

How valuable is corporate adaptation to crisis? Estimates from Covid-19 work-from-home announcements[☆]

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ABSTRACT

This article investigates predictors and benefits of corporate adaptation to crisis, adding a new dimension to studies of flexibility and resilience based on *ex ante* characteristics. We produce a unique sample of work-from-home announcements scraped from company websites during Covid-19. The announcers' valuations increased by 3%–5% and risk declined versus matches, consistent with real-options theory under asymmetric information. We estimate characteristics, including subtle textual topics from 10-Ks, that predicted adaptation, show faster price response following Bloomberg coverage, and real advantages in subsequent operating performance. 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]

1. Introduction

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 Adaptation in the midst of a crisis is particularly important,² as demonstrated by the widespread shift in attention toward corporate flexibility and resilience, especially work-from-home capability, during Covid-19 (Brunnermeier, 2021; Barry et al., 2022; Pagano et al., 2023).³

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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 Risk premia are widely believed to increase in disasters (e.g., Gabaix, 2012; Wachter, 2013). General countercyclical risk premia are discussed in Campbell and Cochrane (1999).

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), Ramelli and Wagner (2020), and Emanuel and Harrington (2024).

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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.

Our analysis centers on observable announcements of corporate adaptation during a crisis, controlling for pre-existing observable characteristics. Among Covid-19 studies, Dingel and Neiman (2020) (“DN”) and Papanikolaou and Schmidt (2022) (“PS”) create measures of labor suitability to work-from-home from surveys and job types. PS further compare the stock returns of high- versus low-suitability firms. 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. In contrast, we compare firms with similar characteristics, but that differ in whether they announced remote-work adaptation before mandatory lockdowns.

The distinction between adaptation and adaptability, an action versus a characteristic, has several dimensions. First, actions are required to operationalize characteristics related to corporate resilience. Second, an important objective of understanding flexibility and resilience is to provide advice to corporate managers, but some key proxies are measured at the industry or sector level, and thus outside the choice set of an individual manager. We provide more fine-grained evidence, comparing firms with similar outward appearance, but where some acted more quickly and decisively in a crisis. Using textual analysis of pre-pandemic 10-Ks, we isolate subtle information that helps to explain the observed differences in actions. Third, market responses to the announced adaptations, in both valuation and risk measures, provide direct measures of perceived economic importance.

To provide a theoretical framework for our analysis, we develop a simple real-options model in an environment of asymmetric information. The model assumes latent firm attributes, known to managers but difficult for markets to discern *ex ante*, related to the ability to adapt. The corporate decision is imperfectly predictable, and announcement of adaptation generates a positive price response and reduction in risk, consistent with our findings. The model is a simple application of a large prior theoretical literature on corporate actions under asymmetric information.⁴

Our sample includes 2549 public firms, of which 273 announced remote-work policies before the first U.S. state-imposed lockdown on March 19, 2020. Logistic regressions establish the *ex ante* characteristics that best predicted these events. We consider labor-suitability (DN and PS), intangible capital (Peters and Taylor, 2017), organizational capital (Eisfeldt and Papanikolaou, 2013), ESG scores (Albuquerque et al., 2020; Ding et al., 2021), and other variables. Among these, DN, PS, and firm size proxies are robustly the strongest predictors. From 6142 predictor combinations, the top models by standard selection criteria always include PS. A prominent flexibility characteristic (PS) therefore strongly predicts announced adaptation, reinforcing the validity of both the PS measure and the new announcement data. Additionally, identifying the characteristics most closely associated with

work-from-home announcements allows us to create matched samples of non-announcers with similar characteristics.

We use event studies to estimate value and risk changes following announcements.⁵ For returns, we use panel regressions with event-window dummies, panel regressions of return differences relative to benchmarks, and scaled abnormal returns (Patell, 1976; Kolari and Pynnönen, 2010). All methods produce 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. Announcement effects also extend to risk. Comparing portfolios of announcers, matches, and other firms, the announcers experienced the strongest event-window declines in exposure to both market and PS-factor risk. We find similar reductions in the default probabilities of Duan et al. (2012). We conclude that the observed adaptations informed markets of higher valuations and lower risk.

One distinction between the work-from-home announcements and traditional unscheduled corporate announcements, such as equity issuances, dividend initiations, and mergers, is the absence of clear reporting requirements.⁶ If a firm wants to issue equity, initiate a dividend, or begin a takeover, it must announce its intention to do so. Conversely, if a firm announces one of these actions and fails to do so, there are well-known associated costs. We acknowledge some potential for slippage between announcements and action for work-from-home. First, firms transitioning to work-from-home pre-lockdown who did so publicly should be in our data, but some firms could have privately communicated transitions to employees. Conversely, a firm could have announced work-from-home but failed to follow through without obvious regulatory or legal penalties. Theory helps us to understand how the possible distinction between announcement and action could impact our findings and their interpretation.

Our theory predicts that if a firm were to optimally adapt, but in a manner unobservable to markets (or observable with delay), the impact would be to price efficiency. Long-run value and operating performance would be the same, but markets would have no announcement to cue immediate incorporation of the anticipated benefits into prices. This mirrors an implication of the dividend-signaling theory of Bhattacharya (1980), where the primary benefit is to advance the timing of information transmission from insiders to markets. Confirming this essential price efficiency role of public signals, within our sample of firms that announced work-from-home transitions, those that appeared on Bloomberg realized abnormal returns more quickly.⁷

Theory also sheds light on the implications of a firm announcing with no follow through, i.e., mimicking an adaptable firm. A large literature (e.g., Spence, 1973) considers requirements for separation of types when observable actions act as signals to the market. When no separation occurs, i.e., in a pooling equilibrium, the market does not respond to the signal/action.⁸ Our empirical results reject the primary prediction of a pooling equilibrium, by showing significant announcement effects.

The base version of our theory rules out mimicking by starting from the assumption that all managers maximize long-run value, but we provide an extension in which some mimicking, corresponding to a partially revealing equilibrium, occurs. In brief, if a small fraction of managers focus on short-term stock price and this trait is unobservable to markets, a partially revealing equilibrium exists where short-run managers always announce to boost short-term stock price, and long-run managers make long-run optimizing decisions.⁹ In such an

⁴ Foundational models in which decisions inform markets include Spence (1973, 2002), Leland and Pyle (1977), Ross (1977), Bhattacharya (1980), and Myers and Majluf (1984). Dynamic real-options models of corporate decisions with asymmetric information include Lucas and McDonald (1990), Grenadier (1999), Lambrecht and Perraudin (2003), Grenadier and Wang (2005), Carlson et al. (2006), Hackbarth and Morellec (2008), Grenadier and Malenko (2011), and Morellec and Schürhoff (2011).

⁵ MacKinlay (1997) and Kothari and Warner (2007) survey event studies.

⁶ Early studies of these events include Asquith and Mullins (1983, 1986), and Asquith et al. (1983).

⁷ See also Fedyk (2024).

⁸ Pooling equilibria include random mixing (or “babbling”) equilibria.

⁹ The extension follows (Fisher and Heinkel, 2008). Markets rationally anticipate manager strategies. Announcement effects are non-zero, but attenuated because of short-run managers who overstate type.

equilibrium, the price response to adaptation is dampened due to the presence of mimicking firms. Theory therefore allows some mimicking in a partially revealing equilibrium with announcement effects, and does not fundamentally change predictions. Putting these discussions together, one can view the work-from-home announcements as an imperfect signal of a latent type that markets believed to be valuable. The announcement effects we document then represent a lower bound on the value the market would attach to perfectly separating information.

To validate our findings and better understand why markets valued observable work-from-home transitions, we consider effects on operating performance. We find neutral to positive abnormal operating performance relative to matches during the Covid period and in the long-run (through fiscal-year 2023), with statistically significant positive effects for growth in R&D and employees in the Covid period.

We also provide evidence for the primary mechanism of our model, that the work-from-home transitions related to hard-to-measure information about firm type. We search for evidence in firms' pre-pandemic 10-Ks, following prior findings that subtle information in corporate communications is underutilized (e.g., Cohen et al., 2020; Bae et al., 2023; Jha et al., 2024). Building on prior methods (e.g., Hassan et al., 2019), we construct a training library from pre-pandemic texts related to remote work, resilience, digital transformation, and adaptability, and use latent semantic analysis (Deerwester et al., 1990) to create text-based topics. We find that announcers possessed pre-pandemic advantages in their attention to remote work and other organizational intangibles, and accelerated these advantages from pre- to post-pandemic.

Disasters and the anticipation of disasters are key drivers of economies and financial markets (Barro, 2006, 2009; Gabaix, 2012; Wachter, 2013). Disasters are difficult to predict, and each is unique in some respect. Our results demonstrate the value of preparation, by showing that pre-pandemic corporate attention to hard-to-measure organizational intangibles predicted early work-from-home transitions. Our findings also suggest that, in a crisis, firms armed with prior preparation that allows them to adapt should inform the market. Timely and prominent disclosures of adaptation reduce information asymmetry, enhance value, and reduce risk, consistent with evidence from other settings (Graham et al., 2005; Lewis, 2011; Balakrishnan et al., 2014).

2. Work-from-home announcements

Our sample of 2549 firms consists of CRSP firms at the beginning of 2020 with a listed common stock on the NYSE, Amex (NYSE MKT), or NASDAQ, a share price higher than two dollars,¹⁰ and a valid company URL in COMPUSTAT. We searched for announcements occurring in the period January 20, 2020–March 19, 2020, which corresponds closely 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.¹¹ During this sample period, work-from-home announcements were voluntary and provided new information to capital markets.

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

forum posts. Following a bag-of-words approach (Loughran and McDonald, 2011), in early June 2020 we searched for the 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”. We checked for false positives and negatives using the Google web interface, confirmed date-time stamps, and ensured that content described a new WFH policy.¹² A thorough investor could in real time gather similar information. By March 19, 2020 when California imposed the first statewide lockdown, 273 of the 2549 sample firms had announced voluntary transition to work-from-home.

Fig. 1 shows several WFH announcements. The examples demonstrate that remote work was often a central part of larger corporate efforts to respond to the Covid-19 pandemic. The announcements commonly referenced broader ideas such as business continuity and safety of employees, customers, and the public. Voluntary transitions to work-from-home revealed firms that were prepared to adapt to the Covid-19 crisis, and the market response shows how investors interpreted this information.

The examples in Fig. 1 also illustrate why non-announcers could not easily imitate announcers to obtain favorable market reactions. The work-from-home policies were not cheap talk, i.e., costless and unverifiable statements without direct payoff implications (Crawford and Sobel, 1982). The policies reflected real decisions with implications for hundreds or thousands of employees. Inaccuracies, either overstatements or omissions, could have costly consequences for operations, misalignment of customer expectations, and managerial reputations.¹³ Thus, despite the absence of specific legal or regulatory disclosure requirements, informal costs of misrepresentation suggest that the work-from-home announcements communicated real preparedness.

Fig. 2 shows a timeline of the remote-work announcements, the S&P 500 index, a Google search index for “work from home”, and a news-article frequency index.¹⁴ 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*. Google search and the newspaper index of attention to work-from-home both increased throughout the fever period. At the end of the fever period, as the S&P 500 reverses, the intensity of interest in work-from-home also reverses. Heightened attention to remote work should naturally imply increased importance to financial markets of news about adaptation.¹⁵

2.1. Theoretical framework

It is widely accepted that stock prices can react to corporate actions when managers possess information about the firm that markets do not have (e.g., Myers and Majluf, 1984). In a dynamic model, market inference about such private information following a corporate action

¹⁰ Minimum price filters are common (e.g., Amihud, 2002; Loughran and McDonald, 2011; Bretscher et al., 2020).

¹¹ Ramelli and Wagner (2020) label January 20 as the “outbreak” beginning, when Chinese authorities confirmed human-to-human transmission. Their “fever” period starts on February 24, after Italy imposed a local lockdown on February 23, and ends on March 20. We end our sample period on March 19 because California declared the first U.S. state-imposed lockdown on that evening.

¹² For 27 companies, an announcement was insufficiently clear that we emailed the companies (up to three times) to clarify whether the posting reflected new work-from-home adoption. We received seven positive responses and categorized the remaining as not announcements.

¹³ Farrell and Gibbons (1989) develop a theory of communication in a multi-audience setting, and show that public statements can enhance truthfulness when each audience disciplines the ability to mislead another audience. Guiso et al. (2015) show empirically that employee-perceived integrity, i.e., the alignment of management's actions with words, is a key driver of firm performance.

¹⁴ Google search is a standard attention measure (Da et al., 2011). News article counts are used to measure policy uncertainty in Baker et al. (2016), and as a measure of attention to different types of macro news in Fisher et al. (2022).

¹⁵ Theories of endogenous attention imply that attention increases when uncertainty or the price of risk associated with an outcome are high, since learning then has more value (Sims, 2003; Bansal and Shaliastovich, 2011; Kacperczyk et al., 2016).

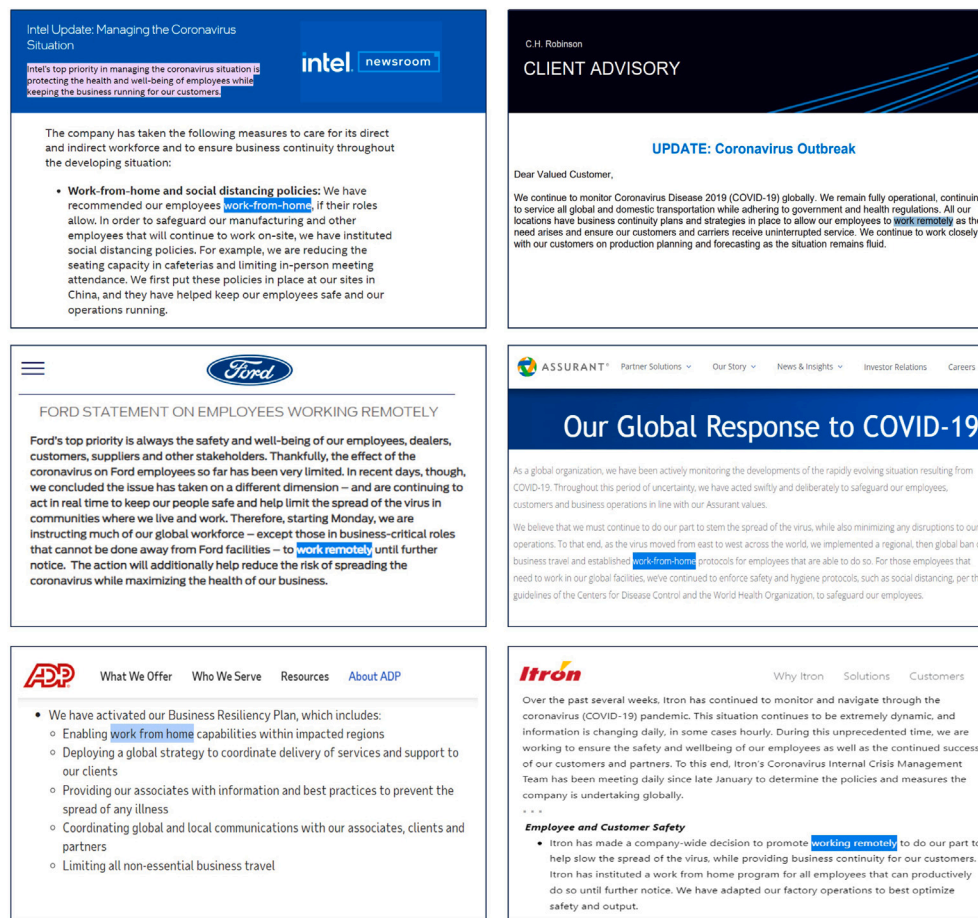


Fig. 1. Work-from-Home Announcements. This figure shows work-from-home announcements for six sample companies (Intel, Ford, ADP, C. H. Robinson, Assurant, and Itron).

can produce an announcement effect (Lucas and McDonald, 1990), and also relate to predictable post-announcement changes in risk (Carlson et al., 2006).

Our focus in this paper is on empirical evidence. Nonetheless, to fix ideas we provide in Appendix A a simple real-options model of corporate adaptation to a rare disaster. The model is driven by asymmetric information about a firm's net benefits from taking an action to adapt to the new state of the world. The primary empirical implications of the model are that (1) announcement effects to adaptation are positive, and (2) adaptation reduces stock-return exposure to the as-yet unknown systematic cash-flow impacts of the disaster. The model also suggests that empirical methods should control for *ex ante* observable firm characteristics, consistent with common practice (e.g., MacKinlay, 1997). In the remainder of this section we identify the *ex ante* observable characteristics that best predict adaptation to work-from-home, and in Section 3 we control for a variety of observable characteristics in estimating announcement effects.

The model implies that non-public, privately observable firm characteristics play an important role in managers' decisions to adapt. In the model, "unobservable" firm characteristics are unknown to markets (or difficult to ascertain and incorporate into prices) prior to the announcement. Nothing prevents, however, that an empiricist using *ex post* analysis might shed light on such difficult-to-observe characteristics. In Section 5, we carry out such an *ex post* investigation using textual analysis of firms' 10-Ks.

2.2. Empirical measures

Among the observable characteristics potentially relevant to the work-from-home decision, the first category we consider captures labor

suitability to remote-work. We use the measures of Dingel and Neiman (2020) ("DN") and Papanikolaou and Schmidt (2022) ("PS"), calculated respectively at the 2-digit level of the North American Industry Classification System (NAICS) using the O*NET database, and at the 4-digit NAICS level using the American Time Use Survey (ATUS).¹⁶

Different types of capital (e.g., physical versus intangible) may also impact the ease of transitioning to remote work. We follow Peters and Taylor (2017) and construct intangible capital (IK) by capitalizing a fraction of selling, general and administrative expenses and R&D expenses. Organizational capital (OK) follows from Eisfeldt and Papanikolaou (2013) and capitalizes a fraction of selling, general and administrative expenses only. We scale both measures by total assets.

We consider additional variables that may help to predict work-from-home adoption. Prior literature proposes that firms with stronger ESG profile were more resilient during Covid-19 (Albuquerque et al., 2020; Ding et al., 2021). Whether ESG relates to adaptation to remote work has not previously been investigated. Among other variables, market capitalization controls for economies of scale and fixed costs associated with remote-work adoption. Number of employees may

¹⁶ The O*NET data is based on classification of occupations adaptable to remote work, whereas the ATUS data is based on demonstrated capability for telecommuting. Our PS measure is the percentage of such occupations for 4-digit NAICS industries prior to 2020, which is one minus the value used in Papanikolaou and Schmidt (2022), affecting only exposition. Other studies using the O*NET and ATUS databases to measure labor suitability to remote work include Pagano et al. (2023), Koren and Pető (2020), Hensvik et al. (2020), and Bai et al. (2021).

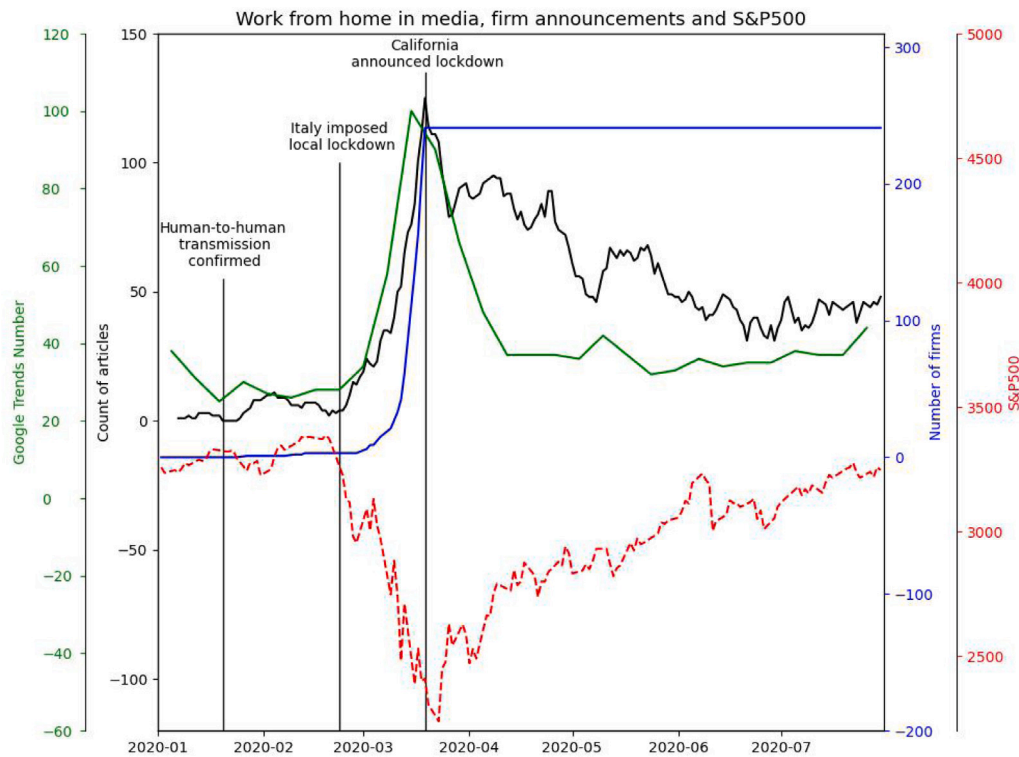


Fig. 2. Timeline of Announcement Sample. This figure shows the timeline of work-from-home announcements along with the S&P 500 index and two indices of attention to remote-work, one from Google Trends, and the other a rolling average of stories in the New York Times and Wall Street Journal.

similarly help to justify fixed costs, and appears in the denominators of DN and PS , both based on employee shares. Additional controls include market beta, the B/M ratio, profitability, investment, and idiosyncratic volatility, which can relate to either fundamental risk or information quality (e.g., [Diamond and Verrecchia, 1991](#); [Rajgopal and Venkatachalam, 2011](#)).

[Table 1](#) provides summary statistics. Panel A shows properties over the full cross-section of firms. The WFH mean indicates that 11 percent of firms in the sample announced remote-work policies in our sample period. The PS share of labor suitable for telecommuting averages 27 percent, varying from 5 percent at the 10th percentile to 55 percent at the 90th percentile. DN shows a higher mean of 44 percent also with large cross-sectional variation. 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 shows summary statistics by type, WFH versus non-WFH, and their differences. Work-from-home firms have significantly higher PS and DN values, consistent with the importance of labor suitability to remote work. Work-from-home firms also have somewhat lower intangible capital IK , insignificantly different organizational capital OK , and higher ESG scores than non-WFH firms. Among the other variables, WFH firms are larger in market capitalization and number of employees, more profitable, and have lower book-to-market ratio and idiosyncratic volatility. These are all univariate relationships, and we next use a multivariate analysis to determine the observable variables that best predicted work-from-home announcers.

2.3. Predicting announcements

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

$$p(WFH_i = 1) = \frac{1}{1 + e^{-\beta'x_i}}, \quad (1)$$

where x_i is a vector of a constant and some combination of the explanatory variables considered in [Table 1](#), and β is a coefficient vector. To allow comparison, we standardize all explanatory variables.

[Table 2](#) shows the results. The first column includes all variables except PS , DN , IK , OK , and ESG . In this base specification, firm size and profitability significantly predict the WFH decision. Column 2 adds PS , which is highly significant. The fitted likelihoods indicate that increasing PS from the 10th to 90th percentile raises the announcement probability from $P_{low} \approx 6$ to $P_{high} \approx 19$ percent, an odds ratio P_{high}/P_{low} above three. Column 3 shows similar, albeit less powerful, results for DN . Neither IK nor OK significantly predicts WFH announcements, controlling for the other variables. With all variables together, PS , DN , and firm size remain significant, and ESG becomes marginally significant. Columns 8–12 include 2-digit NAICS fixed effects. Since DN is defined at the same level, we exclude it from this analysis. Once again PS strongly predicts. IK and OK remain insignificant, and ESG gains significance at the five-percent level. Column 12 uses all variables together, showing that PS remains a strong predictor, with an odds ratio still exceeding three.

We use standard model selection criteria to further understand the predictors of work-from-home announcements. We consider all of the 6142 possible combinations of explanatory variables, and for each specification calculate the Bayesian Information Criterion (BIC), and Akaike Information Criterion (AIC).¹⁷ The BIC-selected model (penultimate column of [Table 2](#)) uses only PS , firm size, and employees, all of which are highly significant.¹⁸ The AIC-selected model (final column)

¹⁷ There are 4095 models from the twelve explanatory variables without industry fixed effects and 2047 models for the eleven variables (excluding DN) with industry fixed effects. The BIC and AIC are commonly used in model selection (e.g., [Greene, 2003](#); [Lemmon et al., 2008](#); [Huber, 2023](#)). These improve (become lower) when R^2 increases, but are penalized for the number of model parameters. The BIC penalizes parameters more severely, producing more conservative models.

Table 1
Summary statistics.

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
ESG	37.46	18.34	3.07	16.41	33.58	65.18	93.28
lnME	21.07	1.98	15.39	18.62	21.05	23.69	27.88
lnEmp	7.56	2.12	1.39	4.78	7.65	10.28	14.65
BM	0.58	0.67	−7.36	0.08	0.49	1.21	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
β^{mkt}	1.16	0.72	−3.21	0.30	1.11	2.04	4.97
iVol	0.05	0.04	0.01	0.02	0.04	0.09	0.55
Panel B. Correlation coefficients							
	WFH	PS	DN	IK			
PS	0.13						
DN	0.10	0.42					
IK	−0.03	0.28	−0.04				
OK	0.00	0.05	−0.19	0.54			
Panel C. Subsamples					Difference		
	WFH firms		Non-WFH firms		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]	
ESG	46.708	42.712	36.155	32.395	10.553	[7.45]	
lnME	22.441	22.312	20.907	20.897	1.535	[12.03]	
lnEmp	8.647	8.589	7.427	7.496	1.220	[10.19]	
BM	0.469	0.326	0.597	0.507	−0.128	[−4.1]	
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]	
β^{mkt}	1.133	1.110	1.159	1.115	−0.026	[−0.67]	
iVol	0.041	0.036	0.054	0.044	−0.013	[−8.12]	

Panel A presents summary statistics: WFH is the dummy variable indicating voluntary WFH announcement. PS is the industry share of labor suitable for ‘telecommuting’ from Papanikolaou and Schmidt (2022). DN is the industry share of labor suitable for work-from-home from Dingel and Neiman (2020). IK (intangible capital, Peters and Taylor (2017)), OK (organizational capital, Eisfeldt and Papanikolaou (2013)), lnEmp (log of firm’s number of employees), BM (book-to-market ratio), Profitability (ratio of revenues minus cost of goods sold to total assets), and Investment (annual growth rate in total assets) use latest accounting data from fiscal years ending in 2018 to ensure availability in early 2020, and market capitalization in the denominator of BM is calculated at the end of 2018. ESG scores are from Refinitiv for the 2018 fiscal year. The log market capitalization lnME is calculated at the end of 2019. β^{mkt} and iVol are beta and idiosyncratic volatility estimated from weekly market-model regressions in calendar-year 2019, requiring all non-missing returns. Panel B shows the correlation matrix between the main variables. Panel C shows the average and median of these variables among WFH and Non-WFH firms as well as the difference between subsamples. Each row is based on non-missing observations of the corresponding variable of full sample of 2549 firms (of it 273 WFH firms).

additionally adds the DN measure and profitability, somewhat reducing the PS coefficient since DN and PS are positively correlated. We use the selected models to calculate propensity scores for benchmarks that are used to estimate announcement effects in the following section.¹⁹

¹⁸ Employees, like firm size, can capture scale economies in work-from-home adoption. In the regressions, employees increase in importance whenever PS or DN is included. Both PS and DN are based on industry-average labor shares, so conditional on a positive coefficient, total firm employees increase the number of employees suitable to remote work.

¹⁹ The R^2 , just above ten percent, are within the range of those reported for traditional corporate events with announcement effects such as dividend initiations and equity issuances (e.g., Bulan et al., 2007; DeAngelo et al., 2010; Dittmar et al., 2020). Like these other decision, the work-from-home announcements show some predictability from observable characteristics, but the unexplained variation leaves ample room for latent managerial information to produce announcement effects.

3. Announcement effects

In this section, we use event-study methods to show increases in value and declines in risk following work-from-home announcements.

3.1. Abnormal returns

To estimate the valuation impacts of announcements, we employ several methods. First, we use panel regressions with market and/or industry returns as controls:

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

where $R_{mkt,t}$ and $R_{industry,t}$ are market and industry returns, and $WFH_{i,0,4}$ and $WFH_{i,5,9}$ are indicators 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. Heteroskedasticity-robust standard errors are clustered by calendar date and adjusted for autocorrelation following Driscoll and Kraay (1998). To control for observable firm

Table 2
Likelihood of firms' voluntary work-from-home decisions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
<i>PS</i>		0.49*** [6.36]					0.40*** [4.33]	0.53*** [4.70]				0.53*** [4.70]	0.49*** [6.43]	0.35*** [4.11]
<i>DN</i>			0.44*** [5.47]				0.24** [2.56]							0.26*** [2.90]
<i>IK</i>				0.06 [0.39]			−0.21 [−0.95]		0.09 [0.63]			−0.08 [−0.36]		
<i>OK</i>					0.04 [0.34]		0.11 [0.66]			0.05 [0.38]		0.04 [0.22]		
<i>ESG</i>						0.20* [1.68]	0.23* [1.83]				0.27** [2.11]	0.27** [2.07]		
<i>LnME</i>	0.75*** [6.01]	0.49*** [3.71]	0.70*** [5.60]	0.75*** [5.96]	0.76*** [5.88]	0.68*** [5.07]	0.47*** [3.19]	0.55*** [3.95]	0.68*** [5.08]	0.70*** [5.07]	0.59*** [4.17]	0.46*** [3.01]	0.45*** [3.95]	0.51*** [4.35]
<i>LnEmp</i>	0.02 [0.16]	0.31** [2.30]	0.19 [1.48]	0.03 [0.23]	0.01 [0.11]	−0.04 [−0.34]	0.21 [1.42]	0.29* [1.94]	0.20 [1.36]	0.18 [1.24]	0.09 [0.58]	0.17 [1.05]	0.43*** [3.47]	0.38*** [2.98]
<i>BM</i>	0.06 [0.62]	0.10 [1.11]	0.06 [0.61]	0.06 [0.67]	0.06 [0.64]	0.06 [0.61]	0.08 [0.92]	0.08 [0.78]	0.06 [0.64]	0.06 [0.61]	0.06 [0.61]	0.08 [0.80]		
<i>Profitability</i>	0.22*** [2.68]	0.17** [2.07]	0.31*** [3.69]	0.20** [2.16]	0.18 [1.34]	0.23*** [2.80]	0.21 [1.48]	0.20** [2.14]	0.24** [2.38]	0.23 [1.60]	0.28*** [3.04]	0.20 [1.35]		0.20** [2.47]
<i>Investment</i>	0.01 [0.15]	0.01 [0.11]	−0.01 [−0.14]	0.01 [0.18]	0.01 [0.16]	0.01 [0.19]	−0.01 [−0.09]	−0.01 [−0.11]	−0.01 [−0.09]	−0.01 [−0.13]	−0.01 [−0.09]	−0.01 [−0.08]		
β_{mkt}	0.05 [0.56]	0.07 [0.80]	0.06 [0.65]	0.05 [0.57]	0.05 [0.60]	0.06 [0.68]	0.09 [0.97]	0.15 [1.48]	0.10 [1.04]	0.10 [1.04]	0.11 [1.11]	0.16 [1.59]		
<i>iVol</i>	−0.04 [−0.38]	−0.17 [−1.28]	0.02 [0.15]	−0.06 [−0.48]	−0.05 [−0.43]	−0.05 [−0.42]	−0.05 [−0.39]	−0.08 [−0.60]	−0.03 [−0.20]	−0.01 [−0.09]	−0.01 [−0.06]	−0.07 [−0.51]		
Industry FE	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	No	No
Pseudo R^2	0.086	0.115	0.107	0.086	0.086	0.088	0.123	0.135	0.119	0.119	0.122	0.138	0.110	0.118
BIC	1373	1340	1350	1381	1381	1385	1366	1441	1464	1464	1467	1467	1308	1312
AIC	1328	1289	1300	1330	1330	1329	1287	1294	1317	1317	1314	1297	1286	1278
P_{low}		0.06	0.08	0.11	0.11	0.08	0.07	0.06	0.10	0.11	0.08	0.06	0.06	0.07
P_{high}		0.19	0.17	0.11	0.11	0.13	0.17	0.19	0.12	0.11	0.14	0.20	0.19	0.16
Odds ratio		3.11	2.26	1.06	1.07	1.60	2.53	3.28	1.10	1.07	1.83	3.31	3.06	2.25

This table shows the results of estimating logistic regressions on the work-from-home indicator, WFH_{it} , which denotes firms that announced a work-from-home transition by March 19, 2020. Regressors are the variables considered in Table 1, standardized to facilitate comparison. Industry fixed effects are at the 2-digit NAICS level. *DN* is defined at the 2-digit NAICS level and is therefore omitted from regressions with industry fixed effects. Specifications with *ESG* additionally include a non-missing indicator as discussed in D. BIC and AIC show the Bayesian Information Criterion and Akaike Information Criterion. P_{low} and P_{high} are the fitted likelihoods of $WFH = 1$ for low (10th percentile) and high (90th percentile) value of the leading explanatory variable. The Odds ratio is the ratio P_{high}/P_{low} . The sample is composed of 2087 firms belonging to 2-digit NAICS classifications 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.

characteristics, we apply panel regressions to return differences:

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

where $R_{it}^{benchmark}$ is one of several benchmarks including quintile portfolios by size, industry-size, and PS-size, with independent sorts. We also use two propensity-score benchmarks, derived from the work-from-home logit specifications that minimize the BIC and AIC criteria (Table 2, columns 13 and 14). Appendix B provides further matching procedure details. Finally, we use event studies of scaled abnormal returns following Kolari and Pynnönen (2010), who extend standard methods (e.g., Patell, 1976) to account for event clustering in calendar time.²⁰ We adapt their approach to accommodate imperfectly overlapping multi-day event windows as shown in Appendix C, accounting for serial correlations.

Table 3 shows the panel regressions. In Panel A, announcement effects are up to one percent per day, or five percent cumulatively, using market returns, industry returns, or both as controls. The coefficients are 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. Panel B shows additional benchmarking using observable characteristics. The market benchmark (column 1) gives announcement effects similar to Panel A. Benchmarking by firm characteristics (columns 2–6) reduces the announcement effects to a range of sixty to seventy basis points per day, or 3–3.5% cumulatively. Despite the somewhat smaller magnitudes, *t*-statistics increase, in all cases significant at the 1% level. The power improvement is natural, since

²⁰ Scaling abnormal returns by their estimated standard deviations places more weight on less volatile observations, improving statistical properties. See, e.g., Kolari and Pynnönen (2010), p. 4002.

better benchmarks reduce noise.²¹ Work-from-home announcement effects thus reach a cumulative 3%–5% of firm value in the five days following announcements.

Table 4 shows scaled abnormal returns. We benchmark by size, industry-size, and PS-size quintiles as well as propensity scores, and further control for market risk and the 3- and 5-factor models of Fama and French (1993, 2015). We calculate scaled abnormal returns in a pre-event window of 10 days prior to the WFH announcement, a five-day event window 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). 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.

Fig. 3 displays the scaled abnormal returns for benchmarks based on industry-size quintiles (Panels A–C) and propensity score (Panels D–F). By row the panels correspond to the market-model, FF3, and FF5. The scaled abnormal returns spike following announcements, and slowly fade through the event window. The blue line, which averages daily

²¹ The marginally lower announcement effects in columns 2–6 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 can also be more simply explained by common exposures to exogenous shocks. We leave further consideration of information spillovers to future research.

Table 3
Announcement effects panel regressions.

Panel A. Returns						
				Industry fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>const</i>	−0.001 [−1.28]	−0.001 [−1.43]	−0.001 [−1.42]			
<i>WFH</i> _{0,4}	0.010*** [3.23]	0.007** [2.43]	0.008*** [2.69]	0.010*** [3.14]	0.007** [2.47]	0.008*** [2.70]
<i>WFH</i> _{5,9}	0.003 [0.88]	0.002 [0.86]	0.002 [0.71]	0.003 [0.85]	0.002 [0.87]	0.002 [0.71]
<i>R</i> _{<i>mkt</i>}	1.09 (0.035)		0.21 (0.032)	1.09 (0.035)		0.21 (0.032)
<i>R</i> _{<i>industry</i>}		0.98 (0.026)	0.81 (0.029)		0.98 (0.026)	0.81 (0.030)
<i>R</i> ²	0.243	0.266	0.267	0.244	0.266	0.267
Panel B. Returns relative to matches						
	Market	Size	Industry -size	PS -size	Propensity score 1	Propensity score 2
<i>const</i>	−0.001 [−1.59]	0.000 [0.85]	0.000 [0.35]	0.000 [0.63]	0.000 [0.67]	−0.000 [−0.42]
<i>WFH</i> _{0,4}	0.010*** [2.72]	0.006*** [7.30]	0.006*** [13.37]	0.006*** [7.11]	0.006*** [6.95]	0.007*** [7.98]
<i>WFH</i> _{5,9}	0.003 [1.02]	0.001 [0.53]	0.001 [0.43]	0.001 [0.43]	−0.000 [−0.11]	−0.000 [−0.17]
<i>R</i> _{<i>mkt</i>}	0.05 (0.026)	−0.06 (0.008)	−0.03 (0.007)	−0.04 (0.007)	−0.04 (0.009)	−0.05 (0.011)
<i>R</i> ²	0.004	0.003	0.002	0.002	0.002	0.003

Panel A 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 Eq. (2). Columns 4–6 include 2-digit NAICS fixed effects. Panel B 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} and aggregate stock market *R*_{*mkt*} as specified in regression Eq. (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 columns 5–6 the average return of the five closest matches by propensity score 1 and 2. The standard errors (Driscoll and Kraay, 1998 with 10 lags) for market and industry returns are in parentheses and *t*-statistics for the indicator variables and constant are omitted in brackets. Significance stars are omitted for market and industry returns. Panel A is based on the full sample of 2549 firms, and Panel B uses the full sample of 273 WFH firms. The time period in both panels 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).

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

These results robustly demonstrate a significant positive stock-price reaction to work-from-home announcements. The findings are consistent with the primary prediction of our theory, that markets should favorably value a firm's announcement of adaptation in a crisis. The findings also imply that markets found the announcements to be informative, consistent with prior evidence that the amount and type of voluntary disclosures can provide credible signals of quality (Lewis, 2011), and more broadly that both managers and markets perceive value in voluntary disclosures that reduce information asymmetry (Graham et al., 2005; Balakrishnan et al., 2014).

3.2. Changes in risk

Corporate adaptation should not only add value, but also mitigate risk. Extreme levels of risk and uncertainty during the Covid crisis are documented by Altig et al. (2020), Baker et al. (2020), and Ramelli and Wagner (2020). We test whether voluntary announcements of work-from-home transitions reduced firm-level risk, considering systematic risk exposures measured by market beta and the Covid-19 risk factor of PS, as well as abnormal default probabilities.

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 tradable since the identities of the eventual WFH announcers were not known in January, but they are nonetheless valid for measuring changes in risk. For each portfolio we run regressions of the form:

$$R_t = \text{const} + \beta_{mkt} R_{mkt,t} + \beta_{PS} R_{PS,t} + \text{post}_t (\Delta \text{const} + \Delta \beta_{mkt} R_{mkt,t} + \Delta \beta_{PS} R_{PS,t}) + \epsilon_t, \quad (4)$$

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 PS-factor returns. To cleanly demarcate between the pre- and post-periods, we omit dates within the fever period (February 24 - March 19). The coefficients Δconst , $\Delta \beta_{mkt}$, and $\Delta \beta_{PS}$ are respectively changes in the intercept, market beta, and PS beta from pre to post. Exposure to Covid-19 risk may be picked up by the market portfolio since Covid-19 was important to the market in this period, but the PS factor should more specifically capture labor-inflexibility risk. We therefore hypothesize that from pre- to post-announcement, WFH firms should experience a decline in PS exposure ($\Delta \beta_{PS} < 0$) relative to matched firms.

Table 5 shows the results. Panel A uses only the market factor. The first column shows that WFH announcers experienced a significant decline in market risk from the pre- to post-announcement periods ($\Delta \beta_{mkt} \approx -0.18$, $p < .05$). Matches and unmatched firms both experienced small to moderate increases in market beta over the same period. The difference $\Delta \beta_{mkt}$ between work-from-home and matched firms, shown in the fourth column, is significantly negative. Market risk

Table 4
Event studies of scaled abnormal returns.

	CAPM			FF3			FF5		
	Pre	Event	Post	Pre	Event	Post	Pre	Event	Post
Panel A. Size									
Mean	0.023	0.258**	0.028	−0.047**	0.209**	0.059	−0.038*	0.221***	0.05
st. err.	(0.03)	(0.113)	(0.096)	(0.023)	(0.081)	(0.072)	(0.021)	(0.077)	(0.069)
t stat	[0.79]	[2.29]	[0.29]	[−2.04]	[2.57]	[0.82]	[−1.83]	[2.85]	[0.73]
Panel B. Industry-size									
Mean	−0.011	0.297***	0.023	−0.038*	0.261***	0.042	−0.035	0.268***	0.037
st. err.	(0.025)	(0.091)	(0.074)	(0.023)	(0.088)	(0.074)	(0.022)	(0.09)	(0.078)
t stat	[−0.42]	[3.27]	[0.31]	[−1.66]	[2.97]	[0.56]	[−1.58]	[2.97]	[0.47]
Panel C. PS-size									
Mean	0.011	0.236***	0.013	−0.032	0.196***	0.048	−0.033	0.209***	0.045
st. err.	(0.026)	(0.09)	(0.075)	(0.021)	(0.071)	(0.061)	(0.02)	(0.076)	(0.065)
t stat	[0.42]	[2.61]	[0.18]	[−1.5]	[2.76]	[0.79]	[−1.64]	[2.76]	[0.68]
Panel D. Propensity score 1									
Mean	−0.003	0.298***	−0.021	−0.017	0.27***	−0.006	−0.014	0.272***	0.006
st. err.	(0.024)	(0.083)	(0.069)	(0.021)	(0.073)	(0.062)	(0.02)	(0.073)	(0.063)
t stat	[−0.12]	[3.59]	[−0.31]	[−0.79]	[3.7]	[−0.1]	[−0.71]	[3.73]	[0.1]
Panel E. Propensity score 2									
Mean	−0.008	0.277***	−0.013	−0.018	0.263***	0.002	−0.016	0.263***	0.026
st. err.	(0.024)	(0.082)	(0.067)	(0.021)	(0.073)	(0.063)	(0.021)	(0.074)	(0.065)
t stat	[−0.33]	[3.39]	[−0.19]	[−0.85]	[3.6]	[0.03]	[−0.77]	[3.56]	[0.4]

The table shows the average scaled abnormal daily return of announcing firms during three periods: 10 days before the WFH announcement (Pre), 5 days starting on the announcement day (Event), and the subsequent 5 days (Post). The scaled abnormal returns with standard errors that account for event clustering and serial correlation are defined in [Appendix C](#). All panels use the full sample of 273 WFH firms. Standard errors are shown in parentheses, and *t*-statistics in brackets. The returns in panels A–C are relative to benchmarks of average returns of firms in the same quintile by Size, Industry-size, and PS-size, respectively, and in panels D–E relative to the average return of the five closest matches by propensity scores 1 and 2. Abnormal returns are measured according to the market model (CAPM) and Fama and French 3- and 5-factor models (FF3, FF5) as indicated at the top of the table.

declined from pre- to post-announcement for work-from-home firms, absolutely and relative to matched firms.

Panel B includes the *PS* factor, which directly relates to labor inflexibility. The results show a large decline in *PS* exposure for WFH announcers ($\Delta\beta_{PS} = -0.175$, $t = -4.39$), while the loadings of matched and unmatched firms increase. The difference-in-differences of *PS* loadings shown in the final two columns are therefore negative and also highly statistically significant ($p < .01$). 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 view of WFH risk mitigation that does not rely on a Covid-19 risk proxy.²² 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 proxy for average change in default risk using the equal-weighted change in default probabilities across all sample firms. [Table 6](#) shows the results. In column 1, benchmarked only to the market average, announcers' abnormal default probabilities are −0.6 basis points per day over the 5-day event window, i.e., −3 basis points cumulatively, but not statistically significant. Benchmarking by firm characteristics in columns 2–6 gives stronger results in both magnitude and significance, with default probabilities reduced by 0.7–1.6 basis points per day or 3.5–8 basis points in total over the 5-day event window, significant at the one-percent level in four of the five cases. The magnitude of up to eight 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 a cumulative abnormal decline of 4–8 basis points is economically meaningful.²³

²² 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. \(2012\)](#). We use default probabilities for maturity of 12 months.

²³ The Internet Appendix shows similar results using the option-implied expected returns of [Martin \(2017\)](#), [Martin and Wagner \(2019\)](#), restricting to

This section has shown statistically significant and economically meaningful increased valuations and reduced risk for work-from-home announcers, relative to otherwise similar firms, by a variety of metrics. The findings are consistent with the key price and risk predictions of our theory in which adaptation to crisis indicates real benefits, in an environment of asymmetric information about latent firm type.

4. Theoretical channels

This section investigates two additional aspects of our real options theory under asymmetric information. First, we consider signal prominence and the effect of Bloomberg coverage. Second, we investigate post-announcement operating performance.

4.1. Signal prominence: Bloomberg announcements

Financial media often cover important company news, and their reporting should be more readily accessible to investors than monitoring company websites. Recent literature shows that more prominent Bloomberg placement increases the speed of price formation ([Fedyk, 2024](#)). We investigate two hypotheses related to Bloomberg coverage of WFH announcements. First, since Bloomberg editorial policy may prioritize more important news, announcement effects may be larger. Second, Bloomberg coverage should be associated with faster price adjustment.²⁴

S&P 500 firms with valid option data. 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 option-implied expected returns are consistent with both decreased risk and increased valuation for WFH firms.

²⁴ Our model directly implies impacts to price efficiency if we assume work-from-home decisions are observed with delay. In the dividend signaling model of [Bhattacharya \(1980\)](#), the primary benefit is to price efficiency, or the timing of information transmission from insiders to the market.

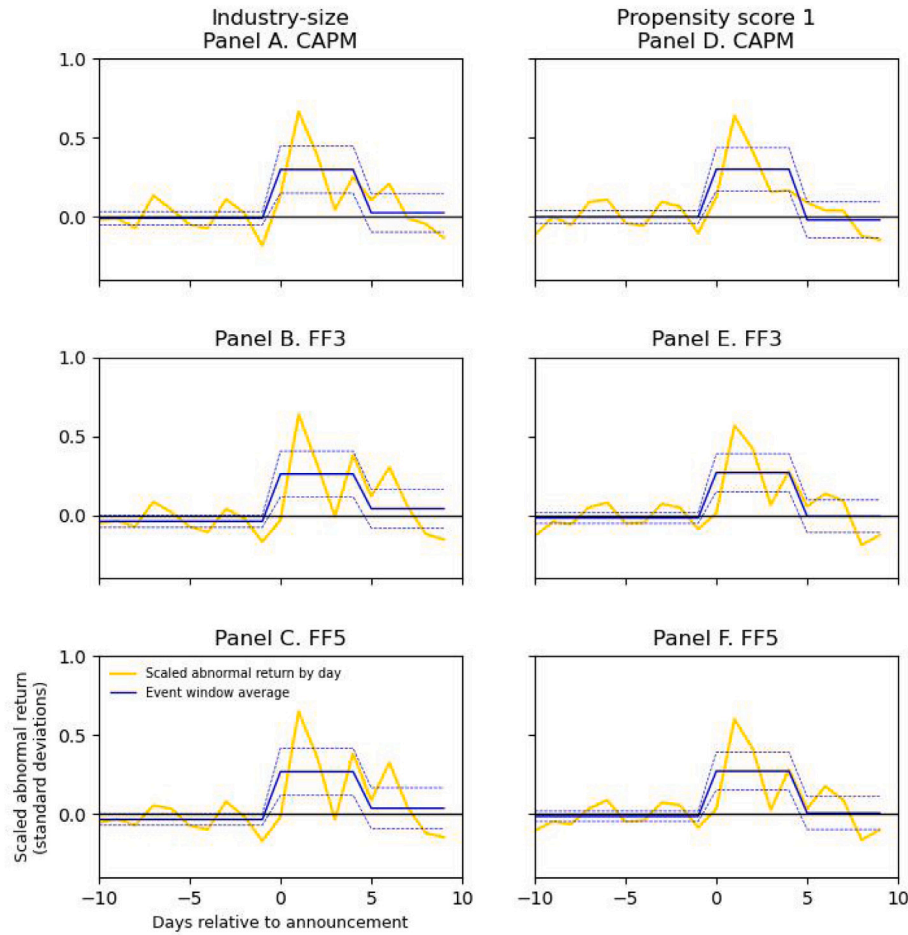


Fig. 3. Scaled Abnormal Announcement Returns. The figure shows daily (gold line) and average (blue line) scaled abnormal announcement returns. The average scaled abnormal returns are calculated during three periods: 10 days before the WFH announcement (pre-event), 5 days starting on the announcement day (event), and the subsequent 5 days (post-event). The scaled abnormal returns with standard errors that account for event clustering and serial correlation are defined in [Appendix C](#). The sample consists of 273 WFH firms, and dotted lines indicate 90% confidence intervals. The returns are relative to benchmarks of firms in the same industry and size quintile (first column) and the five closest matches by propensity score 1 (second column). Panel headings indicate additional controls using the market factor (CAPM) and Fama and French 3- and 5-factor models (FF3, FF5).

For each WFH announcement in our sample, we search Bloomberg for coverage in a window of $\pm$ three days around the appearance on the company website.²⁵ Of the original 273 WFH announcements, Bloomberg reported on 68, or approximately 25%.²⁶ This coverage provides direct evidence of relevance to investors.

We first run the panel regressions:

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

²⁵ For a small sample, we searched over longer windows, and found little additional benefit.

²⁶ We record the timing of Bloomberg coverage relative to announcement on the company website. Forty-eight observations (71% of the Bloomberg sample) appeared on the same day as the company's website, with 25 time-stamped during trading hours and 23 after hours. We allocate after-hour news 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's website, with several articles referencing internal emails or memos privately obtained by Bloomberg reporters. Such efforts to obtain non-public information about work-from-home transitions further indicate that Bloomberg reporters anticipated investor interest in the topic.

where $BB_{04,it}$ and $BB_{59,it}$ are Bloomberg indicators, and $WS_{04,it}$ and $WS_{59,it}$ are website-only indicators. The coefficients on $BB_{04,it}$ and $BB_{59,it}$ are 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 (5–9) and combined (0–9) windows.

Our second specification refines (5) by breaking the announcement window 0–5 into two pieces, days 0–1 and 2–4. We are interested in the speed of price response, 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.²⁷ If $\phi > 1$ the announcement effects are front-loaded, i.e., larger per day in the 0–1 window than the 0–4 average. We allow the parameter to differ between Bloomberg and website-only observations, and test whether Bloomberg coverage increases the speed of price response, i.e., $\phi_{BB} > \phi_{WS}$.

[Table 7](#) presents the results. 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 significantly positive. Our primary result of positive

²⁷ [Appendix E](#) provides estimation and inference details.

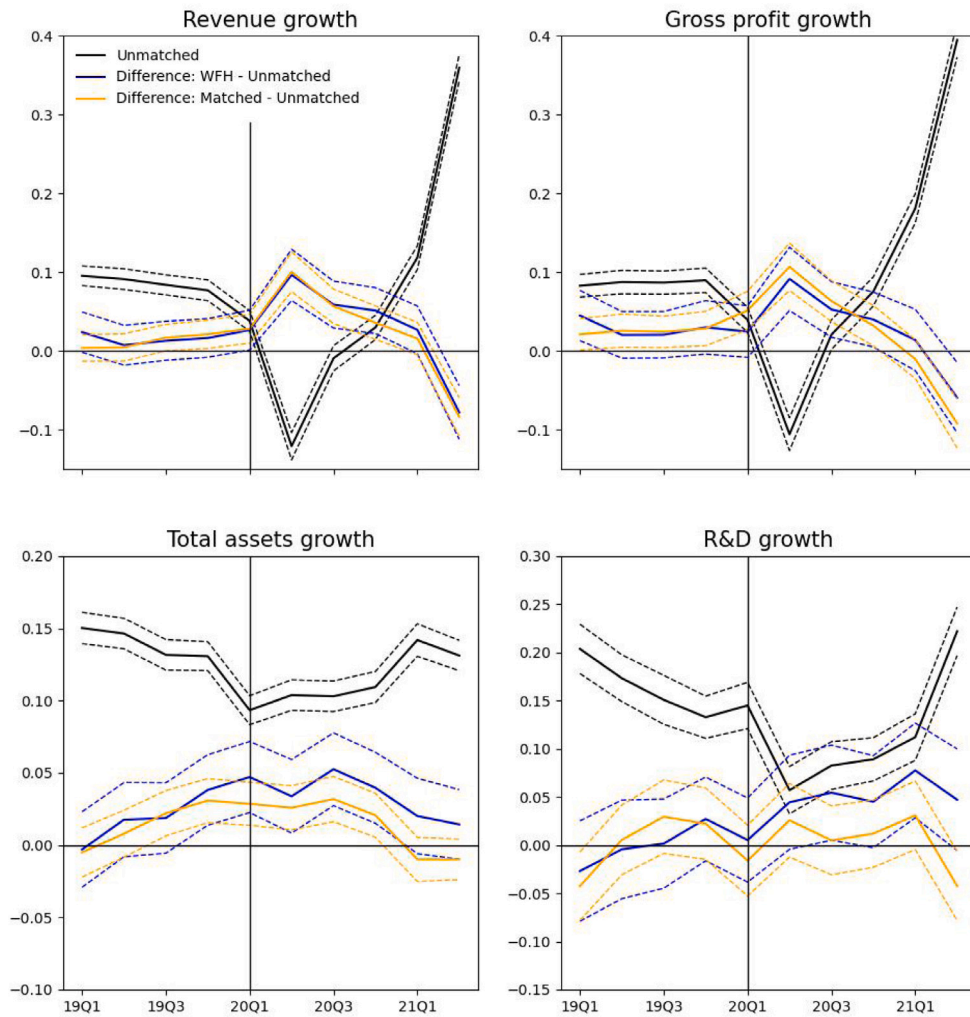


Fig. 4. Operating Performance. The figure shows quarterly average operating performance of unmatched firms (black line), the differences between WFH and unmatched firms (blue line), and the differences between the propensity-score-1 matches of WFH firms and unmatched firms (orange line). The WFH sample consists of work-from-home announcers. For each WFH firm we calculate variable averages over their final propensity-score-1 matches and average over these comparables. Unmatched firms are the remaining non-WFH firms which are not used as final matches. To avoid seasonalities we calculate the growth in the quarterly variables by comparing the same quarters in two consecutive years, e.g., $Sales\ growth_{2019Q1} = \frac{Sales_{2019Q1} - Sales_{2018Q1}}{Sales_{2018Q1}}$. Each panel is based on non-missing observations of the corresponding variable, and dashed lines indicate 90% confidence intervals.

work-from-home announcement effects thus holds in both subsamples, showing robustness.

The hypothesis tests in Panel A show that, over the window 0–4, the Bloomberg announcement effects (1–1.5%/day) are significantly larger than website only (0.5–0.9%/day). In contrast, the return differences between Bloomberg and website-only announcements are not significantly larger for days 5–9, or over the longer window 0–9. One consideration in interpreting these results is that due to confounding factors signal-to-noise ratios tend to be highest in short windows following announcement.²⁸ The larger price impacts of Bloomberg announcements in the 0–5 window, and indistinguishable differences in the 0–9 window, nonetheless suggest faster price adjustment.

To draw stronger conclusions, Panel B uses the refined window 0–1 and associated speed parameter ϕ . The Bloomberg estimate $\hat{\phi}_{BB} \approx 2$ is significantly larger than one in five of six cases, implying a frontloaded

price impact. The proportion of the announcement effect realized in the first two days can be calculated as $2\phi/5 \approx 4/5 = 80\%$, leaving the remaining 20% distributed over the final three days. In contrast, the website-only announcements are not front-loaded. The final row of the panel formally tests for differences in the speed of price adjustment and shows uniformly faster price responses associated with Bloomberg coverage.

These results provide evidence of heterogeneity in the speed of price adjustment consistent with the market-learning channel of our theory. When WFH announcements were covered by Bloomberg and the information therefore more easily acquired by investors, prices responded more quickly to the news.

4.2. Real effects: Operating performance

Section 3 provides strong evidence of announcement effects. We now investigate whether the announcements relate to real outcomes. We compare the pre- and post-pandemic operating performance of WFH firms, their propensity score matches, and other firms. Barry et al. (2022) show differences in post-pandemic operating performance

²⁸ 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 halved.

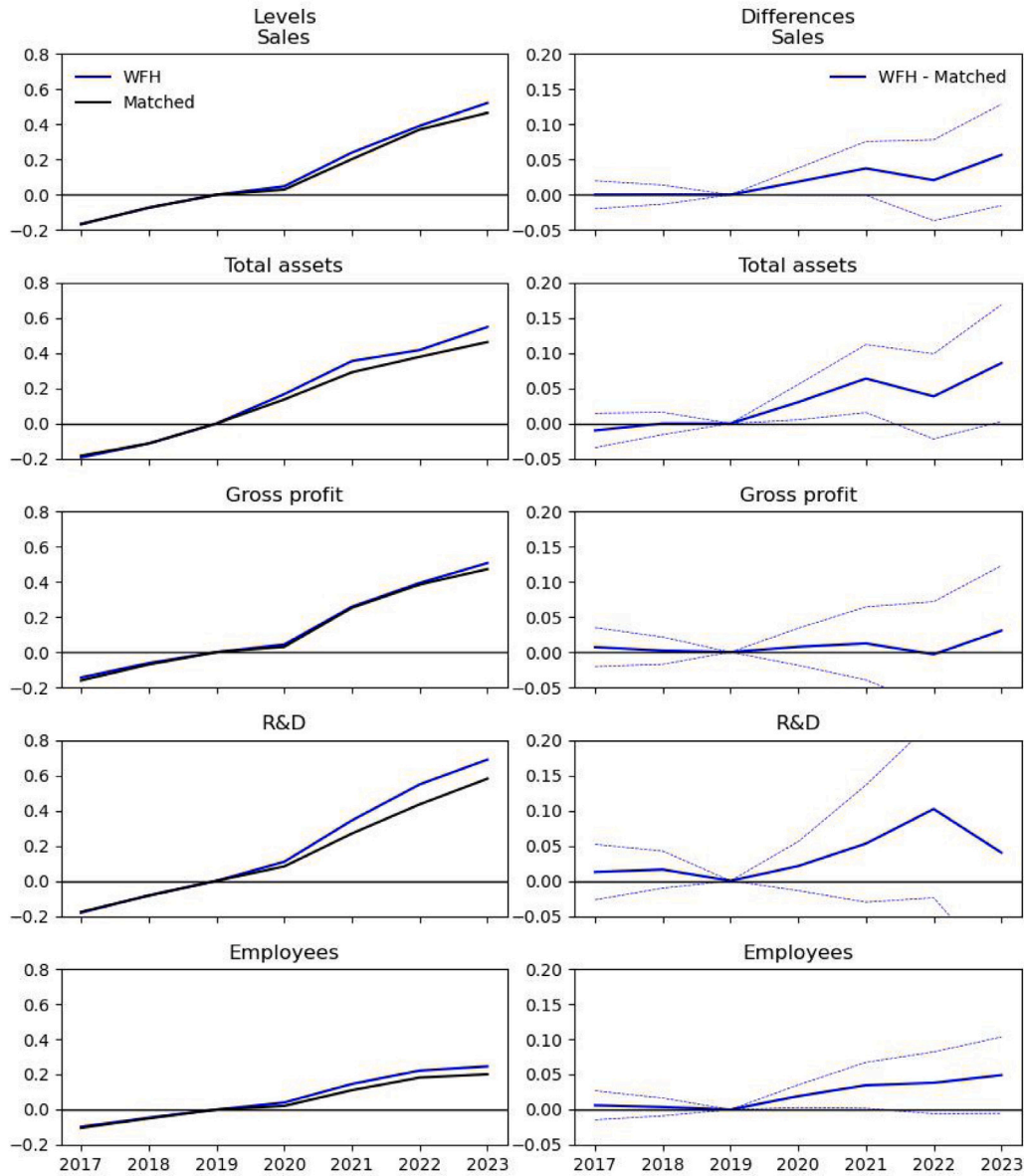


Fig. 5. Long-Run Operating Performance. The figure shows average cumulative operating performance of the WFH firms (blue line) and their propensity-score-1 matches (black line) in the left column and the difference in cumulative operating performance between the WFH firms and their matched firms in the right column. For each WFH firm, we calculate the cumulative growth rate of the corresponding variable normalized to zero in fiscal year ending between July 2019 and June 2020 and then average across the WFH firms. For matched firms, we first calculate the average over the final matches of each WFH firm. Then we average across these comparables. On the x-axis, year t indicates the fiscal year ending between July year t and June $t + 1$, and dashed lines in the right panels indicate 90% confidence intervals.

using pre-existing characteristics, including industry-level labor flexibility. Our analysis focuses on firm-level work-from-home decisions, controlling for pre-existing characteristics.

For each sample firm, beginning in 2019Q1 we calculate the quarterly year-over-year growth in sales, gross profits, total assets, and R&D expenses.²⁹ Fig. 4 plots averages by calendar quarter for the baseline group of non-WFH, non-matched firms (black line). The blue and yellow lines respectively show differences relative to the baseline for WFH firms and matches. Baseline revenue and profit growth began falling in the first quarter of 2020, sharply declined in Q2, and

recovered in the following quarters.³⁰ 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.

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

$$Y_{i,t} = \alpha + \beta_0 \times WFH_i + \beta_1 \times Match_i + \beta_2 \times Covid_t + \beta_3 \times WFH_i \times Covid_t + \beta_4 \times Match_i \times Covid_t + LnME_{i,t} + FE_{i,t}^{ind} + FE_t^Q + \epsilon_{i,t}, \quad (6)$$

²⁹ We drop missing values, which are prevalent in the R&D data, consistent with standard practice (e.g., Li, 2011; Kogan et al., 2021).

³⁰ The low values of revenue and profit in 2020 are denominators in 2021 growth rates and contribute to those variables exceeding their pre-pandemic values.

Table 5
Changes in systematic risk.

	Portfolios			Differences	
	WFH	Matched	Unmatched	WFH-Matched	WFH-Unmatched
Panel A. Market factor					
<i>const</i>	0.001 [1.43]	−0.0 [−0.7]	−0.001 [−1.54]	0.001 [1.21]	0.001 [1.51]
β	1.079 (0.07)	0.926 (0.04)	1.045 (0.09)	0.153 [1.32]	0.034 [0.22]
$\Delta const$	−0.0 [−0.04]	−0.0 [−0.4]	0.001 [1.26]	0.0 [0.12]	−0.001 [−0.64]
$\Delta \beta$	−0.184** [−2.37]	0.111** [2.44]	0.025 [0.28]	−0.294** [−2.44]	−0.209 [−1.3]
R^2	0.958	0.989	0.968	0.120	0.133
Panel B. Market and PS factors					
<i>const</i>	0.0 [0.79]	−0.0 [−0.3]	−0.0 [−0.58]	0.0 [0.63]	0.001 [0.71]
β	1.044 (0.05)	0.936 (0.04)	1.098 (0.05)	0.108 [1.26]	−0.053 [−0.58]
β_{PS}	−0.072** [−2.25]	0.021 [1.64]	0.11*** [3.33]	−0.093** [−2.08]	−0.182*** [−2.81]
$\Delta const$	0.0 [0.07]	−0.0 [−0.46]	0.0 [1.13]	0.0 [0.23]	−0.0 [−0.53]
$\Delta \beta$	−0.063 [−1.18]	0.07* [1.69]	−0.101* [−1.89]	−0.133 [−1.42]	0.038 [0.39]
$\Delta \beta_{PS}$	−0.175*** [−4.39]	0.066*** [2.76]	0.099*** [2.69]	−0.242*** [−3.9]	−0.275*** [−3.67]
R^2	0.986	0.992	0.988	0.611	0.756

The table shows the exposure and the change in exposure of different portfolios (columns) to the market factor (panel A) and to the PS factor and market factor (panel B), before and after the fever period as specified in regression (4). β and β_{PS} are regression coefficients on the market and PS factors, 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 the beginning of January to the 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 in parentheses in the first three columns (significance stars omitted), and *t*-statistics are in brackets. The WFH portfolio consists of work-from-home announcers, and the Matched portfolios of their propensity-score-1 matches. 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.

where $Y_{i,t}$ is the growth rate for variable i in quarter t , $Covid_t$ indicates the Covid-19 period designated as the year 2020, WFH_i and $Match_i$ indicate WFH firms and propensity-score matches, and fixed effects are by 2-digit NAICS and quarter. To focus attention on the period immediately following the Covid crisis, the sample ends in 2020. We run a similar regression for employees, observed annually.

Table 8 shows the results. The second row ($WFH - Match$) shows indistinguishable pre-Covid operating performance for WFH firms versus matches.³¹ The work-from-home firms are also largely similar to unmatched firms pre-Covid (row 1). The *Covid* indicator shows Covid-period declines in baseline operating performance, ranging from 4.8% (assets) to more than 11% (gross profits). The Covid-interaction coefficients indicate that WFH firms outperformed baseline, with statistical significance in four of five cases. The amounts are economically important, for example in the case of sales mitigating 4.7% of the baseline 11.2% decline. The match interaction coefficients are also positive, but smaller than the WFH interactions, and only three are statistically significant. Compared to matches, work-from-home firms thus more broadly show improved operating performance relative to the baseline unmatched firms.

³¹ Rearranging the indicators in (6) provides the marginal effects, as shown in Appendix F.

A more demanding test directly compares WFH announcers and matches, a different test than prior literature since both groups had similar observable characteristics. This comparison, in the final row of Table 8, shows positive point estimates in all cases with two, R&D and employees, statistically significant at the 1% level. The economic magnitudes are meaningful. For example, for R&D growth, matched firms declined by 6.5% (8.4–1.9), whereas WFH firms fell by only 3.8% (8.4–4.6), a substantial mitigation in a comparison of firms with similar observable characteristics. For employment growth, matched firms declined by 4.8% while work-from-home firms fell by 2.6%, a decrease a little more than half as large. Thus, in the immediate aftermath of Covid-19, work-from-home announcers showed stronger operating performance than matched firms, in particular for employment and R&D growth.³²

Fig. 5 shows longer-run operating performance of work-from-home firms relative to matches, setting 2019 as the base year.³³ The left-hand-side panels show cumulative changes for both groups until 2023, and the right-hand-side panels show their differences. The two groups display largely similar performance up until the Covid crisis. Thereafter, we see the short-run improvement in operating performance following Covid-19 that has been already documented, and this initial difference appears sustained over time, with fluctuations up and down but no dramatic continuing outperformance or reversal. Thus, the outperformance of work-from-home announcers appears to concentrate in the immediate aftermath of the Covid-19 crisis.

To summarize, prior studies have shown smaller Covid-crisis declines in operating performance for firms with greater remote-work suitability, using industry-wide measures such as PS. We show improvements controlling for *ex ante* characteristics, according to firm-specific announcements of voluntary work-from-home transitions. The findings support the real benefits of adaptation. The observable work-from-home transitions were not merely cheap talk, but reflected real preparedness. Corporate announcements provided credible and economically meaningful information under an environment of asymmetric information and imperfect contracting, consistent with findings on voluntary disclosures in other settings (e.g., Lewis, 2011).

5. Latent information about firm type

According to our theory, information drove the significant market reactions to firms' work-from-home announcements early in the pandemic. In the model, firms' adaptability is partly determined by directly observable characteristics such as those considered in Table 2, but also by latent attributes that are privately known to managers and more difficult for market participants to ascertain. Firms' actions – announcements of adaptation – can therefore reveal private information to markets, producing positive price responses and declines in risk.

We now seek direct evidence of such hard-to-identify information about adaptability. Our approach builds on recent research showing that corporate disclosures contain complex, but often underutilized information that is not immediately incorporated into stock prices (e.g., Cohen et al., 2020; Bae et al., 2023; Jha et al., 2024). As summarized by Cohen et al. (2020), “Our results suggest that 10-Ks contain rich information, but investors are initially missing a large part.” (p. 1372). Because the Covid crisis was both unprecedented and sudden, investors would have had little incentive *ex ante* to direct attention to subtle cues related to a pandemic. Our analysis focuses on information in 10-Ks

³² Table IA13 shows similar or stronger results in annual data, with significant improvements in operating performance for WFH firms versus matches in four of the five cases.

³³ Barnes et al. (2021) discuss the post-Covid-19 economic recovery, and several studies document more successful implementation and diffusion of remote-work than initially anticipated (Barrero et al., 2021; Aksoy et al., 2022; Bick et al., 2023).

Table 6
Default probabilities.

	Market	Size	Industry -size	PS -size	Propensity score 1	Propensity score 2
<i>const</i>	−0.000 [−0.60]	0.001 [1.09]	0.001 [1.13]	0.001 [1.06]	0.001 [0.97]	0.001 [1.51]
<i>WFH</i> _{0,4}	−0.006 [−1.42]	−0.007* [−1.94]	−0.013*** [−3.99]	−0.010*** [−2.80]	−0.016*** [−8.30]	−0.013*** [−2.78]
<i>WFH</i> _{5,9}	0.002 [0.47]	−0.005 [−1.58]	0.002 [0.36]	−0.004 [−0.81]	0.006 [1.15]	0.009* [1.84]
<i>PrDef_{mkt}</i>	−0.68 (0.024)	−0.50 (0.024)	−0.25 (0.036)	−0.40 (0.021)	−0.24 (0.046)	−0.25 (0.064)
<i>R</i> ²	0.225	0.228	0.063	0.108	0.034	0.036

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 the notes of Table 3) and average daily change in default probabilities across the market *PrDef_{mkt}*, following the structure of Eq. (3). Default probabilities are relative to benchmarks as indicated in the column headings. 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 columns 5–6 the average change in default probabilities of the five closest matches by propensity scores 1 and 2. Standard errors (Driscoll and Kraay, 1998 with 10 lags) are in parentheses, and *t*-statistics in brackets. Significance stars are omitted for *PrDef_{mkt}*. The sample consists of the 272 WFH firms with available default probability data. The sample period is from July 1, 2019 to April 1, 2020 (i.e., end of fever period March 19 plus 10-day announcement window).

Table 7
Bloomberg announcement effects: Size and speed.

	Market	Size	Industry -size	PS -size	Propensity score 1	Propensity score 2
Panel A. Announcement effect size comparison						
<i>a_{BB,04}</i>	0.015*** [5.19]	0.011*** [5.02]	0.01*** [5.91]	0.011*** [4.29]	0.01*** [4.94]	0.011*** [5.53]
<i>a_{WS,04}</i>	0.009*** [2.30]	0.005*** [5.70]	0.006*** [7.22]	0.005*** [4.81]	0.006*** [5.66]	0.006*** [5.77]
<i>a_{BB,59}</i>	−0.001 [−0.47]	−0.001 [−1.17]	−0.001 [−0.46]	−0.002 [−1.51]	−0.002 [−1.22]	−0.003*** [−3.55]
<i>a_{WS,59}</i>	0.004 [1.12]	0.001 [0.54]	0.001 [0.41]	0.001 [0.46]	0.0 [0.05]	0.0 [0.03]
<i>R</i> ²	0.005	0.004	0.002	0.003	0.003	0.003
Bloomberg marginal effects						
<i>(a_{BB} − a_{WS})_{0,4}</i>	0.006** [2.45]	0.005** [2.39]	0.004* [1.83]	0.006** [2.23]	0.004** [2.06]	0.005** [2.55]
<i>(a_{BB} − a_{WS})_{5,9}</i>	−0.005** [−2.09]	−0.003 [−1.47]	−0.002 [−0.89]	−0.003 [−1.52]	−0.002 [−0.78]	−0.003 [−1.33]
<i>(a_{BB} − a_{WS})_{0,9}</i>	0.001 [0.35]	0.001 [0.79]	0.001 [0.92]	0.002 [1.00]	0.001 [0.76]	0.001 [0.73]
Panel B. Announcement effect speed comparison						
<i>a_{BB,04}</i>	0.015*** [4.41]	0.011*** [6.77]	0.01*** [6.31]	0.011*** [6.67]	0.01*** [4.89]	0.011*** [5.89]
<i>a_{WS,04}</i>	0.009*** [2.87]	0.005*** [5.01]	0.006*** [8.43]	0.005*** [4.79]	0.006*** [5.73]	0.006*** [5.90]
<i>φ_{BB} − 1</i>	0.42 [1.35]	0.967** [2.34]	0.983** [2.46]	0.989** [2.30]	0.907** [2.09]	0.967** [2.60]
<i>φ_{WS} − 1</i>	−0.742*** [−5.66]	−0.495** [−2.43]	−0.294 [−1.59]	−0.407 [−1.62]	−0.08 [−0.30]	−0.142 [−0.46]
<i>R</i> ²	0.006	0.005	0.003	0.003	0.003	0.004
Bloomberg marginal effects						
<i>φ_{BB} − φ_{WS}</i>	1.162*** [5.07]	1.462*** [4.82]	1.277*** [4.56]	1.396*** [4.8]	0.987*** [4.28]	1.109*** [6.33]

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 Eq. (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 − 2/3 *BB*₂₄) and (*WS*₀₁ − 2/3 *WS*₂₄) as specified in regression Eq. (E.2) 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 3. *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).

Table 8
Operating performance.

	Growth in				
	Sales	Gross profits	Assets	R&D	Employees
<i>WFH</i>	−0.016 [−1.11]	−0.008 [−0.58]	−0.013 [−0.52]	−0.068** [−2.05]	−0.018 [−1.03]
<i>(WFH − Match)</i>	0.004 [0.44]	0.005 [0.49]	0.002 [0.13]	−0.008 [−0.33]	0.004 [0.39]
<i>Covid</i>	−0.112*** [−6.20]	−0.113*** [−3.78]	−0.048*** [−2.66]	−0.084*** [−6.28]	−0.064*** [−6.13]
<i>WFH × Covid</i>	0.047** [2.54]	0.045 [1.63]	0.028* [1.94]	0.046*** [4.22]	0.038*** [4.01]
<i>Match × Covid</i>	0.038** [2.30]	0.043 [1.60]	0.014 [0.99]	0.019*** [2.83]	0.016* [1.80]
<i>LnME</i>	0.007** [1.99]	0.009*** [2.94]	0.007*** [2.69]	0.012** [2.14]	0.008*** [3.33]
<i>R²</i>	0.093	0.086	0.041	0.055	0.097
Comparison of WFH vs. matches during Covid-19					
<i>(WFH − Match) × Covid</i>	0.010 [0.65]	0.002 [0.10]	0.014 [1.33]	0.026*** [3.82]	0.022** [2.55]

This table reports the results of estimating regression of the form: $Y_{i,t} = \alpha + \beta_0 \times WFH_i + \beta_1 \times Match_i + \beta_2 \times Covid_i + \beta_3 \times WFH_i \times Covid_i + \beta_4 \times Match_i \times Covid_i + LnME_{i,t} + FE^{Ind} + FE^Q + \epsilon_{i,t}$, 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 1, respectively. $Covid_i$ 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. The indicators are rearranged to obtain marginal effects as described in Appendix F. Each column is based on non-missing observations of the corresponding variable for the full sample of 2549 firms. The data is at quarterly frequency except for the number of employees which is at annual frequency. To avoid potential seasonalities, 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., $Y_{i,2019Q1} = \frac{Sales_{i,2019Q1} - Sales_{i,2018Q1}}{Sales_{i,2018Q1}}$. Regressions include 2-digit NAICS fixed effects and, except for the last column, quarter fixed effects. Standard errors are clustered by 2-digit NAICS. The sample period is from Q1 2019 to Q4 2020.

about topics related to organizational capabilities and adaptability to remote work. We use 10-Ks for the fiscal years 2016–2018 to evaluate pre-pandemic conditions, and 10-Ks for 2020 to evaluate changes after the pandemic.³⁴

5.1. Text-based topics

We build on recent literature by training our language model in a task-relevant domain Hassan et al. (e.g., 2019), Hansen et al. (e.g., 2021), Leippold et al. (e.g., 2022), Hassan et al. (e.g., 2024). Drawing on established insights (e.g., Saliola and Islam, 2020; Allas et al., 2021), we hypothesize four aspects of organizational capabilities that could be difficult to evaluate from directly observable sources such as the PS measure, could be reflected in corporate language, and could predict ability to sustain operations during a systematic disruption:

1. direct discussion of **remote work**;
2. **corporate resilience** in the face of disasters and emergencies;
3. digital capabilities and **digital transformation**;
4. general **corporate adaptability** and agility.

For each area we identify a top-selling book published before the beginning of our 10-K sample, written by a well-known researcher or consultant for a business and corporate strategy audience (Fried and Hansson, 2013; Engemann and Henderson, 2014; Westerman et al., 2014; Kotter, 2012). These texts form our training library.

We build a topic model from these texts using Latent Semantic Analysis (LSA) (Deerwester et al., 1990; Landauer et al., 1998), a well-established machine learning technique used for a variety of document classification, comparison, and information retrieval tasks, with diverse applications in economics and finance (e.g., Iaria et al., 2018; Bertrand et al., 2021; Cong et al., 2024).³⁵ LSA factors, or topics, capture underlying themes by grouping words that tend to appear in

similar settings, while permitting that words can belong to multiple topics, with different positive or negative weightings. These properties make LSA an attractive choice for identifying textual characteristics associated with work-from-home capability.

Our approach of constructing an LSA topic model from a training library builds on prior methods. For example, Hassan et al. (2019) uses an inclusion/exclusion rule to create topics from bigrams contained in one training document (e.g., an undergraduate textbook on U.S. politics) and not contained in another document (an undergraduate textbook on accounting). Their methodology produces word lists that distinguish between one topic and another topic.³⁶ We use LSA as a natural way to automate decomposition of a training library into topics, and we validate the effectiveness of this approach within the context of the training library as well as the sample of 10-Ks.

We implement LSA on the term-frequency-inverse-document-frequency (tf-idf) matrix of document bigrams. Following common practice, bigrams enhance ability to capture more complex meanings

³⁵ LSA is based on singular value decomposition, providing an orthogonal set of textual factors or dimensions, which can be regarded as topics, that optimally compress a high-dimensional text representation into a lower-dimensional space. Stevens et al. (2012) show good performance of LSA in comparison with related topic modeling approaches, including Latent Dirichlet Analysis (LDA) and nonnegative matrix factorization. LDA in particular has proven advantageous in a number of economics and finance applications (Hansen et al., 2018; Lopez-Lira, 2023; Bybee et al., 2024), and while providing benefits described in these studies, requires iterative estimation through algorithms such as expectations maximization, and produces topics that can be highly correlated. For our study, important benefits of LSA are its simplicity in giving a fixed set of ranked orthogonal topics, similar to the good performance for LSA also reported in Iaria et al. (2018), Bertrand et al. (2021), and Cong et al. (2024), and the linear relation between bigrams and topic weights which aids interpretation.

³⁶ Hassan et al. (2019) further develop analysis of political subtopics and extend to word embeddings to focus on topics used in connection with risk and uncertainty. See also Hassan et al. (2024).

³⁴ Appendix G describes the 10-K text preparation and provides details of our methods.

relative to individual words, and tf-idf captures frequency of usage relative to the broader set of documents. For simplicity, the analysis we present here focuses on $k = 4$ topics, which is sufficient to distinguish among topics and show our main results.³⁷

The LSA topics can be “unpacked,” or given meaning, by examining their relationships with documents and word groupings. To this end, Table 9, Panel A, provides average LSA topic loadings, by training library book.³⁸ For the first topic $LSA1$, all of the average weights are positive. The average $LSA1$ loadings are highest for the book focused on digital transformation (0.43), followed by the texts centered on resilience (0.28), adaptability (0.16), and remote work (0.15). The weightings on the other LSA topics are sometimes positive and sometimes negative according to book. Reading Panel A by rows, we can view each of the books as on average a linear combination of LSA topics, and each book appears somewhat concentrated in one of the topics.

To better understand how the books relate to the LSA topics, Table 9, Panel B, allocates each book chapter to one of the topics according to its largest normalized LSA weight.³⁹ The results validate that the topic model distinguishes between the language used in each of the books. Panel C further clarifies the interpretation of the LSA topics, by showing each LSA factor (column-wise) as a linear combination of idealized “books” in a rotated factor space.⁴⁰ The results show that $LSA1$ represents a broad-based set of latent topics, with positive weighting on all of the books, particularly strongly for resilience and digital transformation, and a more modest weight on adaptability. $LSA2$ loads positively on resilience and negatively on digital transformation, with neutral weights on the other books, implying that this topic captures mostly differences between two books. $LSA3$ loads heavily on remote work with a milder positive weighting on adaptability, and mild negative weightings on the other two books. $LSA4$ focuses heavily on adaptability, with mild negative weights on the other books. These relationships between the LSA factors and the training-library texts aid the interpretation of our results for corporate 10-Ks below.

Panel D shows the top ten bigrams by weight in each of the LSA topics.⁴¹ These show interpretability and distinction across the topics. For example, the top bigram associated with $LSA1$ is “digital transformation,” the top bigram associated with $LSA2$ is “business continuity,” and the top bigram for $LSA3$ is “remote work.” In the next subsection, we dig more deeply into the bigrams associated with each topic to show what drives our results, and it is not just the “obvious” top ten bigrams.

The LSA topic model thus distinguishes between documents in the training library, and the words associated with each topic help to give the model interpretability and meaning. We now apply the model to corporate 10-Ks before and after the pandemic.

5.2. Latent information in 10-Ks

This section applies the LSA topic model from the training library to corporate 10-Ks from the 2016–2018 fiscal years (pre-pandemic), and to the 2020 fiscal year (post-pandemic). We find statistically significant predictability from the pre-pandemic 10-K topic loadings to realized work-from-home decisions.

³⁷ The Internet Appendix Section IA.2 shows the model with $k = 15$ topics and similar results.

³⁸ For each chapter-document, we calculate the LSA topic loadings, and average across the chapters by book to produce Panel A.

³⁹ This corresponds to the maximum cosine similarity of each chapter with each of the $k = 4$ topics. See Appendix G.

⁴⁰ In particular, denote the $k \times k$ matrix in Panel A by $\bar{W}$. Each row of $\bar{W}$ corresponds to a book, and entry w_{ij} of the matrix tells us the average loading of book i on LSA topic j . The operation $\bar{W}^{-1}$ acts as a rotation from the LSA factor space back into the book space.

⁴¹ A fuller list of the top thirty positive and bottom ten negative bigrams associated with each factor, and their weights, are provided in Table IA14.

Table 10 shows logit regressions of the work-from-home announcement indicator on firm characteristics, using the same methods and sample as Table 2, where we now include the pre-pandemic 10-K topic loadings $LSA1, \dots, LSA4$ for each firm as predictors. Among the textual components, $LSA1$ and $LSA3$ significantly predict the work-from-home realizations. Their significance is robust individually (1 and 3), in combination (5), and controlling for the AIC- and BIC-selected predictors from Table 2 (regressions 6 and 7). In particular, the R^2 of (6) and (7) relative to Table 2 regressions (13) and (14) increase by about 1.5% (from 11.0 to 12.6 and from 11.8 to 13.1 in (6) and (7) respectively). Comparing coefficient estimates across regressions, $LSA1$ and $LSA3$ appear to relate most closely, among the directly observable controls, to the PS variable.⁴² Textual topics from 10-Ks therefore provide information beyond the directly observable firm characteristics previously considered, and enhance prediction of firms’ work-from-home announcements.

Table IA15 repeats the previous predictive regressions after eliminating the top ten highest-weighted bigrams (corresponding to the list from Table 9, Panel D) from the calculation of each LSA variable. The results show small changes in coefficient estimates and R^2 , while maintaining the economic magnitudes and statistical significance of $LSA1$ and $LSA3$. The power of these variables in predicting work-from-home announcements is therefore not driven solely by their top bigrams, but spreads more deeply through the high-dimensional vector of topic bigrams and weights. These results are consistent with the idea that the LSA topics capture complex textual information that could have been difficult for investors to easily incorporate into prices *ex ante*.

5.3. Influential bigrams and post-pandemic changes in language

We next delve into the contributions of individual bigrams to the predictive power of the LSA components, and to post-pandemic changes in language. A powerful aspect of the LSA factorization is that by compressing a high-dimensional vector of tf-idf bigram weights into a lower-dimensional space, we achieve tight parameterization, good identification, and interpretability of the coefficient estimates in Table 10. Equally attractive, we can invert this compression, and infer the contribution of individual bigrams to the fitted likelihood of work-from-home announcement, as well as decompose those contributions into individual effects through each LSA component.

Appendix G.2 describes how to infer the influence of an individual bigram on the fitted likelihood of work-from-home, given Table 10 results.⁴³ Using this method, we rank influential bigrams for the work-from-home decision. Table 11 lists these influential bigrams, with an additional restriction that a bigram must also be *individually* important in at least one of three ways: (i) pre-pandemic, a statistically significant difference in tf-idf for WFH versus non-WFH firms (useful in univariate prediction); (ii) pre- to post-pandemic, a statistically significant change in tf-idf across all firms (usage changed during the pandemic); (iii) pre-to-post pandemic, significant difference-in-change in tf-idf for WFH versus non-WFH (difference-in-difference).

The list of influential bigrams in Table 11 shows the benefits of LSA. Some bigrams are mentioned infrequently in 10-Ks, but LSA aggregates information according to training-library usage, providing

⁴² The coefficient estimates on $LSA1$ and $LSA3$ fall from 0.56 and 0.35 in (5) to 0.31 and 0.24 in (6) and 0.26 and 0.23 in (7), while remaining significant. Conversely, comparing to Table 2 regressions (13) and (14), the presence of the LSA components in (6) and (7) reduces the coefficient estimates on PS from 0.50 and 0.36 to 0.35 and 0.24, and eliminates the significance of profitability, while leaving the coefficient estimates for the other AIC- and BIC-selected variables mostly the same.

⁴³ See in particular Eqs. (G.4) and (G.5). The decomposition we present focuses on regression (5) of Table 10.

Table 9
Latent topics and top bigrams from training library.

	Components			
	LSA1	LSA2	LSA3	LSA4
Panel A. Average LSA component loadings by book				
Digital transf.	0.432	−0.332	−0.121	−0.088
Resilience	0.276	0.347	−0.035	−0.041
Remote work	0.148	−0.048	0.687	−0.183
Adaptability	0.157	−0.021	0.116	0.480
Panel B. By book, chapter counts according to maximum scaled LSA loading (cosine similarity)				
Digital transf.	13			
Resilience	3	14		
Remote work			7	
Adaptability				12
Panel C. Loadings of the LSA factors in the rotated “books” space				
Digital transf.	1.273	−1.100	−0.446	−0.358
Resilience	1.273	1.813	−0.223	−0.284
Remote work	0.217	−0.088	1.300	−0.388
Adaptability	0.423	−0.082	0.395	1.844
Panel D. Top 10 bigrams of the LSA topics				
	digital transformation	business continuity	remote work	guiding coalition
	business continuity	crisi event	remote worker	major change
	crisi event	case study	working remotely	change effort
	digital master	alternate site	work remotely	shortterm win
	digital technology	incident commander	work done	new vision
	case study	emergency management	remote working	transformation effort
	customer experience	risk management	coffee shop	quality program
	business model	datum center	work fromhome	change project
	digital vision	normal operation	every day	change vision
	alternate site	senior management	make sure	new approach

Panel A shows the average LSA loadings of the book chapters on the four LSA latent components (topics) associated with the four largest singular values. The loadings correspond to the $x_i B_k$ transformation, where x_i is the i th column of the tf-idf matrix of the training library X_0 . Panel B shows the number of chapters of each book allocated to the individual components. A chapter is allocated to one of the components according to its largest normalized LSA loading, corresponding to its maximum cosine similarity over the $k = 4$ components. Panel C shows the loadings of the LSA components on the four books in the rotated “books” space, as described in footnote 40. Panel D shows the top ten bigrams for each topic based on the weights (importance) within the topic. The bigram weights in each component are the entries from the matrix B_k . The LSA procedure and further details are described in [Appendix G](#).

Table 10
LSA topics and work-from-home decisions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>LSA1</i>	0.42*** [6.92]				0.56*** [8.61]	0.32*** [4.21]	0.27*** [3.54]
<i>LSA2</i>		0.11 [1.37]			−0.02 [−0.30]		
<i>LSA3</i>			0.21*** [2.94]		0.34*** [5.25]	0.23*** [3.53]	0.22*** [3.38]
<i>LSA4</i>				0.10 [1.39]	−0.06 [−0.87]		
<i>PS</i>						0.33*** [4.01]	0.24** [2.57]
<i>LnME</i>						0.47*** [3.99]	0.50*** [4.14]
<i>LnEmp</i>						0.34*** [2.59]	0.34** [2.56]
<i>DN</i>							0.23** [2.49]
<i>Profitability</i>							0.13 [1.41]
Pseudo R^2	0.033	0.001	0.006	0.001	0.054	0.126	0.131
P_{low}	0.07	0.10	0.09	0.10			
P_{high}	0.16	0.12	0.12	0.12			
Odds ratio	2.23	1.18	1.35	1.23			

This table shows the results of estimating logistic regressions of the work-from-home indicator, WFH_i , on the loadings of the firms’ 10-Ks on the LSA topics and control variables. The loadings on the LSA topics correspond to the transformation $X_F B_k$, where X_F is the tf-idf matrix of the firms’ 10-Ks. The detailed description of the text cleaning and the LSA procedure is in [Appendix G](#). The control variables consist of the variables underlying the propensity score 1 and 2 defined in [Table 2](#), columns 13 and 14, respectively. P_{low} and P_{high} are the fitted likelihoods of $WFH = 1$ for low (10th percentile) and high (90th percentile) value of the leading explanatory variable. The Odds ratio is the ratio P_{high}/P_{low} . The fitted probabilities and the odds ratio are omitted in columns 5–7. The sample consists of 2087 firms, identical to [Table 2](#).

Table 11
Influential bigrams.

Bigram	Weights $\hat{\eta}$					2018 counts		2018 WFH-nonWFH differences			2020 vs. 2018 time differences			Difference in differences		
	Total	LSA1	LSA2	LSA3	LSA4	nonWFH	WFH	TFIDF	t stat	Sig.	TFIDF	t stat	Sig.	TFIDF	t stat	Sig.
remote work	98.1	5.94	0.11	88.49	3.57	0	1	0.011	[2.89]	***	0.401	[17.38]	***	0.253	[3.4]	***
remote worker	82.51	4.9	0.09	74.44	3.08	4	0	-0.002	[-0.65]		0.013	[3.76]	***	0.019	[1.74]	*
working remotely	76.53	4.67	0.08	68.94	2.83	2	1	0.004	[1.64]		0.415	[20.21]	***	0.241	[3.63]	***
work remotely	37.1	2.25	0.04	33.42	1.38	7	1	0.009	[1.81]	*	0.281	[17.78]	***	0.186	[3.63]	***
work done	34.83	2.1	0.04	31.39	1.3	18	7	0.015	[1.74]	*	-0.002	[-0.96]		0.014	[2.09]	**
remote working	26.08	1.57	0.03	23.51	0.96	2	0	-0.001	[-0.48]		0.285	[14.63]	***	0.214	[3.4]	***
coffee shop	24.07	1.48	0.03	21.62	0.93	9	2	0.017	[1.78]	*	-0.0	[-0.15]		-0.004	[-0.49]	
every day	19.78	1.94	0.04	17.18	0.62	140	35	0.048	[2.46]	**	0.036	[6.4]	***	0.003	[0.19]	
make sure	19.71	2.07	0.06	16.85	0.74	30	5	0.022	[2.57]	**	0.001	[0.32]		-0.002	[-0.16]	
person work	16.44	1.73	0.05	14.0	0.67	6	6	0.022	[4.55]	***	0.006	[2.33]	**	0.002	[0.28]	
conference call	14.43	1.1	0.0	12.8	0.52	85	25	0.036	[3.22]	***	0.008	[2.53]	**	0.001	[0.1]	
customer support	12.95	0.9	0.02	11.54	0.49	349	87	0.319	[6.98]	***	-0.017	[-2.26]	**	-0.009	[-0.36]	
get done	12.44	0.76	0.01	11.19	0.47	2	3	0.014	[4.22]	***	0.009	[2.73]	***	0.031	[2.9]	***
screen sharing	11.37	0.71	0.01	10.23	0.41	0	3	0.015	[4.82]	***	-0.001	[-0.5]		-0.005	[-1.44]	
great idea	11.3	0.98	0.02	9.87	0.43	4	1	0.006	[1.47]		0.001	[0.66]		-0.01	[-2.2]	**
instant messaging	11.16	1.11	0.03	9.6	0.42	14	5	0.013	[2.25]	**	-0.001	[-0.8]		-0.0	[-0.09]	
phone call	11.04	0.67	0.01	9.95	0.41	37	12	0.034	[1.66]	*	-0.001	[-0.38]		0.014	[1.71]	*
make sense	9.92	1.52	0.05	8.18	0.18	9	6	0.008	[1.69]	*	0.002	[1.0]		-0.007	[-1.47]	
operating system	9.74	1.42	-0.03	8.06	0.3	394	89	0.395	[7.93]	***	-0.026	[-2.69]	***	-0.087	[-2.75]	***
business continuity	9.35	17.86	-1.34	-8.56	1.39	425	71	0.051	[1.8]	*	0.131	[12.09]	***	0.085	[2.41]	**
especially important	8.51	0.65	0.01	7.66	0.18	19	3	-0.0	[-0.08]		0.001	[0.66]		0.008	[1.9]	*
person working	8.37	0.9	0.02	7.32	0.12	47	5	-0.004	[-0.52]		0.015	[4.24]	***	0.017	[1.46]	
company owner	8.35	0.49	0.01	7.55	0.31	3	1	0.003	[1.16]		-0.0	[-0.5]		0.002	[2.23]	**
major change	7.79	4.62	0.02	9.62	-6.47	198	23	-0.01	[-0.75]		-0.01	[-3.83]	***	-0.0	[-0.02]	
via email	7.73	0.57	0.0	6.86	0.29	48	10	0.014	[1.2]		-0.004	[-2.39]	**	-0.007	[-1.11]	
video conferencing	6.81	0.56	0.01	5.99	0.25	18	7	0.035	[3.86]	***	0.011	[2.94]	***	-0.016	[-1.26]	
start small	6.79	0.41	0.01	6.12	0.25	0	2	0.02	[4.06]	***	-0.001	[-0.72]		-0.007	[-2.09]	**
key reason	6.68	0.63	0.02	5.76	0.27	9	0	-0.003	[-0.86]		0.003	[2.33]	**	0.014	[2.83]	***
best person	6.58	0.39	0.01	5.94	0.25	41	7	-0.001	[-0.05]		0.022	[4.1]	***	0.003	[0.17]	
best work	6.58	0.39	0.01	5.94	0.25	6	2	0.008	[1.64]		0.035	[7.09]	***	0.042	[2.63]	***
done remotely	6.32	0.37	0.01	5.7	0.24	1	0	-0.001	[-0.35]		0.007	[2.63]	***	0.027	[3.35]	***
work across	6.27	0.63	0.02	5.39	0.24	15	9	0.028	[4.88]	***	0.004	[1.56]		-0.006	[-0.72]	
employee work	6.2	0.98	0.01	4.95	0.27	81	11	-0.003	[-0.24]		0.081	[12.27]	***	0.064	[2.99]	***
work get	6.18	0.37	0.01	5.57	0.23	0	3	0.016	[5.01]	***	0.007	[2.4]	**	0.021	[2.13]	**
good time	6.07	0.74	0.02	5.35	-0.03	6	1	0.007	[1.8]	*	-0.002	[-1.27]		-0.008	[-1.97]	**
make progress	5.89	1.02	0.03	4.73	0.11	22	8	0.016	[3.15]	***	0.011	[3.58]	***	-0.005	[-0.51]	
digital transformation	5.89	27.97	1.28	-26.17	2.81	55	27	0.054	[1.52]		0.067	[4.74]	***	0.224	[4.92]	***
natural disaster	5.84	1.2	-0.06	4.42	0.28	1664	215	0.081	[2.15]	**	0.06	[5.36]	***	0.003	[0.08]	
company culture	5.8	1.01	0.04	4.49	0.26	90	19	0.054	[3.17]	***	0.041	[8.16]	***	0.014	[0.84]	
long term	5.73	1.14	-0.02	4.82	-0.21	731	91	0.031	[1.09]		-0.036	[-4.61]	***	0.018	[0.69]	
case study	5.51	10.2	-0.76	-4.7	0.77	43	8	0.015	[1.98]	**	-0.004	[-2.75]	***	-0.01	[-1.83]	*
great way	5.45	1.04	0.03	4.31	0.07	5	0	-0.002	[-0.73]		-0.001	[-0.92]		0.007	[2.22]	**
social activity	5.44	0.75	0.01	5.3	-0.62	3	1	0.001	[1.02]		0.009	[3.52]	***	-0.009	[-1.09]	
leadership management	5.36	0.71	0.01	5.17	-0.53	3	0	-0.001	[-0.58]		0.003	[2.56]	**	-0.004	[-0.89]	
person want	5.32	0.71	0.01	5.1	-0.5	7	2	0.007	[1.49]		0.002	[0.94]		0.012	[1.72]	*
real time	5.24	2.89	0.1	2.07	0.18	245	50	0.061	[1.1]		-0.018	[-2.33]	**	0.019	[0.75]	
decision making	5.24	3.48	-0.06	2.47	-0.66	221	40	0.044	[2.28]	**	-0.004	[-0.8]		-0.013	[-0.76]	
taking advantage	4.93	0.67	0.02	4.04	0.2	184	21	-0.002	[-0.16]		-0.007	[-2.23]	**	-0.016	[-1.52]	
help make	4.93	1.0	0.02	4.38	-0.48	20	9	0.028	[4.09]	***	0.005	[2.04]	**	-0.011	[-1.32]	
two person	4.74	0.66	0.01	4.58	-0.5	33	2	0.001	[0.08]		-0.004	[-2.1]	**	-0.007	[-1.19]	

This table shows the influential bigrams from the LSA components with significant differences in their tf-idf values between WFH and non-WFH firms or over time. The weights $\hat{\eta}$ are defined in Eq. (G.4) and indicate the importance of the bigrams in forecasting the WFH announcements. The column Total is the sum of the four component weights. The heading “2018 counts” indicates the number of firms where the bigrams occur in the 10-Ks. The heading “2018 WFH-nonWFH differences” shows the differences in the tf-idf values of the bigrams between the WFH and non-WFH firms. The heading “2020 vs. 2018 time differences” shows the difference in the average tf-idf values between 2018 and 2020. The last heading “difference in differences” shows how the differences in the tf-idf values between WFH and non-WFH firms changed between 2018 and 2020. The table shows the top 50 bigrams ranked by the total weight which are significant in at least one of the three differences. Year 2018 comprises the firms’ available 10-Ks from 2016 to 2018.

structure and enhancing identification. Many top bigrams clearly relate to remote work, but some focus on related technologies (screen sharing, video conferencing). Other key terms include business continuity, customer support, natural disaster, company culture, and digital transformation.⁴⁴ The list of influential bigrams sheds additional light on earlier results. Intuition and previous research suggests that

⁴⁴ Table IA18 considers influential bigrams extending beyond the top 50 that remain individually significant, including: new feature, datum center, customer experience, critical operation, rapidly changing, information technology, recovery time, disaster recovery, new strategy, strategic planning, and recovery plan.

intangible capital and organization capital should relate to work-from-home transitions (e.g., Eberly et al., 2021), yet the traditional quantitative measures *IK* and *OK* show no predictive power for remote-work announcements in Table 2 with controls. The top bigrams include a variety of terms related to adaptability and organizational capabilities, consistent with the idea that harder-to-measure aspects of intangible and organizational capital were important to remote-work decisions.

We finally compress the high-dimensional information from the top bigram lists into simpler global statistics. Our first approach is based on logistic regression (5) of Table 10, which uses all four LSA components and no controls, with data from the pre-pandemic

Table 12
Differences in LSA topics related to work-from-home.

	All firms	WFH	Non-WFH	Difference
Panel A. Text-based probability				
2016–2018	0.108 (0.007)	0.155 (0.015)	0.103 (0.006)	0.052*** [<0.001]
2020	0.264 (0.025)	0.369 (0.042)	0.251 (0.023)	0.118*** [<0.001]
Difference	0.156*** [<0.001]	0.215*** [<0.001]	0.149*** [<0.001]	0.066*** [<0.001]
Panel B. Text-based residual probability (prop. score 1)				
2016–2018	−0.0 (0.0)	0.022 (0.007)	−0.003 (0.001)	0.025*** [<0.001]
2020	0.086 (0.027)	0.141 (0.045)	0.08 (0.025)	0.061*** [<0.001]
Difference	0.086*** [<0.001]	0.119*** [<0.001]	0.083*** [<0.001]	0.036*** [0.003]
Panel C. Text-based residual probability (prop. score 2)				
2016–2018	−0.0 (0.0)	0.019 (0.006)	−0.002 (0.001)	0.021*** [<0.001]
2020	0.076 (0.026)	0.123 (0.043)	0.071 (0.024)	0.052*** [<0.001]
Difference	0.076*** [<0.001]	0.104*** [0.002]	0.073*** [<0.001]	0.031** [0.011]

This table shows the fitted probabilities (Panel A) and fitted residual probabilities (Panels B and C) based on the LSA loadings of the firms' 10-Ks and their differences between WFH and non-WFH firms and over time. The fitted probabilities 2016–2018 in Panel A are calculated from the logistic regressions of the WFH announcements on the LSA loadings of the firms' 2016–2018 10-Ks, equivalent to column 5 Table 10. For the fitted residual probabilities in 2016–2018 in Panels B and C, we first calculate the residual probabilities from the BIC and AIC selected logit models (columns 13 and 14 in Table 2). We then regress these residual probabilities on the LSA loadings of the firms' 2016–2018 10-Ks. The fitted residual probabilities are the fitted values given these estimates. For the fitted probabilities in 2020, we apply the estimated coefficients from 2016–2018 to the firms' LSA loadings from 2020 10-Ks, i.e., holding the parameters constant but allowing a change in firms' LSA loadings. The fitted residual probabilities in 2020 are calculated equivalently. Further details are in footnote 45. The row difference shows the difference between 2016–2018 and 2020. Column headings describe the groups, and the last column shows the differences between the WFH and non-WFH firms. The entry in the bottom right corner corresponds to the difference-in-difference. To account for parameter estimation error, we use a bootstrap as described in Appendix G.2. Standard errors are in parentheses, and *p*-values for the null hypothesis of a difference less than zero are in brackets. Significance stars are shown only for the differences.

period. Given the estimated parameter vector $\hat{\beta}_{L,pre}$, we calculate fitted probabilities $\hat{p}_{i,pre}$ and averages for WFH firms, non-WFH firms, and their difference, shown in the first row of Table 12, Panel A. To understand how topic-related language changed from pre- to post-pandemic, we apply the pre-pandemic parameter estimates $\hat{\beta}_{L,pre}$ to the post-pandemic 10-K data $LSA_{1,i,post}, \dots, LSA_{4,i,post}$, giving fitted probabilities $\hat{p}_{i,post}$, corresponding to the counterfactual scenario of observing the post-data in the pre-period. The averages of $\hat{p}_{i,post}$ for each group, and their differences, are reported in the second line of Panel A. These tell us how the language observed in the post-pandemic period would have been interpreted in terms of fitted work-from-home probabilities in the pre-pandemic period. The final row shows differences from the pre- to post-periods across each group, with the final column being a difference-in-difference.

The results of Table 12, Panel A, provide additional evidence of advantages for WFH firms. The first row shows that LSA exposures alone could have predicted a 5.2% larger probability of announcing for WFH versus other firms (final column, "Difference"). In the other table dimension, the first column shows that if the average post-pandemic 10-K were counter-factually observed pre-pandemic, the LSA loadings would have predicted a 15.6% larger probability of early WFH adoption (from 10.8 to 26.4%). The difference in language across time is thus more than three times larger than the pre-pandemic WFH-versus-non-WFH difference, and highlights an additional advantage of the WFH firms. Their pre-pandemic LSA exposures reflected the direction the

entire universe of firms would move post-pandemic, demonstrating an early mover advantage in focus. The final row and column, difference-in-difference, shows an additional advantage. The WFH firms were not only pre-positioned well, but also accelerated their remote-work-related topic exposures relative to other firms in the post-pandemic period.

Panels B and C of Table 12 employ a similar approach, but control for observable characteristics using the AIC- and BIC-selected regressions of Table 2.⁴⁵ The results show similar effects to Panel A, but with attenuated economic magnitudes because the controls absorb some of the effect of the LSA topics. Regardless of the presence of controls, the LSA topic exposures of WFH firms predicted their subsequent announcements, showed a pre-positioning advantage relative to changes for all firms post-pandemic, and demonstrated further ability to accelerate movement in the same direction post-pandemic.

6. Conclusion

Firms that announced a voluntary transition to remote work early in the Covid-19 pandemic experienced positive stock-market announcement effects and declines in risk relative to matched samples. The observable characteristics that best predicted work-from-home announcements include the measures of labor suitability to remote work of Dingel and Neiman (2020) and Papanikolaou and Schmidt (2022). Valuation improvements range from 3%–5% of market capitalization, and risk exposures fell according to market and labor-inflexibility factors as well as abnormal default probabilities. Work-from-home announcers also showed improved post-Covid operating performance relative to matches. We provide a simple real-options theory consistent with these findings, in which adaptation provides an observable signal of latent firm attributes observable to managers. Textual analysis of 10-Ks provides evidence of such latent traits, and improves explanation of work-from-home announcements beyond directly observable firm characteristics.

Crises and disasters play a key role in financial economics (e.g., Barro, 2006), and heightened uncertainty is a critical dimension of disasters, especially during the Covid-19 crisis (Baker et al., 2020, 2023). Pre-existing preparations by firms as well as actions in response to crisis can play important roles in risk mitigation. Our estimates provide direct evidence of the value of adaptation at the firm level, and in future work could be used to calibrate models of corporate investments in adaptability and disaster resilience.

Further, we develop firm-year, text-based measures that capture hard-to-quantify aspects of firm intangibles. We identify two latent factors that predict work-from-home decisions and also strongly relate to post-pandemic changes in language for all firms. By their associations with bigrams and training-library documents, one of these variables more directly relates to remote work, while the second is a broad-based measure of organizational intangibles. Expanding the analysis of such text-based measures of firm intangibles can be further pursued in future research.

⁴⁵ Specifically, we use the regressions (13) and (14) of Table 2 to obtain fitted values and residuals for each firm, which depend only on the respective observable controls. We then regress the pre-announcement LSA variables on the residuals, obtaining estimates $\hat{\beta}_{L,pre,AIC}$ and $\hat{\beta}_{L,pre,BIC}$ that capture the ability of the LSA components to capture unexplained variation from the residuals of the logit regressions based on observable variables. The first row shows averages by group of the fitted values from the regressions of logit-residuals on LSA components. The second row applies the pre-pandemic parameter estimates $\hat{\beta}_{L,pre,AIC}$ and $\hat{\beta}_{L,pre,BIC}$ to the post-pandemic data $LSA_{1,i,post}, \dots, LSA_{4,i,post}$, in each case giving the counterfactual of the impact on predicted probability of WFH if the post-pandemic textual data had been observed in the pre-pandemic period.

CRedit authorship contribution statement

Adlai Fisher: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jiří Knesl:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ryan C.Y. Lee:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors have no conflict of interest and nothing to disclose.

Appendix A. A simple model of announcement effects

We provide a simple model of announcement effects associated with corporate adaptation to crisis. Consider a baseline model where firms i are exposed to heterogeneous disaster risks fully captured by observable characteristics. There are three dates, $t \in \{0, 1, T\}$, where $T > 2$ is the terminal date, and risk-free rates at all dates and maturities are zero. Firm exposures to disaster risk are observable at $t = 0$, and denoted by θ_i^o . At $t = 1$, a disaster occurs with probability $p > 0$. The occurrence of disaster is observable at $t = 1$, but cash flow impacts are not yet known. All cash flows are realized at the terminal date T , with no intermediate cash flows. The timeline is:

t	event
0	firm disaster exposures θ_i^o are observable to markets
1	disaster occurs with probability $p > 0$
T	cash flows are realized

We specify the terminal cash flows as:

$$V_{iT} = \begin{cases} X & \text{if no disaster} \\ X - Z\theta_i^o & \text{if the disaster occurs,} \end{cases}$$

where X and Z are random variables, $Z > 0$. For convenience, all firms have unit beta with respect to X , but differ in their exposures to the disaster realization Z . Assume traded assets for X and Z with prices at $t = 1$ in the disaster state $P_{1,D}(X) = \delta_X \bar{X}$ and $P_{1,D}(Z) = \delta_Z \bar{Z}$, so that $0 < \delta_X, \delta_Z \leq 1$ are discount factors (i.e., the inverse of required returns) for X and Z . Firm prices at $t = 1$ in the disaster state are

$$P_{i1,D} = \delta_X \bar{X} - \theta_i^o \delta_Z \bar{Z}.$$

If disaster occurs, firms with greater disaster exposure will have (1) lower contemporaneous returns at $t = 1$, and (2) larger ongoing exposure and risk premia associated with the disaster cash-flow risks Z . Prior studies, including Papanikolaou and Schmidt (2022), have already emphasized the importance of *ex ante* observable firm characteristics, such as labor flexibility, in determining exposure to Covid-19 risk.

To accommodate adaptation, we allow an additional observable firm action at $t = 2$, after the realization that a disaster has occurred at $t = 1$, but before the terminal cash flows are realized at T . We model adaptation as a real option. The benefits of adaptation depend not only on the observable characteristics θ_i^o , but also on firm attributes θ_i^u that are not known to markets, but are understood by firm managers. We specifically assume that terminal firm cash flows are:

$$V_{iT,D} = X - Z\theta_i^o + Z a(\theta_i^o, \theta_i^u) b(\theta_i^o, \theta_i^u), \quad (\text{A.1})$$

where $a(\theta_i^o, \theta_i^u) \in \{0, 1\}$ is the firm action and $b(\theta_i^o, \theta_i^u)$ are the net benefits of adaptation. Under the assumption that managers maximize

terminal firm value under their own information set, optimization is straightforward: adapt ($a = 1$) whenever $b(\theta_i^o, \theta_i^u) > 0$; otherwise $a = 0$. Terminal values are then:

$$V_{iT,D} = X - Z\theta_i^o + Z b^+(\theta_i^o, \theta_i^u), \quad \text{where} \quad (\text{A.2})$$

$$b^+(\theta_i^o, \theta_i^u) \equiv \max \{b(\theta_i^o, \theta_i^u), 0\}. \quad (\text{A.3})$$

Market valuations at $t = 1$ and $t = 2$ depend on market information. At $t = 1$, observable firm characteristics θ_i^o are known. At $t = 2$, firm actions a_i are observed, which can convey information about the unobservable firm attributes θ_i^u and adaptation benefits, resulting in an announcement effect. To simplify pricing, assume that firms i are atomistic and that the distributions of θ_i^u conditional on observable θ_i^o are independent across firms and independent of the systematic risks X and Z . This implies that firm announcement risks are idiosyncratic, and expected cash flows can be priced at $t = 2$ using the same discount factors δ_X and δ_Z as at $t = 1$.⁴⁶

Managers have complete information about firm type and their intrinsic valuations at $t = 1, 2$ can be written:

$$V_{i1,D} = V_{i2,D} = \delta_X \bar{X} - \delta_Z \bar{Z} [\theta_i^o - b^+(\theta_i^o, \theta_i^u)]. \quad (\text{A.4})$$

The second term captures gross disaster exposures net of adaptation benefits. Let $\bar{a}(\theta^o) \equiv \mathbb{E}[a(\theta^o, \theta^u) | \theta^o]$ denote the expected announcement decision of a firm of observable type θ^o . Also let $\bar{b}(\theta^o) \equiv \mathbb{E}[b^+(\theta^o, \theta^u) | \theta^o, b^+(\theta^o, \theta^u) > 0]$. Market prices are:

$$P_{1,D}(\theta^o) \equiv \mathbb{E}(V_{1,D} | \theta^o) = \delta_X \bar{X} - \theta_{net}^o \delta_Z \bar{Z}, \quad (\text{A.5})$$

$$P_{2,D}(\theta^o, a) \equiv \mathbb{E}(V_{2,D} | \theta^o, a) = \delta_X \bar{X} - \theta_{net}^o \delta_Z \bar{Z} + [a - \bar{a}(\theta^o)] \delta_Z \bar{Z} \bar{b}(\theta^o), \quad (\text{A.6})$$

$$\theta_{net}^o \equiv \theta^o - \mathbb{E}[b^+(\theta^o, \theta^u) | \theta^o] = \theta^o - \bar{a}(\theta^o) \bar{b}(\theta^o). \quad (\text{A.7})$$

The price change $\Delta P \equiv P_2 - P_1$ is:

$$\Delta P(a; \theta^o) = [a - \bar{a}(\theta^o)] \delta_Z \bar{Z} \bar{b}(\theta^o). \quad (\text{A.8})$$

The announcement effect relative to a non-announcing match is the difference-in-difference:

$$\Delta P(a = 1; \theta^o) - \Delta P(a = 0; \theta^o) = \delta_Z \bar{Z} \bar{b}(\theta^o) > 0, \quad (\text{A.9})$$

and also reduces exposure to disaster risk in terminal cash flows.

The key assumption for a positive announcement effect, which appears suitable to Covid-19 work-from-home decisions, is asymmetric information between managers and financial markets about the net benefits of adaptation. A different model could assume asymmetric information about disaster risk exposure. If, in addition, all firms faced identical (or similar enough) adaptation costs, one could obtain a negative announcement effect.⁴⁷ While there certainly was uncertainty and potentially asymmetric information about firm exposures to Covid-19 risk, we believe asymmetric information about the ability of individual firms to adapt to the pandemic was crucial, particularly in the first months of the pandemic.

In our model, the action a_i fits within the broad definition of a “signal” given by Spence (1973), as an observable attribute within the control of the agent (p. 357).⁴⁸ Our model does not, however, involve “costly signaling” as in Spence (1973), which requires for a separating equilibrium that signal cost (e.g., acquiring an education) negatively

⁴⁶ Recall that the risk-free rate is zero, so if no information about X and Z enters markets from $t = 1$ to $t = 2$ then the same discount factors for X and Z apply in both periods.

⁴⁷ For example, replace the terminal cash flows (A.1) with $V_{iT,D} = X - Z[(\theta_i^o + \theta_i^u)(1 - b_a a(i)) - c_a a(i)]$, where $a(i)$ is the decision to adapt, b_a scales mitigation benefits of adaptation, and c_a is a known fixed cost of adaptation. In this case, firms adapt when their potential damages from the crisis are larger, which is partially private information to the firm. This alternative setup would produce a negative announcement effect from adaptation, and increase the market's perception of disaster exposure after adaptation, both counterfactual to our empirical findings.

correlates with productive capability (p. 358). Spence (2002) reviews more general models in which a signal can be costly to acquire or transmit, the signal can additionally enhance productivity, and the *ex ante* hidden attributes could become observable *ex post* and contribute to payoffs. In these more general environments, a separating equilibrium no longer requires the signaling cost to be negatively correlated with unobserved type, but more broadly the criterion becomes that the net benefits of issuing the signal should positively relate to the unseen attribute (p. 441). In our model, managers adapt ($a = 1$) when the net benefits of doing so are positive.⁴⁹

A.1. Unobservable actions and price efficiency

The model allows us to evaluate the benefit of communication, as distinct from corporate action. Consider an environment identical to the model above, but where the action a_i is unobservable to investors at time $t = 2$. With this modification, the managerial action a_i and terminal payoff V_{IT} are unchanged from the original model, but the price at $t = 2$ does not have any new information to incorporate and $P_{1D} = P_{2D}$ regardless of the manager's choice of a_i . Thus, long-term firm value is unaffected, but prices become less efficient at $t = 2$. The primary advantage of the observability of a_i is therefore, as in the dividend-signaling model of Bhattacharya (1980, p.3), to advance the timing of information transmittal from insiders to markets. Our model does not contain an explicit benefit from price efficiency, but a large literature shows a variety of ways in which more efficient prices can be beneficial to firms and shareholders (e.g., Fishman and Hagerty, 1989; Balakrishnan et al., 2014).

A.2. Mimicking firms and partial revelation

The key assumption of our model that rules out mimicry (i.e., low type beneficially imitating high type) is that each manager chooses a_i to maximize terminal firm value under their own information set, i.e., managers maximize $V_{IT,D}$. Because of this assumption, market updating of the price $P_{2,D}(\theta_i^0, a_i)$ upon seeing a_i does not feed back into the manager's choice of a_i . The manager focuses on long-run value, and uses a_i only to maximize long-run value, not to manipulate the short-term stock price.

To consider mimicking, we follow Fisher and Heinkel (2008), who model unobserved heterogeneity in managerial focus on short-term versus long-term payoffs.⁵⁰ We consider the simplest possible extension of our model where a fraction $0 < \alpha < 1$ of managers are *short-term* managers whose objective is solely to maximize the short-term stock price

⁴⁸ Spence distinguishing among observable attributes. Some are unalterable (what he describes as “indices,” giving examples such as race, sex, and age), corresponding to the *ex ante* characteristics θ_i^0 of our model. Spence reserves use of the word “signal” for an observable attribute that is within the control of the agent (p. 357). In Spence's terminology, the observable action a of our model is a signal. Spence's distinction between “indices” and “signals” is identical to the distinction we draw between “*ex ante* characteristics” and “actions”. Both terminologies split observable traits into those that are outside the control of the decision maker, and those that are controlled by the decision maker, because this is the essential distinction for determining decision-making and Bayesian updating in an environment of asymmetric information.

⁴⁹ Spence (2002) also distinguishes between equilibria that are inefficient, due to signaling that has no productive benefit, and equilibria that are efficient (or “non-dissipative,” e.g., Bhattacharya (1980), Heinkel (1982)). The signals in our model are non-dissipative since managers maximize expected fundamental value.

⁵⁰ In their model, long-run managers report firm value truthfully to build reputation, while short-term managers always overstate to boost short-term stock price. They develop a single-period version of this model in which the value of reputation is exogenous, and show that the value of reputation can be supported endogenously in an infinite horizon model.

$P_{2,D}(\theta_i^0, a_i)$. We assume the trait of being a short-term versus long-term manager to be unobservable to markets, uncorrelated with the benefits $b_a(\theta_i^0, \theta_i^u)$ of adaptation, and embedded in the unobservable type θ_i^u . To facilitate mimicking, we distinguish between the announcement of an action a_i^0 and the action itself which we continue to denote a_i , but is now unobservable at $t = 2$.⁵¹ For simplicity, we assume that long-term managers always report truthfully $a_i^0 = a_i$, which could be supported endogenously by a variety of reputational, compensation, or other truth-telling mechanisms. We also assume that short-term managers continue to take value-maximizing actions,⁵² but endogenously always claim to adapt in order to boost their short-term stock price.

In this environment, prices are given by:

$$P_{2,D}(\theta^0, a^0) \equiv \mathbb{E}(V_{2,D} | \theta^0, a^0) = \delta_X \bar{X} - \theta_{net}^0 \delta_Z \bar{Z} + [\bar{a}(\theta^0, a^0) - \bar{a}(\theta^0)] \delta_Z \bar{Z} \bar{b}(\theta^0), \quad (\text{A.10})$$

where

$$\bar{a}(\theta^0, a^0 = 1) \equiv \mathbb{E}[a = 1 | \theta^0, a^0 = 1] = \frac{\bar{a}(\theta^0)}{\bar{a}(\theta^0) + \alpha(1 - \bar{a}(\theta^0))} < 1 \quad (\text{A.11})$$

$$\bar{a}(\theta^0, a^0 = 0) \equiv \mathbb{E}[a = 1 | \theta^0, a^0 = 0] = 0, \quad (\text{A.12})$$

are the conditional probabilities that the firm adapts given the announcement. In (A.11), the conditional probability that the firm actually adapts following an announcement of adaptation is less than one, due to mimicking. In (A.12), managers know that if a firm does not announce adaptation, it is not an adaptable type.

The announcement effect is the difference in difference

$$\Delta P(a^0 = 1; \theta^0) - \Delta P(a^0 = 0; \theta^0) = \Delta \bar{a}(\theta^0) \delta_Z \bar{Z} \bar{b}(\theta^0) > 0, \quad (\text{A.13})$$

where

$$0 < \Delta \bar{a}(\theta^0) \equiv \bar{a}(\theta^0, a^0 = 1) - \bar{a}(\theta^0, a^0 = 0) < 1. \quad (\text{A.14})$$

By (A.14), the announcement effect is positive but smaller than the announcement effect (A.9) in the original model. Attenuation follows from the reduction in signal quality due to the mimicking short-run managers.

This extension shows that our empirical methods are robust to some degree of mimicking, overstatement, or error in our classification of work-from home announcements. In particular, Eqs. (A.11)–(A.14) are general and also apply to the case where some firms that adapt do not announce or are misclassified (i.e., $a_i = 1$ and $a_i^0 = 0$, or Type II versus Type I error). As long as conditional beliefs satisfy $0 < \Delta \bar{a}(\theta^0) < 1$, then (A.13) holds and the announcement effect is positive but attenuated compared to the base case where the announcement is fully separating.

A.3. Signal versus action: Leveraging the announcement effect

Given (A.1), our base model implies that the announcement effect is completely driven by the benefits b_i produced by the action a_i . Literally interpreted, the 3%–5% valuation impact we find empirically would solely relate to the direct benefits and value produced by the work-from-home decision. We can leverage the impact of the action a_i by broadening the specification of terminal cash flows:

$$V_{IT,D} = X - Z\theta_i^0 + Z\alpha(\theta_i^0, \theta_i^u)b(\theta_i^0, \theta_i^u) + Zc(\theta_i^0, \theta_i^u), \quad (\text{A.15})$$

where the final term captures, through $c(\theta_i^0, \theta_i^u)$, some complementary benefits of the latent type θ_i^u in the disaster state that do not depend on

⁵¹ We can alternatively consider a variant where the announcement and action remain tied and observable, and mimicking requires the short-term manager to take an action that harms long-run value, but we omit this alternative for brevity.

⁵² They are indifferent to the long-run so this assumption is a convenience, but could be supported as a strict preference with small weight on the long run.

the action a_i . In particular, we assume that, conditional on any observed θ_i^o , the density of $c(\theta_i^o, \theta_i^u)$ is stochastically monotone and increasing in $b(\theta_i^o, \theta_i^u)$,⁵³ which guarantees:

$$\Delta \bar{c}(\theta_i^o, \theta_i^u) \equiv \mathbb{E}[c(\theta_i^o, \theta_i^u) | a(\theta_i^o, \theta_i^u) = 1] - \mathbb{E}[c(\theta_i^o, \theta_i^u) | a(\theta_i^o, \theta_i^u) = 0], \quad (\text{A.16})$$

$$= \mathbb{E}[c(\theta_i^o, \theta_i^u) | b(\theta_i^o, \theta_i^u) > 0] - \mathbb{E}[c(\theta_i^o, \theta_i^u) | b(\theta_i^o, \theta_i^u) \leq 0] \geq 0. \quad (\text{A.17})$$

For any θ_i^o , the conditional expectation of complementary benefits $c(\theta_i^o, \theta_i^u)$ is larger when the firm adapts ($a_i = 1$) than when it does not ($a_i = 0$). This assumption captures the idea that firms which adapted to work-from-home might have had other latent advantages during the crisis. For example, client communications, technology, corporate culture, disaster preparedness, and adaptability could be more generalizable latent firm aspects correlated with ability to transition to work-from-home, and produce broader business benefits. In other words, a_i can act as a signal for larger benefits c_i , even though the choice of a_i has no impact on whether c_i is realized.

Given the previous assumptions of manager incentives in our model, the addition of complementary benefits $c(\theta_i^o, \theta_i^u)$ has no impact on managers' choice of a_i , regardless of the particular specification. Further allowing that announcements a_i^o are imperfect signals of a_i , as in the previous Appendix A.2, the announcement effect becomes:⁵⁴

$$\Delta P(a^o = 1; \theta^o) - \Delta P(a^o = 0; \theta^o) = \Delta \bar{a}(\theta^o) \delta_Z \bar{Z} [\bar{b}(\theta^o) + \Delta \bar{c}(\theta_i^o, \theta_i^u)] > 0. \quad (\text{A.18})$$

Relative to (A.13), which has no complementary benefits, the announcement effect (A.18) is multiplied by $1 + \Delta \bar{c}(\theta_i^o, \theta_i^u) / \bar{b}(\theta^o) \geq 1$. When adaptation provides broader information about latent advantages, the announcement effect is amplified.

Appendix B. Matching methodology

We match by propensity score using the BIC (score 1) and AIC (score 2) selected specifications of regression (1), corresponding to the final two columns of Table 2.⁵⁵ We match with replacement. For WFH firm i , we calculate the absolute propensity-score difference for all potential matches j , i.e., $|p_i - p_j|$, restricting matches to firms within the same 2-digit NAICS and size quintile that have not previously announced work-from-home. For nine WFH observations from insufficiently populated 2-digit NAICS, we drop the industry match requirement. We select the five closest matches and form an equal-weighted benchmark. If a match later announces, we replace it with the next closest available match from the original list. To obtain matches for WFH firms with missing PS or employees, we use propensity scores calculated from DN and $LnME$ (BIC), and Profitability (AIC). On average, the first and fifth matches are within 0.6 and 2.5% of the WFH firm propensity score, as further detailed in the Internet Appendix.

We additionally use benchmarks formed from quintiles by size, industry-size, and PS-size, equal-weighted daily. For size, we use all stocks in the same quintile. For industry-size, we use the intersection of stocks in the same NAICS 2-digit industry and independently-sorted size quintile. For PS-size, we independently sort quintiles for size and

⁵³ That is, we assume for all c^* and $b_2 \geq b_1$,

$$\mathbb{P}[c(\theta_i^o, \theta_i^u) \geq c^* | \theta_i^o, b(\theta_i^o, \theta_i^u) = b_2] \geq \mathbb{P}[c(\theta_i^o, \theta_i^u) \geq c^* | \theta_i^o, b(\theta_i^o, \theta_i^u) = b_1].$$

Equivalently, the density of c conditional on b_2 stochastically dominates the density of c conditional on b_1 whenever $b_2 \geq b_1$ (Siburg and Strothmann, 2021). For example, if b and c have a bivariate normal distribution conditional on θ^o , then $Cov[b(\theta_i^o, \theta_i^u), c(\theta_i^o, \theta_i^u) | \theta_i^o] > 0$ guarantees the condition holds.

⁵⁴ The period one price (A.5) must account for the change $\theta_{net}^o = \theta^o - \bar{a}(\theta^o) \bar{b}(\theta^o) - \mathbb{E}[c(\theta_i^o, \theta_i^u) | \theta^o]$.

⁵⁵ Propensity score matching (Rosenbaum and Rubin, 1983; Heckman et al., 1998) is common in finance (e.g., Deng et al., 2013; Gao et al., 2013; Bennett et al., 2020; Brown and Huang, 2020)

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.

Appendix C. Event studies and scaled abnormal returns

Consider a set of N firm-events indexed by i , occurring at dates τ_i . Given an announcement window of W days, abnormal returns on calendar date t within the announcement window are calculated as: $AR_{it} = R_{it} - \hat{\beta}_i' x_t$, where x_t is a vector of explanatory variables such as the market return or other factors, including a constant, and $\hat{\beta}_i$ is a firm-specific parameter vector estimated in a pre-announcement estimation window with a matrix of explanatory variables denoted X (e.g., MacKinlay, 1997). Scaled abnormal returns (Patell, 1976) are defined by

$$A_{it} = \frac{AR_{it}}{\hat{\sigma}_i \sqrt{1 + d_i}}, \quad (\text{C.1})$$

where $\hat{\sigma}_i$ is the estimated residual variance and $d_i = x_i' (X'X)^{-1} x_i$. The associated t -statistic is $t_A = \bar{A} / \sqrt{\text{var}(\bar{A})}$. If the scaled abnormal returns are independent, the variance of their mean is estimated by $1/N$ times the sample variance. Kolar and Pynnönen (2010) ("KP") address cross-sectional dependence induced by clustering of events in calendar time, focusing on the special case where all events occur on a single day.⁵⁶ Their key insight is that because scaled abnormal returns have the same variance σ_A^2 , the variance of the t -statistic is a simple function of the average correlation $\bar{\rho}$ between scaled abnormal returns, i.e., $\text{var}(\bar{A}) = \sigma_A^2(1 + (n-1)\bar{\rho})/n$. They discuss that common multi-day event windows can use a similar test statistic if return correlations do not change with the return-measurement window, i.e., if single-day return cross-correlations are identical to multi-day return cross-correlations,⁵⁷ a condition they observe is satisfied when returns are serially independent (p. 4003).

Deviations from serial independence, including autocorrelations and cross-serial correlations, are well established (e.g., Lo and MacKinlay, 1990; Chan, 1993; Cohen and Frazzini, 2008; Boguth et al., 2016). We observe that the KP methodology accommodates serial correlations by applying their logic for correlations to autocorrelations and cross-serial correlations. Let $\tau_i^e = \tau_i + W - 1$ denote the end date of the i th announcement window. The average scaled abnormal return is:

$$\bar{A} = \frac{1}{N \times W} \sum_{i=1}^N \sum_{t=\tau_i}^{\tau_i^e} A_{i,t}. \quad (\text{C.2})$$

The variance of the average scaled abnormal return is:

$$\begin{aligned} \text{var}(\bar{A}) &= \text{var}\left(\frac{1}{NW} \sum_{i=1}^N \sum_{t=\tau_i}^{\tau_i^e} A_{i,t}\right) \\ &= \left(\frac{1}{NW}\right)^2 \sum_{i=1}^N \sum_{j=1}^N \sum_{t_1=\tau_i}^{\tau_i^e} \sum_{t_2=\tau_j}^{\tau_j^e} \text{cov}(A_{i,t_1}, A_{j,t_2}) \\ &= \left(\frac{1}{NW}\right)^2 \left[\sum_{i=1}^N \sum_{t=\tau_i}^{\tau_i^e} \text{var}(A_{i,t}) + \sum_{i=1}^N \sum_{j=1}^N \sum_{\substack{t_1=\tau_i \\ t_2 \neq t_1}}^{\tau_i^e} \sum_{\substack{t_2=\tau_j \\ t_2 \neq t_1}}^{\tau_j^e} \text{cov}(A_{i,t_1}, A_{j,t_2}) \right] \quad (\text{C.3}) \end{aligned}$$

Inside the square brackets, the first term captures the standard variance of the scaled abnormal returns, the second term captures the covariances that are the focus of KP, and the third and fourth terms

⁵⁶ The write, "We consider the problem induced by cross-correlation in the simple setting of testing for zero-mean abnormal returns with a t -ratio on a single common event day" (p. 3999).

⁵⁷ See also Kolar et al. (2018).

are respectively due to autocorrelations and cross-serial correlations. Focusing on serial correlations up to lag $W - 1$, the variance simplifies to:

$$\text{var}(\bar{A}) = \left(\frac{\sigma_A}{NW}\right)^2 \left[NW + \sum_{i=1}^N \sum_{j=i+1}^N 2\rho_{i,j} \max(W - |\tau_i - \tau_j|, 0) + \sum_{i=1}^N \sum_{k=1}^{W-1} 2\rho_{i,i,k} (W - k) + \sum_{i=1}^N \sum_{j \neq i}^N \sum_{t_1=\tau_i}^{\tau_i^e} \sum_{t_2=\tau_j}^{\tau_j^e} \rho_{i,j,t_1-t_2} \right], \quad (\text{C.4})$$

where $\rho_{i,j}$, $\rho_{i,i,k}$, and $\rho_{i,j,k}$, are respectively contemporaneous correlations, autocorrelations of lag k , and cross-serial correlations of lag k . We estimate $\hat{\rho}_i$ for each firm in the sixty trading days ending before the ten-day pre-announcement window. Consistent with KP, we estimate the correlations $\rho_{i,j}$, $\rho_{i,i,k}$, and $\rho_{i,j,k}$ in the estimation period, and σ_A^2 permits increased announcement-window variance. We further incorporate firm-specific benchmarking by allowing the returns R_{it} to be the returns in excess of any of the matching methods discussed in Appendix B.

Appendix D. ESG scores

We use ESG data from Refinitiv (now LSEG), which has the broadest coverage of our sample, but still contains 657 missing observations. To accommodate missing values, we use an indicator $\mathbb{1}_{ESG}$ equal to one for non-missing observations and zero otherwise, combined with zero-filling of missing values of ESG . Using the 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 observations. The indicator uses an additional degree of freedom that the BIC and AIC account for.

Appendix E. Speed of price adjustment

To obtain the regressions from Table 7, Panel B, first refine regression (5) by breaking the 0–4 event window into periods of days 0–1 and 2–4:

$$R_{it} - R_{it}^{\text{benchmark}} = \text{const} + \beta_{mkt} R_{mkt,t} + a_{BB,01} BB_{01,it} + a_{WS,01} WS_{01,it} + a_{BB,24} BB_{24,it} + a_{WS,24} WS_{24,it} + a_{BB,59} BB_{59,it} + a_{WS,59} WS_{59,it} + \epsilon_{it}. \quad (\text{E.1})$$

Using the transformations $a_{04} \equiv 0.4a_{01} + 0.6a_{24}$ and $\phi \equiv a_{01}/a_{04}$, we obtain the regression estimated in Table 7, Panel B:

$$R_{it} - R_{it}^{\text{bench}} = \text{const} + \beta_{mkt} R_{mkt,t} + a_{BB,04} BB_{04,it} + a_{WS,04} WS_{04,it} + (\phi_{BB} - 1)a_{BB,04} BB_{04,it} (BB_{01} - (2/3)BB_{24}) + (\phi_{WS} - 1)a_{WS,04} WS_{04,it} (WS_{01} - (2/3)WS_{24}) + a_{BB,59} BB_{59,it} + a_{WS,59} WS_{59,it} + \epsilon_{it}. \quad (\text{E.2})$$

Appendix F. Operating performance regressions

To obtain marginal effects in the operating performance regressions, we reorganize (6):

$$Y_{it} = \alpha + \beta_0 \times (WFH_i + Match_i) + \beta_1^m \times Match_i + \beta_2 \times Covid_i + \beta_3 \times WFH_i \times Covid_i + \beta_4 \times Match_i \times Covid_i + LnME_{it} + FE_i^{\text{ind}} + FE_i^Q + \epsilon_{it}. \quad (\text{F.1})$$

This regression has the same fitted values and R^2 as (6), and all coefficients are identical except that β_1^m is the marginal effect of matches relative to work-from-home, i.e., the opposite of the coefficients ($WFH - Match$) reported in row 2 of Table 8. These marginal effects are of interest because they show that the operating performances of

work-from-home firms and their matches are indistinguishable in the pre-Covid period.

Similarly, to obtain the marginal effects on the interaction terms shown in the last row of Table 8, we run the equivalent regression:

$$Y_{it} = \alpha + \beta_0 \times WFH_i + \beta_1 \times Match_i + \beta_2 \times Covid_i + \beta_3^m \times WFH_i \times Covid_i + \beta_4 \times (WFH_i + Match_i) \times Covid_i + LnME_{it} + FE_i^{\text{ind}} + FE_i^Q + \epsilon_{it}. \quad (\text{F.2})$$

The coefficient β_3^m captures the marginal Covid-interaction effect of work-from-home firms relative to matches, shown in the last row of the table.

Appendix G. Textual analysis

We download pre-cleaned 10Ks from Loughran and McDonald: <https://sraf.nd.edu/sec-edgar-data/cleaned-10x-files/>. We define fiscal years as in Compustat, and treat fiscal years ending between June of year t and May of year $t+1$ as year t , aligning with our timing for Compustat variables. From the 10-K, we select Item 1, typically named “Business,” including Item 1 A, “Risk Factors”.⁵⁸ For each firm, we combine the texts from Item 1 from the available 10-Ks from years 2016–2018 into a single document. The 10-Ks from 2020 are maintained as separate documents.

Additionally, we lowercase all characters, delete duplicate spaces, and keep only alphabetical and word-separating characters. We tokenize using “word_tokenize” from the Python nltk package. We singularize the tokenized text using the function “singular_noun” from the package “inflect”. We manually combine “work from home” to “work fromhome” and construct bigrams. We clean the bigrams, removing those containing a stop word or a major U.S. city, U.S. state, country, month, or company name, and a small selection of other common words. We calculate the tf-idf matrix using the function TfidfVectorizer from the scikit package.

G.1. Training library

We use a training library of prominent business texts published before the pandemic, addressing areas relevant to work-from-home adaptation in a crisis. The specific texts cover remote work (Fried and Hansson, 2013); business resilience (Engemann and Henderson, 2014); digital transformation (Westerman et al., 2014); and business change and adaptation (Kotter, 2012). The texts provide a structured and thematically distinct basis for constructing our LSA topic model. We treat each of the forty-nine book chapters as a separate document, cleaned from the book and chapter titles. We clean the texts following the steps above, remove bigrams related to the books’ authors, limit the dictionary to bigrams contained in at least three documents, and obtain a tf-idf matrix for the complete set of documents in the training library.

G.2. Latent semantic analysis

We construct topics from the training library using Latent Semantic Analysis (LSA) with singular value decomposition (Deerwester et al., 1990). Let X_0 denote the $m \times n_0$ tf-idf matrix of the training library, where m is the number of bigrams and n_0 is the number of documents. The rank- k approximation to the original tf-idf matrix is:

$$\hat{X}_{0k} = B_k \Sigma_k D_{0k}' \quad (\text{G.1})$$

where the $m \times k$ matrix B_k assigns the m bigrams weights, which may be positive or negative, in the k topics, Σ_k is a diagonal matrix of

⁵⁸ Selecting the relevant sections of the 10-Ks depending on the purpose of the analysis is common, e.g., Israelsen and Yonker (2017), Lopez-Lira (2023) select Item 1 A for examining human capital and riskiness, Eisdorfer et al. (2022) select the whole Section 1 for examining competition.

positive singular values, which reflect topic importance, and D'_{0k} is a $k \times n_0$ matrix that captures topic loadings across the documents. The LSA representation of the training documents reported in Table 9 is given by $L_{0k} = D_{0k} \Sigma_k = X'_0 B_k$. In Panel A of Table 9, we report columnwise averages of the rows of L_{0k} that correspond to each book. In Panel B, we report the number of chapters of each book with maximum similarity to each topic. For this calculation, note that the identity matrix I_k has rows (and columns) that can be thought of as idealized documents, each having a loading of 1 on an individual topic and a zero for all other topics, in the same normalized document-topic space of D_{0k} (recalling that the singular value decomposition imposes $D'_{0k} D_{0k} = B'_k B_k = I_k$). Let d_i denote the i th row of D_{0k} . The cosine similarity of document i with each idealized topic-document is given by the elements of $d_i I_k / (d_i d'_i)^{(1/2)}$, implying that the maximum cosine similarity of a document with a topic is given by selecting the maximum element of d_i . Panel B of Table 9 therefore obtains the maximum cosine similarity of each document with each topic by selecting for each document (row) the column of D_{0k} with the largest value.

We use the same semantic space of the training library to calculate the topic loadings of the 10-K filings. Let X_F denote the $m \times n_F$ matrix of tf-idf scores for the bigrams of 10-K filings. The representation of the filings in the k -dimensional semantic space is:

$$D_{Fk} = X'_F B_k \Sigma_k^{-1}, \quad (G.2)$$

which has dimension $n_F \times k$. The LSA scores used in our topic analysis, denoted $LSA_1, LSA_2, \dots, LSA_k$, are given by the columns of $L_k = D_{Fk} \Sigma_k$.

Consider the logit regression (1) of work-from-home announcement indicators on firm characteristics. Table 10 includes as explanatory variables in these regressions the vector of pre-announcement 10-K scores on the LSA topics

$$\ell_i = [LSA_{1i}, LSA_{2i}, LSA_{3i}, LSA_{4i}], \quad (G.3)$$

producing the 1×4 vector of estimates $\hat{\beta}_L$.⁵⁹ Textual information from 10-Ks thereby contributes the total fitted value $\hat{f}_i = \hat{\beta}_L \ell_i'$ to the logit regression for firm i .

We decompose the contributions of the textual LSA variables into the effects of individual bigrams. Define

$$\hat{\eta} = B_k \hat{\beta}_L', \quad (G.4)$$

which is an $m \times 1$ vector that captures the effects of individual bigrams on the text-related fitted components $\hat{f}_i$ from the remote-work logit regression. Consider bigram $j \in \{1, \dots, m\}$ for which firm i has tf-idf value given by element (j, i) of the matrix X_F , denoted $x_{j,i}$. A one unit increase in the tf-idf value of $x_{j,i}$ produces an $\hat{\eta}_j$ increase in the estimated text-related component $\hat{f}_i$ in the remote-work logit regression. Further, the total effect $\hat{\eta}_j$ can be decomposed according to (G.4) into four components:

$$\hat{\eta}_j = \sum_{\kappa=1}^k b_{j,\kappa} \hat{\beta}_{L,\kappa}, \quad (G.5)$$

where $b_{j,\kappa}$ is element (j, κ) of B_k , giving the weight of bigram j in LSA component κ , and $\hat{\beta}_{L,\kappa}$ is the estimated coefficient on LSA_κ from the remote-work logit regression. In Table 11, we report in the first column $\hat{\eta}_j$, the estimated total effect of bigram j on the remote work decision, and in each of the four subsequent columns report the decomposition of the sum on the right-hand-side of (G.5) into each of the LSA topics.

Table 12, Panel A, is based on fitted probabilities $\hat{p}_{i,pre}$ from regression (5) of Table 10 and the counterfactual probabilities $\hat{p}_{i,post}$ obtained

by applying the regression (5) estimates $\hat{\beta}_{L,pre}$ to the post-pandemic data $\ell_{i,post}$. To account for estimation error in $\hat{\beta}_L$, the standard errors and p -values in Table 12 are obtained by a bootstrap procedure. We randomly draw with replacement 1000 samples of the same size as the original data, and for each sample calculate the group averages and differences in Table 12. The statistics reported in Table 12 are the means, standard deviations, and p -values for the test of a difference greater than zero from the bootstrap samples. Panels B and C of Table 12 are based on residuals from regressions (13) and (14) of Table 2 (see footnote 45), and use a similar bootstrap procedure to account for estimation error.

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⁵⁹ The coefficients reported in Table 10 correspond to an otherwise identical regression where each LSA variable has been standardized prior to estimation. In the remaining discussion and in Table 11 we use variables that have not been standardized, which impacts only scaling.

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