covid-19 risk decline from pre- to post- periods, relative to other firms. Exposure to Covid-19 risk may be picked up by the market portfolio since Covid-19 was important to market returns in this period, but the PS factor should more specifically capture exposure to labor-inflexibility risk. We therefore hypothesize that from pre- to post-announcement, WFH firms will experience a decline in PS exposure ($\Delta_{PS} < 0$) absolutely and relative to other firms.

Table 6 shows the regression results. Panel A uses only the market factor. The first column shows that WFH announcers experienced a highly significant decline in market risk from the pre- to post-announcement periods ($\Delta\beta_{mkt} \approx -0.26$, $t \approx -3.0$). Matches and unmatched firms both experienced small increases in market beta over the same period, resulting in significantly negative differences in $\Delta\beta_{mkt}$, shown in the final two columns. Market risk declined from pre- to post-announcement for work-from-home firms, absolutely and relative to other firms.

Panel B also includes exposure to the PS factor, which directly relates to labor-inflexibility risk. The results show a large decline in PS risk for WFH firms from pre- to post-announcement ($\Delta\beta_{PS} = -0.23$, $t = -5.16$), while matched firms have essentially no change in PS risk and the exposure of the portfolio of unmatched firms increases. The differences-in-differences of PS loadings shown in the final two columns are therefore negative and also highly statistically significant ($\Delta\beta_{PS} = -0.24$ with $t = -3.98$ relative to matches, and $\Delta\beta_{PS} = -0.39$ with $t = -4.83$ relative to unmatched). Figure 4 displays the PS loadings, differences, and the differences-in-differences in event time, providing a visual depiction of the result. Consistent with the hypothesis of corporate adaptation to crisis mitigating risk, WFH announcers experienced significant declines in exposure to the Covid-19 risk factor of PS, absolutely and relative to other firms.

Abnormal changes in default probabilities offer a different way to look at WFH risk mitigation that does not rely on a proxy for Covid-19 risk. For default probabilities, we use data from the Risk Management Institute (RMI) of the National University of Singapore, used in prior studies such as 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.[15] We repeat regression (3) using changes in WFH-announcer default probabilities relative to benchmarks on the left-hand-side. On the right-hand-side we use as a proxy for average change in default risk the equal-weighted change in

[15] The default probabilities are a nonlinear function of twelve firm-level and four aggregate variables. The daily updated variables are distance to default and idiosyncratic volatility, both impacted by firm returns, the market return, and the risk-free rate of the matched maturity.

default probabilities across all firms in our sample, including non-announcers.

Table 7 shows results. In column 1, benchmarked only to the market, announcers' abnormal default probabilities are -0.6 basis points per day over the 5-day event window, i.e, 3 basis points cumulative, but not statistically significant. Benchmarking by firm characteristics in columns 2-5 gives stronger results in both magnitude and significance, with default probabilities reduced by 0.7-1.4 basis points per day or 3.5-7 basis points cumulative over the 5-day event window, significant at the ten- and one-percent levels. For essential firms in Panel B, the results are weaker. For non-essential firms in panel C, all benchmarks show strong reduction in default probabilities with magnitudes ranging from 1-2.5 basis points per day, i.e., 5-12.5 basis points over the entire window, significant at the five- and one-percent levels. The cumulative magnitude of up to 12.5 basis points over a five day period may seem small, but the average default probability of firms in our sample is typically in the range of 1%, so an abnormal decline of 5-12.5 basis points is economically meaningful.

We further verify these results in the Internet Appendix using the option-implied lower bounds on expected returns of Martin (2017) and Martin and Wagner (2019) (see also Pagano et al. (2023)), restricting to the subsample of S&P 500 firms with valid option data used in the prior literature. We find that the post-pandemic increase in option-implied expected returns is significantly lower for work-from-home firms than either propensity-score matches or unmatched S&P 500 firms. Relative declines in expected returns are consistent with both decreased risk and increased valuation for work-from-home announcers.

We conclude that financial markets rewarded corporate announcements of adaptation to remote work. Announcing firms experienced positive abnormal stock returns within the announcement windows, declines in exposure to market risk and the Covid-19 risk factor of PS, and relative declines in default probabilities as well as option-implied expected returns.

3. Additional Results

We provide additional tests that build on the finding of positive market reaction to corporate work-from-home announcements. First, Bloomberg coverage results in faster price response to remote-work adoption. Second, ESG scores help to predict work-from-home announcements, but have little impact on announcement effects. Third, work-from-home announcers and their matched samples have stronger operating performance than other firms during the Covid period, and announcers experience modestly smaller declines in employment and R&D than the matched samples.

3.1. Bloomberg announcements

Financial media often cover important company news, and their reporting should be more readily accessible to investors than monitoring company websites. We investigate the impact of coverage by Bloomberg. Recent literature shows that prominent news dissemination on Bloomberg increases the immediacy of price effects (Fedyk, 2022).

We hypothesize two possible impacts of Bloomberg coverage. First, announcement effects may be larger since editorial policy should prioritize important news, and because reporting may enhance news awareness among investors within our announcement windows. Second, Bloomberg coverage reaches investors quickly and synchronously, whereas announcements appearing on company websites but not Bloomberg must reach investors by other means, suggesting slower diffusion of information through markets and slower incorporation of the news into prices.

An additional point of interest is whether we can identify announcement effects at all for the non-Bloomberg sample. Prior event studies focus on items routinely reported in financial media such as earnings announcements. We are unaware of any prior study that has shown announcement effects for events scraped from company websites.

For each WFH announcement in our sample, we conduct a Bloomberg search for coverage in a window of +/- three days around appearance on the company website.[16] Of the original 273 WFH announcements, Bloomberg covered 68, or approximately 25%. Substantial Bloomberg reporting on work-from-home transitions provides *prima facie* evidence of the relevance of such news to investors, consistent with the announcement effects we have already documented.

We further record the timing of Bloomberg coverage relative to the announcement date on the company website. Of all Bloomberg observations, 48 (71%) appeared the same day as on the company's website, with 25 time-stamped during trading hours and 23 after hours. We allocate news that appeared after hours to the next trading day. Nine observations (13%) appeared on Bloomberg at least one day after publication on the company's website. Eleven (16%) appeared on Bloomberg *before* being posted on the company website, often citing an internal email or memo privately obtained by Bloomberg reporters. These efforts to obtain non-public information further indicate interest in work-from-home transitions.

[16]For a small sample, we searched over longer windows, and found little additional benefit.

We first run the panel regressions:

$$
\begin{aligned}
R_{it} - R_{it}^{benchmark} &= const + \beta_{mkt} R_{mkt,t} + a_{BB,04} BB_{04,it} + a_{WS,04} WS_{04,it} \\
&\quad + a_{BB,59} BB_{59,it} + a_{WS,59} WS_{59,it} + \epsilon_{it}, \qquad (5)
\end{aligned}
$$

where $BB_{04,it}$ and $BB_{59,it}$ are announcement-window indicators for observations covered by Bloomberg, and $WS_{04,it}$ and $WS_{59,it}$ are indicators for the remaining website-only observations. The coefficients on $BB_{04,it}$ and $BB_{59,it}$ are daily total Bloomberg effects. Marginal Bloomberg effects are denoted $(a_{BB} - a_{WS})_{04} \equiv a_{BB,04} - a_{WS,04}$ for the event window, and similarly for the post-event (days 5-9) and combined (days 0-9) windows.

Our second regression specification refines regression (5) by breaking the day 0-5 announcement window into two pieces, days 0-1 and 2-4. We are interested in the speed of price responses, which corresponds to the front-loading of announcement effects early in the event window. We define the transformed variable $\phi \equiv a_{01}/a_{04}$, measuring the average announcement effect in the first two days relative to the entire five-day window.[17] If $\phi > 1$ the announcement effects are front-loaded, i.e., larger per day in the 0-1 window than the 0-4 average. The parameter thus captures the relative rate at which the total five-day announcement effects are realized early in the window. We allow the parameter to differ between announcements covered by Bloomberg and those appearing on the corporate website only, and test whether Bloomberg coverage increases the speed of price response, i.e., $\phi_{BB} > \phi_{WS}$.

Table 8 presents results, with Panel A showing the specification (5) which focuses on announcement effect magnitudes and Panel B showing results for refined announce-

[17]The Appendix provides estimation and inference details.

ment windows and the speed parameters ϕ_{BB} and ϕ_{WS}. In Panel A, the event-window effects (days 0-4) are uniformly positive and statistically significant for both Bloomberg and website-only announcements, relative to all benchmarks. In the post-event windows (days 5-9) none of the abnormal returns are significant. Our primary result of positive work-from-home announcement effects thus holds in both subsamples, showing robustness.

The hypothesis tests in Panel A reject equal announcement effects in the 0-4 day event window. The Bloomberg announcement effects (1-1.5%/day) are significantly larger than website-only (0.5-0.9%/day). We do not know when the announcements are fully reflected in prices, but the lack of significant effects in the 5-9 day windows suggests that little information remains after five days. Over the longer 0-9 day window average return differences between Bloomberg and website-only announcements are statistically indistinguishable. This difficulty of distinguishing magnitudes over longer windows is not surprising. The signal-to-noise ratio for event studies tends to be highest in short windows following announcement. Over longer windows, confounding information makes inference more difficult and reduces statistical power.[18] We note an additional implication of this logic. If corporations did not announce their remote-work decisions, but investors had to learn over time which firms adapted by watching real performance or other signals, we would have little hope of distinguishing whether investors valued adaptation to crisis. We could only see whether *ex ante* characteristics associated with adaptibility, flexibility, or resilience affected pricing and outcomes. Our study is thus

[18]Given that variances grow approximately with horizon T, if an event window is multiplied by four but does not incorporate more event-related information, t-statistics should be approximately cut in half.

different, showing market reaction to a corporate action – announcement of adaptation to Covid-19 by transition to remote work, controlling for *ex ante* characteristics.

Panel B compares the speeds of price response to Bloomberg and website-only announcements. The Bloomberg announcements show speed parameter $\phi_{BB} \approx 2$, statistically significantly greater than one, implying higher news impact on returns in the 0-1 window than in days $2-4$. The point estimate of the proportion of the total announcement effect realized in the first two days is given by $2\phi/5 \approx 4/5 = 80\%$, leaving the remaining 20% distributed over the final three days.[19] The website-only announcements are different, and in particular price reaction is not front-loaded. The speed coefficients ϕ_{WS} either cannot be distinguished from one or are lower than one. The final rows of the panel formally test for differences in the speed of price adjustment and show uniformly faster price response for Bloomberg coverage.

3.2. ESG scores

Prior literature proposes that firms with stronger ESG profile were more resilient in the Covid-19 crisis (Albuquerque et al., 2020, Ding et al., 2021). ESG could relate to work-from-home announcements since firms with greater concern for employee health or public health (social good), or better ability to make decisions in a crisis (governance), might transition more readily to remote work.

We re-run the logit regression (1) beginning from the Table 2 model with the lowest BIC (column 11), and adding ESG information to the predictors. We use ESG data from Refinitiv, which has the best coverage of our sample firms. To avoid dropping

[19]The Internet Appendix provides an alternative but equivalent formulation of the regression where parameters are the level of announcement effects in each sub-window.

657 observations with missing ESG data, we use an indicator variable $\mathbb{1}_{ESG}$ equal to one for non-missing observations and zero otherwise. The variable ESG is the Refinitiv ESG score with missing data zero-filled. Using these two variables together, the indicator allows an arbitrary shift of the difference between missing and non-missing data, providing a flexible empirical specification while not dropping data. The indicator uses an additional degree of freedom that the BIC criterion accounts for.

Table 9 shows results. Panel A provides logit estimations for, in the first three columns, ESG by itself, with size, and with size and PS together. ESG alone is highly significant with a coefficient of 0.65 and a t-statistic exceeding eight. Adding size as a control reduces the coefficient to 0.23 and the t-statistic to about 2.2. The substitution between ESG and size implies that larger firms have higher ESG values, likely because smaller firms are more likely to have missing ESG data and be zero-filled. Adding PS in column (3) raises the ESG coefficient to 0.33 ($t = 3.1$). The PS coefficient is 0.44 with $t = 5.8$, both slight increases from the model without ESG (Table 2, column 11). ESG and PS are thus complements, with each raising the economic and statistical significance of the other. In columns 4-6, the non-missing indicator is significant and positive by itself, but becomes insignificant in specifications with the other variables. Neither size nor PS are meaningfully impacted by including $\mathbb{1}_{ESG}$. Columns 7-9 show ESG and the non-missing indicator together. With all variables (column 9), the non-missing indicator is insignificant with a point estimate close to zero, and all other variables are very similar to specification (3) without the non-missing indicator. Thus the dummy variable for missing values is superfluous, and zero-filling missing ESG values appears to fit the data.[20]

The BIC criterion adds nuance. Compared to the best model without ESG (Table 2, column 11, BIC = 1195), the only specification in Panel A that improves BIC is column (3), which adds ESG but not the missing data dummy (BIC = 1193). Further adding the missing data indicator in (9), BIC worsens to 1201. ESG score thus provides enough information to justify one additional parameter, but not two.

Putting aside the missing-data technicalities, ESG positively predicts work-from-home adoption, consistent with prior literature reporting improved Covid-19 resilience for high-ESG firms (Albuquerque et al., 2020, Ding et al., 2021). We find similar results for remote-work adoption, and the ESG and PS variables appear to complement one another in predicting remote-work transitions.

In Panels B and C, we take specification (3) from Panel A as our propensity score benchmark, thereby including ESG information, and carry out the panel regression for announcement effects (compare to Table 4 without ESG) and the scaled abnormal returns event study (compare to Table 5). Both Panels B and C show that the announcement effects are robust and largely unchanged compared to prior results that did not incorporate ESG in benchmarking. The event-window abnormal returns are positive and significant in all cases, with no significant pre- or post-event drift.

We conclude that, if missing values are treated as zeros, ESG adds marginal value to explaining voluntary work-from-home adoption. ESG complements PS, each slightly raising the power of the other to predict remote-work transitions. Including ESG in the propensity-score benchmark, announcement effects are robust and remain strongly

[20] A caveat is that a researcher could not have known without regression (9) that zero-filling missing ESG data would be appropriate.

positive.

3.3. Operating performance

We compare the pre- and post-pandemic operating performance of WFH firms, their propensity score matches, and other firms. Previously, Papanikolaou and Schmidt (2022) show stock returns for high- and low-PS firms. Barry et al. (2022) use a similar measure of employment flexibility from the ATUS, and show differencs in post-pandemic performance based on this and other characteristics. Our analysis differs first because our primary focus is on firms that announced a voluntary transition to work-from-home. Additionally, we compare to firms that did not announce but had similar propensity score based on their characteristics.

For each sample firm, beginning in 2019Q1 we calculate quarterly the year-over-year growth in sales, operating profits, total assets, and R&D expenses. Figure 5 plots the average growth rate of each variable by calendar quarter for the baseline group of non-WFH, non-matched firms (black line). The figure also shows differences relative to the baseline for i) WFH firms (blue), and ii) matches (yellow). Baseline revenue and profit growth began falling in the first quarter of 2020, sharply declined in Q2, and recovered considerably in the following quarters.[21] Asset and R&D growth move more slowly, appearing depressed for four quarters before returning to prior levels. The WFH firms and their matches follow the baseline before the pandemic, but do not decline as severely in 2020, with relative operating performance moderating or reversing in 2021. In several quarters, the Covid-19 outperformance of WFH firms and their matches

[21]The abnormally low values of revenue and profit in 2020 are denominators in 2021 growth rates and contribute to those variables exceeding their pre-pandemic values.

relative to baseline is statistically significant.[22]

We aggregate information across quarters and add controls with the regression:

$$\begin{aligned} Y_{i,t} = & \alpha + \beta_0 \times WFH_i + \beta_1 \times Match_i + \beta_2 \times Covid_t \\ & + \beta_3 \times WFH_i \times Covid_t + \beta_4 \times Match_i \times Covid_t \\ & + LnME_{i,t} + FE^{ind} + FE^{Q} + \epsilon_{i,t}, \end{aligned} \tag{6}$$

where $Y_{i,t}$ is the growth rate for variable i in quarter t, $Covid_t$ indicates belonging to the Covid-19 period designated as the calendar year 2020, $Match_i$ indicates propensity-score matches, $LnME$ is log market capitalization, and fixed effects are by industry and quarter. To avoid the Covid-19 rebound dynamics, we end the sample in 2020Q4. We run a similar regression for employees, which is observed annually.

Table 10 shows results. The WFH and $Match$ indicators are statistically indistinguishable from zero, consistent with no pre-Covid differences from baseline. The *Covid* indicator captures baseline performance declines during the Covid period. Baseline declines range from 4.5% (assets) to more than 10% (sales), all highly economically significant and also statistically significant. The interaction coefficients show that WFH firms outperformed the baseline during the Covid period for all growth rates, with statistical significance in four of the five cases. The amounts are economically important, reversing approximately 25-50% of the Covid underperformance (e.g., for sales mitigating 4.4% of the baseline 10.4% decline). The interaction coefficients of matches are all positive, but smaller than for WFH and only one is statistically significant at the

[22] See, for example, revenue and gross profit growth in 2020Q2-Q3, and for WFH total asset growth in 2020Q1-Q4 and R&D growth in 2020Q4-2021Q2.

10% level (employment). Thus, the operating performance of the WFH announcers can be statistically distinguished from baseline during the Covid period, while their matches generally cannot. The identities of the announcers provide useful additional information beyond *ex ante* characteristics, which are similar between the two groups.

A more demanding test directly compares WFH announcers and matches, shown in the final row of Table 10. In two cases the performance of WFH announcers and matches can be statistically distinguished. First, WFH firms had smaller declines in labor growth than matches, offsetting 2% of the overall 4.6% fall in employment for matches (baseline -6.54% + 1.8%), statistically significant at the 1% level. Adaptation to remote-work directly demonstrates labor flexibility, and the predictive power of WFH announcement on employment growth shows significant real impact. WFH announcers also experienced significantly better R&D growth ($t = 1.93$) relative to matches. Baseline R&D growth is -8.1% during Covid-19. Matches do marginally but insignificantly better (-8.1+1.6=-6.5%), and WFH firms experience a decline of only 3.5% (6.5-3). In these two cases, WFH announcers experienced significantly smaller declines during Covid-19 than their matches with similar *ex ante* characteristics.

An important question remains: If the event studies identify a statistically significant increase in value from remote-work adoption, should it bother us that we do not see statistically significant increases in seemingly value-relevant variables such as sales and gross profits? We first note that event-study identification relies on large announcement effects relative to random variations in the event window. Since the announcement effect is a one-time occurence, larger event windows eventually dilute information content. Similarly, operating performance over long periods is driven by many random factors, and the effect of any one event, such as announcement of work-from-home, may be difficult to detect. Second, small changes in earnings growth can be consistent with large changes in valuation. For example, a 1% difference in earnings growth is well within the range that could not be statistically distinguished from zero based on the standard errors in Table 10. Following from the Gordon growth model, a transitory 1% increase in growth produces only a 1% value increase. However, a persistent 1% increase in growth can have much larger effect.[23] Third, independent of cash flows, declines in priced risks for work-from-home announcers relative to matches imply lower costs of capital and higher valuations. For these reasons, we do not see a contradiction between strong event-window announcement effects in returns and positive but insignificant differences in sales and gross profits.

Moreover, announcement effects are summations, over all future states of the world, of the value of a firm that has taken a specific action versus an otherwise *ex ante* observationally equivalent firm that did not take that action (e.g., Carlson et al., 2006). As pointed out by Pagano et al. (2023), in the depths of the pandemic when our announcements took place many future states of the world were bleak. Uncertainty abounded about whether vaccines would be produced and effective, and how firms would adapt. Our WFH firms were among the first to demonstrate any concrete adaptation to Covid-19 by voluntarily transitioning to work-from-home. Given the already well-documented uncertainty and concern at the time, corporate adaptation should have had very high value, reflected in the initial price response that we find. Pagano et al. (2023) discuss that over time the worst disasters became less likely. Remote-work transitions

[23]This follows from the standard valuation formula $P = E_0 * g/(r - g)$.

were more successful than anticipated and remote-work technology diffused rapidly (Barrero et al., 2021, Bick et al., 2022). The announcement effects we document reflect the value of adaptation during the worst times of the crisis. These are ideal conditions to establish a positive value for corporate adaptation using an event study.

The Internet Appendix provides supplementary results including additional controls, robustness tests, and complementary findings.

4. Conclusion

Considerable prior literature emphasizes the importance of corporate characteristics associated with flexibility and resilience. As opposed to characteristics, we study a specific corporate *action* associated with adaptation to a crisis, the announcement of voluntary transition to remote work during the Covid-19 pandemic. We develop the first event study aimed at measuring market response to corporate adaptation, controlling specifically for observable firm characteristics. We show evidence of an increase in valuation and decline in risk following observable corporate adaptation. Our results broaden the study of corporate flexibility and resilience to include corporate actions alongside corporate characteristics.

Remote work has become widespread throughout the economy, but early in the pandemic the ability of firms to transition effectively to work-from-home was far from certain. Financial markets responded strongly and positively to news of corporate adaptation. Even if it is difficult to say now what type of resilience will be important in future crises, corporate actions, not just characteristics, will be important. Our results demonstrate measurable benefits for firms prepared to adapt.

A. Appendix

A.1. Matching Details

We match by propensity score using the regression (1) specification that minimizes BIC in Table 2, column 11:

$$p\left(WFH_i = 1\right) \;=\; \frac{1}{1 + e^{PS_i + ME_i}}, \tag{7}$$

We match with replacement so a firm can be used as a match for more than one WFH announcer. For each announcing WFH firm i, we calculate the absolute distance in the propensity score for all potential matches j, i.e., $|p_i - p_j|$. We restrict potential matches to firms within the same NAICS 2-digit industry and size quintile that have not previously become WFH announcers themselves. For nine WFH observations belonging to insufficiently populated NAICS 2-digit industries we drop the industry match requirement. We select the five closest matches and form an equal-weighted benchmark. If a selected match later announces, we replace it with the next closest available match from the original list. On average, the first and fifth matches are within 0.6 and 2.2% of the WFH firm propensity score, with further details provided in the Internet Appendix.

We additionally use benchmarks formed from quintiles by size, industry-size, and PS-size. These are equal-weighted daily. For size we use all stocks in the same size quintile as the WFH firm. For industry-size, we use the intersection of stocks in the same NAICS 2-digit industry and the same independently-sorted size quintile as the WFH firm. For PS-size, we independently sort quintiles for size and non-missing PS, add an additional PS group for missing observations to allow benchmarking for all sample firms, and intersect the size and PS groups.

A.2. Event Study Details: Scaled Abnormal Returns

We extend the event-study methodology of Kolari and Pynnönen (2010) by explicitly considering event windows that span multiple days, and event windows that cluster in time but need not be exactly identical across all observations. Our method is based on expanding the scaled normal abnormal returns test-statistic and accounting for the cross-correlation, serial correlation, and cross-serial correlation terms that naturally arise.[24]

The scaled abnormal returns test statistic is defined as:

$$t = \frac{\bar{A}\sqrt{N \times W}}{\sqrt{var\left(\bar{A}\right)}}, \tag{8}$$

where $\bar{A}$ is the average scaled abnormal daily event return:

$$\bar{A} \quad = \quad \frac{1}{N \times W} \sum_{i=1}^{N} \sum_{\tau=1}^{W} A_{i,\tau,t}, \tag{9}$$

N is the number of WFH firms, and W is the length of the event window (5 days), $A_{i,\tau,t}$ denotes the scaled abnormal return for firm i on day τ of the event window at calendar time t. To calculate the scaled abnormal daily event return $A_{i,\tau,t}$, following standard methodology we first calculate the abnormal daily event return and then rescale it. For each WFH firm we estimate the regression:

$$R_t^{i,WFH} - R_t^{i,benchmark} = const^i + \beta^i R_{mkt,t} + \epsilon_t^i, \tag{10}$$

using one of four different benchmarks $R_t^{i,benchmark}$: size quintile, industry-size quintile, PS-size quintile and five closest matches by propensity score. We also use FF3 and FF5 factors as control variables in regression 10. The regressions are estimated for each firm over an estimation period of 60 days before the WFH announcement.

The abnormal daily event return $\epsilon_{\tau,t}^i$ is the difference between the dependent variable and the model-implied variable $\left(R_{\tau,t}^{i,WFH} - R_t^{i,benchmark}\right) - const^i - \hat{\beta}^i R_{mkt,t}$ on specific event day τ that falls on calendar day t. Then, the scaled abnormal daily event return can be calculated as:

$$A_{i,\tau,t} = \frac{\epsilon_{\tau,t}^i}{\sigma_{\epsilon,i}\sqrt{1+d}}, \tag{11}$$

where $\sigma_{\epsilon,i}$ is the standard deviation of the residuals over the estimation period and d_t is the correction term of the form $x_t' \left(X'X\right)^{-1} x_t$ due to the estimation of the regression parameters in the estimation period with $x_t = [1 \; R_{mkt,t}]'$ and X being the matrix of the

[24] Kolari et al. (2018) extend their methodology to partially overlapping event windows accounting for cross-correlations due to partially overlapping event windows, but do not address cross-serial correlations.

explanatory variables during the estimation period (see Kolari and Pynnönen (2010)).

The variance of the average abnormal daily event return is:

$$\begin{aligned} var\left(\bar{A}\right) &= var\left(\frac{1}{W \times N}\sum_{i=1}^{N}\sum_{\tau=1}^{W}A_{i,\tau,t}\right) = \left(\frac{1}{W \times N}\right)^{2} var\left(\sum_{i=1}^{N}\sum_{\tau=1}^{W}A_{i,\tau,t}\right) \\ &= \left(\frac{1}{W \times N}\right)^{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{\tau_1=1}^{W}\sum_{\tau_2=1}^{W} cov\left(A_{i,\tau_1,t_1}, A_{j,\tau_2,t_2}\right). \end{aligned} \tag{12}$$

We rewrite the last expression as:

$$\begin{aligned} var\left(\bar{A}\right) &= \left(\frac{1}{W \times N}\right)^{2}\left[\sum_{i=1}^{N}\sum_{\tau=1}^{W} cov\left(A_{i,\tau,t}, A_{i,\tau,t}\right) + \sum_{i=1}^{N}\sum_{\tau_1=1}^{W}\sum_{\tau_2\neq\tau_1} cov\left(A_{i,\tau_1,t_1}, A_{i,\tau_2,t_2}\right)\right. \\ &\quad \left. + \sum_{i=1}^{N}\sum_{j\neq i}\sum_{\tau_1=1}^{W}\sum_{\tau_2=1}^{W} cov\left(A_{i,\tau_1,t_1}, A_{j,\tau_2,t_2}\right)\right]. \end{aligned} \tag{13}$$

The first term is composed of variances of individual scaled abnormal daily event returns. The second term captures autocovariances, i.e., covariances of individual scaled abnormal daily event return of the same stock on different event days. The third term is composed of cross-covariances including cross (serial) covariances, i.e., covariances of abnormal daily event returns of different stocks on the same or different calendar days.

We further split the last (third) term into contemporaneous cross-covariances and lagged cross-covariances (i.e., cross-serial covariances):

$$\begin{aligned} var\left(\bar{A}\right) &= \left(\frac{1}{W \times N}\right)^{2}\left[\sum_{i=1}^{N}\sum_{\tau=1}^{W} var\left(A_{i,\tau,t}\right) + \sum_{i=1}^{N}\sum_{\tau_1=1}^{W}\sum_{\tau_2\neq\tau_1} cov\left(A_{i,\tau_1,t_1}, A_{i,\tau_2,t_2}\right)\right. \\ &\quad + \sum_{i=1}^{N}\sum_{j\neq i}\sum_{\tau_1=1}^{W}\sum_{\tau_2=1}^{W} cov\left(A_{i,\tau_1,t}, A_{j,\tau_2,t}\right) \\ &\quad \left. + \sum_{i=1}^{N}\sum_{j\neq i}\sum_{\tau_1=1}^{W}\sum_{\tau_2=1}^{W}\sum_{k=-W+1,k\neq 0}^{W-1} cov\left(A_{i,\tau_1,t}, A_{j,\tau_2,t-k}\right)\right]. \end{aligned} \tag{14}$$

Now the third term expresses the contemporaneous cross covariances and the cross-serial covariances are captured in the fourth term.

Using the methodology from Kolari and Pynnönen (2010), we further simplify the expression by noting:

1. Since the abnormal daily returns are scaled, they have the same variance: $var\left(A_{i,\tau,t}\right) = \sigma_A^2$ for all i and τ.

2. The cross-covariances can be expressed as $cov\left(A_{i,\tau_1,t}, A_{j,\tau_2,t}\right) = \rho_{i,j}\sigma_A$, where $\rho_{i,j}$ is the pairwise correlation between stock i and stock j from the estimation period.

We note that the autocovariances can be expressed as: $cov\left(A_{i,\tau_1,t_1}, A_{i,\tau_1,t_2}\right) = \sigma_A^2 AC_{i,1}$ (and similar for other lags), where $AC_{i,1}$ is autocorrelation of stock $i's$ returns at one lag. The cross-serial-covariances can be expressed as $cov\left(A_{i,\tau_1,t}, A_{j,\tau_2,t-k}\right) = \sigma_A^2 CSC_{i,j,k}$, where $CSC_{i,j,k}$ is the cross-serial correlation between stock i and stock j at lag k. Although the cross-serial correlation could theoretically be calculated for any lag (i.e. if event windows of two stocks are apart by the corresponding number of days to accommodate such a lag), we consider cross-serial correlations at lags of up to the length of the event window W. This is broadly consistent (with difference of one lag) with the number of possible lags for autocorrelations $AC_{i,k}$, which are truly limited by the length of the event window minus one, i.e., $W-1$. The variance of scaled abnormal returns then simplifies to:

$$\begin{aligned} var\left(\bar{A}\right) = \left(\tfrac{1}{W\times N}\right)^2 \sigma_A^2 \Bigg[& (W\times N) + \sum_{i=1}^{N} \sum_{k=-W+1,k\neq 0}^{W-1} (W-k)\, AC_{i,k} \\ & + \sum_{i=1}^{N} \sum_{j\neq i} \sum_{\tau_1=1}^{W} \sum_{\tau_2=1}^{W} \rho_{i,j} \mathbf{1}_{\{\tau_1 \& \tau_2 \text{ are on the same } t\},i,j,\tau_1,\tau_2} \\ & + \sum_{i=1}^{N} \sum_{j\neq i} \sum_{\tau_1=1}^{W} \sum_{\tau_2=1}^{W} \sum_{k=-W+1,k\neq 0}^{W-1} CSC_{i,j,k} \mathbf{1}_{\{\text{cross lag=k}\},i,j,\tau_1,\tau_2} \Bigg], \end{aligned} \tag{15}$$

where $\mathbf{1}_{\{\text{cross lag=k}\},i,j,\tau_1,\tau_2} = \mathbf{1}_{\{\tau_1 \& \tau_2 \text{ are exactly k days apart}\},i,j,\tau_1,\tau_2}$ indicates that the stock $i's$ event day τ_1 is exactly k days apart from stock $j's$ event day τ_2.

Following Kolari and Pynnönen (2010), we estimate the pairwise contemporaneous cross-correlations, $\rho_{i,j}$, of abnormal returns in the estimation period. We extend this methodology to the estimation of the autocorrelations $AC_{i,k}$ and cross-serial-correlations $CSC_{i,j,k}$, and estimate these parameters from the abnormal returns during the estimation period.

A.3. Announcement Speed Regression

The announcement speed parameters and regression results in Table 8, Panel B, can equivalently be derived from two different regressions. First, refining regression (5) to break the 0-4 event window into periods of days 0-1 and 2-4 gives a linear regression:

$$\begin{aligned} R_{it} - R_{it}^{benchmark} \quad = \quad & const + \beta_{mkt} R_{mkt,t} + a_{BB,01} BB_{01,it} + a_{WS,01} WS_{01,it} \\ & + a_{BB,24} BB_{24,it} + a_{WS,24} WS_{24,it} \\ & + a_{BB,59} BB_{59,it} + a_{WS,59} WS_{59,it} + \epsilon_{it}. \end{aligned} \tag{16}$$

Consider the parameter transformations $a_{04} \equiv 0.4a_{01} + 0.6a_{24}$ and $\phi \equiv a_{01}/a_{04}$. We can rewrite a regression equivalent to (16) in the transformed parameters by taking linear combinations and interactions of the original regressors:

$$\begin{aligned} R_{it} - R_{it}^{bench} \quad = \quad & const + \beta_{mkt} R_{mkt,t} + a_{BB,04} BB_{04,it} + a_{WS,04} WS_{04,it} \\ + \quad & (\phi_{BB} - 1) a_{BB,04} BB_{04,it} \left(BB_{01} - (2/3) BB_{24} \right) \\ + \quad & (\phi_{WS} - 1) a_{WS,04} WS_{04,it} \left(WS_{01} - (2/3) WS_{24} \right) \\ + \quad & a_{BB,59} BB_{59,it} + a_{WS,59} WS_{59,it} + \epsilon_{it}. \end{aligned} \tag{17}$$

Table 8 presents regression results and test statistics from the regression (17). The interpretation of the parameters $\phi \equiv a_{01}/a_{04}$ is the average announcement effect in days 0-1 divided by the average announcement effect in days 0-4, i.e., the relative speed at which the total five day announcement effects are realized in the first two days. If $\phi > 1$ the announcement effects are front-loaded. The Internet Appendix provides parameter estimates for the equivalent regression (16).

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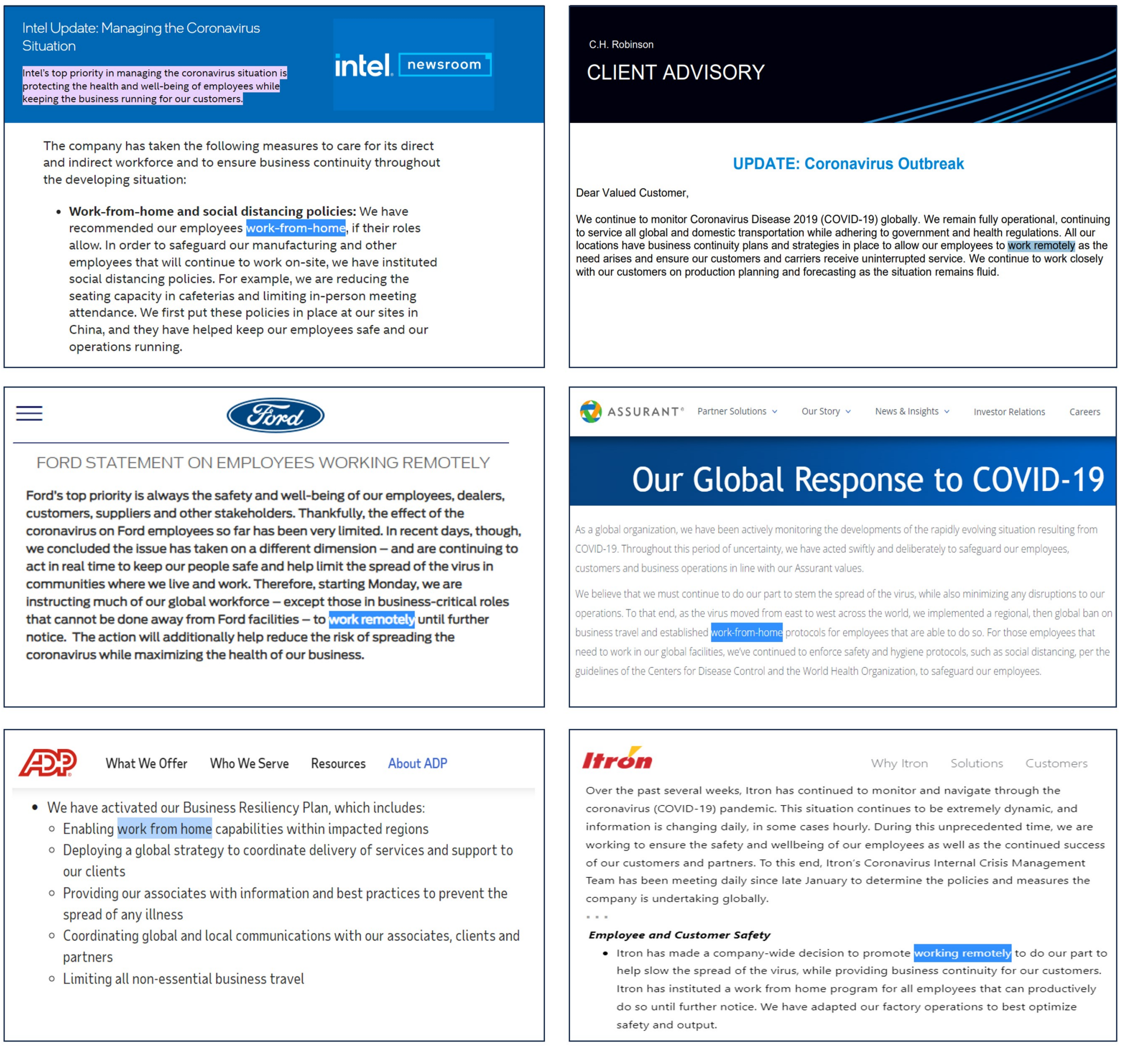
Figure 1: Work-from-Home Announcements. This figure shows work-from-home announcements for six sample companies (Intel, Ford, ADP, C. H. Robinson, Assurant, and Itron).



Intel Update: Managing the Coronavirus Situation

Intel's top priority in managing the coronavirus situation is protecting the health and well-being of employees while keeping the business running for our customers.

intel. newsroom

The company has taken the following measures to care for its direct and indirect workforce and to ensure business continuity throughout the developing situation:

- **Work-from-home and social distancing policies:** We have recommended our employees work-from-home, if their roles allow. In order to safeguard our manufacturing and other employees that will continue to work on-site, we have instituted social distancing policies. For example, we are reducing the seating capacity in cafeterias and limiting in-person meeting attendance. We first put these policies in place at our sites in China, and they have helped keep our employees safe and our operations running.

C.H. Robinson

CLIENT ADVISORY

UPDATE: Coronavirus Outbreak

Dear Valued Customer,

We continue to monitor Coronavirus Disease 2019 (COVID-19) globally. We remain fully operational, continuing to service all global and domestic transportation while adhering to government and health regulations. All our locations have business continuity plans and strategies in place to allow our employees to work remotely as the need arises and ensure our customers and carriers receive uninterrupted service. We continue to work closely with our customers on production planning and forecasting as the situation remains fluid.

FORD STATEMENT ON EMPLOYEES WORKING REMOTELY

Ford's top priority is always the safety and well-being of our employees, dealers, customers, suppliers and other stakeholders. Thankfully, the effect of the coronavirus on Ford employees so far has been very limited. In recent days, though, we concluded the issue has taken on a different dimension – and are continuing to act in real time to keep our people safe and help limit the spread of the virus in communities where we live and work. Therefore, starting Monday, we are instructing much of our global workforce – except those in business-critical roles that cannot be done away from Ford facilities – to work remotely until further notice. The action will additionally help reduce the risk of spreading the coronavirus while maximizing the health of our business.

ASSURANT® Partner Solutions Our Story News & Insights Investor Relations Careers

Our Global Response to COVID-19

As a global organization, we have been actively monitoring the developments of the rapidly evolving situation resulting from COVID-19. Throughout this period of uncertainty, we have acted swiftly and deliberately to safeguard our employees, customers and business operations in line with our Assurant values.

We believe that we must continue to do our part to stem the spread of the virus, while also minimizing any disruptions to our operations. To that end, as the virus moved from east to west across the world, we implemented a regional, then global ban on business travel and established work-from-home protocols for employees that are able to do so. For those employees that need to work in our global facilities, we've continued to enforce safety and hygiene protocols, such as social distancing, per the guidelines of the Centers for Disease Control and the World Health Organization, to safeguard our employees.

What We Offer Who We Serve Resources About ADP

- We have activated our Business Resiliency Plan, which includes:
  - Enabling work from home capabilities within impacted regions
  - Deploying a global strategy to coordinate delivery of services and support to our clients
  - Providing our associates with information and best practices to prevent the spread of any illness
  - Coordinating global and local communications with our associates, clients and partners
  - Limiting all non-essential business travel

Why Itron Solutions Customers

Over the past several weeks, Itron has continued to monitor and navigate through the coronavirus (COVID-19) pandemic. This situation continues to be extremely dynamic, and information is changing daily, in some cases hourly. During this unprecedented time, we are working to ensure the safety and wellbeing of our employees as well as the continued success of our customers and partners. To this end, Itron's Coronavirus Internal Crisis Management Team has been meeting daily since late January to determine the policies and measures the company is undertaking globally.

. . .

Employee and Customer Safety

- Itron has made a company-wide decision to promote working remotely to do our part to help slow the spread of the virus, while providing business continuity for our customers. Itron has instituted a work from home program for all employees that can productively do so until further notice. We have adapted our factory operations to best optimize safety and output.

Figure 2: Timeline of Announcement Sample. This figure shows the timeline of work-from-home announcements along with the S&P 500 index and two indices of attention to remote-work, one from Google Trends, and the other a rolling average of stories in the New York Times and Wall Street Journal.

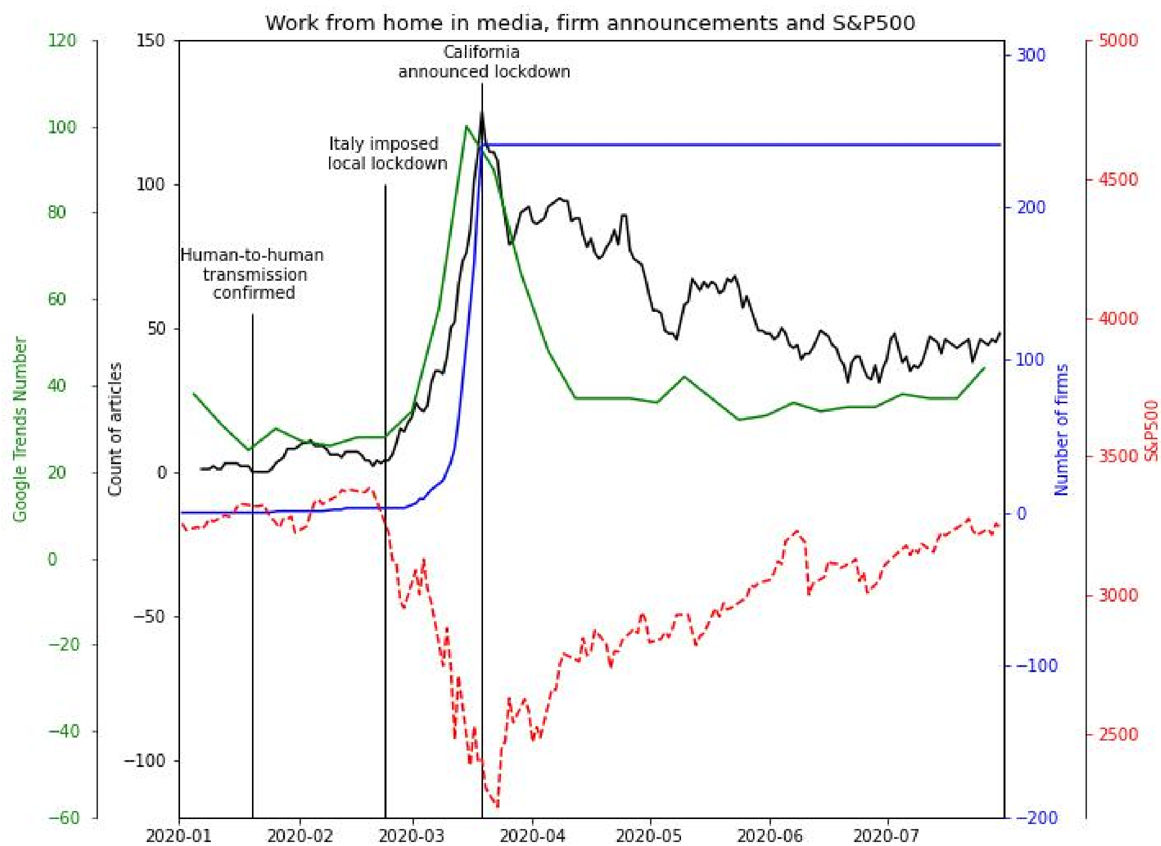


Figure 3: Scaled Abnormal Announcement Returns. The figure shows daily (gold line) and average (blue line) scaled abnormal announcement returns. The average scaled abnormal returns are calculated during three subsequent periods: 10 days before the WFH announcement (pre-event), 5 days starting on the announcement day (event), and the subsequent 5 days (post-event). The scaled abnormal returns following Kolari and Pynnönen (2010)) are defined in Appendix A.2 equation 11. The returns in the first (second) column are relative to benchmark of firms in the same industry and size quintile (five closest matches by propensity score) and further control for factors of CAPM or Fama and French 3-factor or 5-factor models as indicated in panel headings. The first column uses the full sample of 273 WFH firms and the second column uses the 229 WFH firms with available propensity-score benchmark. Dotted lines indicate the 90% confidence intervals based on standard errors that account for contemporaneous cross-correlation, auto-correlation, and cross-serial-correlation as detailed in the Appendix.

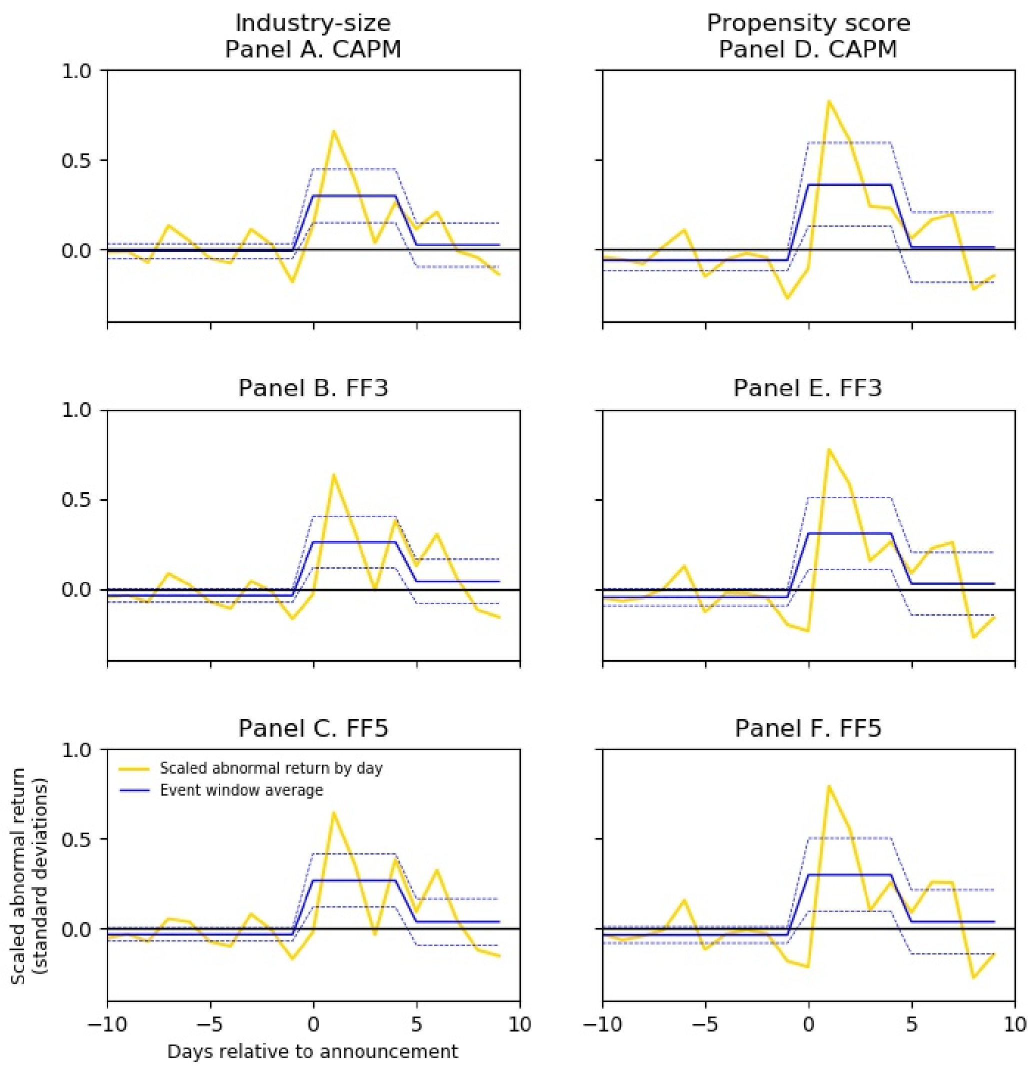


Figure 4: PS Loading Changes: WFH vs. Benchmarks. Panel A shows PS-factor loadings for WFH, Matched, and Unmatched portfolios before and after the Covid-fever period. Panel B shows changes from before to after the fever period (post-pre). Panel C shows differences between WFH and Matched, and WFH and Unmatched portfolio loadings. Panel D shows differences-in-differences: post- minus pre-fever differences in loadings for WFH vs. Match and WFH vs. Unmatched portfolios. The underlying regressions, time period, and standard-errors are given in the notes to table 6. Shaded areas indicate 90% confidence intervals. The WFH portfolio consists of work-from-home announcers (restricted to those with propensity-score matches). The Matched portfolio consists of propensity-score matches and the Unmatched portfolio consists of firms without voluntary work-from-home announcement that are also not used as matches. Portfolios are value-weighted.

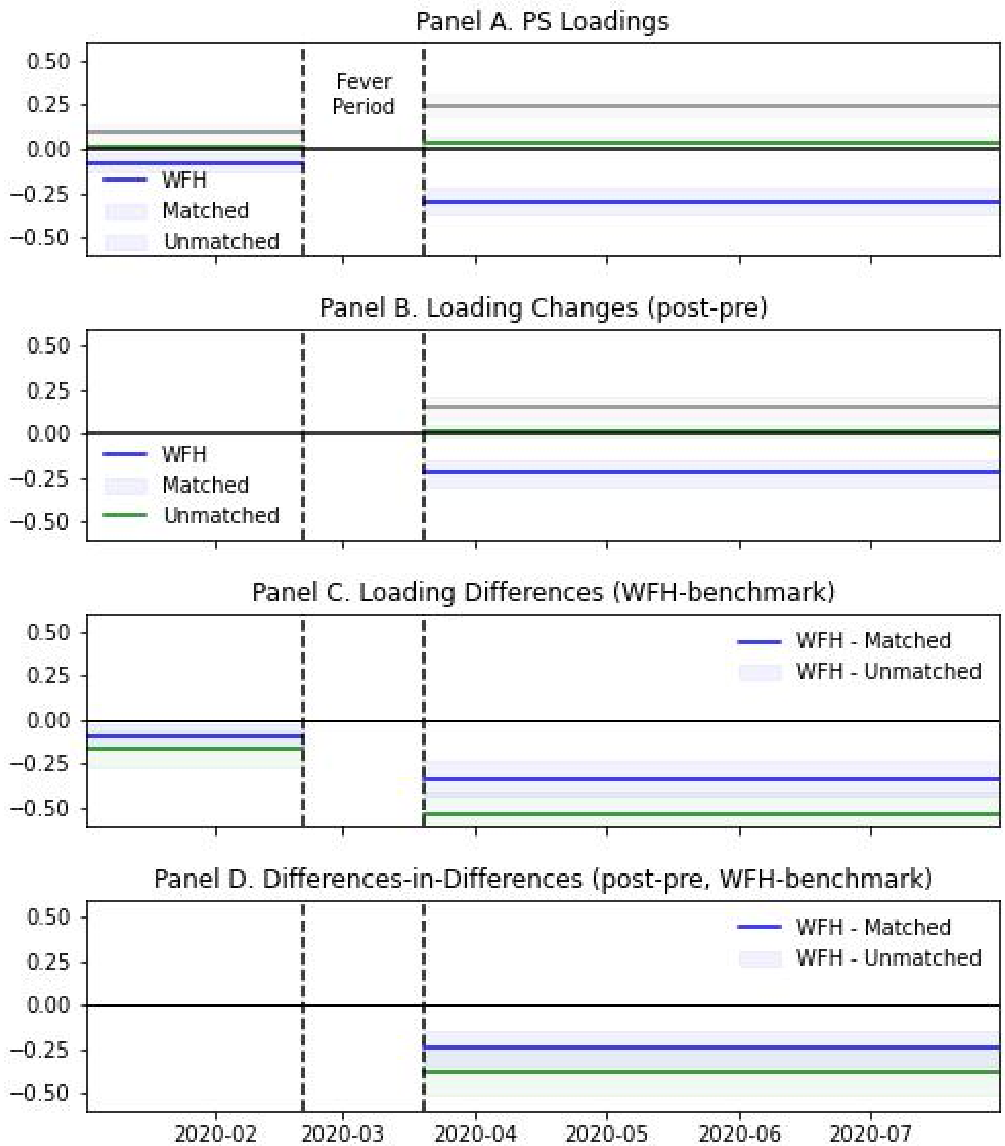


Figure 5: Operating Performance. The figure shows quarterly average operating performance of unmatched firms (black line), the differences between WFH and unmatched firms (blue line), and the differences between the matches of WFH firms and unmatched firms (orange line). The WFH sample consists of WFH firms with valid propensity-score matches and non-missing observation of the corresponding variable. For each WFH firm we calculate variable averages over their final matches and the line shown averages over these comparables. Unmatched firms are the remaining non-WFH firms which are not used as final matches. Each panel is based on non-missing observations of the corresponding variable. To avoid seasonalities we calculate the growth in the quarterly variables by comparing the same quarters in two consecutive years, e.g., $Sales\ growth_{2019Q1} = \frac{Sales_{2019Q1} - Sales_{Q2018Q1}}{Sales_{2018Q1}}$. Dashed lines indicate the 90% confidence intervals.

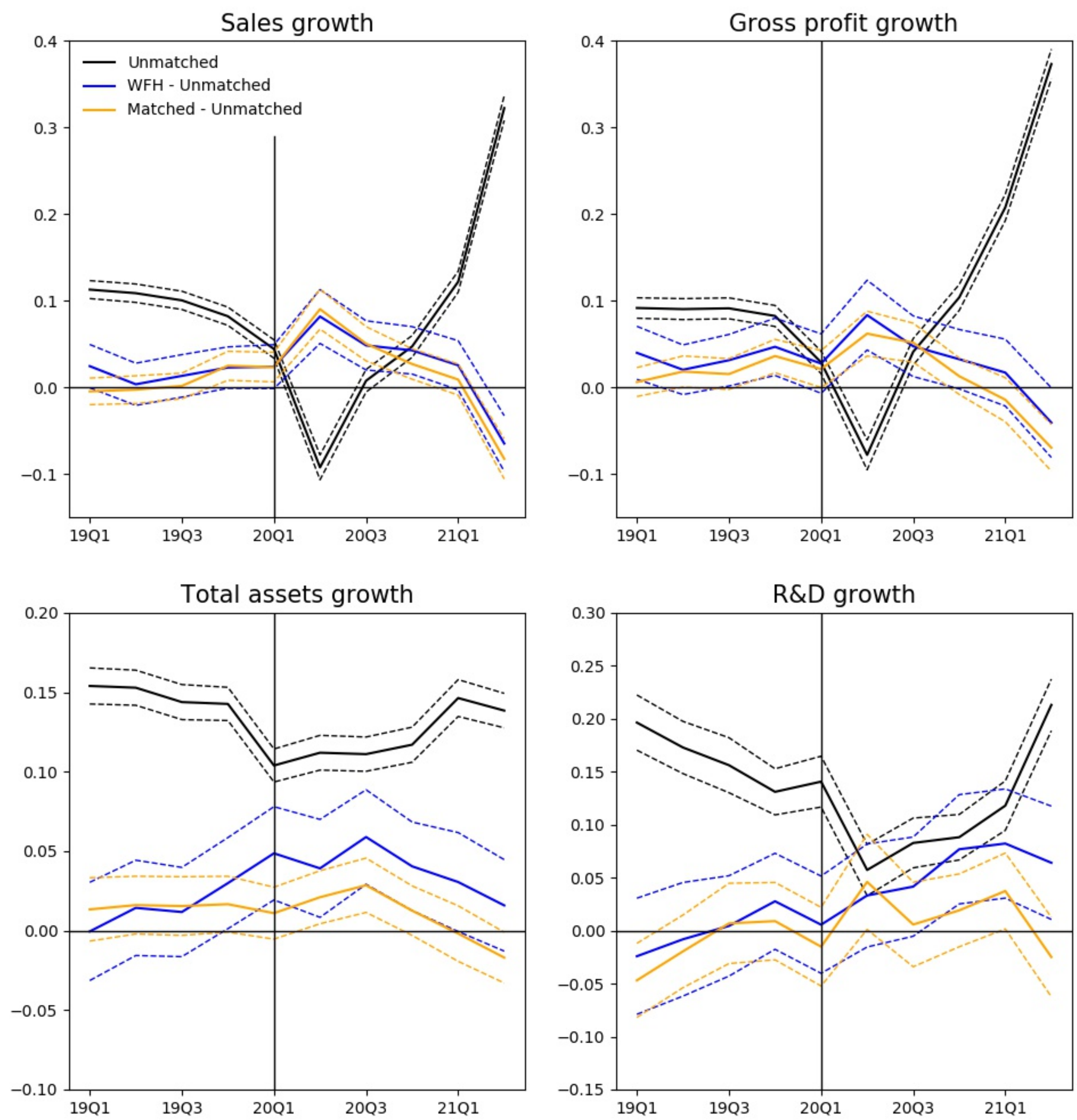


Table 1: Summary Statistics. Panel A presents summary statistics of these variables: WFH (dummy variable indicating whether a firm made a voluntary WFH announcement), PS (industry's share of labor suitable for 'telecommuting' from Papanikolaou and Schmidt (2022)), DN (industry's share of labor suitable 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), Investment (annual growth in total assets) and Beta (market beta). Panel B shows the correlation matrix between the main variables. Panel C shows the average and median of these variables among Non-WFH firms and WFH firms as well as the difference of the average between WFH and Non-WFH subsamples. Each row is based on non-missing observations of the corresponding variable of full sample of 2549 firms (of it 273 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	2.01	16.75
lnME	20.90	1.93	14.68	18.49	20.87	23.43	27.38
lnEmp	7.56	2.12	1.39	4.78	7.65	10.28	14.65
BM	0.64	0.59	0.00	0.13	0.53	1.22	9.73
Profitability	0.25	0.32	-2.07	0.02	0.23	0.59	3.31
Investment	0.25	1.32	-0.78	-0.09	0.05	0.56	31.14
Beta	1.13	0.70	-8.01	0.36	1.08	1.98	5.24

Panel B. Correlation Coefficients

	WFH	PS	DN	IK	OK
WFH	1.00				
PS	0.13	1.00			
DN	0.10	0.42	1.00		
IK	-0.03	0.28	-0.04	1.00	
OK	0.00	0.05	-0.19	0.54	1.0

Panel C. Subsamples

	WFH firms		Non-WFH firms		Difference WFH - Non-WFH	
	Mean	Median	Mean	Median	Diff.	t-stat
PS	0.340	0.336	0.263	0.234	0.077	[5.54]
DN	0.518	0.720	0.431	0.250	0.087	[5.15]
IK	0.428	0.361	0.497	0.262	-0.069	[-2.21]
OK	0.825	0.633	0.812	0.432	0.012	[0.21]
lnME	22.238	22.126	20.736	20.720	1.503	[12.05]
lnEmp	8.647	8.589	7.427	7.496	1.220	[10.19]
BM	0.504	0.364	0.659	0.543	-0.155	[-5.06]
Profitability	0.323	0.300	0.244	0.222	0.080	[4.68]
Investment	0.197	0.060	0.255	0.051	-0.059	[-1.46]
Beta	1.014	0.992	1.142	1.093	-0.128	[-3.9]

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 indicates firms that announced a voluntary work-from-home regime by March 19, 2020 and x_i is one or all of four main explanatory variables: PS, DN, IK, and OK, except in column 1. Regressions include a set of control variables v_i: $LnME$, $LnEmp$, BM, $Profitability$, $Investment$ and β^{mkt}. 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. The sample is composed of 1889 firms belonging to 2-digit NAICS industries with at least one WFH firm, and having non-missing values of all regressors. In this and subsequent tables, ***, **, and * indicate 99%, 95%, and 90% significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
PS		0.49***				0.38***	0.49***			0.49***	0.40***
		[6.03]				[3.87]	[4.24]			[4.12]	[5.36]
DN			0.43***			0.24**					
			[5.13]			[2.52]					
IK				0.16		0.00		0.18		0.08	
				[1.28]		[0.02]		[1.25]		[0.39]	
OK					0.10	0.07			0.09	0.01	
					[0.75]	[0.39]			[0.61]	[0.06]	
$LnME$	0.83***	0.61***	0.75***	0.84***	0.86***	0.65***	0.66***	0.79***	0.81***	0.67***	0.76***
	[5.87]	[4.25]	[5.25]	[5.95]	[5.83]	[4.27]	[4.19]	[5.11]	[5.10]	[4.04]	[9.54]
$LnEmp$	-0.06	0.24	0.10	-0.03	-0.07	0.24	0.18	0.09	0.04	0.19	
	[-0.40]	[1.62]	[0.67]	[-0.20]	[-0.48]	[1.54]	[1.05]	[0.54]	[0.25]	[1.09]	
BM	0.09	0.16	0.07	0.11	0.10	0.14	0.14	0.12	0.11	0.14	
	[0.82]	[1.59]	[0.59]	[1.02]	[0.87]	[1.33]	[1.32]	[1.09]	[1.05]	[1.35]	
$Profitability$	0.14	0.08	0.24**	0.09	0.06	0.09	0.12	0.15	0.13	0.09	
	[1.44]	[0.90]	[2.50]	[0.86]	[0.38]	[0.60]	[1.13]	[1.36]	[0.83]	[0.58]	
$Investment$	0.05	0.01	0.02	0.05	0.05	-0.00	-0.01	0.02	0.01	-0.01	
	[0.52]	[0.06]	[0.20]	[0.54]	[0.54]	[-0.00]	[-0.08]	[0.14]	[0.12]	[-0.06]	
β^{mkt}	-0.16*	-0.19**	-0.15*	-0.17**	-0.16*	-0.18**	-0.15	-0.16*	-0.16*	-0.15	
	[-1.85]	[-2.26]	[-1.73]	[-1.98]	[-1.82]	[-2.04]	[-1.58]	[-1.81]	[-1.76]	[-1.60]	
Industry FE	No	No	No	No	No	No	Yes	Yes	Yes	Yes	No
Pseudo R^2	0.084	0.112	0.105	0.085	0.085	0.118	0.128	0.114	0.114	0.128	0.102
BIC	1248	1219	1229	1255	1255	1235	1328	1345	1346	1343	1195
Fitted likelihoods, 10-90 percent variation in PS or other lead variable											
Low		0.06	0.08	0.10	0.10	0.07	0.06	0.10	0.10	0.06	0.07
High		0.19	0.17	0.12	0.12	0.17	0.19	0.12	0.12	0.19	0.17

Table 3: Announcement Effects Panel Regressions. The table shows the results of regressing a panel of daily stock returns on a constant, the variable $WFH_{0,4}$ indicating the five-day window from the firm's announcement (starting at day zero), the variable $WFH_{5,9}$ indicating the subsequent five-day window, the stock market return R_{mkt}, and the industry return $R_{industry}$ as specified in regression equation 2. Columns 4-6 include industry fixed effects at NAICS 2-digit level. The standard errors (Driscoll and Kraay (1998) with 10 lags) for market and industry returns are in parentheses and the equivalently calculated t-statistics for the indicator variables and constant in brackets. Significance stars are omitted for market and industry returns. The table is based on the full sample of 2549 firms, 1663 essential and 886 non-essential. The panel is from July 1, 2019 to April 1, 2020 (i.e., the end of the fever period on March 19 plus the 10-day announcement window).

				Industry fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All firms						
const	-0.000	0.000	0.000			
	[-0.10]	[0.78]	[0.42]			
$WFH_{0,4}$	0.010***	0.007**	0.008***	0.010***	0.007**	0.008***
	[3.14]	[2.47]	[2.70]	[3.23]	[2.43]	[2.69]
$WFH_{5,9}$	0.003	0.002	0.002	0.003	0.002	0.002
	[0.85]	[0.87]	[0.71]	[0.88]	[0.86]	[0.71]
R_{mkt}	1.09		0.22	1.09		0.22
	(0.035)		(0.032)	(0.035)		(0.031)
$R_{industry}$		0.98	0.81		0.98	0.81
		(0.026)	(0.030)		(0.026)	(0.029)
R^2	0.244	0.266	0.267	0.243	0.266	0.267
Panel B. Essential Firms						
const	-0.000	0.000	0.000			
	[-0.11]	[0.65]	[0.47]			
$WFH_{0,4}$	0.008***	0.007***	0.008***	0.008***	0.007***	0.007***
	[3.39]	[2.90]	[3.04]	[3.49]	[2.89]	[3.04]
$WFH_{5,9}$	0.001	-0.000	-0.000	0.001	-0.000	-0.000
	[0.53]	[-0.14]	[-0.15]	[0.57]	[-0.17]	[-0.16]
R_{mkt}	1.08		0.14	1.08		0.14
	(0.031)		(0.038)	(0.031)		(0.038)
$R_{industry}$		0.96	0.85		0.96	0.86
		(0.025)	(0.036)		(0.024)	(0.035)
R^2	0.225	0.251	0.252	0.225	0.251	0.252
Panel C. Non-essential Firms						
const	-0.000	-0.001	-0.001			
	[-0.17]	[-0.68]	[-0.53]			
$WFH_{0,4}$	0.012***	0.008**	0.010**	0.012***	0.008**	0.010**
	[2.75]	[2.08]	[2.50]	[2.84]	[2.09]	[2.54]
$WFH_{5,9}$	0.004	0.004	0.004	0.004	0.005	0.004
	[1.01]	[1.54]	[1.15]	[1.03]	[1.58]	[1.18]
R_{mkt}	1.11		0.36	1.11		0.36
	(0.044)		(0.038)	(0.044)		(0.038)
$R_{industry}$		1.01	0.71		1.01	0.71
		(0.032)	(0.053)		(0.032)	(0.053)
R^2	0.285	0.300	0.303	0.285	0.299	0.303

Table 4: Announcement Effects Relative to Matches. The table shows the results of regressing daily stock returns of WFH firms relative to a benchmark on a constant, the variables $WFH_{0,4}$ and $WFH_{5,9}$ (defined in notes of Table 3) and aggregate stock market R_{mkt} as specified in regression equation 3. The benchmark adjusted return on the left-hand side is the return difference between the WFH firm and the benchmark indicated in the columns. The benchmark in column 1 is value-weighted market return, in columns 2-4 the average return of firms in the same quintile by Size, Industry-size, and PS-size, respectively, and in column 5 the average return of the five closest matches by propensity score. Standard errors (Driscoll and Kraay (1998) with 10 lags) are in parentheses and t-statistics in brackets. Significance stars are omitted for market returns. Columns 1-4 use the full sample of 273 WFH firms, 145 essential. Column 5 requires non-missing PS to calculate propensity score (229 WFH, 130 essential). The panel is from July 1, 2019 to April 1, 2020 (i.e., end of fever period March 19 plus 10-day announcement window).

	Market	Size	Industry -size	PS -size	Propensity score
Panel A. All Firms					
const	-0.001	0.000	0.000	0.000	-0.000
	[-1.59]	[0.83]	[0.32]	[0.61]	[-0.87]
$WFH_{0,4}$	0.010***	0.006***	0.006***	0.006***	0.008***
	[2.72]	[7.39]	[13.23]	[7.17]	[11.18]
$WFH_{5,9}$	0.003	0.001	0.001	0.001	0.000
	[1.02]	[0.52]	[0.44]	[0.42]	[0.13]
R_{mkt}	0.05	-0.06	-0.03	-0.04	-0.02
	(0.026)	(0.008)	(0.007)	(0.007)	(0.010)
R^2	0.004	0.003	0.002	0.002	0.002
Panel B. Essential Firms					
const	-0.001	0.000	0.000	0.000	-0.000
	[-1.48]	[0.75]	[0.47]	[0.54]	[-0.02]
$WFH_{0,4}$	0.008***	0.004**	0.006***	0.005***	0.007***
	[2.96]	[2.29]	[7.35]	[3.61]	[8.06]
$WFH_{5,9}$	0.002	-0.000	-0.001	-0.000	0.000
	[0.62]	[-0.10]	[-0.27]	[-0.15]	[0.12]
R_{mkt}	0.06	-0.05	-0.04	-0.04	-0.03
	(0.031)	(0.011)	(0.010)	(0.011)	(0.014)
R^2	0.004	0.002	0.003	0.002	0.002
Panel C. Non-essential Firms					
const	-0.001	0.000	-0.000	0.000	-0.000
	[-1.31]	[0.42]	[-0.05]	[0.26]	[-1.24]
$WFH_{0,4}$	0.011**	0.008***	0.007***	0.006***	0.010***
	[2.39]	[6.61]	[7.14]	[5.84]	[6.56]
$WFH_{5,9}$	0.005	0.002	0.002	0.002	0.000
	[1.33]	[0.96]	[1.06]	[0.96]	[0.12]
R_{mkt}	0.04	-0.07	-0.02	-0.05	-0.01
	(0.024)	(0.013)	(0.008)	(0.008)	(0.011)
R^2	0.005	0.005	0.002	0.003	0.002

Table 5: Event Studies of Scaled Abnormal Returns. The table shows the average scaled abnormal daily return of announcing firms during three subsequent periods: 10 days before the WFH announcement (Pre), 5 days starting on the announcement day (Event), and the subsequent 5 days (Post) for different models (CAPM, Fama and French 3-factor model, and Fama and French 5-factor model) as indicated at the top of the table. The scaled abnormal returns following Kolari and Pynnönen (2010)) are defined in the Appendix. The returns in panels A-C are relative to benchmark of average returns of firms in the same quintile by Size, Industry-size, and PS-size, respectively, and in panel D relative to the average return of the five closest matches by propensity score. Panels A-C use the full sample of 273 WFH firms, panel D requires non-missing PS to calculate propensity score (229 WFH firms). Standard errors reported in parentheses account for contemporaneous cross-correlation, auto-correlation, and cross-serial-correlation as detailed in the Appendix. *t*-statistics are in brackets.

	CAPM			FF3			FF5		
	Pre	Event	Post	Pre	Event	Post	Pre	Event	Post
Panel A. Size									
Mean	0.023	0.258**	0.027	-0.046**	0.209***	0.057	-0.038*	0.22***	0.049
st. err.	(0.03)	(0.112)	(0.096)	(0.023)	(0.081)	(0.071)	(0.021)	(0.077)	(0.069)
t stat	[0.78]	[2.3]	[0.28]	[-2.03]	[2.58]	[0.8]	[-1.82]	[2.87]	[0.71]
Panel B. Industry-size									
Mean	-0.011	0.295***	0.023	-0.037	0.26***	0.041	-0.034	0.267***	0.036
st. err.	(0.025)	(0.09)	(0.074)	(0.023)	(0.087)	(0.074)	(0.022)	(0.09)	(0.078)
t stat	[-0.42]	[3.26]	[0.32]	[-1.62]	[2.98]	[0.56]	[-1.54]	[2.97]	[0.47]
Panel C. PS-size									
Mean	0.011	0.235***	0.013	-0.031	0.196***	0.047	-0.032	0.209***	0.043
st. err.	(0.026)	(0.09)	(0.075)	(0.021)	(0.071)	(0.061)	(0.02)	(0.075)	(0.065)
t stat	[0.44]	[2.6]	[0.17]	[-1.46]	[2.77]	[0.78]	[-1.61]	[2.78]	[0.67]
Panel D. Propensity Score									
Mean	-0.062*	0.358**	0.01	-0.047	0.308**	0.028	-0.036	0.298**	0.037
st. err.	(0.034)	(0.141)	(0.119)	(0.029)	(0.123)	(0.106)	(0.027)	(0.123)	(0.109)
t stat	[-1.82]	[2.54]	[0.08]	[-1.64]	[2.51]	[0.26]	[-1.32]	[2.42]	[0.34]

Table 6: Changes in Systematic Risk. The table shows the exposure and the change in exposure of different portfolios (columns) to market return (panel A) and to the PS-factor and market (panel B) before and after the fever period as specified in regression 18. β and β_{PS} are coefficients of market return and the PS factor, respectively. $\Delta const$ is coefficient of a dummy variable indicating post-fever period, i.e., from March 20, 2020. $\Delta\beta$, and $\Delta\beta_{PS}$ indicate the change in the respective coefficients after the fever period. The regressions are estimated from beginning of January to end of July 2020 (skipping the fever period February 23 to March 19, 2020). Standard errors adjusted for autocorrelation and heteroscedasticity using Newey and West (1987) with 10 lags are reported for market beta β in parentheses in the first three columns and the equivalently calculated t-statistics for the remaining estimates in brackets. Significance stars are omitted for β in the first three columns. The WFH portfolio consists of work-from-home announcers with valid propensity-score matches. The Matched portfolio consists of propensity-score matches and the Unmatched portfolio consists of non-announcing, unmatched firms. Portfolios are value-weighted. The last two columns show long-short portfolios with a long position in the WFH portfolio and a short position either in the Matched portfolio or the Unmatched portfolio as indicated.

	Portfolios			Differences	
	WFH	Matched	Unmatched	WFH-Matched	WFH-Unmatched
Panel A. Market Factor					
$const$	0.001	0.0	-0.001**	0.001	0.002
	[1.21]	[1.0]	[-2.1]	[0.75]	[1.62]
β	1.145	0.929	1.0	0.216*	0.145
	(0.08)	(0.05)	(0.07)	[1.73]	[1.01]
$\Delta const$	0.0	-0.0	0.001	0.001	-0.001
	[0.07]	[-1.49]	[1.35]	[0.48]	[-0.54]
$\Delta\beta$	-0.262***	0.085*	0.091	-0.348***	-0.353**
	[-3.1]	[1.68]	[1.24]	[-2.71]	[-2.33]
R^2	0.942	0.989	0.963	0.113	0.131
Panel B. Market and PS Factors					
$const$	0.001	0.0	-0.001	0.0	0.001
	[0.78]	[1.46]	[-1.45]	[0.29]	[1.08]
β	1.111	0.938	1.04	0.173*	0.071
	(0.06)	(0.04)	(0.04)	[1.81]	[0.8]
β_{PS}	-0.07**	0.019**	0.082**	-0.089**	-0.152**
	[-2.23]	[2.4]	[2.45]	[-2.3]	[-2.36]
$\Delta const$	0.0	-0.001*	0.001	0.001	-0.001
	[0.09]	[-1.71]	[1.45]	[0.64]	[-0.6]
$\Delta\beta$	-0.125**	0.063	-0.034	-0.189*	-0.092
	[-2.08]	[1.31]	[-0.77]	[-1.83]	[-0.98]
$\Delta\beta_{PS}$	-0.227***	0.017	0.163***	-0.244***	-0.39***
	[-5.28]	[0.8]	[4.26]	[-4.07]	[-4.92]
R^2	0.981	0.989	0.988	0.577	0.758

Table 7: Default Probabilities. The table shows the results of regressing a panel of daily changes in default probabilities for WFH firms relative to benchmarks on a constant, announcement-window indicator variables $WFH_{0,4}$ and $WFH_{5,9}$ (defined in notes of Table 3) and average daily change in default probabilities across the market $PrDef_{mkt}$, following the structure of equation (3). To calculate default probabilities relative to benchmarks we use the benchmarks indicated in the columns. The benchmark in column 1 is daily average change in default probabilities across the market, in columns 2-4 the average change in default probabilities of firms in the same quintile by Size, Industry-size, and PS-size, respectively, and in column 5 the average change in default probabilities of the five closest matches by propensity score. Standard errors (Driscoll and Kraay (1998) with 10 lags) are in parentheses and t-statistics in brackets. Significance stars are omitted for $PrDef_{mkt}$. Columns 1-4 use the sample of 272 WFH firms with available default probability data, 145 essential. Column 5 additionally requires non-missing PS to calculate propensity score (229 WFH, 130 essential). The panel is from July 1, 2019 to April 1, 2020 (i.e., end of fever period March 19 plus 10-day announcement window).

	Market	Size	Industry -size	PS -size	Propensity score
Panel A. All Firms					
const	-0.000	0.001	0.001	0.001	0.001
	[-0.60]	[1.10]	[1.13]	[1.06]	[1.42]
$WFH_{0,4}$	-0.006	-0.007*	-0.013***	-0.010***	-0.014***
	[-1.42]	[-1.89]	[-3.98]	[-2.71]	[-3.22]
$WFH_{5,9}$	0.002	-0.005	0.002	-0.004	0.006
	[0.47]	[-1.55]	[0.37]	[-0.83]	[0.94]
$PrDef_{mkt}$	-0.68	-0.50	-0.25	-0.39	-0.17
	(0.024)	(0.024)	(0.036)	(0.020)	(0.050)
R^2	0.225	0.227	0.062	0.108	0.015
Panel B. Essential Firms					
const	-0.000	0.001	0.001	0.001	0.001
	[-1.44]	[0.98]	[1.27]	[0.91]	[1.25]
$WFH_{0,4}$	-0.001	-0.005	-0.014***	-0.010**	-0.006
	[-0.19]	[-1.56]	[-4.42]	[-2.51]	[-1.22]
$WFH_{5,9}$	0.001	-0.004	0.001	-0.001	0.003
	[0.52]	[-1.47]	[0.23]	[-0.16]	[0.65]
$PrDef_{mkt}$	-0.79	-0.58	-0.31	-0.43	-0.23
	(0.018)	(0.022)	(0.039)	(0.025)	(0.051)
R^2	0.414	0.335	0.103	0.148	0.032
Panel C. Non-essential Firms					
const	-0.000	0.001	0.001	0.001	0.001
	[-0.01]	[1.17]	[0.89]	[1.14]	[1.46]
$WFH_{0,4}$	-0.014***	-0.010**	-0.013***	-0.011**	-0.025***
	[-3.29]	[-2.27]	[-3.55]	[-2.13]	[-4.80]
$WFH_{5,9}$	0.004	-0.005	0.003	-0.007	0.011
	[0.62]	[-1.24]	[0.59]	[-1.45]	[0.88]
$PrDef_{mkt}$	-0.56	-0.41	-0.17	-0.36	-0.09
	(0.032)	(0.029)	(0.032)	(0.028)	(0.050)
R^2	0.118	0.140	0.030	0.076	0.005

Table 8: Bloomberg Announcement Effects: Size and Speed. Panel A shows the results of regressing daily stock returns of WFH firms relative to benchmarks on a constant, the market return, announcement-window indicators $BB_{04,it}$ and $BB_{59,it}$ for announcements reported by Bloomberg, and indicators $WS_{04,it}$ and $WS_{59,it}$ for announcements not covered by Bloomberg, as specified in equation 5. The panel reports the estimated coefficients $a_{BB,04,}$, $a_{BB,59}$, $a_{WS,04}$ and $a_{WS,59}$ of the announcement-window indicators and omits reporting the constant and market-return coefficient. The Bloomberg marginal effects section reports the marginal effects of Bloomberg relative to website-only announcements, i.e., $a_{BB} - a_{WS}$. Panel B shows results of regressions that additionally include the interactions with the indicators $(BB_{01} - 2/3BB_{24})$ and $(WS_{01} - 2/3WS_{24})$ as specified in regression equation 17 in the Appendix to estimate the speed parameters ϕ_{BB} and ϕ_{WS}. The panel omits coefficients for the constant, market return and days 5-9 announcement indicators. The Bloomberg marginal effects section reports the difference in the speed parameters ϕ_{BB} and ϕ_{WS}. Benchmarks (column headings) are defined in the notes to Table 4. t-statistics (Driscoll and Kraay (1998) with 10 lags) are in brackets. The panel is from July 1, 2019 to April 1, 2020 (i.e., end of fever period March 19 plus 10-day announcement window).

	Market	Size	Industry -size	PS -size	Propensity score
Panel A. Announcement Effect Size Comparison					
$a_{BB,04}$	0.015***	0.011***	0.01***	0.011***	0.015***
	[5.19]	[5.01]	[5.84]	[4.26]	[5.50]
$a_{WS,04}$	0.009**	0.005***	0.006***	0.005***	0.007***
	[2.30]	[5.79]	[7.12]	[4.84]	[7.86]
$a_{BB,59}$	-0.001	-0.001	-0.001	-0.002	-0.002
	[-0.47]	[-1.20]	[-0.45]	[-1.52]	[-1.06]
$a_{WS,59}$	0.004	0.001	0.001	0.001	0.0
	[1.12]	[0.53]	[0.42]	[0.46]	[0.12]
R^2	0.005	0.004	0.002	0.003	0.003
Bloomberg Marginal Effects					
$(a_{BB} - a_{WS})_{0,4}$	0.006**	0.005**	0.004*	0.006**	0.008**
	[2.45]	[2.38]	[1.80]	[2.21]	[2.54]
$(a_{BB} - a_{WS})_{5,9}$	-0.005**	-0.003	-0.002	-0.003	-0.002
	[-2.09]	[-1.48]	[-0.90]	[-1.52]	[-0.93]
$(a_{BB} - a_{WS})_{0,9}$	0.001	0.001	0.001	0.002	0.003
	[0.35]	[0.78]	[0.91]	[0.99]	[1.13]
Panel B. Announcement Effect Speed Comparison					
$a_{BB,04}$	0.015***	0.011***	0.01***	0.011***	0.015***
	[4.41]	[6.80]	[6.34]	[6.66]	[5.13]
$a_{WS,04}$	0.009***	0.005***	0.006***	0.005***	0.007***
	[2.87]	[5.08]	[8.44]	[4.84]	[8.33]
$\phi_{BB} - 1$	0.42	0.973**	1.003**	0.995**	0.881**
	[1.35]	[2.35]	[2.50]	[2.32]	[2.21]
$\phi_{WS} - 1$	-0.742***	-0.494**	-0.31*	-0.422*	-0.124
	[-5.66]	[-2.46]	[-1.68]	[-1.69]	[-0.58]
R^2	0.006	0.005	0.003	0.003	0.003
Bloomberg Marginal Effects					
$\phi_{BB} - \phi_{WS}$	1.162***	1.467***	1.313***	1.417***	1.005***
	[5.07]	[4.81]	[4.68]	[4.89]	[3.44]

Table 9: ESG and Work-from-home: Announcement Decisions and Returns. Panel A shows results of estimating the logit model from equation 1 adding two ESG variables to those considered in Table 2. The variable ESG is ESG score with missing values filled to the value zero, and 1_{ESG} is an indicator for nonmissing ESG score. The fitted likelihoods are for the 10th and 90th percentiles of the ESG variable, except for columns 4-6, where Low is for $1_{ESG} = 0$ and High for $1_{ESG} = 1$. Panel B reports panel-regression announcement effects (equivalent to Table 4) for the ESG-propensity-score benchmark based on the BIC-minimizing logit model in column 3 of Panel A. Panel C shows the scaled abnormal returns (equivalent to Table 5) for the ESG-propensity-score benchmark. ESG data is from Refinitiv.

Panel A. Likelihood of Voluntary WFH Decisions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ESG	0.65***	0.23**	0.33***				0.70***	0.24*	0.34***
	[8.72]	[2.21]	[3.07]				[7.42]	[1.95]	[2.63]
1_{ESG}				1.04***	0.27	0.41	-0.25	-0.06	-0.03
				[4.45]	[1.07]	[1.62]	[-0.82]	[-0.21]	[-0.10]
$LnME$		0.61***	0.51***		0.74***	0.70***		0.60***	0.51***
		[5.50]	[4.55]		[8.82]	[8.25]		[5.43]	[4.51]
PS			0.44***			0.41***			0.44***
			[5.76]			[5.50]			[5.76]
Industry FE	No	No	No	No	No	No	No	No	No
Pseudo R^2	0.060	0.084	0.109	0.019	0.081	0.104	0.061	0.084	0.109
BIC	1242	1219	1193	1296	1223	1200	1249	1227	1201
Fitted likelihoods, variation in ESG (see table notes)									
Low	0.04	0.08	0.07	0.05	0.09	0.08	0.04	0.08	0.07
High	0.21	0.13	0.15	0.13	0.11	0.11	0.22	0.14	0.15

Panel B. Panel Regression Announcement Effects with ESG-Propensity-Score Benchmark

	$const$	$WFH_{0,4}$	$WFH_{5,9}$	R_{mkt}	Industry FE	R^2
Propensity score	-0.000	0.009***	0.001	-0.018	No	0.002
	[-0.97]	[8.76]	[0.29]	[-1.33]		

Panel C. Scaled Abnormal Returns Event Study with ESG-Propensity-Score Benchmark

	CAPM			FF3			FF5		
	Pre	Event	Post	Pre	Event	Post	Pre	Event	Post
Mean	-0.044	0.356***	0.035	-0.039	0.319***	0.038	-0.03	0.306***	0.06
st. err.	(0.029)	(0.108)	(0.089)	(0.026)	(0.101)	(0.086)	(0.025)	(0.108)	(0.093)
t stat	[-1.54]	[3.31]	[0.39]	[-1.52]	[3.17]	[0.44]	[-1.22]	[2.84]	[0.64]

Table 10: Operating Performance: WFH Announcers and Matches. This table reports the results of estimating regression of the form: $Y_{i,t} = \alpha + \beta_0 \times WFH_i + \beta_1 \times Match_i + \beta_2 \times Covid_t + \beta_3 \times WFH_i \times Covid_t + \beta_4 \times Match_i \times Covid_t + LnME_{i,t} + FE^{ind} + FE^{Q} + \epsilon_{i,t}$, where $Y_{i,t}$ is year-to-year growth in one of these variables: sales, gross profits, total assets, R&D and number of employees. WFH_i and $Match_i$ are (time-constant) dummy variables indicating WFH announcers and their final matches by propensity score, respectively. $Covid_t$ 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 designated as the calendar year 2020. $LnME$ is log market capitalization. Each column is based on non-missing observations of the corresponding variable of full sample of 2549 firms. 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 as year-to-year growth rate, i.e., 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 industry fixed effects at 2-digit NAICS and, except for the last column, quarter fixed effects. Standard errors are clustered at 2-digit NAICS industries. The panel of firms spans the period from Q1 2019 to Q4 2020.

	Growth in				
	Sales	Gross profits	Assets	R&D	Employees
WFH	-0.006	0.007	0.004	-0.025	-0.001
	[-0.49]	[0.62]	[0.14]	[-0.96]	[-0.04]
$Match$	-0.012	-0.002	-0.003	-0.012	-0.000
	[-1.02]	[-0.14]	[-0.15]	[-0.72]	[-0.01]
$Covid$	-0.104***	-0.068***	-0.045**	-0.081***	-0.064***
	[-6.45]	[-3.76]	[-2.32]	[-5.72]	[-6.15]
$WFH \times Covid$	0.044**	0.019	0.026**	0.046***	0.038***
	[2.45]	[0.97]	[2.00]	[4.61]	[3.73]
$Match \times Covid$	0.033	0.012	0.014	0.016	0.018*
	[1.39]	[0.47]	[0.81]	[0.82]	[1.66]
$LnME$	-0.002	-0.003**	-0.001	-0.001	0.002
	[-1.18]	[-2.42]	[-0.39]	[-0.30]	[1.19]
R^2	0.102	0.066	0.039	0.049	0.092
Comparison of WFH vs. Matches During Covid-19					
$(WFH - Match) \times Covid$	0.010	0.007	0.012	0.030*	0.020***
	[0.58]	[0.48]	[0.83]	[1.93]	[2.70]

Internet Appendix to

How Valuable is Corporate Adaptation to Crisis?
Estimates from Covid-19 Work-from-Home Announcements

Intended for online publication.

IA. Supplementary Results

Additional PS-factor exposure characteristic in logistic regressions. Table IA1 supplements Table 2 of the main paper by adding the PS-factor beta (Papanikolaou and Schmidt, 2022) to the set of characteristics predicting work-from-home announcement in the logistic regression specification. (The negative sign of the estimated β_{PS} coefficient maps to the positive sign of the estimated coefficient of the PS variable in Table 2 in the paper since β_{PS} measures exposure to low-high PS portfolio.)

Matching statistics: Table IA2 provides summary statistics for match accuracy.

Additional event study figures: Figure IA1 supplements Figure 3 of the main paper by showing additional results for size and PS-size matches. (Figure 3 of the main paper shows results for industry-size and propensity score matches.)

Daily average announcement effects in calendar time: Figure IA2 shows average abnormal announcement returns by calendar day for each day in the sample, with the number of observations on each day.

Additional fixed effects: Table IA3 supplements Table 3 in the paper by adding additional calendar-day fixed effects, and calendar-day fixed effects interacted with industry.

Additional benchmarks for event studies: We supplement Table 4 in the paper with Table IA4, which adds FF3 (Panel A) and FF5 (Panel B) factors. Table IA5 further adds the PS factor.

Table IA6 supplements Table 5 in the paper, which already includes FF5 factors, by additionally adding the PS factor.

Earnings and corporate control news: Table IA7 supplements Table 3 in the paper by removing 14 sample firms that have either earnings news (11 firms) or corporate control news (3 firms) in the announcement windows. These firm-specific news events are unlikely to be related to work-from-home announcements and therefore would not create a bias. Nonetheless, greater variability of non-WFH announcement news could generate outliers. The results show no substantial difference from the main results in the paper.

Additional ESG-propensity-score benchmark: Table IA9 supplements Table 6 in the paper using the ESG-propensity-score benchmark described in Section 4.2.

Alternative specification for Bloomberg announcements: Table IA10 supplements Table 8 in the paper by providing estimates from the alternative representation, equation (16) in the paper, of the announcement speed regression.

Option-implied expected return lower bounds: For the subsample of S&P 500 firms considered in Martin and Wagner (2019) and Pagano et al. (2023), we calculate option-implied lower bounds on expected returns using the method of Martin and Wagner (2019) for horizon of 365 days. We use a sample of 403 firms with valid option data in the period from January 1 to April 30, 2020, of which 97 are WFH announcers.[25] We create a matched sample by propensity-score matching without replacement to a single non-WFH firm.[26] This procedure creates a WFH sample of 97 firms, a matched sample of 97 firms, and 209 unmatched firms from the S&P 500. To minimize the effect of outliers noted in the earlier literature, we winsorize the firm-level expected returns at the 5 percent level daily, and construct value-weighted portfolios of WFH firms, their matches, and unmatched firms. For each portfolio, we run regressions:

$$\underline{\mu}_t = \underline{\mu}_{pre} * PreFever_t + \underline{\mu}_{Fever} * Fever_t + \underline{\mu}_{post} * PostFever_t + \epsilon_t,$$

where $PreFever_t$, $Fever_t$, and $PostFever_t$ are indicators equal to one during the respective time periods January 1 to February 23, February 24 to March 19, and March 20 to April 30. The results show smaller increases in expected returns in the post-fever period for work-from-home firms relative to matches and other firms. The results therefore supplement the main paper findings of reduced risk for remote-work announcers, as well as increases in valuation through a cost-of-capital channel.

[25] There are 407 firms with valid option-implied expected return bounds at any time in this sample period, but we exclude firms with missing data on more than three days, which eliminates four non-WFH firms. The final sample of 403 firms includes two firms with missing data on less then three days (one WFH firm and one non-WFH firm).

[26] For each WFH firm we order the potential matches by closeness to the WFH firm. We calculate the distance between the WFH and the closest match, and the matching algorithm prioritizes the WFH firms with the largest distance to the best match. Twenty-two WFH firms do not have propensity score because of a missing PS score. These are matched by size to non-WFH firms that are also missing a PS score.

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Figure IA1: Daily Scaled Abnormal Announcement Returns (Size and PS-Size Benchmarks). The figure shows daily (gold line) and average (blue line) scaled abnormal announcement returns. The average scaled abnormal returns are calculated during three subsequent periods: 10 days before the WFH announcement (pre-event), 5 days starting on the announcement day (event), and the subsequent 5 days (post-event). The scaled abnormal returns following Kolari and Pynnönen (2010)) are defined in Appendix A.2 equation 11. The returns in the first (second) column are relative to benchmark of firms in the same size quintile (same PS-size quintile) and further control for factors of CAPM or Fama and French 3-factor or 5-factor models as indicated in panel headings. The figure uses the full sample of 273 WFH firms. Dotted lines indicate the 90% confidence intervals based on standard errors that account for contemporaneous cross-correlation, auto-correlation, and cross-serial-correlation as detailed in the Appendix.

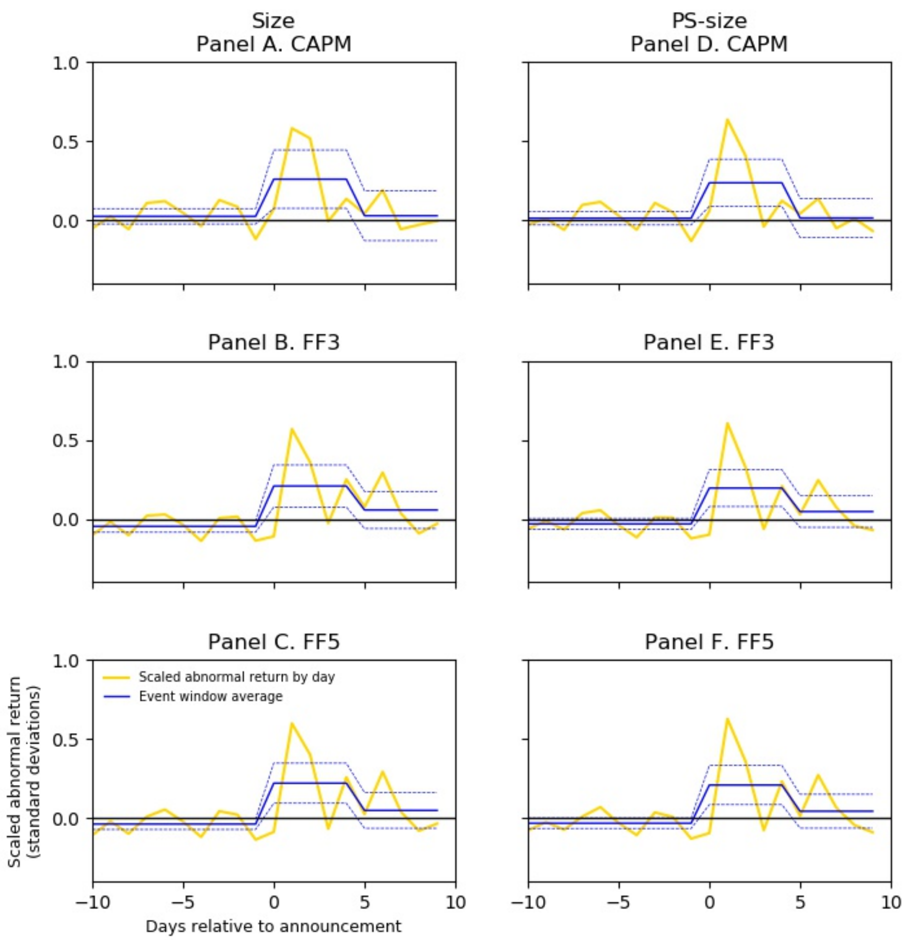

Figure IA2: Daily Event Abnormal Announcement Returns. The figure shows daily average abnormal returns on the announcement days. The abnormal return is defined as the difference between the daily return of the announcing firm and the daily benchmark return. The benchmarks are indicated in the panel headings. The announcement days are in the five-day window starting on the day of the WFH announcement. The daily abnormal returns are averaged across all firms whose five-day announcement window includes the day. The number of observations on each day is shown above or below the bar.

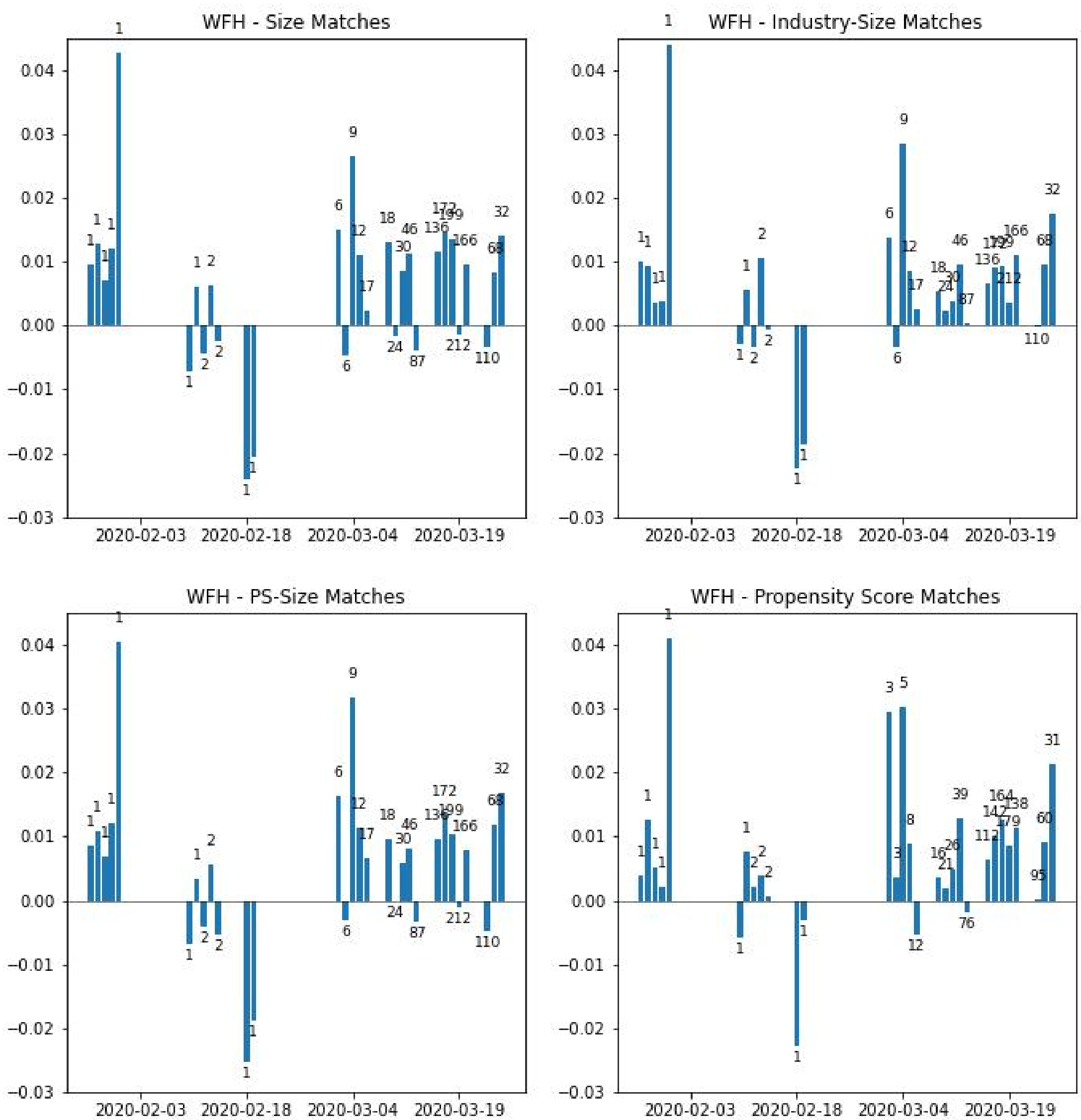

Table IA1: Likelihood of Firms' Voluntary Work-from-home Decisions and Exposure to the PS Factor. This table shows the results of estimating the logit model $p(WFH_i = 1) = \frac{1}{1+e^{x_i+v_i}}$, where WFH_i indicates firms that announced a voluntary work-from-home regime by March 19, 2020 and x_i is the main explanatory variables β_{PS} (firm's exposure to the PS factor from Papanikolaou and Schmidt (2022)). The control variables v_i are PS, $lnME$, $LnEmp$, BM, $Profitability$, $Investment$ and β^{mkt}. The logit model is estimated from cross section of firms with explanatory variables from year 2018. β_{PS} is estimated from daily stock returns using multivariate regression controlling for market excess return. The estimation period for β_{PS} is from the beginning of January 2020 (limited by the availability of PS data) until beginning of the Fever Period on February 23, 2020. Second half of the table (Fitted likelihoods) reports the fitted likelihood of $WFH = 1$ for low (10th percentile) and high (90th percentile) value of β_{PS}. Industry fixed effects are at 2-digit NAICS. The sample is composed of 1889 firms belonging to 2-digit NAICS industries with at least one WFH firm, and having non-missing values of all regressors. ***, **, and * indicate 99%, 95%, and 90% significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β_{PS}	-0.21***	-0.23**	-0.15*	-0.13	-0.10	-0.19**	-0.16	-0.14*	-0.10	-0.09
	[-2.67]	[-2.29]	[-1.92]	[-1.27]	[-1.00]	[-2.31]	[-1.59]	[-1.70]	[-0.97]	[-0.79]
PS			0.40***	0.38***	0.48***			0.57***	0.46***	0.48***
			[5.48]	[5.03]	[5.72]			[5.09]	[4.00]	[4.11]
$LnME$		0.76***		0.74***	0.60***		0.79***		0.75***	0.66***
		[9.66]		[9.38]	[4.23]		[9.55]		[9.02]	[4.15]
$LnEmp$					0.24					0.17
					[1.58]					[1.04]
BM					0.16*					0.15
					[1.65]					[1.37]
$Profitability$					0.08					0.12
					[0.86]					[1.10]
$Investment$					0.01					-0.01
					[0.07]					[-0.07]
β^{mkt}					-0.19**					-0.14
					[-2.16]					[-1.48]
Industry FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.005	0.084	0.028	0.103	0.113	0.031	0.109	0.052	0.122	0.128
BIC	1314	1219	1292	1201	1226	1408	1314	1388	1305	1335
Fitted likelihoods, 10-90 percent variation in PS or other lead variable										
Low	0.13	0.13	0.12	0.12	0.12	0.13	0.12	0.12	0.12	0.12
High	0.09	0.09	0.09	0.10	0.10	0.09	0.09	0.10	0.10	0.10

Table IA2: Matching Statistics. The table summarizes the statistics of matching work-from-home firms with their matches using propensity score based on the BIC-minimizing logit model with PS and $LnME$. The columns indicate the order of the matches. Number of matches is the number of WFH firms with a matched firm. Av. absolute distance is the average of absolute differences in propensity score between the WFH firms and their initial matches. The matching technique is described in detail in the paper's Appendix.

	1^{st} match	2^{nd} match	3^{rd} match	4^{th} match	5^{th} match
Number of matches	229.0	229.0	229.0	229.0	229.0
Av. absolute distance initial match	0.006	0.01	0.014	0.018	0.022

Table IA3: Panel Regressions with Calendar-Time Fixed Effects. The table shows the results of regressing a panel of daily stock returns on the variable $WFH_{0,4}$ indicating the five-day window from the firm's announcement (starting at day zero), the variable $WFH_{5,9}$ indicating the subsequent five-day window, the industry return $R_{industry}$ as specified in regression equation 2 with added calendar-time fixed effects. Columns 3-4 include industry fixed effects at NAICS 2-digit level, and column 5 interacts calendar-time fixed effects with industry fixed effects. Calendar-time fixed effects are within period of WFH announcements, from January 27 to April 1, 2020, which lowers large number of interaction terms with industry fixed effects outside of period of WFH announcements. The standard errors (Driscoll and Kraay (1998) with 10 lags) for industry returns are in parentheses and the equivalently calculated t-statistics for the indicator variables in brackets. Significance stars are omitted for industry returns. The table is based on the full sample of 2549 firms, 1663 essential and 886 non-essential. The panel is from July 1, 2019 to April 1, 2020 (i.e., the end of the fever period on March 19 plus the 10-day announcement window). We omit estimates for specification with calendar-time fixed effects interacted with industry fixed effects (column 5) in sample of non-essential firms, where standard errors could not be computed because of highly singular covariance matrix.

	(1)	(2)	(3)	(4)	(5)
Panel A. All firms					
$WFH_{0,4}$	0.007***	0.006***	0.007***	0.006***	0.007***
	[3.16]	[3.78]	[3.18]	[3.77]	[4.54]
$WFH_{5,9}$	0.001	0.001	0.001	0.001	0.001
	[0.37]	[0.55]	[0.32]	[0.54]	[0.36]
$R_{industry}$		0.71		0.71	
		(0.026)		(0.026)	
Industry FE	No	No	Yes	Yes	No
Day FE	Yes	Yes	Yes	Yes	No
Industry×Day FE	No	No	No	No	Yes
R^2	0.271	0.289	0.271	0.289	0.263
Panel B. Essential Firms					
$WFH_{0,4}$	0.003	0.003**	0.003	0.003**	0.004***
	[1.50]	[1.98]	[1.50]	[2.00]	[3.48]
$WFH_{5,9}$	0.000	-0.000	0.000	-0.000	0.000
	[0.25]	[-0.13]	[0.19]	[-0.11]	[0.24]
$R_{industry}$		0.78		0.78	
		(0.028)		(0.029)	
Industry FE	No	No	Yes	Yes	No
Day FE	Yes	Yes	Yes	Yes	No
Industry×Day FE	No	No	No	No	Yes
R^2	0.250	0.271	0.251	0.271	0.247
Panel C. Non-essential Firms					
$WFH_{0,4}$	0.013***	0.012***	0.013***	0.011***	
	[3.92]	[4.33]	[3.93]	[4.30]	
$WFH_{5,9}$	0.000	0.001	0.000	0.001	
	[0.09]	[0.36]	[0.03]	[0.31]	
$R_{industry}$		0.56		0.56	
		(0.021)		(0.021)	
Industry FE	No	No	Yes	Yes	
Day FE	Yes	Yes	Yes	Yes	
Industry×Day FE	No	No	No	No	
R^2	0.324	0.335	0.325	0.335	

Table IA4: Announcement Effects Relative to Matches with FF3 and FF5. The table shows the results of regressing daily stock returns of WFH firms relative to a benchmark on a constant, the variables $WFH_{0,4}$ and $WFH_{5,9}$ (defined in notes of Table 3) and aggregate stock market R_{mkt} as specified in regression equation 3 and, additionally, size R_{smb} and value R_{hml} factors from Fama and French 3-factor model Fama and French (1993) in panel A, further, investment R_{cma} and profitability R_{rmw} factors from Fama and French 5-factor model Fama and French (2015) in panel B, and additionally the PS factor from Papanikolaou and Schmidt (2022) in Panel C. The benchmark adjusted return on the left-hand side is the return difference between the WFH firm and the benchmark indicated in the columns. The benchmark in column 1 is value-weighted market return, in columns 2-4 the average return of firms in the same quintile by Size, Industry-size, and PS-size, respectively, and in column 5 the average return of the five closest matches by propensity score. Standard errors (Driscoll and Kraay (1998) with 10 lags) are in parentheses and t-statistics in brackets. Significance stars are omitted for market and factor returns. Columns 1-4 use the full sample of 273 WFH firms, 145 essential. Column 5 requires non-missing PS to calculate propensity score (229 WFH, 130 essential). The panel is from July 1, 2019 to April 1, 2020 (i.e., end of fever period March 19 plus 10-day announcement window).

	Market	Size	Industry -size	PS -size	Propensity score
Panel A. 3-Factor Model					
const	-0.000	-0.000	-0.000	-0.000	-0.000
	[-0.06]	[-0.72]	[-0.40]	[-0.50]	[-0.99]
$WFH_{0,4}$	0.008***	0.006***	0.006***	0.006***	0.008***
	[5.43]	[9.79]	[10.94]	[8.50]	[9.01]
$WFH_{5,9}$	0.004	0.001	0.001	0.001	0.000
	[1.51]	[0.32]	[0.36]	[0.29]	[0.11]
R_{mkt}	0.03	-0.03	-0.02	-0.03	-0.02
	(0.012)	(0.006)	(0.006)	(0.005)	(0.010)
R_{smb}	0.52	-0.10	-0.04	-0.10	-0.04
	(0.041)	(0.022)	(0.015)	(0.026)	(0.022)
R_{hml}	0.13	-0.16	-0.06	-0.08	-0.01
	(0.043)	(0.017)	(0.015)	(0.024)	(0.017)
R^2	0.026	0.006	0.003	0.004	0.002
Panel B. 5-Factor Model					
const	0.000	-0.000	-0.000	-0.000	-0.000
	[0.00]	[-0.77]	[-0.42]	[-0.52]	[-0.99]
$WFH_{0,4}$	0.008***	0.006***	0.006***	0.006***	0.008***
	[8.04]	[9.20]	[11.98]	[8.63]	[9.68]
$WFH_{5,9}$	0.003	0.000	0.001	0.000	0.000
	[1.36]	[0.20]	[0.32]	[0.23]	[0.11]
R_{mkt}	0.01	-0.03	-0.02	-0.02	-0.02
	(0.013)	(0.006)	(0.006)	(0.006)	(0.010)
R_{smb}	0.48	-0.12	-0.06	-0.10	-0.06
	(0.033)	(0.025)	(0.020)	(0.032)	(0.030)
R_{hml}	0.08	-0.11	-0.03	-0.06	0.02
	(0.052)	(0.028)	(0.022)	(0.037)	(0.025)
R_{cma}	-0.20	-0.05	-0.06	0.02	-0.12
	(0.040)	(0.057)	(0.027)	(0.066)	(0.040)
R_{rmw}	-0.11	-0.11	-0.04	-0.05	0.00
	(0.078)	(0.061)	(0.040)	(0.063)	(0.050)
R^2	0.027	0.007	0.003	0.004	0.002

Table IA5: Announcement Effects Relative to Matches with FF5 and PS. The table shows the results of regressing daily stock returns of WFH firms relative to a benchmark on a constant, the variables $WFH_{0,4}$ and $WFH_{5,9}$ (defined in notes of Table 3), factors from Fama and French 5-factor model Fama and French (2015) and the PS factor from Papanikolaou and Schmidt (2022). The benchmark adjusted return on the left-hand side is the return difference between the WFH firm and the benchmark indicated in the columns. The benchmark in column 1 is value-weighted market return, in columns 2-4 the average return of firms in the same quintile by Size, Industry-size, and PS-size, respectively, and in column 5 the average return of the five closest matches by propensity score. Standard errors (Driscoll and Kraay (1998) with 10 lags) are in parentheses and t-statistics in brackets. Significance stars are omitted for market and factor returns. Columns 1-4 use the full sample of 273 WFH firms, 145 essential. Column 5 requires non-missing PS to calculate propensity score (229 WFH, 130 essential). The panel is from Januray 2, 2020 (limited by availability of the PS factor) to April 1, 2020 (i.e., end of fever period March 19 plus 10-day announcement window).

	Market	Size	Industry -size	PS -size	Propensity score
$const$	-0.000	-0.001	-0.001	-0.001	-0.001*
	[-0.62]	[-1.48]	[-1.54]	[-1.25]	[-1.96]
$WFH_{0,4}$	0.008***	0.006***	0.006***	0.006***	0.008***
	[7.67]	[8.49]	[10.44]	[7.51]	[8.96]
$WFH_{5,9}$	0.004	0.001	0.001	0.001	0.001
	[1.49]	[0.51]	[0.59]	[0.43]	[0.55]
R_{mkt}	-0.00	-0.03	-0.02	-0.02	-0.03
	(0.006)	(0.006)	(0.009)	(0.008)	(0.012)
R_{smb}	0.49	-0.08	-0.06	-0.07	-0.06
	(0.036)	(0.030)	(0.021)	(0.033)	(0.037)
R_{hml}	0.11	-0.10	-0.03	-0.07	0.02
	(0.072)	(0.047)	(0.041)	(0.055)	(0.049)
R_{cma}	-0.16	0.07	-0.07	0.15	-0.14
	(0.043)	(0.080)	(0.035)	(0.086)	(0.051)
R_{rmw}	-0.15	-0.22	-0.10	-0.18	-0.08
	(0.110)	(0.081)	(0.058)	(0.077)	(0.080)
R_{ps}	-0.00	-0.06	-0.02	-0.03	-0.03
	(0.020)	(0.024)	(0.012)	(0.017)	(0.014)
R^2	0.037	0.010	0.005	0.006	0.005

Table IA6: Event Studies of Scaled Abnormal Returns Controlling for FF5 and PS Factors. The table shows the average scaled abnormal daily return of announcing firms during three subsequent periods: 10 days before the WFH announcement (Pre), 5 days starting on the announcement day (Event), and the subsequent 5 days (Post) for Fama and French 5-factor model combined with the PS factor from Papanikolaou and Schmidt (2022). The scaled abnormal returns following Kolari and Pynnönen (2010)) are defined in the Appendix of the paper. The returns in panels A-C are relative to benchmark of average returns of firms in the same quintile by Size, Industry-size, and PS-size, respectively, and in panel D relative to the average return of the five closest matches by propensity score. Panels A-C use the full sample of 273 WFH firms, panel D requires non-missing PS to calculate propensity score (229 WFH firms). Standard errors reported in parentheses account for contemporaneous cross-correlation, auto-correlation, and cross-serial-correlation as detailed in the Appendix. *t*-statistics are in brackets.

	Pre	Event	Post
Panel A. Size			
Mean	-0.027*	0.129***	0.018
st. err.	(0.014)	(0.047)	(0.044)
t stat	[-1.91]	[2.72]	[0.4]
Panel B. Industry-size			
Mean	-0.019	0.155***	0.02
st. err.	(0.014)	(0.048)	(0.044)
t stat	[-1.3]	[3.23]	[0.45]
Panel C. PS-size			
Mean	-0.025*	0.124***	0.019
st. err.	(0.014)	(0.047)	(0.043)
t stat	[-1.79]	[2.66]	[0.45]
Panel D. Propensity Score			
Mean	-0.018	0.164***	0.031
st. err.	(0.017)	(0.062)	(0.059)
t stat	[-1.06]	[2.67]	[0.52]

Table IA7: Panel Regressions Excluding Earnings and Corporate Control News. The table shows the results of regressing a panel of daily stock returns on a constant, the variable $WFH_{0,4}$ indicating the five-day window from the firm's announcement (starting at day zero), the variable $WFH_{5,9}$ indicating the subsequent five-day window, the stock market return R_{mkt}, and the industry return $R_{industry}$ as specified in regression equation 2, excluding firms with earnings, M&A or change in corporate control announcements. Columns 4-6 include industry fixed effects at NAICS 2-digit level. The standard errors (Driscoll and Kraay (1998) with 10 lags) for market and industry returns are in parentheses and the equivalently calculated t-statistics for the indicator variables and constant in brackets. Significance stars are omitted for market and industry returns. The table is based on a sample of 2534 firms (2549 firms in the original sample excluding 14 firms with earnings, M&A and change in corporate control announcements), 1658 essential and 877 non-essential. The panel is from July 1, 2019 to April 1, 2020 (i.e., the end of the fever period on March 19 plus the 10-day announcement window).

				Industry fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All firms						
const	-0.000	0.000	0.000	-0.001	-0.001	-0.001
	[-0.10]	[0.78]	[0.43]	[-1.28]	[-1.44]	[-1.43]
$WFH_{0,4}$	0.010***	0.007**	0.008**	0.010***	0.007**	0.008**
	[3.05]	[2.36]	[2.59]	[3.14]	[2.33]	[2.58]
$WFH_{5,9}$	0.003	0.002	0.002	0.003	0.002	0.002
	[0.86]	[0.90]	[0.74]	[0.89]	[0.90]	[0.74]
R_{mkt}	1.09		0.21	1.09		0.21
	(0.035)		(0.032)	(0.035)		(0.032)
$R_{industry}$		0.98	0.81		0.98	0.81
		(0.026)	(0.030)		(0.026)	(0.029)
R^2	0.243	0.266	0.267	0.243	0.266	0.267
Panel B. Essential Firms						
const	-0.000	0.000	0.000	-0.001	-0.001	-0.001
	[-0.11]	[0.65]	[0.47]	[-1.19]	[-1.21]	[-1.21]
$WFH_{0,4}$	0.009***	0.008***	0.008***	0.009***	0.008***	0.008***
	[3.55]	[3.08]	[3.22]	[3.66]	[3.09]	[3.24]
$WFH_{5,9}$	0.001	-0.000	-0.000	0.001	-0.000	-0.000
	[0.54]	[-0.14]	[-0.15]	[0.57]	[-0.15]	[-0.15]
R_{mkt}	1.08		0.14	1.08		0.14
	(0.031)		(0.038)	(0.031)		(0.037)
$R_{industry}$		0.96	0.86		0.97	0.86
		(0.025)	(0.036)		(0.025)	(0.035)
R^2	0.225	0.251	0.252	0.225	0.251	0.251
Panel C. Non-essential Firms						
const	-0.000	-0.001	-0.001	-0.001	-0.001*	-0.001
	[-0.17]	[-0.68]	[-0.53]	[-1.28]	[-1.66]	[-1.58]
$WFH_{0,4}$	0.012**	0.007*	0.009**	0.012**	0.007*	0.009**
	[2.50]	[1.75]	[2.17]	[2.57]	[1.75]	[2.20]
$WFH_{5,9}$	0.004	0.005	0.004	0.005	0.005*	0.004
	[1.03]	[1.62]	[1.23]	[1.06]	[1.66]	[1.26]
R_{mkt}	1.11		0.36	1.11		0.36
	(0.044)		(0.038)	(0.044)		(0.038)
$R_{industry}$		1.01	0.71		1.01	0.71
		(0.032)	(0.052)		(0.032)	(0.053)
R^2	0.285	0.300	0.304	0.285	0.300	0.304

Table IA8: Announcement Effects Excluding Earnings and Corporate Control News. The table shows the results of regressing daily stock returns of WFH firms relative to a benchmark on a constant, the variables $WFH_{0,4}$ and $WFH_{5,9}$ (defined in notes of Table 3) and aggregate stock market R_{mkt} as specified in regression equation 3, excluding firms with earnings, M&A, or change in corporate control announcements. The benchmark adjusted return on the left-hand side is the return difference between the WFH firm and the benchmark indicated in the columns. The benchmark in column 1 is value-weighted market return, in columns 2-4 the average return of firms in the same quintile by Size, Industry-size, and PS-size, respectively, and in column 5 the average return of the five closest matches by propensity score. Standard errors (Driscoll and Kraay (1998) with 10 lags) are in parentheses and t-statistics in brackets. Significance stars are omitted for market returns. Columns 1-4 use the sample of 259 WFH firms (original 273 WFH firms excluding 14 firms with earnings, M&A and change in corporate control announcements), 140 essential. Column 5 requires non-missing PS to calculate propensity score (220 WFH, 128 essential). The panel is from July 1, 2019 to April 1, 2020 (i.e., end of fever period March 19 plus 10-day announcement window).

	Market	Size	Industry -size	PS -size	Propensity score
Panel A. All Firms					
const	-0.001*	0.000	-0.000	0.000	-0.000
	[-1.72]	[0.50]	[-0.09]	[0.17]	[-0.94]
$WFH_{0,4}$	0.010***	0.006***	0.006***	0.005***	0.008***
	[2.68]	[8.07]	[14.47]	[8.18]	[9.81]
$WFH_{5,9}$	0.003	0.001	0.001	0.001	0.000
	[1.02]	[0.61]	[0.53]	[0.47]	[0.05]
R_{mkt}	0.05	-0.05	-0.03	-0.04	-0.02
	(0.027)	(0.007)	(0.006)	(0.006)	(0.008)
R^2	0.004	0.003	0.002	0.002	0.002
Panel B. Essential Firms					
const	-0.001	0.000	0.000	0.000	0.000
	[-1.40]	[0.85]	[0.58]	[0.61]	[0.05]
$WFH_{0,4}$	0.008***	0.004**	0.006***	0.005***	0.007***
	[3.13]	[2.31]	[8.52]	[4.00]	[8.63]
$WFH_{5,9}$	0.002	-0.000	-0.001	-0.000	0.000
	[0.61]	[-0.11]	[-0.34]	[-0.23]	[0.02]
R_{mkt}	0.06	-0.04	-0.04	-0.03	-0.03
	(0.032)	(0.011)	(0.010)	(0.009)	(0.012)
R^2	0.004	0.002	0.002	0.002	0.002
Panel C. Non-essential Firms					
const	-0.001	-0.000	-0.000	-0.000	-0.000
	[-1.61]	[-0.06]	[-0.68]	[-0.28]	[-1.37]
$WFH_{0,4}$	0.011**	0.008***	0.007***	0.005***	0.009***
	[2.20]	[5.42]	[5.84]	[4.97]	[4.70]
$WFH_{5,9}$	0.005	0.003	0.003	0.002	0.000
	[1.34]	[1.10]	[1.29]	[1.11]	[0.08]
R_{mkt}	0.04	-0.07	-0.01	-0.05	-0.01
	(0.024)	(0.012)	(0.008)	(0.009)	(0.010)
R^2	0.005	0.005	0.002	0.002	0.002

Table IA9: Changes in Systematic Risk with ESG-Propensity-Score Benchmark. The table shows the exposure and the change in exposure of different portfolios (columns) to market return (panel A) and to the PS-factor and market (panel B) before and after the fever period as specified in regression 18. β and β_{PS} are coefficients of market return and the PS factor, respectively. $\Delta const$ is coefficient of a dummy variable indicating post-fever period, i.e., from March 20, 2020. $\Delta\beta$, and $\Delta\beta_{PS}$ indicate the change in the respective coefficients after the fever period. The regressions are estimated from beginning of January to end of July 2020 (skipping the fever period February 23 to March 19, 2020). Standard errors adjusted for autocorrelation and heteroscedasticity using Newey and West (1987) with 10 lags are reported for market beta β in parentheses in the first three columns and the equivalently calculated t-statistics for the remaining estimates in brackets. Significance stars are omitted for β in the first three columns. The WFH portfolio consists of work-from-home announcers with valid propensity-score matches. The Matched portfolio consists of matches by propensity score based on PS, $lnME$, and ESG and the Unmatched portfolio consists of non-announcing, unmatched firms. Portfolios are value-weighted. The last two columns show long-short portfolios with a long position in the WFH portfolio and a short position either in the Matched portfolio or the Unmatched portfolio as indicated.

	Portfolios			Differences	
	WFH	Matched	Unmatched	WFH-Matched	WFH-Unmatched
Panel A. Market Factor					
$const$	0.001	-0.0	-0.001	0.001	0.001
	[1.21]	[-0.18]	[-1.41]	[1.05]	[1.32]
β	1.145	0.939	0.983	0.206	0.162
	(0.08)	(0.05)	(0.06)	[1.62]	[1.18]
$\Delta const$	0.0	-0.0	0.001	0.0	-0.001
	[0.07]	[-0.93]	[0.97]	[0.31]	[-0.34]
$\Delta\beta$	-0.262***	0.075	0.103	-0.337**	-0.366**
	[-3.1]	[1.37]	[1.61]	[-2.57]	[-2.53]
R^2	0.942	0.988	0.968	0.104	0.137
Panel B. Market and PS Factors					
$const$	0.001	0.0	-0.0	0.0	0.001
	[0.78]	[0.41]	[-0.78]	[0.57]	[0.8]
β	1.111	0.951	1.016	0.16*	0.095
	(0.06)	(0.04)	(0.03)	[1.68]	[1.09]
β_{PS}	-0.07**	0.026**	0.069**	-0.096**	-0.139**
	[-2.23]	[2.54]	[2.46]	[-2.33]	[-2.35]
$\Delta const$	0.0	-0.0	0.001	0.0	-0.0
	[0.09]	[-1.26]	[1.09]	[0.46]	[-0.38]
$\Delta\beta$	-0.125**	0.051	-0.01	-0.176*	-0.115
	[-2.08]	[0.99]	[-0.28]	[-1.68]	[-1.28]
$\Delta\beta_{PS}$	-0.227***	0.008	0.161***	-0.235***	-0.389***
	[-5.28]	[0.31]	[5.15]	[-3.65]	[-5.4]
R^2	0.981	0.988	0.992	0.541	0.787

Table IA10: Bloomberg Announcement Effects, Alternative Specification. Panel A shows the results of regressing daily stock returns of WFH firms relative to benchmarks on a constant, market return, announcement-window indicators $BB_{01,it}$, $BB_{24,it}$ and $BB_{59,it}$ for announcements reported by Bloomberg, and indicators $WS_{01,it}$, $WS_{24,it}$ and $WS_{59,it}$ for announcements not covered by Bloomberg as specified in regression equation 16 in the paper's appendix. The panel reports the estimated coefficients $a_{BB,01}$, $a_{BB,24}$, $a_{WS,01}$ and $a_{WS,24}$ of the corresponding announcement-window indicators and omits reporting the constant and coefficients of the days 5-9 indicators and the market return. The marginal effects section reports the difference in daily announcement returns between the first two and the following three announcement days, i.e., $(a_{BB,01} - a_{BB,24})$ and $(a_{WS,01} - a_{WS,24})$ for Bloomberg and website announcements, respectively, as well as the difference in these quantities between Bloomberg and website announcements, i.e., $(a_{BB,01} - a_{BB,24}) - (a_{WS,01} - a_{WS,24})$. Benchmarks (column headings) are defined in notes to table 4 in the paper. t-statistics (Driscoll and Kraay (1998) with 10 lags) are in brackets. The panel is from July 1, 2019 to April 1, 2020 (i.e., end of fever period March 19 plus the 10-day announcement window).

	Market	Size	Industry -size	PS -size	Propensity score
$a_{BB,01}$	0.021***	0.021***	0.019***	0.022***	0.028***
	[2.69]	[4.13]	[3.86]	[4.66]	[3.40]
$a_{WS,01}$	0.002	0.003***	0.004***	0.003**	0.006***
	[0.57]	[2.79]	[3.43]	[2.42]	[3.79]
$a_{BB,24}$	0.011***	0.004	0.003*	0.004	0.006**
	[8.01]	[1.29]	[1.66]	[0.97]	[2.17]
$a_{WS,24}$	0.013***	0.007***	0.007***	0.006***	0.007***
	[5.17]	[4.50]	[6.52]	[3.99]	[5.54]
R^2	0.006	0.005	0.003	0.003	0.003
Marginal Effects					
$(a_{BB,01} - a_{BB,24})$	0.01	0.017**	0.016**	0.018**	0.022**
	[1.35]	[2.35]	[2.50]	[2.32]	[2.20]
$(a_{WS,01} - a_{WS,24})$	-0.011***	-0.005**	-0.003*	-0.003*	-0.001
	[-5.68]	[-2.48]	[-1.70]	[-1.71]	[-0.60]
$(a_{BB,01} - a_{BB,24}) - (a_{WS,01} - a_{WS,24})$	0.021***	0.022***	0.019***	0.021***	0.023***
	[3.28]	[3.52]	[3.67]	[3.30]	[2.76]

Table IA11: Changes in Option-Implied Expected Returns. The table shows the results of regressing the option-implied expected returns on indicator variables indicating the pre-fever period (January 1 to February 23, 2020), the fever period (February 24 to March 19, 2020, omitted in reported results) and the post-fever period (March 20 to April 30, 2020). $\underline{\mu}_{pre}$ is the average option-implied expected return during the pre-fever period, and $\underline{\mu}_{post}$ is the equivalent for the post-fever period. $\Delta\underline{\mu}$ is the change between option-implied expected returns during the post-fever period relative to the pre-fever period. Option-implied expected returns are the lower bounds of expected returns from Martin and Wagner (2019) for horizon of 365 days. The regressions are estimated from beginning of January to end of April 2020. Standard errors adjusted for autocorrelation and heteroscedasticity using Newey and West (1987) with 10 lags are reported for average option-implied expected returns in parentheses in the first three columns and the equivalently calculated t-statistics for the remaining estimates in brackets. Significance stars are omitted for $\underline{\mu}_{pre}$ and $\underline{\mu}_{post}$ in the first three columns. Following Martin and Wagner (2019), Pagano et al. (2023) the sample consists of firms in S&P500 with available data for option-implied expected returns. The WFH portfolio consists of work-from-home announcers in S&P500 index with propensity-score matches as described in this Internet Appendix. The Matched portfolio consists of propensity-score matches, and the Unmatched portfolio consists of non-announcing, unmatched firms. Portfolios are value-weighted, and underlying individual stock expected returns are winsorized at 5 percent level. The last two columns show long-short portfolios with a long position in the WFH portfolio and a short position either in the Matched portfolio or the Unmatched portfolio as indicated.

	Portfolios			Differences	
	WFH	Matched	Unmatched	WFH-Matched	WFH-Unmatched
$\underline{\mu}_{pre}$	2.547	2.275	2.693	0.273***	-0.145***
	(0.03)	(0.01)	(0.02)	[10.49]	[-4.88]
$\underline{\mu}_{post}$	6.767	8.077	9.37	-1.31***	-2.603***
	(0.07)	(0.27)	(0.32)	[-5.77]	[-9.34]
R^2	0.699	0.708	0.711	0.667	0.688
Difference: post-pre					
$\Delta\underline{\mu}$	4.22***	5.803***	6.677***	-1.583***	-2.458***
	[57.68]	[21.48]	[20.7]	[-6.93]	[-8.77]