Essays in Asset Pricing

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To L S A,
my love, my life, my light.

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Chapter 1

Introduction

This thesis consists of three essays investigating the asset pricing implications of technologies and corporate adaptation. The first essay examines the role and impact of technology stocks on the value premium. The second essay shows the value and risk implications of corporate adaptation to the Covid crisis based on information shocks from voluntary work-from-home announcements. The third essay studies firms' stock and operational performances in adopting new technologies.

In Chapter 2 (the first essay), I show that the rise of technology stocks explains the recent decline in the value premium. The value premium is one of the most studied and robust cross-sectional phenomena in the asset pricing literature. However, recent studies document that the value premium has become low and disappearing for the past 30 years (e.g., Fama and French (2021) and Linnainmaa and Roberts (2018)). These findings have sparked a debate on why the value premium is gone in the recent data. At the core of this phenomenon, it is unclear why the disappearance occurs.

In this essay, I show that the decline in the value premium can be attributed to an industrial composition effect of technology stocks. To examine the role of technology stocks, I decompose the value premium into tech and non-tech components and quantify that the tech component explains 45% of the time variation in the HML and materially reduces the HML return. I argue that the misclassification of tech stocks is the main channel to reduce the HML return because valuation ratios are not comparable across tech and non-tech industries. Tech stocks are characterized by high valuations driven by innovation-driven productivity and cash flow growth.[1] Given the tech stocks' nature of high valuation (i.e., low B/M ratios), using standard NYSE breakpoints to sort stocks can disproportionately allocate tech stocks to the growth portfolio. The rapid growth in the tech market capitalization has only exacerbated this classification effect for the past 30 years, leading to a sizeable decline in the value premium in the recent data.

Although tech stocks have demonstrated a styled fact about high valuation, a natural solution to meaningfully classifying tech stocks is to compare a tech (non-tech) stock with its tech (non-tech) peers. In practice, the idea is as simple as sorting tech (non-tech) stocks within the tech (non-tech) industry. By using tech (non-tech) breakpoints, tech (non-tech) stocks can be meaningfully and proportionally benchmarked as value or growth stocks relative to their tech (nontech) peers. Accordingly, I show that the value premium through this tech-adjusted approach triples from 0.17% (t= 1.00) to 0.56% (t= 4.18) per month during the post-1991 period.[2] The value premium is also shown to be large and robust among both tech stocks (0.88%, t= 5.11) and non-tech stocks (0.49%, t= 3.65). Overall, the results suggest that tech (non-tech) breakpoints are meaningful benchmarks in forming portfolios and capturing the value effect.

[1]See Romer (1990), Kung and Schmid (2015) and Kogan et al. (2017).

[2]The main results are robust to using alternative tech classifications, risk-adjusted returns, equal-weighted portfolios, the post-tech-bubble sample, and the global setting.

Given that the tech composition plays a vital role in identifying the value effect post-1991, an empirical asset pricing model incorporating this tech-adjusted value factor (called HML–T) is expected to capture variation in asset returns more effectively. Building on the classic Fama and French 1993 three-factor model (called FF3), I propose to substitute HML with HML–T in a new three-factor model (called FF3Tech) to evaluate the risk-adjusted performance of stock anomalies. I hypothesize that the alpha of the FF3Tech model becomes smaller than that of the FF3 model when anomalies are regressed on the factors. I examine 153 stock anomalies from Jensen et al. (2022) and find that the average of anomaly alphas shrinks by 18% from 25 bps per month in the FF3 model to 20 bps in the FF3Tech model. The change of –5 bps is statistically significant (t= –3.41). Furthermore, the number of significant anomaly alphas at the 1% level is reduced by 21%. In other words, one-fifth of the anomalies can be explained by the new model and become no longer significant. In summary, the alphas of stock anomalies are found to be lower and less significant in the FF3Tech model, suggesting that the FF3Tech model can more effectively explain the variation in anomaly returns.

This chapter contributes to three strands of literature. First, this essay contributes to the classic asset pricing literature that investigates the value premium (e.g., Fama and French (1992, 1993, 2006, 2017), Davis, Fama, and French (2000), Asness, Moskowitz, and Pedersen (2013)) and its recent undesirable performance (Linnainmaa and Roberts (2018) and Fama and French (2021)). To understand the rationales, I link the value premium to the recent trend of technological developments and the predominance of technology stocks. Distinguished from other recent papers that propose "new" measures for capturing the value effect (e.g., Gonçalves and Leonard (2023), Arnott et al. (2021), Eisfeldt, Kim, and Papanikolaou (2021), Lev and Srivastava (2021)), this study keeps the properties of the standard B/M but provides a straightforward solution to recovering the value premium by addressing the composition of tech stocks as a new economy. I show that the standard B/M continues to capture the value effect if industry characteristics are taken into account.

Second, this essay is complementary to, but distinct from, the emerging literature on the asset pricing implications of innovations on stock returns (e.g., Hirshleifer, Hsu, and Li (2013, 2018), Kogan and Papanikolaou (2013, 2014, 2019)).[3] In this respect, I focus on tech stocks and their industry composition effect on the factor performance. Finally, this essay highlights the unique industry characteristics of technology stocks as a new economy and adds evidence to industry-peer-based valuations in accounting (e.g., Alford (1992), Bhojraj and Lee (2002)) and IPO literature (e.g., Kim and Ritter (1999)).

In Chapter 3 (the second essay, joint with Adlai Fisher and Jiri Knesl), we study corporations' ability to adapt to the Covid crisis and identify the financial-market value of corporate adaptation. Corporate adaptation – also called flexibility or resilience – has long been studied as a source of value-creation and risk-mitigation in literature (e.g., Stigler (1939), Pindyck (1982), Trigeorgis (1996), Graham and Harvey (2001), Reinartz and Schmid (2016), and Gu, Hackbarth, and Johnson (2018)). Adaption in bad times is particularly essential. The Covid-19 pandemic crystalized the importance of corporate adaptation and provided an ideal natural setting to examine how firms adapt to a new social-distancing condition through a work-from-home transition.[4]

[3]See also Chan, Lakonishok, and Sougiannis (2001), Pástor and Veronesi (2006, 2009), Cohen, Diether, and Malloy (2013), and Hsu, Wang, and Yang (2022) for the effects of innovations and technologies on stocks. For relations between technologies and the aggregate stock market, see Greenwood and Jovanovic (1999), Hobijn and Jovanovic (2001), and Hsu (2009).

[4]See also Papanikolaou and Schmidt (2022), Pagano, Wagner, and Zechner (2021), and Barry et al. (2022)). Surveys indicate that remote-work transitions were more successful than initially anticipated (Barrero, Bloom, and Davis (2021)) and remote-work technology diffused quickly through the economy (Bick, Blandin, and Mertens (2021)).

Early in the Covid pandemic, we scraped corporate websites and used textual analysis methodology to capture the work-from-home firms. Using voluntary work-from-home announcements as an information shock, we show that market reactions provide new information about the value and risk implications of corporate adaptation. During the crisis, some firms promptly announced a work-from-home transition before mandatory lockdowns. We find that the financial market values the action of corporate adaptation. Specifically, our event studies show up to 5 percent abnormal returns over five days following the work-from-home announcement. We also find significant declines in risk exposure relative to the matched firms. Overall, this essay provides new evidence that financial markets perceived higher value and less risk for firms adapting to Covid by voluntarily announcing a work-from-home transition.

Our empirical identification strategy is new to the literature on Covid-19 resilience precisely and corporate flexibility more generally. We not only use cross-sectional comparisons as in previous studies (e.g., Papanikolaou and Schmidt (2022), Dingel and Neiman (2020), Novy-Marx (2011), Campello, Graham, and Harvey (2010)), but uniquely exploit the information-shock nature of announcements of corporate adaptation. Our event study uses matching and other control methods to compare firms with *similar observable characteristics*, but *different observable actions*. In our case, the observable action is the voluntary announcement of a work-from-home policy. In short windows immediately following a work-from-home announcement, the value of announcers increased, and risk decreased, relative to controls. We thus add to prior literature investigating corporate flexibility or resilience as a firm characteristic by showing positive market reaction both statistically and economically to an observable corporate action – adaptation to work-from-home.

This chapter contributes to the literature in three main aspects. First, this essay contributes to the corporate flexibility literature (e.g., Stigler (1939), Pindyck (1982), Trigeorgis (1996), Graham and Harvey (2001)), particularly during Covid crisis (e.g., Barry et al. (2022), Papanikolaou and Schmidt (2022), Fahlenbrach, Rageth, and Stulz (2021), Au, Dong, and Tremblay (2021)), by providing new evidence about the financial-market value of corporate adaptation. We confirm the significance of workplace flexibility to financial-market pricing. Second, prior Covid research addresses the pre-existing characteristics that made some firms more or less "immune" to the effects of Covid-19 (e.g., Ding et al. (2021), Li et al. (2021), Albuquerque et al. (2020)). We add to the Covid literature by showing market response to announcements of corporate *actions*. Work-from-home announcements demonstrate corporate adaptation, distinct from assessments of *ex ante* corporate susceptibility. Finally, we methodologically extend the single-day clustered event-study approach of Kolari and Pynnönen (2010) to imperfect clustering and multi-day event windows to account for cross-serial correlations.

In Chapter 4 (the third essay), I study the firm performance in adopting new technologies in the retail industry. The industrial revolution has transformed the production and operation of manufacturing firms over the last century. In contrast, retail firms have benefited little from the revolution and experienced a bottleneck in productivity growth. Until recently, IT-based technologies have been argued to be pivotal in helping the service/retail industry scale up production and productivity across locations (Hsieh and Rossi-Hansberg (2023)). In this essay, I build on Hsieh and Rossi-Hansberg (2023) and ask what technologies the retail firms implement in the wave of the industrial revolution and how much the retail firms grow by adopting new technologies.

To identify the new technologies, I use a textual analysis methodology to capture new technologies at the firm level. Building on the innovative work of Bloom et al. (2021) that creates a list of 221 bigrams of disruptive technologies,[5] I examine the text of these 221 bigrams in annual reports (10-Ks) and document that the new technologies the retail firms most often use are “search engine,” “cloud computing,” “social networking,” and “mobile commerce” in 2019. These technologies are directly linked to sales strategies that can facilitate retail firms to achieve greater production (i.e., sales). Moreover, the percentage of retail firms adopting at least one technology substantially increases from 15% in the early 2000s to almost 65% in 2019.

I examine how much growth a firm can gain by adopting new technologies. I assume that the first year of the technology disclosure in the 10-Ks marks the beginning of an event of technology adoption. Event studies show that firms experience an increase in sales and gross profit growth by 4 percentage points p.a. over three years following an adoption of new technologies. The stock performance also positively responds to technology adoptions by 8% p.a. over the three-year period. Overall, the results suggest that operational performance and stock return positively respond to the news about disruptive technologies that are the critical driver for a firm’s growth. This essay highlights the impact of new technologies on firm operations and performance.

This essay contributes to the vast literature on how technological changes affect the real economy (e.g., Caroli and Van Reenen (2001), Hobijn and Jovanovic (2001), Rosenberg and Trajtenberg (2004), Syverson (2017)) and, especially, the retail industry (e.g., Hortaçsu and

[5] Bloom et al. (2021) use a supervised approach through machine learning and human audits to generalize 221 bigrams associated with 29 disruptive technologies. One key advantage is that the language of the bigrams is classified by algorithm from technical terms into business terms used by investors and executives. Therefore, the bigrams provide a sound basis for textual analysis of the 10-Ks.

Syverson (2015), Gordon and Sayed (2020), Hsieh and Rossi-Hansberg (2023)). I implement a text-based approach based on the 10-Ks to capture new technologies at the firm level. In this respect, I directly respond to the call from Hsieh and Rossi-Hansberg (2023) to identify the key technologies adopted by retail firms and quantify how these technologies affect firm performance in event studies. Accordingly, this essay also contributes to the innovation literature by linking technological advancements to firm performance (e.g., Hsu (2009), Hirshleifer, Hsu, and Li (2013, 2018), Kogan, Papanikolaou, et al. (2017), Stoffman, Woeppel, and Yavuz (2022)).

Chapter 2

Resurrecting The Value Effect: The Role of Technology Stocks

ABSTRACT

The disappearance of the value premium is due to the rise of the tech stocks. I decompose the Fama-French HML portfolio return into tech and non-tech components. I find that the tech component explains 45% of the time variation in the HML return and reduces the average HML return by offsetting two-thirds of the non-tech component, leading to a small and insignificant HML return in the post-1991 period. I argue that misclassification of tech stocks is the main channel because book-to-market ratios are not comparable across tech and non-tech industries. Instead, the value effect can be recovered by using different breakpoints for tech and non-tech stocks. As a result, the value premium goes from 0.17% (t=1.00) to 0.56% (t=4.18) when the tech adjustment is applied.

2.1 Introduction

The value premium has been pervasively studied as a mimicking factor in asset pricing and an investment strategy in the industry.[1] The premium has been shown to be large and robust in the US and foreign markets.[2] However, whether the value premium has been diminishing for the last 30 years is disputable. Recent studies report that the post-1991 value premium is low (Schwert (2003) and Linnainmaa and Roberts (2018)) and not statistically different from zero (Fama and French (2021)). Although a few recent papers argue for the book-value mismeasurement in B/M ratios, it is still an open question what explains the substantial decline in the value premium during the post-1991 period.[3]

The recent wave of new technologies, especially in computing and internet applications, has created unprecedented growth prospects for the new economy and affected the pricing of tech firms. Theories posit that technological innovations drive growth and valuation (Romer (1990), Kung and Schmid (2015) and Kogan, Papanikolaou, et al. (2017)).[4] Tech firms benefit from innovation-driven productivity and cash flow growth and show a stylized fact about high valuation being indicated by low B/M ratios. Meanwhile, industry valuation can also

[1]The value premium is defined as the hedged portfolio return by going long value (high B/M, book-to-market) stocks and short growth (low B/M) stocks.

[2]See Rosenberg, Reid, and Lanstein (1985), Fama and French (1992, 1993, 2006), Davis, Fama, and French (2000), and Chen, Petkova, and Zhang (2008) for the US evidence. Additionally, see Chan, Hamao, and Lakonishok (1991), Asness, Moskowitz, and Pedersen (2013), and Fama and French (2017) for the global evidence. Despite different explanations, literature has shown the economic origins of the value effect in behavioral biases (De Bondt and Thaler (1985) and Lakonishok, Shleifer, and Vishny (1994)), production (Zhang (2005)), duration (Lettau and Wachter (2007) and Gonçalves (2021)), and sample selection (Kothari, Shanken, and Sloan (1995) and Conrad, Cooper, and Kaul (2003)), among others.

[3]Gonçalves and Leonard (2023) propose that fundamental equity is a better book-value measure than book equity. Lev and Srivastava (2021), Arnott et al. (2021), and Eisfeldt, Kim, and Papanikolaou (2021) discuss the intangible-adjusted B/M ratio by capitalizing intangibles into book equity.

[4]Also see Pástor and Veronesi (2009), who discuss how firm valuation is affected by uncertainty about new technologies in a general equilibrium model. Garleanu, Panageas, and Yu (2012) also examine the relationship between technological growth and asset prices surrounding large infrequent technological innovations. These models, nonetheless, assume that the arrival of new technologies is exogenous.

be affected by investor behaviors. Institutional investors have been documented to herd to industry styles (e.g.,"hot" industry), which in turn impacts industry valuation (Barberis and Shleifer (2003) and Choi and Sias (2009)). In the data, the B/M ratios of tech stocks are nearly half of those of non-tech stocks, implying that the valuation of tech stocks is almost twice as high as that of non-tech stocks.[5] As tech firms emerge with unique growth trajectories as a new economy, valuation for tech firms can differ from that for the old economy.[6]

In this paper, I hypothesize that tech stocks explain the decline in the value premium. Given that tech stocks exhibit a stylized fact regarding high valuation being indicated by universally low B/M ratios, comparing B/M ratios across tech and non-tech industries is less meaningful.[7] Using standard NYSE breakpoints to sort stocks can disproportionately allocate tech stocks to the growth portfolio (i.e., short-leg) from the other end (i.e., the "neutral" or "value" portfolios that yield higher expected returns); that is, the cause of the value premium decline is the disproportional classification of tech stocks as "growth" stocks. The rapid growth in the tech market capitalization has only exacerbated this classification effect for the past thirty years, leading to a substantial decrease in the value premium post-1991.

To investigate the impact of tech stocks, I begin by decomposing the high-minus-low

[5]For example, the 30th percentile B/M of tech stocks is 0.23 on average, whereas the 30th percentile B/M of non-tech stocks is 0.43.

[6]High valuation characterizes tech stocks. Cohen, Polk, and Vuolteenaho (2003) show that up to 80% of dispersion of B/M ratios is caused by variation in cash-flow growth. To explain the high valuation of tech stocks, I examine whether tech stocks have higher cash-flow growth than non-tech stocks. Indeed, the sales growth of tech stocks is significantly higher than that of non-tech stocks in virtually all B/M-sorted portfolios 1 to 5 years after portfolio formation. Similarly, tech stocks exhibit higher forecasted long-term EPS growth than non-tech stocks by at least 4.5 percentage points.

[7]The incomparability of B/M across industries is consistent with accounting literature. Lev and Srivastava (2021) state that owing to accounting practices and conservatism, "book values thus are incomparable across firms from different industries and with different growth strategies and at different stages of their life cycles."

(HML) return into tech and non-tech components. The variance decomposition shows that the tech component explains 45% of the time variation in the HML return during the post-1991 period. Moreover, the tech component substantially reduces the HML return. Specifically, the tech component generates an average return of –0.29% (t=–2.34), whereas the non-tech component generates 0.46% (t=3.38). The tech component offsets almost two-thirds of the non-tech component (0.46%–0.29%), making the HML return (0.17%) statistically indistinguishable from zero.[8] Comparably, not a single industry from the non-tech component materially reduces the value premium. The decompositions highlight the critical role of tech stocks in explaining declines in the value effect in the recent sample.

Despite the high valuation and growth trajectory for tech stocks, a natural solution to benchmarking tech stocks is to compare a tech (non-tech) stock with its tech (non-tech) peers.[9] Practically, the idea is as simple as sorting tech (non-tech) stocks within the tech (non-tech) industry.[10] To form portfolios, I obtain tech (non-tech) breakpoints by ranking tech (non-tech) stocks and sort tech (non-tech) stocks based on these tech (non-tech) breakpoints. Then I pool tech and non-tech stocks and collectively form portfolios in the standard approach of Fama and French (1993). This industry-adjusted approach using tech and non-tech breakpoints is hereafter called *HML-T*.[11] HML-T is the long-short portfolio that goes long value stocks and short growth stocks. Namely, HML-T is constructed in the same way

[8] In contrast, the HML was significantly large (0.44%, t=2.69) before 1991. The tech component generates a monthly return of –0.14% (t=–1.84) while the non-tech component generates 0.58% (t=4.61).

[9] A two-industry analysis between tech and non-tech was also applied in Pástor and Veronesi (2009) to study the predominant role of the tech industry.

[10] Broadly speaking, sorting on within-industry B/M is not new. However, previous literature did not find a meaningfully higher HML return by adjusting industries (in the sample until the late 1990s). Asness, Porter, and Stevens (2000) sort stocks by B/M within 48 industries, yielding a HML return of 0.45%, which is 0.01% above the standard HML (0.44%). Lewellen (1999) construct an industry-adjusted HML based on 13 industries, yielding a return of 0.44%, compared with 0.38% of the standard HML.

[11] More details are discussed in Section 4.2.

as HML, except that tech (non-tech) stocks are sorted by tech (non-tech) breakpoints.[12]

By using tech (non-tech) breakpoints, tech (non-tech) stocks can be meaningfully and proportionally benchmarked as value or growth stocks relative to their tech (non-tech) peers. Take Apple Inc. for example. Owing to its low B/M, Apple is commonly considered a growth stock in 75% of listing years vis-à-vis its NYSE peers based on standard NYSE breakpoints. Surprisingly, if Apple is compared with its tech peers based on tech breakpoints, less than half of Apple's listing years would be seen as growth years. Within-industry benchmarking is critical, particularly for the past thirty years, in which tech stocks have dominated the market by more than 30% of capitalization. Through this approach, apples are not compared with oranges if they differ in industry characteristics. This notion highlights the unique industry characteristics of tech stocks as a new economy and is consistent with industry-peer-based valuation in accounting (e.g., Alford (1992), Bhojraj and Lee (2002)) and IPO literature (e.g., Kim and Ritter (1999)).[13]

As a result, the *HML-T* return triples to 0.56% (t= 4.18) from 0.17% (t=1.00) of the Fama-French HML during the post-1991 period. The performances of these two value strategies were almost identical before the mid-1980s when the impact of tech stocks was small. The portfolio return difference has diverged since then and remained consistently large at 0.39% (t=4.81) after 1991. Moreover, the HML-T within the tech (non-tech) subsample generates a return of 0.88% with t=5.11 (0.49% with t=3.65), both statistically and economically significant. This result suggests that the value effect exists among tech (non-tech) stocks and

[12] Note that HML-T is not about exclusively using a tech subsample, but using tech and non-tech breakpoints to sort tech and non-tech stocks, respectively, and collectively forming an HML portfolio.

[13] Selecting comparable firms from the same industry is fundamental for equity valuations (for example, using the price multiples of comparable firms) as firms in the same industries tend to have a similar growth profile and use the same accounting practices.

that tech (non-tech) breakpoints are meaningful benchmarks for sorting stocks relative to their peers.

To address potential concerns on data mining, I carry out the same exercise in the various settings that are commonly applied in the literature. First, the HML-T performance is robust to using different tech classifications from Ward (2020) based on the NAICS industry codes and from Campello and Graham (2013) and Brown, Fazzari, and Petersen (2009) based on the SIC industry codes. Second, tech firms are arguably technologically innovative. Instead of using the industry codes, I employ the innovation measures to define tech firms based on patent value (Kogan, Papanikolaou, et al. (2017)) and R&D intensity (Chan, Lakonishok, and Sougiannis (2001)). The HML-T, constructed by innovation characteristics, also yields sizeable raw returns and CAPM alphas. Third, the 19-plus-tech industry-adjusted HML yields a substantially higher return than the 19 industry-adjusted HML, implying that the within-industry HML is better off when the tech industry is separately considered.[14] Meanwhile, lumping 19 industries into one non-tech industry may increase power, and thus, the HML-T (by sorting stocks within-tech and non-tech) generates the highest return. Last but not least, the HML-T performance is also robust in risk-adjusted returns, equal-weighted portfolios, and the recent post-2001 period.

Given that the tech industry composition plays an important role in identifying the value effect post-1991, an empirical asset pricing model incorporating HML-T is expected to capture variation in asset returns more effectively. Building on the classic Fama and French (1993) three-factor model (called *FF3*), I propose to substitute *HML* with *HML-T* in a new three-factor model (called *FF3Tech*) to evaluate the risk-adjusted performance of stock anomalies. I hypothesize that the alpha of the FF3Tech model becomes smaller than

[14]The 19 industries are defined at the 2-digit NAICS level.

that of the FF3 model, when anomalies are regressed on the factors. Accordingly, I examine 153 stock anomalies from Jensen, Kelly, and Pedersen (2022) and find that the average of the alphas shrinks by 18% from 25 bps per month in the FF3 model to 20 bps in the FF3Tech model. The change of –5 bps is statistically significant (t=–3.41). Furthermore, the number of significant anomaly alphas at the 1% level is reduced by 21%. The types of disappearing anomalies are mainly related to "risk" (downside beta and idiosyncratic volatility), "investment" (CAPEX and asset growth), and "value" (payout yield and stock issuance). The FF3Tech model is also favored with a slightly lower GRS (Gibbons, Ross, and Shanken (1989)) F-stat. In summary, the alphas of the anomaly factors are found to be lower and less significant when benchmarked against the FF3Tech model, suggesting that the FF3Tech model can better explain the variation in anomaly returns.

An interesting out-of-sample exercise is to investigate whether HML-T generates meaningful positive returns in countries whose tech industry consists of a large market capitalization share. I carry the same HML-T exercise in the seven main developed stock markets post-2001. I find that HML-T generates statistically significant positive returns in Korea (0.63%, t=2.97), the US (0.32%, t=2.39), Europe (0.24%, t=1.82), Hong Kong (0.38%, t=1.82), and Japan (0.29%, t=2.02) where tech stocks account for large market capitalization, but generates zero or negative returns in Canada (0.30%, t=1.36) and the UK (–0.04%, t=–0.24) where the tech industry is fairly small.[15] In contrast, the Fama-French HML appears to be low and insignificant in all these countries, except Korea, in the same period. Therefore, I conclude that HML-T performs economically and statistically well in an international setting and that the tech composition effect appears to be a global phenomenon.

[15]The percentage of capitalization belonging to the tech industry as of 2019 is 43% (Korea), 39% (the US), 22% (Europe), 21% (Hong Kong), 19% (Japan), 15% (the UK), and 8% (Canada).

Overall, this paper offers a direct explanation for the recent decrease in the value premium during the post-1991 period. I quantify that tech stocks explain up to 45% of the HML variation and negatively contribute to the HML return. Characterized by their high valuation and cash-flow growth, tech stocks are traditionally seen as growth stocks when compared with their non-tech counterparts. However, when compared to their tech peers, many are not considered growth stocks. After adjusting for industry benchmarking by tech and non-tech breakpoints, the value effect can be better identified; value stocks outperform growth stocks by 6.7% per annum. The value effect also exists among both tech stocks and non-tech stocks. In short, this paper suggests that the recent rapid growth of tech stocks plays a crucial role in explaining the decline in the value premium. The results highlight an industry composition effect over the past thirty years due to the substantial market capitalization growth of tech stocks.

This article contributes to classic asset pricing literature on the value premium (e.g., Fama and French (1992, 1993, 2006, 2017), Davis, Fama, and French (2000), Asness, Moskowitz, and Pedersen (2013)) and on its recent undesirable performance (Linnainmaa and Roberts (2018) and Fama and French (2021)). To understand the rationales, I link the value premium to the recent trend of technological developments. Distinguished from the recent papers that propose "new" measures for capturing the value effect (e.g., Gonçalves and Leonard (2023), Arnott et al. (2021), Eisfeldt, Kim, and Papanikolaou (2021), Lev and Srivastava (2021)), I keep properties of the standard B/M but provide a straightforward solution to recovering the value premium by addressing the composition of tech stocks as a new economy. I show that the standard B/M continues to capture the value effect if industry characteristics are taken into account.

This paper is complementary to, but distinct from, the emerging and vast literature on the asset pricing implications of innovations and technologies on stock returns (e.g., Hirshleifer, Hsu, and Li (2013, 2018), Kogan and Papanikolaou (2013, 2014, 2019)).[16] I focus on tech stocks and their industry composition effect on the factor performance. Finally, this paper contributes to accounting literature on peer-based equity valuations (e.g., Alford (1992), Kim and Ritter (1999), Bhojraj and Lee (2002)). In this regard, evidence of the within-industry comparability for the book-to-market ratio is presented. Despite different explanations for the value premium, the findings of this paper do not attempt to distinguish between the rational and irrational stories of the value effect. This paper instead highlights the predominant characteristics of the tech industry and the importance of employing industry adjustments for forming factors.

The remainder of this article proceeds as follows: Section 4.2 describes the data and methodology; Section 2.3 examines the relation between tech stocks and the value premium; Section 2.4 proposes the industry-adjusted value premium by using tech and non-tech breakpoints and investigates its implications and out-of-sample tests, and Section 4.4 concludes the paper.

2.2 Data and Methodology

I use returns data from CRSP, accounting data from Compustat, and analyst forecasts data from IBES. The sample includes all common stocks (share codes 10 and 11) traded on NYSE/AMEX/NASDAQ (exchange codes 1,2, and 3) in the CRSP/Compustat universe

[16] Also see Chan, Lakonishok, and Sougiannis (2001), Pástor and Veronesi (2006, 2009), Cohen, Diether, and Malloy (2013), and Hsu, Wang, and Yang (2022) for the effects of innovations and technologies on stocks. For relations between technologies and the aggregate stock market, see Greenwood and Jovanovic (1999), Hobijn and Jovanovic (2001), and Hsu (2009).

unless explicitly specified for an inclusion of the IBES data.[17] I follow Fama and French (1993)'s methodology to construct the HML portfolio.[18] Firms with negative book equity, negative market equity, or Compustat data availability less than two years are excluded from the sample. Portfolios are value-weighted, held from July of year t to June of year t+1, and rebalanced annually. The HML return, namely, the value premium, is the return difference between the value portfolio (the average of small-value and big-value) and the growth portfolio (the average of small-growth and big-growth).

The classification of tech industries is from the U.S. Bureau of Labor Statistics (BLS) and is defined by the 4-digit NAICS codes based on the occupation data.[19] The tech classification of BLS is commonly used in literature (Autor et al. (2020), Azoulay et al. (2020), Decker et al. (2020), Gallipoli and Makridis (2018), and Brander, Egan, and Hellmann (2010)). The scope concentrates on IT-related manufacturing and service industries, for example, semiconductors, computers, electronic products, software, and internet and data processing services.[20][21] To account for the rise of tech stocks and avoid a small sample in the early

[17]IBES analysts forecast data are documented to have a smaller coverage over the US-listed stocks and are biased toward big stocks.

[18]Specifically, a B/M ratio of year t is defined as market equity (ME) in the calendar yearend of t-1 divided by book equity (BE) in the fiscal yearend in calendar year t-1, where ME is the sum of all shares at the permco level, and BE is the stockholders' equity plus deferred taxes and investment tax credit minus the book value of preferred stocks (depending on the availability of redemption, liquidation, or par values in this priority). The accounting information of year t is obtained from the data for fiscal yearend in calendar year t-1. NYSE breakpoints of B/Ms are constructed by ranking NYSE stocks on the bottom 30%, middle 40%, and top 30% of B/M ratios, whereas NYSE breakpoints of size are constructed by ranking NYSE stocks by the top and bottom 50% of market equity in June from calendar year t. At the end of June each year, stocks are split into six (3 by 2) portfolios based on these three B/M and two size breakpoints.

[19]The NAICS codes for tech industries are 3254, 3341, 3342, 3344, 3345, 3364, 5112, 5179, 5182, 5191, 5413, 5415, and 5417. The detailed list of tech industries is shown in Appendix Table A2.1. See more details in the BLS report by Hecker (2005).

[20]These industries are considered tech-intensive (level 1) because employment in tech-oriented occupations constitutes 24.7% or more in their total employment, which is at least five times the average for all industries. In other words, at least a quarter of employees in these industries are engaged in scientific, engineering, and technician occupations.

[21]Examples of the largest tech firms in 2019 are Apple, Microsoft, Alphabet, Facebook, Johnson & Johnson,

years, at least 100 tech stocks in each of the portfolios are required; accordingly, the sample period in this study starts from 1968.

The growing role of tech stocks is evident. Figure 2.1 plots the time series of the aggregate market capitalization of tech stocks. The market capitalization of tech stocks accounted for approximately 15% of the total market capitalization before the 1990s.[22] Following the beginning of the popularization of personal computers and the World Wide Web, the tech industry gained a significant increase in market capitalization, which surged to more than 40% during the tech-bubble period in the late 1990s and fell back to less than 30% in early 2001. Since then, the tech market capitalization has gradually grown to 40% in 2019, reaching almost triple the value three decades ago.

To better capture the value effect, tech (non-tech) breakpoints are proposed in this study to allocate tech (non-tech) stocks, holding other procedures of portfolio construction equal. Specifically, in June of year t, tech (non-tech) breakpoints are obtained by ranking tech (non-tech) stocks on the 30th and 70th percentile for B/M. Tech (non-tech) stocks are sorted into portfolios based on these tech (non-tech) breakpoints. Figure 2.2 illustrates how stocks are sorted by tech and non-tech breakpoints compared with NYSE breakpoints. For example, tech stocks with B/M ratios smaller than the 30th percentile tech B/M breakpoint are allocated to the growth portfolio; likewise, non-tech stocks with B/M ratios smaller than the 30th percentile non-tech B/M breakpoint are allocated to the growth portfolio.[23] After tech and non-tech stocks are separately sorted by tech and non-tech breakpoints, I pool tech and non-tech stocks and collectively calculate the value-weighted portfolio returns using the

Intel, Merck, Pfizer, Cisco, Boeing, Oracle, and Adobe.

[22]Many computer-related tech firms were listed in the 1980s, such as Apple, Dell, Microsoft, and Oracle. A wave of tech IPOs later took place in the 1990s.

[23]To closely mimic the portfolio construction by Fama and French (1993), I use tech (non-tech) breakpoints for size based on the 50th percentile ME by the same approach.

standard approach of Fama and French (1993). *HML-T* is the long-short portfolio that goes long the value portfolio (H) and short the growth portfolio (L).

To summarize, I separately sort tech and non-tech stocks by their industry breakpoints and collectively form the portfolios. HML-T takes into account the unique properties of tech stocks as tech stocks have universally higher valuation and cash flow growth than non-tech stocks (more details will be discussed later). Therefore, tech (non-tech) stocks can be meaningfully compared with their tech (non-tech) peers.

2.3 Tech Stocks and Value Premium

2.3.1 Tech Stocks' Impact on Value Premium

In this section, I begin by showing the Fama and French HML performance and then explore the role of tech stocks in explaining the decline in HML through the HML decompositions. Table 2.1 shows the value premium. Consistent with Fama and French (2021), the post-1991 HML return is low and statistically indistinguishable from zero. The HML average return is only 0.17% per month (t=1.00) during the 1991-2019 period, despite a robust performance of 0.44% (t=2.69) during the 1968-1991 period.[24]

Given that tech stocks have experienced substantial growth in market capitalization over the past three decades, investigations should be conducted to ascertain whether (and by how much) tech stocks have contributed to the recent decline in HML returns. If so, what channel can explain the underperformance of HML? To understand the influence of tech stocks over

[24]The replicated HML return in this study is 98.3% correlated with the Fama and French HML return (from Ken French's website) with a 0.026% difference in the averaged return in the full sample.

HML returns, I begin with a simple decomposition of the HML portfolio return into tech and non-tech components:

$$
\begin{aligned}
HML_t &= R_t^H - R_t^L \\
&= \left[\omega_t^{HT} R_t^{HT} + (1-\omega_t^{HT}) R_t^{HN}\right] - \left[\omega_t^{LT} R_t^{LT} + (1-\omega_t^{LT}) R_t^{LN}\right] \\
&= \left[\omega_t^{HT} R_t^{HT} - \omega_t^{LT} R_t^{LT}\right] + \left[(1-\omega_t^{HT}) R_t^{HN} - (1-\omega_t^{LT}) R_t^{LN}\right] \\
&= HML_t^T + HML_t^N \qquad (2.1)
\end{aligned}
$$

where HML_t is the Fama and French (1993) HML portfolio return; R_t^H is the value-weighted return of the value portfolio; R_t^L is the value-weighted return of the growth portfolio; T represents tech stocks; N represents non-tech stocks; ω_t^{HT} is the weight for tech stocks in the value portfolio, and ω_t^{LT} is the weight for tech stocks in the growth portfolio.

Using Equation 2.1, the variance of HML_t equals the sum of the covariances between HML_t and each component:

$$
var\left(HML_t\right) = cov\left(HML_t, HML_t^T\right) + cov\left(HML_t, HML_t^N\right) \qquad (2.2)
$$

Dividing both sides of Equation 2.2 by $var\left(HML_t\right)$ yields the percentage contribution of each component to the total variances, shown as β^T and β^N in Equation 2.3.

$$
1 = \beta^T + \beta^N \qquad (2.3)
$$

Panel A of Table 2.1 reports the decompositions of the HML return into tech and non-tech components. Columns 1 and 2 show the return decomposition of Equation 2.1. The non-tech component (HML_t^N) yields a sizeable positive return of 0.58% (t=4.61) in the pre-1991 period and 0.46% (t=3.38) in the post-1991 period, both economically and statistically significant. Surprisingly, the average return of the tech component (HML_t^T) is –0.14% (t=–1.84) in the pre-1991 period and further deteriorates to –0.29% (t=–2.34) in the post-1991 period. Such a negative return of the tech component offsets almost two-thirds of the positive return of the non-tech component to 0.17% (=0.46%–0.29%) during the post-1991 period, thus making the HML return statistically indistinguishable from zero. Although five other industries in the non-tech component also contribute negative returns to the HML (for example, manufacturing=–0.03% and retail=–0.02%), their collective negative returns are negligible. Comparably, the tech industry alone has by far the largest negative impact on the HML return.

In Columns 3 and 4, the variance decomposition of Equation 2.3 shows that the tech component (β^T) explains up to 45% of the variances of the HML return in the post-1991 period, suggesting that tech stocks have played an influential role in explaining almost half of the time variation in the value premium. In contrast, the non-tech component (β^N) accounts for only 55% of the HML variation after 1991, decreasing from 69% in the pre-1991 period.

In Panel B, I further investigate the negative impact of the tech component by controlling the return of tech stocks. By construction, high returns or large market capitalization of tech stocks can lead to negative HML returns because tech stocks are disproportionately allocated to the short leg portfolio. Simply put, when the tech return is high (low), the HML return is low (high). This negative relation is expected to be amplified when the tech market capitalization becomes large in the post-1991 period. Therefore, I split the sample by the median returns of tech stocks into the high tech-return and low tech-return periods. Then, I distinguish the effect of market capitalization from returns. Holding the high (low) tech-return period constant, the HML return is –1.04% (+0.76%) in the pre-1991 period and further decreases (increases) to –1.86% (+1.28%) in the post-1991 period. These results suggest that the growing market weight of tech stocks exacerbates this negative relation between tech returns and HML returns after 1991, when tech stocks take on a greater weight of capitalization.[25]

To be more specific regarding the role of market capitalization of tech stocks, I further split the sample into the low tech-cap period in Column 3 and the high tech-cap period in Column 4, which roughly correspond to the pre-1991 and post-1991 periods, respectively. The amplifying effect of the tech market capitalization is even stronger. Controlling for the high (low) tech-ret period, the HML return changes from –0.97% (+0.77%) in the low tech-cap period to –2.00% (+1.32%) in the high tech-cap period.

In summary, the return and variance decompositions show that the growing role of tech stocks can explain the recent decline in the value premium. I find that the tech component negatively contributes to the HML return and explains up to 45% of the HML variation in the post-1991 period because of the substantial increase in the weight of the tech.

[25] Under the unconditional split (unreported), the results remain similar. During the high tech-ret period, the tech component turns from –1.08% (t=–13.16) in the pre-1991 period to –1.81% (t=–15.20) in the post-1991 period, whereas during the low tech-ret period, the tech component goes from 0.72% (t=9.96) in the pre-1991 period to 1.33% (t=9.24) in the post-1991 period.

2.3.2 Tech Stocks' Properties

High Valuation

Tech stocks are often considered growth stocks with high valuations. Based on the B/M metrics, tech stocks have low B/M ratios and would more likely be classified as growth stocks. Figure 2.3 shows the times series of B/M ratios at the 30th and 70th percentiles. Tech stocks (solid lines) always have lower B/M ratios than non-tech (dash lines) by at least 20 percentage points. This difference in the B/M levels between tech and non-tech is persistent throughout the sample. For example, the tech 30th percentile B/M (red solid) fluctuates around 0.2, whereas the non-tech 30th percentile B/M (red dash) moves around 0.4, suggesting that the valuation of tech growth stocks is twice as high as non-tech growth stocks.[26] If standard NYSE breakpoints are used to form the HML portfolios, more than 50% of tech stocks will be allocated as growth stocks, as shown in Panel B of Figure 2.3.

Table 2.2 shows the descriptive statistics of tech and non-tech industries from the post-1991 sample. Industries are classified at the 2-digit NAICS level, whereas the tech industry is exclusively defined at the 4-digit level discussed above. The tech industry accounts for one-quarter of all firms and one-third of the total market capitalization, making it the most predominant industry in the market. Not a single non-tech industry is comparable to the tech industry in size. For example, the manufacturing industry, the second-largest industry, has 15% fewer firms and 35% less market capitalization than the tech industry. Moreover, the tech industry has universally lower B/M ratios than non-tech (and any other single non-tech) industry. Overall, the tech industry has become the most predominant industry boasting high valuations.

[26]Note that the non-tech breakpoints are close to the NYSE breakpoints, as shown in Appendix Figure A2.1, as NYSE mainly comprises non-tech stocks.

High Cash Flow Growth

To explain the high valuation (i.e., low B/M) of tech stocks as a new economy, I examine whether tech stocks have higher cash-flow growth than non-tech stocks. I build on the seminal papers by Vuolteenaho (2002) and Cohen, Polk, and Vuolteenaho (2003). They decompose the B/M ratio and quantify that up to 80% of the cross-sectional variations in B/M ratios are due to cash-flow growth. Campbell, Polk, and Vuolteenaho (2010) further show that the economic origin of the value effect can be attributed to cash flows. Therefore, I hypothesize that the pervasively low levels of B/M ratios reflect high future cash flows for tech stocks.

Although the clean-surplus return on equity (ROE) is used as the profitability identity for cash flows in Vuolteenaho (2002) and Cohen, Polk, and Vuolteenaho (2003), the ROE-based (or earnings-based) accounting identity may not be an appropriate cash-flow measure for the valuation of tech firms (Amir and Lev (1996) and Trueman, Wong, and Zhang (2000)). This is because a significant portion of tech firms struggle to make positive earnings in their early life cycle, and investors place less weight on earnings in their valuations.[27][28]

Instead, tech firms focus on growth: sales growth. Accounting literature suggests that the "top line" (i.e., sales) is the key to understanding the growth prospect of tech firms (Demers and Lev (2001) and Core, Guay, and Van Buskirk (2003)). Following Donangelo (2021) among others, I use the sales growth rate as the main proxy for cash-flow growth.

[27] Ritter and Welch (2002) note that the rise in the percentage of tech firms during the 1990s can be mirrored to the number of firms with negative earnings. Gao, Ritter, and Zhu (2013) further show that more than 33% (78%) of big (small) tech firms had negative earnings three years after their IPO during 2001-2011. Tech firms that had negative earnings in the early stage include big names such as Twitter, Qualcomm, Micron, and Booking.com.

[28] Tech firms try hard to achieve operating efficiency (Bakos and Brynjolfsson (1999)), while others dispense a large portion of subsidies to customers for a winner-takes-most strategy (Autor et al. (2020)) or re-invest in R&D to pursue further growth and expansion (Brown, Fazzari, and Petersen (2009) and Cornell and Damodaran (2014))

Alternatively, as high valuation can be derived from ex-ante expected growth rates, I turn to the analyst forecasts data from IBES and use the long-term expected growth rates of EPS ("LTG" hereafter) as an alternative proxy.[29] The R&D intensity is also utilized as another alternative proxy as R&D can translate into future sales growth (Core, Guay, and Van Buskirk (2003), Cohen, Diether, and Malloy (2013) and Acemoglu et al. (2018)).

Table 2.3 shows the cash flow growth of tech stocks versus non-tech stocks.[30] Panel A reports the average sales growth rates for each portfolio. Sales growth rates of the tech industry monotonically increase from 6.2% for the value portfolio to 28.8% for the growth portfolio in year 1. In comparison, the sales growth rates of the non-tech industry also monotonically increase, but at a lower rate, from 6.2% for the value portfolio to 20.7% for the growth portfolio. The growth difference between tech and non-tech portfolios is economically and statistically significant for the growth portfolio (8.1%) and neutral portfolio (3.3%) in year 1. Furthermore, in year 3 (up to year 5), the growth difference between tech and non-tech portfolios is economically and statistically significant for all three portfolios. Collectively, sales growth suggests that tech cash flows grow faster than their non-tech counterparts.

Panel B reports the average of ex-ante expected long-term growth rates of EPS in each portfolio. Tech LTG is significantly higher than non-tech LTG by 7.1%, 6.2%, and 4.5% for the growth, neutral, and value portfolios, respectively. The ex-ante long-term growth again suggests that the expected cash flows of tech firms are higher than those of non-tech firms. Panel C reports the average of R&D intensity in each portfolio. Tech R&D intensity

[29]LTG is defined as the expected annual increase in operating earnings over the next full business cycle ranging from 3 to 5 years. Nonetheless, it is worth noting that the IBES data come with less coverage on stocks and a short sample period. IBES is employed in the subsample to calculate the average LTG in the portfolios defined above.

[30]Sales growth is the annual growth rate of sales; EPS growth the is long-term expected growth rates of EPS (mean of forecasts), and R&D intensity is R&D expenses scaled by total assets with missing R&D values treated as zeros. All cash-flow measures are winsorized by 2% on both ends to avoid extreme values.

is significantly higher than non-tech R&D intensity by 8.5%, 7.7%, and 6.4% in year 1 for the growth, neutral, and value portfolios, respectively. The R&D intensity difference between tech and non-tech remains large and significant for all portfolios up to year 5. The results again indicate that tech firms invest more in R&D. Surprisingly, non-tech firms make insignificant investments in R&D, ranging from 0.6% to 1.7% of total assets; in contrast, tech firms heavily invest in R&D, which can potentially generate future growth. This evidence is consistent with the stylized fact that tech firms are an intangible-rich new economy (Hand and Lev (2003) and Teece (2015)) when compared to non-tech firms, which are considered as the old economy.

Overall, I find that tech stocks have statistically and economically higher cash-flow growth than non-tech stocks throughout the five years post portfolio formation. The results highlight the stark difference in growth prospects between tech and non-tech industries.[31].

2.4 Tech-Adjusted Value Premium

2.4.1 HML–T

Tech stocks have high valuations and cash-flow growth—the characteristics that are reflected by universally low levels of B/M ratios throughout the sample. Using classic NYSE breakpoints would disproportionately classify tech stocks as growth stocks because NYSE is mainly composed of non-tech stocks that have higher B/M ratios. Moreover, the NYSE stocks have become less representative of the whole market, whereas tech stocks (mostly listed on NASDAQ) presently account for almost 40% of the total market capitalization. Using NYSE

[31] Appendix A2.2 repeats the same exercise of Table 2.3 as a robustness check by using gross profitability, the median of LTG forecasts, and the selling, general, and administrative expenses (SG&A) in Panel A, B, and C, respectively. The findings qualitatively confirm the aforementioned results.

breakpoints may devalue the role of tech stocks in portfolios. That said, one simple solution is to assign the relevant breakpoints for each industry-peer group when the portfolios are formed: using tech breakpoints for tech stocks and non-tech breakpoints for non-tech stocks and holding other portfolio-constructing procedures equal.[32]

The purpose of using tech-specific treatments is to meaningfully compare tech stocks with their relevant peers. Suppose we ask whether Apple is a growth stock. The answer will depend on whether Apple is compared with its tech peers. Figure 2.4 shows that 75% of Apple's listing years are considered growth compared with its NYSE peers (see orange indicators. 1=growth, 2=neutral, and 3=value). However, surprisingly, if Apple is compared with its tech peers (blue indicators), less than half of Apple's listing years would be seen as growth years. In the recent sample, Apple would noticeably not be seen as a growth stock because its fundamentals are also growing rapidly. Overall, the key benefit of using tech breakpoints for sorting tech stocks is to meaningfully understand whether tech stocks are considered growth or value stocks when compared with their relevant peers.

Table 2.4 shows the performance of industry-adjusted HML portfolios, *HML-T*, by sorting tech (non-tech) stocks by tech (non-tech) breakpoints and collectively forming the portfolios.[33] HML-T demonstrates statistically and economically positive returns of 0.62% (t=3.86) and 0.56% (t=4.18) in the pre-1991 and post-1991 periods, respectively. In other words, the HML-T portfolio makes a sizeable return of 6.72% per annum in the post-1991 period. Similarly, CAPM alphas of HML-T are also robustly large throughout the sample.

[32] To address the growth properties of the tech industry and its predominant market weight in the economy, a two-industry setting is employed, which was inspired by Pástor and Veronesi (2009)'s two-industry analysis between tech and non-tech industries.

[33] Appendix A2.3 reproduces Table 2.4 by arbitrarily excluding pharmaceutical and aerospace industries from the BLS tech classification. This refined BLS tech classification concentrates on the IT-related industries. Appendix A2.3 exhibits qualitatively similar results.

The advantage of using tech (non-tech) breakpoints is to fairly compare tech (non-tech) stocks with their tech (non-tech) peers. Through this change, the value effect can be better captured within each industry.[34] I next show the value effect in the tech (non-tech) industry subsample. In the tech subsample, the HML-T (namely, tech value stocks minus tech growth stocks) generates a sizeable average return of 0.88% (t=5.11) per month in the post-1991 period; that is, using tech breakpoints for allocating tech stocks is meaningful for capturing the value effect among tech stocks. Interestingly, the result is somehow contrary to the recent popular understanding that buying tech growth stocks is "almost" the most profitable strategy. Although tech growth stocks, such as Google, produce impressively positive returns during the post-1991 period, tech value stocks still outperform tech growth stocks by 0.88 percentage points, equivalently to around 10% per annum. Similarly, in the non-tech subsample, the HML-T (namely, non-tech value stocks minus non-tech growth stocks) also yields 0.49% (t=3.65) in the post-1991 period, suggesting that non-tech breakpoints work well to reveal the value effect among non-tech stocks. These results are more robust if HML-T is constructed by equal weights (EW).

The outperformance of HML-T relative to HML is statistically and economically robust. Specifically, HML-T outperforms HML by 0.39 (t=4.76) percentage points during the post-1991 period, increasing from 0.18 (t=2.91) percentage points in pre-1991 years. Figure 2.5 demonstrates the cumulative (sum of log) return of these two value strategies and shows that HML-T began leading HML in the mid-1980s as the market capitalization of tech stocks substantially grew. The change in industry composition facilitates the difference between HML-T and HML. Since then, the outperformance of HML-T has been on a persistently

[34] An alternative approach to HML-T is to further sort stocks within the 19 non-tech industries. This strategy has a slightly less desirable performance. See details in Appendix A2.4.

upward trend (red line). Overall, HML-T (black line) exhibits a sizeable cumulative return, reaching nearly 320% in the full sample, and less severe drawdowns particularly when the tech bubble burst in early 2000.

To further explore the recent period in which HML makes a zero return, I show the HML performance during the 2001-2019 period in Column 3. HML-T generates an average return of 0.32% (t=2.39) and outperforms HML by 0.29 (t=3.50) percentage points, though the overall performances in this period are slightly lower than those in the previous period. The results also hold for CAPM alphas and equally weighted portfolios. Panel B of Table 2.4 shows volatility. HML and HML-T volatilities are fairly similar in the pre-1991 period. However, the standard deviation of HML increases to 3.13, and the annual Sharpe ratio drops to 0.19 in the post-1991 period. In contrast, HML-T's standard deviation decreases to 2.46, but the annual Sharpe ratio remains at a high level of 0.78 in the same period. In summary, HML-T exhibits lower volatility and a higher Sharpe ratio than HML, implying a less risky dimension for HML-T.

Next, I use alternative tech classifications to examine the performance of HML-T as robustness checks. To define whether a stock belongs to the tech industry, I employ tech classifications from Ward (2020) (Ward) based on the NAICS codes and from Campello and Graham (2013) (CG) and Brown, Fazzari, and Petersen (2009) (BFP) based on the SIC codes. Furthermore, tech firms are arguably technologically innovative. I utilize two innovation measures to define tech firms: patent value and R&D intensity. Patent value from Kogan, Papanikolaou, et al. (2017) is measured as the sum of patent values scaled by total assets at the firm level.[35] The R&D intensity is defined as R&D expenses scaled by book

[35] Firms that are not involved in patenting are given a value of zero. I am thankful to Leonid Kogan, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman for sharing their patents data.

equities (Chan, Lakonishok, and Sougiannis (2001)) at the firm level. A firm is treated as a tech firm if the patent value (R&D intensity) is beyond the median of the measure among patenting (positive R&D) firms; otherwise, a non-tech firm.[36]

Table 2.5 reports the main result based on the alternative tech measures.[37] The HML-T performances based on the alternative measures are statistically and economically significant for raw returns (0.43% to 0.54%) and CAPM alphas (0.56% to 0.66%) in the post-1991 period. The difference is small between the baseline and the alternative measures, ranging from 0.02% to 0.13% in raw returns and from –0.03% to 0.07% in CAPM alphas. Similarly, the equally-weighted portfolios in Panel B also demonstrate qualitatively similar patterns relative to the baseline result.

In Appendix A2.4, I further compare three different within-industry-sorted HML strategies: (1) 19 industries at the 2-digit NAICS level, (2) 19-plus-tech industries, and (3) non-tech (lumping 19 industries) and tech industries. The 19-plus-tech industry-adjusted HML yields a substantially higher return than the 19 industry-adjusted HML, implying that the within-industry HML is better off when the tech industry is separately considered. Meanwhile, lumping 19 industries into one non-tech industry may increase power and thus the HML-T (by sorting stocks within tech and non-tech) generates the highest return.

To look into HML-T, Table 2.6 shows the detailed excess returns of the 2–by–3 size–B/M sorted portfolios by using tech and non-tech breakpoints during 1991-2019. Low returns for growth portfolios (L) are common in the two size groups. Average returns monotonically

[36] One main advantage of using patents and R&D is that these measures can capture the time variation in the technological innovation at different stages. In contrast, the common tech classifications by the NAICS or the SIC codes are relatively static, unless a firm changes its industry code.

[37] The correlations between the BLS and alternative tech measures are 68% (Ward), 64% (CG), 64% (BFP), 25% (Patents), and 51% (R&D).

increase from growth portfolios (L) to value portfolios (H). Consistent with Fama and French (2012), the value premium is larger for small stocks (0.98%, t=6.32) than for big stocks (0.13%, t=0.85). The portfolios by equal weights demonstrate a stronger pattern of the value premium shown on the right of Panel A.

Panel B (C) shows the portfolios within the tech (non-tech) subsample. Similarly, average returns monotonically increase from growth portfolios to value portfolios in all the size groups, with small stocks having a greater value effect. Noticeably, the value premium is stronger among tech stocks (0.88%, t=5.11, shown in Panel B) than non-tech stocks (0.49%, t=3.65, shown in Panel C). Overall, the result is supportive of the value effect among tech (non-tech) stocks. In addition, the CAPM alphas of Table 2.6 can be found in Appendix A2.5, which shows a qualitatively identical pattern and statistically significant risk-adjusted returns of the HML-T portfolios.

2.4.2 HML–T in Fama and French Three Factor Model

Given that the composition of the tech industry plays an essential role in identifying the value effect in the post-1991 period, an empirical asset pricing model that incorporates HML-T is expected to explain the variation in asset returns more effectively. Several recent papers (Jensen, Kelly, and Pedersen (2022) and Hou, Xue, and Zhang (2020)) have investigated the performance of stock anomalies that have been proposed for the past three decades. Building on the Fama–French three–factor model (FF3) of Fama and French (1993), I propose to substitute *HML* with *HML-T* in a new three-factor model (FF3Tech, consisting of MKT, SMB, and HML-T) to evaluate the risk-adjusted performance of anomalies. I hypothesize that the alpha (i.e., the intercept when anomaly returns are regressed on the three factors) of the FF3Tech model becomes smaller than that of FF3 as FF3Tech further absorbs the return variation of anomalies.

I examine 153 stock anomalies from Jensen, Kelly, and Pedersen (2022) and regress each anomaly on the FF3Tech factors.[38] Panel A of Table 2.7 reports the alphas of the anomalies constructed by value weights. Among 153 anomalies, 90 experience a decrease in alphas from the FF3 model to the FF3Tech model. The number of significant alphas at the 1% level is reduced by 21%, from 57 in FF3 to 45 in FF3Tech.[39] The average of alphas shrinks by 18%, from 25 bps per month in FF3 to 20 bps in FF3Tech. The change of –5 bps is statistically significant (t=–3.41). Furthermore, I use the GRS (Gibbons, Ross, and Shanken (1989)) F-stat to test the null hypothesis that all the alphas are jointly zero. Though the GRS test unsurprisingly rejects the null hypothesis (implying that either model cannot completely explain the variation in anomaly returns), the FF3Tech model is marginally favored with a slightly smaller F-stat.

Panel B demonstrates a similar pattern for the anomalies constructed by equal weights. The FF3Tech model is favored over the FF3 model, as the former better fits the data and explains the variation in anomaly returns. The average alpha shrinks by 7 bps (t=–5.47), equivalent to a 16% reduction in alphas. The number of alphas that are significant at the 1% level is reduced by 14% from 98 to 84. The GRS F-stat shrinks from 6.71 in FF3 to 6.17 in FF3Tech.

[38] I am thankful to Theis Jensen, Brian Kelly, and Lasse Heje Pedersen for sharing their anomaly returns data.

[39] Specifically, 18 anomaly alphas become no longer significant at the 1% level in the FF3Tech model, whereas 6 anomaly alphas become significant. Appendix A2.6 reports a detailed list of these anomalies. The disappearing anomaly alphas concentrate on the topics associated with "risk" (downside beta and idiosyncratic volatility), "investment" (CAPEX and asset growth), and "value" (payout yield and stock issuance) out of the 14 topics. With HML replaced by HML-T, FF3Tech appears to better capture the dimension of a firm's fundamental risk. Therefore, the abnormal return of the fundamental-based anomalies becomes lower and insignificant.

In summary, the value effect can be better identified by using different breakpoints for tech and non-tech stocks. By substituting HML with HML-T, the FF3Tech model can more effectively evaluate the risk-adjusted performance of anomaly factors. As a result, alphas of anomaly factors are found to be lower and less significant when benchmarked against the FF3Tech model, suggesting that the FF3Tech model can better explain the variation in anomaly returns.

2.4.3 HML–T Global Evidence

An interesting out-of-sample test is to investigate whether HML-T performs well, relative to HML, in countries whose tech industry consists of a large market capitalization share. I carry the same exercise in the seven major developed stock markets during the post-2001 period with global equity data sourced from Reuters Eikon.[40] Owing to the quality and limitation of global data, I winsorize returns by the top and bottom 3% and require the sample with at least 300 stocks in each country-year, leading to this sample starting from 2001.

Column 1 of Table 2.8 shows the market capitalization of tech stocks as of 2019. Unsurprisingly, Korea and the US have a substantial tech share of around 40% of the total market capitalization. The tech industry accounts for approximately 20% of market capitalization in Europe, Hong Kong, and Japan, whereas the tech industry is relatively light in the UK and Canada. Interestingly, I find that HML-T generates significantly positive returns in Korea (0.63%, t=2.97), the US (0.32%, t=2.39), Europe (0.24%, t=1.82), Hong Kong (0.38%, t=1.82), and Japan (0.29%, t=2.02) where the tech industry has a large market capitaliza-

[40] I focus on major developed markets with a reasonably large number of tech stocks and overall sample: Korea, the US, Continental Europe (including Germany, France, the Netherlands, Belgium, Switzerland, Austria, Sweden, Norway, Finland, Denmark, Ireland, Spain, Italy, Portugal, and Greece), Hong Kong, Japan, the UK, and Canada.

tion share, but generates negative or zero returns in the UK (–0.04%, t=–0.24) and Canada (0.30%, t=1.36) where the tech industry is fairly small. HML-T by equal weights demonstrates more robust performances. In contrast, the Fama and French HML appears to be low and insignificant in all these countries except Korea in the same period.

In short, the value premium does not disappear if we can appropriately benchmark tech stocks. HML-T not just performs well in the US during the post-1991 period but also emerges as a global phenomenon in the countries where the tech industry has a greater weight.

2.4.4 Additional Results

Recent studies draw attention to the importance of intangible capital, which is shown to be an essential driver of the output and productivity of a firm (e.g., Peters and Taylor (2017), Kung and Schmid (2015), Ai, Croce, and Li (2013)). However, intangibles have long been expensed rather than capitalized due to accounting treatments. Thus, Arnott et al. (2021), Eisfeldt, Kim, and Papanikolaou (2021), and Lev and Srivastava (2021) propose to refine the B/M measure by capitalizing intangible expenses into the book equity in order to capture the value effect. One common practice of capitalizing intangibles is to use the perpetual method in calculating the discounted sum of all R&D and 30% of SG&A expenses, according to Peters and Taylor (2017). In this section, I incorporate Peters and Taylor (2017)'s capitalized intangibles into the HML (called *iHML*) and HML-T (called *iHML-T*) and examine the performances of these strategies.[41]

Table 2.9 shows the performance of intangibles-adjusted value strategies. Consistent with Arnott et al. (2021) among others, iHML performs well in the post-1991 period with an

[41] I am thankful to Ryan Peters and Lucian Taylor for sharing their capitalized intangibles data.

average return of 0.27% (t=1.85), but decreases to 0.12% (t=0.75) in the post-2001 period. To consider the unique properties of tech stocks, iHML-T was constructed by combining the critiques of intangibles with HML-T. The iHML-T strategy yields sizeable returns: 0.68% (t=5.05) in the post-1991 period and 0.36% (t=2.28) in the post-2001 period. iHML-T also outperforms both iHML and HML-T strategies. Panel B shows the volatility of each strategy. iHML-T overall has a higher Sharpe ratio than iHML and a slightly better Sharpe ratio than HML-T, mostly due to higher returns.

Figure 2.6 shows the cumulative (sum of log) returns of each HML strategy. iHML-T (red line) outperforms all other strategies and has made a cumulative return of approximately 400% since 1968. HML-T (pink) also yields a sizeable cumulative return of 350%. Both iHML-T and HML-T demonstrate a stable long-term upward trend. Moreover, three interesting results stand out. First, iHML-T began to outperform HML-T in the early 1990s, possibly due to the effect of intangible investments. Second, both tech-adjusted strategies (iHML-T and HML-T) began to outperform the Fama-French-based strategies (iHML and HML) in the mid-1980s, when tech stocks started growing their market weights. Third, during the early 2000s, both tech-adjusted strategies (iHML-T and HML-T) suffered less from the Internet-bubble drawdowns. The result reflects the advantage of using tech and non-tech breakpoints that better identify the value and growth stocks relative to industry peers.

2.5 Conclusion

The value premium was shown to be robust and existent everywhere. However, the value premium has become low and diminishing for the past 30 years. At the core of this phenomenon, it is still unclear why the disappearance occurs. To answer this question, I argue that the rise of tech stocks can explain the decline in the value premium.

In this paper, I decompose the Fama-French HML return into tech and non-tech components and quantify that the tech component explains 45% of the time variation in the HML and materially reduces the HML return. Tech stocks are characterized by high valuation and cash-flow growth. With universally low levels of B/M ratios, tech stocks are disproportionately classified into the growth portfolio from the other end (the neutral or value portfolios that yield higher expected returns). As tech stocks have gained a substantial increase in market capitalization over the past 30 years, the growing weight of tech stocks exacerbates their impact on the growth portfolio, leading to a sizeable decline in the HML return during the post-1991 period.

A potential solution to the industry composition is to compare tech (non-tech) stocks with their relevant tech (non-tech) industry peers in forming the HML portfolio. Using the tech (non-tech) breakpoints to allocate tech (non-tech) stocks can cater to their unique growth properties and better capture the value effect. Therefore, the value effect exists once investors meaningfully adjust the industry composition of tech stocks. The value effect also appears within both the tech industry and the non-tech industry.

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2.7 Figures

Figure 2.1. Capitalization of Technology Stocks

The figure shows the time series of the tech stocks' market capitalization relative to the whole market (in percentage). Tech classification is defined at 4-digit NAICS from the US Bureau of Labor Statistics. Sample period is from July 1968 to December 2019.

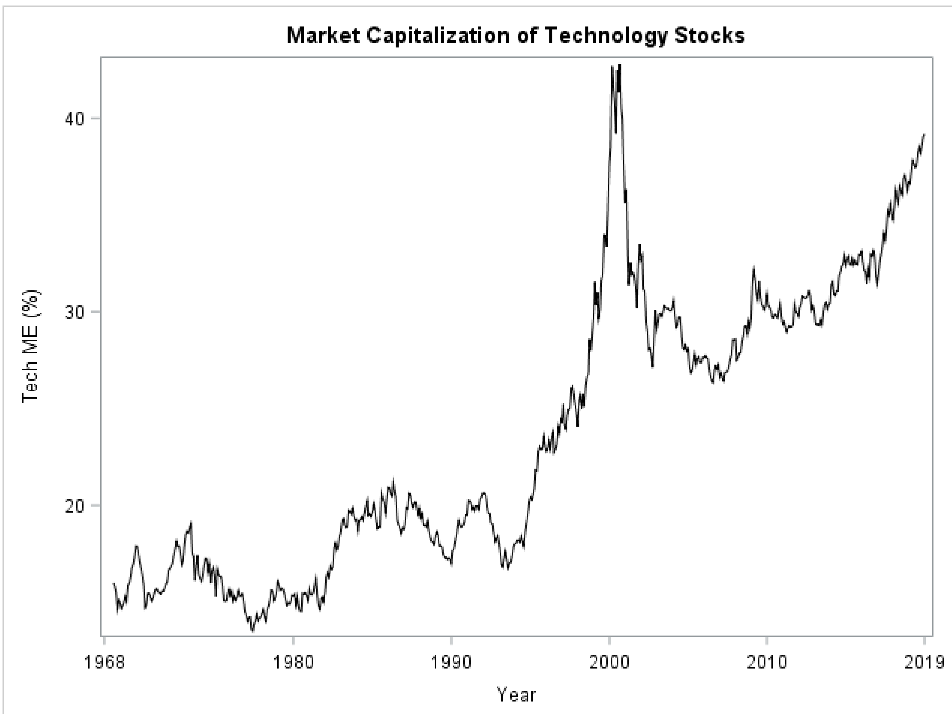


Figure 2.2. Stock Allocation for HML Portfolio

The figure illustrates how stocks are allocated into the value portfolio (H) and the growth portfolio (L) based on tech and non-tech breakpoints in the left panel (HML-T) and NYSE breakpoints in the right panel (HML).

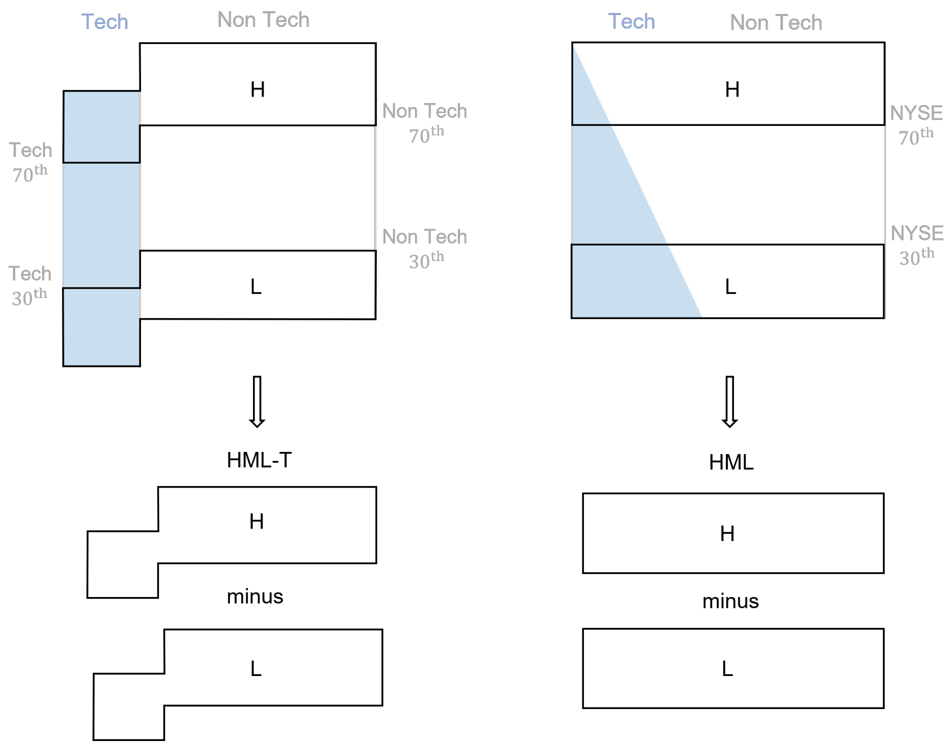


Figure 2.3. Book-to-Market Ratios

The figure shows the trend of book-to-market ratios for tech and non-tech stocks. Panel A shows the time series of the book-to-market ratios at the 30th percentile (red lines) and 70th percentile (black lines). Solid lines are for tech stocks. Dashed lines are for non-tech stocks. Panel B shows the allocation of tech stocks (in percentage) based on standard NYSE breakpoints of book-to-market ratios. Sample period is from July 1968 to December 2019.

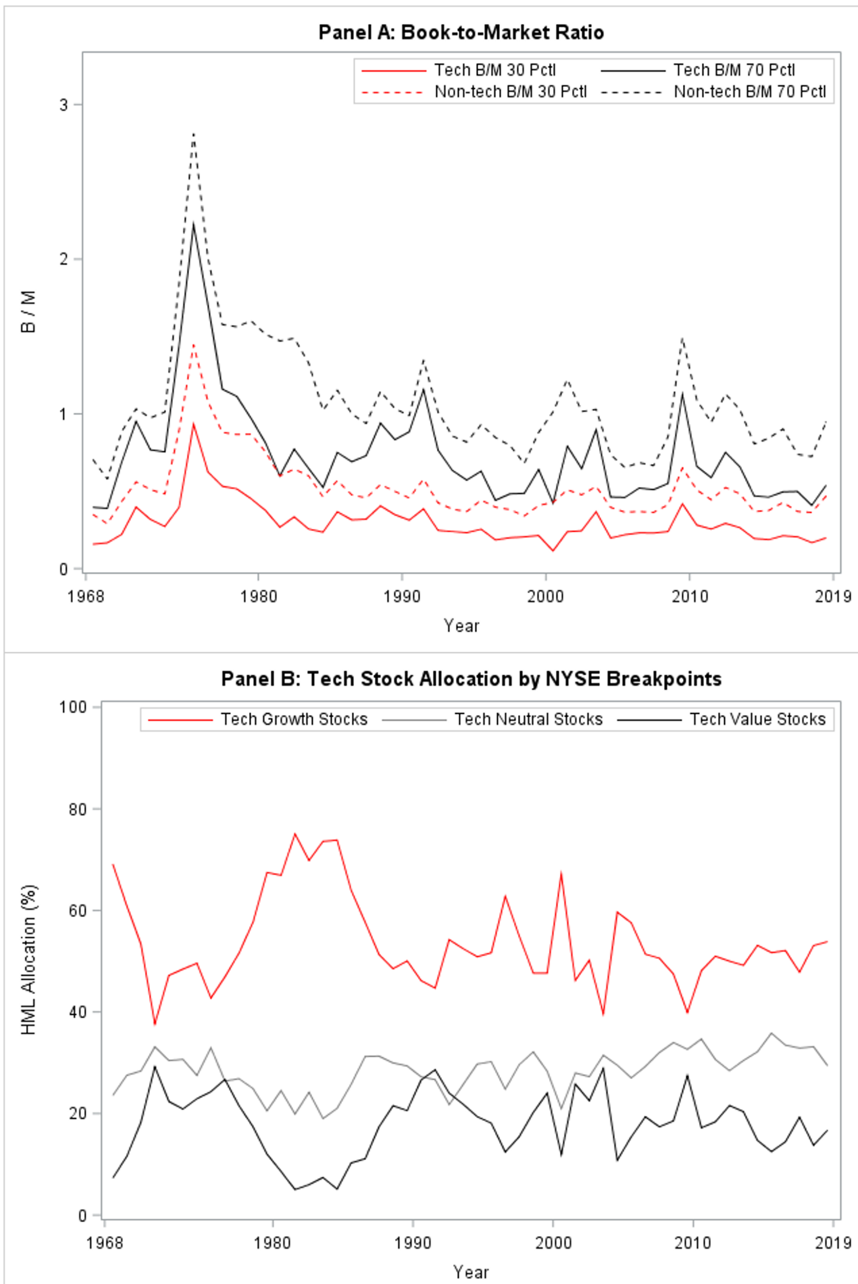


Figure 2.4. B/M Portfolio Migration: Apple

The figure shows how Apple Inc is allocated to the B/M-sorted portfolios by NYSE breakpoints and tech breakpoints. 1, 2 and 3 indicate the growth (bottom 30 percentile), neutral (30-70 percentile), and value (top 30 percentile) portfolios, respectively. Sample period is Apple's listing years from 1982 to 2019.

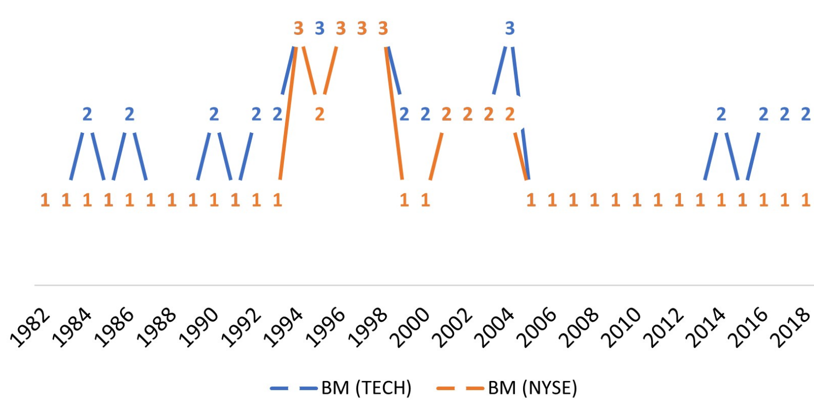


Figure 2.5. Value Premium

The figure shows the cumulative (sum of log) returns of value strategies. HML is based on Fama and French (1993) methodology. HML-T is industry-adjusted HML by applying tech (non-tech) breakpoints to tech (non-tech) stocks. Sample period is from July 1968 to December 2019.

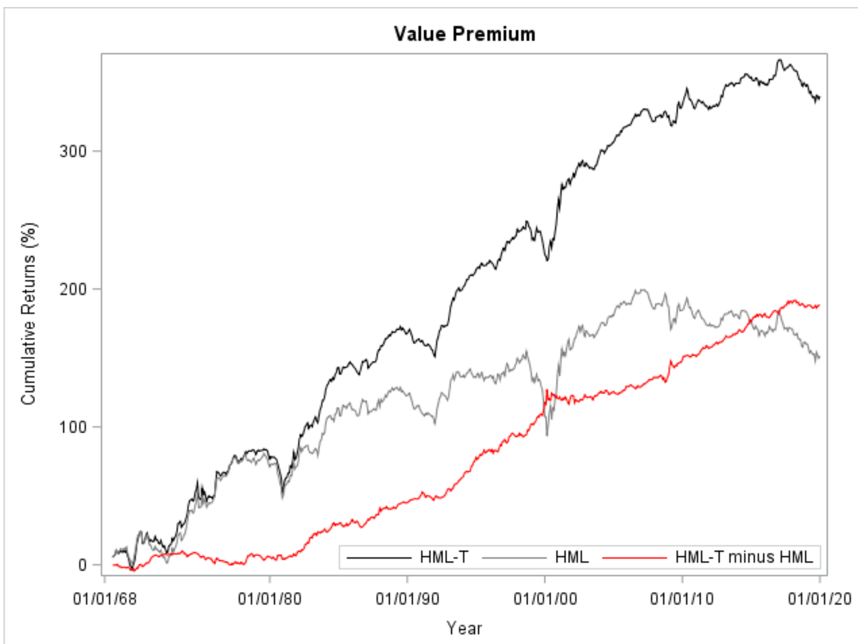
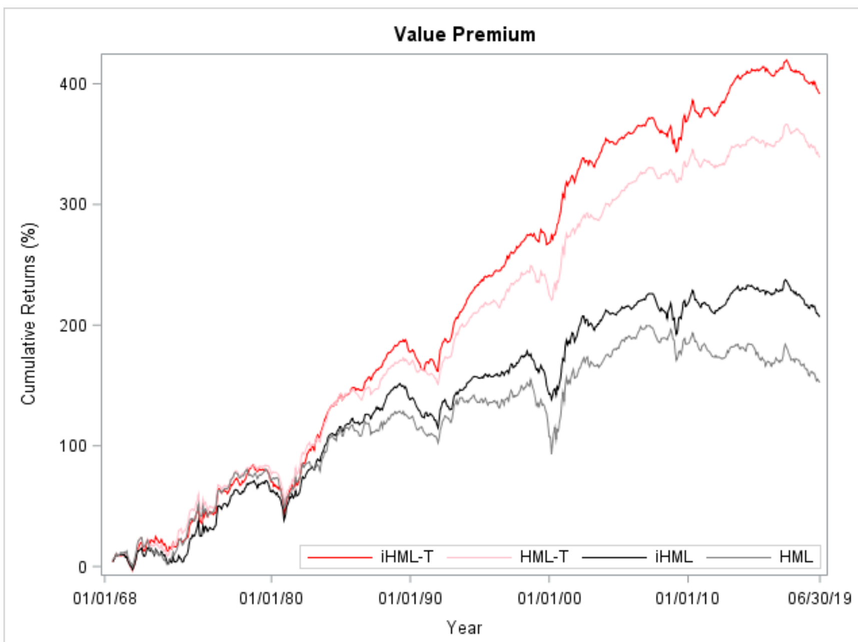


Figure 2.6. Value Premium Extension

The figure shows the cumulative (sum of log) returns of value strategies. HML is based on Fama and French (1993) methodology. HML-T is industry-adjusted HML by applying tech (non-tech) breakpoints to tech (non-tech) stocks. iHML and iHML-T are the extended HML and HML-T strategies, respectively, by capitalizing intangibles of Peters and Taylor (2017) into book equity when constructing book-to-market ratios. Capitalized intangibles data come from Peters and Taylor (2017) with the sample ending in December 2017. Sample period is from July 1968 to June 2019.



2.8 Tables

Table 2.1

HML Portfolio Decomposition

The table reports the return and variance decompositions of the HML portfolio into the technology and non-technology components. In Panel A, HML is the monthly value-weighted portfolio return (%) based on the methodology of Fama and French (1993). Panel B shows the sub-period analysis on the tech component of HML. Tech classification is defined at 4-digit NAICS from the US Bureau of Labor Statistics. Other industries are defined at 2-digit NAICS. High (Low) Tech Ret Period is the months when tech stock returns are above (below) the median. High (Low) Tech Cap Period is the months when tech market cap is above (below) the median. T-statistics are in brackets. Sample period is from July 1968 to December 2019. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Panel A: Portfolio Decomposition

	Portfolio Return Decomp				Portfolio Variance Decomp	
	1968-1991		1991-2019		1968-1991	1991-2019
	Return		Return		Variance (%)	Variance (%)
HML	**0.44**	**[2.69]**	**0.17**	**[1.00]**		
HML: Tech Component	**-0.14**	**[-1.84]**	**-0.29**	**[-2.34]**	**31%**	**45%**
HML: Non-tech Component	**0.58**	**[4.61]**	**0.46**	**[3.38]**	**69%**	**55%**
Agriculture, Forestry, Fishing and Hunting	0.00	[-0.16]	0.00	[-1.55]	0%	0%
Mining	0.00	[0.15]	0.04	[1.77]	7%	3%
Utilities	0.17	[4.45]	0.14	[4.25]	1%	7%
Construction	0.01	[1.41]	0.02	[2.74]	1%	1%
Manufacturing	0.14	[2.64]	-0.03	[-1.11]	24%	7%
Wholesale	0.02	[3.41]	0.01	[1.94]	2%	1%
Retail	-0.04	[-1.78]	-0.02	[-1.66]	6%	4%
Transportation and Warehousing	0.06	[3.75]	0.03	[2.15]	0%	2%
Information	0.04	[1.75]	-0.01	[-0.34]	5%	5%
Finance and Insurance	0.11	[3.23]	0.29	[3.31]	-1%	19%
Real Estate Rental and Leasing	0.00	[1.19]	0.01	[1.81]	1%	1%
Professional, Scientific, and Technical Services	-0.01	[-2.03]	0.00	[-1.28]	1%	1%
Administrative and Support Services	-0.01	[-1.84]	-0.01	[-1.66]	2%	1%
Educational Services	0.00	[-1.25]	0.00	[-0.73]	0%	0%
Health Care and Social Assistance	-0.01	[-1.76]	0.00	[0.06]	1%	1%
Arts, Entertainment, and Recreation	0.00	[-0.26]	0.00	[1.46]	0%	0%
Accommodation and Food Services	-0.02	[-2.96]	-0.01	[-1.21]	2%	0%
Other Services	0.00	[0.12]	0.00	[1.24]	0%	0%
Others	0.11	[3.33]	0.01	[0.67]	15%	2%

Panel B: Sub-period Analysis

	Portfolio Return Decomp							
	1968-1991		1991-2019		Low Tech-Cap Period		High Tech-Cap Period	
HML: Tech Component	Return		Return		Return		Return	
High Tech-Ret Period	-1.04	[-12.94]	-1.86	[-15.44]	-0.97	[-12.82]	-2.00	[-15.77]
Low Tech-Ret Period	0.76	[10.31]	1.28	[9.06]	0.77	[11.37]	1.32	[8.49]

Table 2.2

Summary Statistics

The table reports the summary statistics of tech and non-tech industries. Tech classification is defined at 4-digit NAICS from the US Bureau of Labor Statistics. Other industries are defined at 2-digit NAICS. B/M is the book-to-market ratio by Fama and French (1993). The last three columns report the B/M ratios for the 30th, 50th, and 70th percentiles. Sample period is from July 1991 to December 2019.

Industry	N Firms	Capitalization	Return	B/M 30 Pctl	B/M 50 Pctl	B/M 70 Pctl
Tech	**1143**	**4348**	**1.10**	**0.23**	**0.38**	**0.59**
Non Tech	**3189**	**9760**	**0.86**	**0.43**	**0.64**	**0.91**
Agriculture, Forestry, Fishing and Hunting	11	26	1.06	0.41	0.57	0.90
Mining	170	501	0.76	0.45	0.65	0.92
Utilities	122	502	0.87	0.70	0.83	0.97
Construction	57	57	0.76	0.56	0.77	1.07
Manufacturing	967	2840	0.88	0.36	0.54	0.80
Wholesale	142	186	0.79	0.43	0.65	0.95
Retail	199	936	1.01	0.34	0.56	0.88
Transportation and Warehousing	86	298	0.97	0.47	0.70	1.00
Information	151	993	0.76	0.36	0.56	0.87
Finance and Insurance	781	2339	1.02	0.62	0.79	1.00
Real Estate Rental and Leasing	81	101	1.11	0.41	0.63	0.92
Professional, Scientific, and Technical Services	55	68	0.84	0.29	0.48	0.72
Administrative and Support Services	94	126	0.73	0.33	0.52	0.74
Educational Services	17	20	0.68	0.26	0.43	0.68
Health Care and Social Assistance	89	94	0.82	0.33	0.49	0.74
Arts, Entertainment, and Recreation	25	25	1.05	0.42	0.66	1.06
Accommodation and Food Services	88	201	1.12	0.33	0.52	0.81
Other Services	15	15	0.92	0.43	0.65	0.89
Others	38	431	0.85	0.38	0.61	0.92

Table 2.3

Cash Flow and Operating Performance

The table reports proxies for cash flows by annual sales growth, long-term EPS growth forecasts, and R&D intensity in each B/M-sorted portfolio. H, N, and L indicate high, neutral, and low B/M portfolios (top 30%, middle 40%, and bottom 30%), respectively. Sales Growth is the mean of annual growth rates for sales. EPS Growth is the mean of analysts' growth forecasts in long-term EPS from IBES. R&D Intensity is the mean of R&D expenses scaled by total assets. All measures are winsorized by 2 percent on both ends. T-statistics are reported in brackets. Sample period is from 1968 to 2019 for Panel A and C. Subsample in intersection with IBES coverage is used for Panel B from 1981 to 2019.

Panel A: Sales Growth (Annual)

Portfolio	Tech		Non Tech		**Tech Minus Non Tech**	
			Year 1 (T : T+1)			
H	6.2%	[7.22]	6.2%	[8.14]	**-0.1%**	[-0.13]
N	15.3%	[15.43]	12.0%	[14.31]	**3.3%**	[6.76]
L	28.8%	[18.71]	20.7%	[17.36]	**8.1%**	[9.69]
			Year 3 (T+2 : T+3)			
H	8.5%	[9.98]	7.3%	[9.60]	**1.2%**	[2.58]
N	12.0%	[14.42]	9.8%	[12.61]	**2.2%**	[5.09]
L	16.7%	[18.74]	12.8%	[16.08]	**3.8%**	[7.42]
			Year 5 (T+4 : T+5)			
H	8.8%	[10.05]	7.8%	[10.61]	**1.0%**	[2.11]
N	11.0%	[14.31]	8.9%	[11.16]	**2.1%**	[5.72]
L	14.1%	[20.01]	10.9%	[14.07]	**3.2%**	[7.49]

Panel B: EPS Growth (Long-term Forecasts)

			Long-term Growth			
H	16.9%	[26.98]	12.4%	[38.43]	**4.5%**	[10.86]
N	19.8%	[32.11]	13.6%	[57.26]	**6.2%**	[15.11]
L	24.3%	[32.70]	17.2%	[46.97]	**7.1%**	[7.09]

Panel C: R&D Intensity

			Year 1 (T : T+1)			
H	6.9%	[13.26]	0.6%	[21.57]	**6.4%**	[12.43]
N	8.4%	[14.50]	0.8%	[31.93]	**7.7%**	[13.46]
L	10.1%	[15.10]	1.7%	[20.00]	**8.5%**	[14.27]
			Year 3 (T+2 : T+3)			
H	6.5%	[15.65]	0.6%	[26.08]	**5.9%**	[14.43]
N	8.0%	[16.03]	0.8%	[43.18]	**7.2%**	[14.65]
L	9.8%	[16.02]	1.5%	[22.13]	**8.3%**	[15.08]
			Year 5 (T+4 : T+5)			
H	6.2%	[17.04]	0.6%	[24.60]	**5.6%**	[15.58]
N	7.5%	[18.27]	0.8%	[40.49]	**6.7%**	[16.58]
L	9.3%	[17.64]	1.5%	[24.42]	**7.8%**	[16.47]

Table 2.4

Value Premium

The table reports the monthly return (%) of HML portfolios. HML is based on the methodology of Fama and French (1993). HML-T is the industry-adjusted HML by applying tech (non-tech) breakpoints to tech (non-tech) stocks. The tech industry classification is defined by the U.S. Bureau of Labor Statistics (BLS). EW represents the portfolios with equal weights. Alpha is the CAPM alpha. Stdev is the standard deviation of monthly returns. Sharpe is the annualized Sharpe ratio. T-statistics are reported in brackets. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Sample period is from July 1968 to December 2019.

Panel A: HML Return

	1968-1991	1991-2019	2001-2019
HML	**0.44*** **	**0.17**	**0.03**
	[2.69]	[1.00]	[0.17]
CAPM Alpha	0.51***	0.29*	0.00
	[3.40]	[1.71]	[-0.01]
HML-T	**0.62*** **	**0.56*** **	**0.32** **
	[3.86]	[4.18]	[2.39]
CAPM Alpha	0.68***	0.63***	0.28**
	[4.54]	[4.74]	[2.09]
Tech Subsample	0.72***	0.88***	0.64***
	[3.57]	[5.11]	[3.40]
Non-tech Subsample	0.60***	0.49***	0.24*
	[3.64]	[3.65]	[1.69]
HML-T (EW)	**0.74*** **	**0.70*** **	**0.43*** **
	[4.62]	[4.86]	[3.15]
CAPM Alpha	0.81***	0.83***	0.47***
	[5.60]	[5.94]	[3.38]
Tech Subsample	0.74***	0.86***	0.51***
	[3.90]	[4.60]	[2.74]
Non-tech Subsample	0.73***	0.65***	0.40***
	[4.42]	[4.45]	[2.68]
HML-T minus HML	0.18***	0.39***	0.29***
	[2.91]	[4.76]	[3.43]
HML-T (EW) minus HML	0.30***	0.53***	0.41***
	[3.27]	[5.17]	[3.88]

Panel B: HML Volatility

HML				
	Stdev	2.69	3.13	2.43
	Sharpe	0.56	0.19	0.04
HML-T				
	Stdev	2.66	2.46	2.00
	Sharpe	0.80	0.78	0.55
HML-T (EW)				
	Stdev	2.66	2.66	2.04
	Sharpe	0.96	0.91	0.73

Table 2.5

Value Premium:
Alternative Tech Classifications or Innovation Measures

The table reports the main result of Table 2.4 by using alternative tech classifications from Ward (2020) (Ward), Campello and Graham (2013) (CG), and Brown, Fazzari, and Petersen (2009) (BFP) or using innovation measures from Kogan, Papanikolaou, et al. (2017) (Patents) and Chan, Lakonishok, and Sougiannis (2001) (R&D). Panel A reports monthly portfolio returns (%) with value weights, and Panel B reports portfolio returns with equal weights. Alpha is the CAPM alpha. T-statistics are reported in brackets. Sample period is from July 1968 to December 2019.

Panel A: HML-T (Value Weighted)

	Raw Return				CAPM Alpha			
	1968-1991		1991-2019		1968-1991		1991-2019	
	Return		Return		Alpha		Alpha	
HML-T (Baseline)	0.62	[3.86]	0.56	[4.18]	0.68	[4.54]	0.63	[4.74]
HML-T (Ward)	0.59	[3.64]	0.43	[2.64]	0.65	[4.33]	0.55	[3.35]
HML-T (CG)	0.61	[3.83]	0.48	[3.54]	0.67	[4.49]	0.56	[4.10]
HML-T (BFP)	0.61	[3.88]	0.49	[3.58]	0.67	[4.56]	0.56	[4.13]
HML-T (Patents)	0.64	[3.72]	0.52	[3.23]	0.70	[4.43]	0.66	[4.15]
HML-T (R&D)	0.59	[3.62]	0.54	[4.11]	0.64	[4.21]	0.59	[4.46]

Panel B: HML-T (Equally Weighted)

HML-T (Baseline)	0.74	[4.62]	0.70	[4.86]	0.81	[5.60]	0.83	[5.94]
HML-T (Ward)	0.73	[4.46]	0.60	[3.63]	0.81	[5.50]	0.77	[4.85]
HML-T (CG)	0.73	[4.58]	0.67	[4.70]	0.80	[5.54]	0.80	[5.76]
HML-T (BFP)	0.72	[4.56]	0.68	[4.71]	0.80	[5.52]	0.80	[5.77]
HML-T (Patents)	0.73	[4.28]	0.66	[3.77]	0.81	[5.32]	0.83	[4.91]
HML-T (R&D)	0.75	[4.64]	0.74	[5.10]	0.82	[5.59]	0.86	[5.96]

Table 2.6

Excess Returns of 2-by-3 Size-B/M Sorted HML-T Portfolios

The table reports the monthly excess returns (%) of 2-by-3 size-B/M sorted portfolios. HML-T is the industry-adjusted HML by applying tech (non-tech) breakpoints to tech (non-tech) stocks based on the tech classification from BLS. H, N, and L indicate high, neutral, and low B/M portfolios (top 30%, middle 40%, and bottom 30%), respectively. S and B indicate small and big portfolios (top 50% and bottom 50%), respectively. Excess returns are the value-weighted portfolio returns in excess of the one-month Treasury bill rate, which is obtained from Ken French's website. T-statistics are reported in brackets. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Sample period is from July 1991 to December 2019.

Panel A: HML-T

	Value-weighted				Equal-weighted			
	L	N	H	**HML-T**	L	N	H	**HML-T**
S	0.19	0.93	1.17	**0.98**	0.43	1.06	1.46	**1.03**
	[0.50]	[3.11]	[3.75]	**[6.32]**	[1.05]	[3.45]	[4.57]	**[5.86]**
B	0.70	0.72	0.83	**0.13**	0.69	0.96	1.06	**0.37**
	[3.07]	[3.14]	[3.26]	**[0.85]**	[2.21]	[3.45]	[3.46]	**[2.45]**
				0.56				**0.70**
				[4.18]				**[4.86]**

Panel B: Tech Subsample

	Value-weighted				Equal-weighted			
	L	N	H	**HML-T**	L	N	H	**HML-T**
S	0.35	1.29	1.69	**1.34**	0.84	1.47	1.99	**1.14**
	[0.69]	[2.68]	[4.00]	**[6.30]**	[1.54]	[2.97]	[4.58]	**[4.84]**
B	0.88	0.92	1.31	**0.43**	0.85	1.24	1.43	**0.58**
	[2.94]	[3.07]	[3.72]	**[1.73]**	[1.88]	[3.20]	[3.68]	**[2.75]**
				0.88				**0.86**
				[5.11]				**[4.60]**

Panel C: Non-Tech Subsample

	Value-weighted				Equal-weighted			
	L	N	H	**HML-T**	L	N	H	**HML-T**
S	0.16	0.87	1.03	**0.87**	0.29	0.94	1.27	**0.98**
	[0.48]	[3.36]	[3.54]	**[5.26]**	[0.77]	[3.56]	[4.32]	**[5.22]**
B	0.64	0.68	0.75	**0.11**	0.64	0.86	0.96	**0.31**
	[2.98]	[2.99]	[2.85]	**[0.69]**	[2.28]	[3.25]	[3.16]	**[2.16]**
				0.49				**0.65**
				[3.65]				**[4.45]**

Table 2.7

Anomaly Alpha:
HML-T Applied in Fama-French Three-factor Model

The table reports the asset pricing test alphas for 153 anomalies. Alphas are the intercepts by regressing each anomaly on FF3 or FF3Tech factors. FF3 is the Fama and French (1993) three-factor model. FF3Tech is an alternative three-factor model by substituting *HML* with *HML-T* and keeping the same MKT and SMB factors. Factor return data (monthly, %) come from Jensen, Kelly, and Pedersen (2022). Mean is the average of 153 alphas. The Gibbons, Ross, and Shanken (1989) (GRS) F-stat tests the null hypothesis that all of the alphas are jointly zero. p(GRS) is the p-values for the GRS test. Panel A and B report the results of the anomalies constructed by value weights and equal weights, respectively. Sample period is from July 1991 to December 2019.

	Alpha of FF3	Alpha of FF3Tech	Difference (T-stat)	Change %
Panel A: Anomaly Constructed by Value Weights				
Mean of alphas	0.25	0.20	-0.05 (-3.41)	-18%
Number of alphas at 1% sig. level	57	45	-12	-21%
GRS F-stat	2.34	2.31		
p(GRS)	0.00	0.00		
Panel B: Anomaly Constructed by Equal Weights				
Mean of alphas	0.41	0.35	-0.07 (-5.47)	-16%
Number of alphas at 1% sig. level	98	84	-14	-14%
GRS F-stat	6.71	6.17		
p(GRS)	0.00	0.00		

Table 2.8

Global Value Premium

The table reports HML and HML-T on the main seven developed markets: Korea, Hong Kong, Japan, US, Canada, UK, and Continental Europe (including Germany, France, Netherlands, Belgium, Switzerland, Austria, Sweden, Norway, Finland, Denmark, Ireland, Spain, Italy, Portugal, and Greece). Global equity return data come from Reuters Eikon. EW represents equally-weighted portfolios. T-statistics are reported in brackets. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Sample period starts from July 2001 since the sample requires a minimum of 300 stocks from each market, until December 2019.

Market	2019 Tech Market Cap	HML	HML-T	HML-T (EW)
Korea	43.2%	0.48**	0.63***	0.72***
		[2.13]	[2.97]	[4.42]
United States	39.2%	0.03	0.32**	0.43***
		[0.17]	[2.39]	[3.15]
Europe	21.5%	0.22	0.24*	0.18*
		[1.55]	[1.82]	[1.84]
Hong Kong	21.2%	0.32	0.38*	0.93***
		[1.57]	[1.82]	[6.17]
Japan	19.2%	0.23	0.29**	0.33***
		[1.54]	[2.02]	[2.96]
United Kingdom	15.1%	0.07	-0.04	0.28***
		[0.48]	[-0.24]	[2.96]
Canada	8.1%	0.23	0.30	0.34
		[0.93]	[1.36]	[1.62]

Table 2.9

Extension - Intangible-adjusted Value Premium

The table reports monthly returns of various HML strategies. iHML and iHML-T are the extended HML and HML-T strategies, respectively, by capitalizing intangibles of Peters and Taylor (2017) into book equity when constructing book-to-market ratios. Capitalized intangibles data come from Peters and Taylor (2017) with the sample ending in December 2017. HML is based on the Fama and French (1993) methodology. HML-T is based on the methodology of this paper. Sharpe is the annualized Sharpe ratio. T-statistics are reported in brackets. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Sample Period is from July 1968 to June 2019.

	Panel A: Return		
	1968-1991	1991-2019	2001-2019
HML	0.44***	0.17	0.03
	[2.69]	[1.00]	[0.17]
iHML	0.49***	0.27*	0.12
	[3.22]	[1.85]	[0.75]
HML-T	**0.62*** **	**0.56*** **	**0.32** **
	[3.86]	[4.18]	[2.39]
iHML-T	**0.66*** **	**0.68*** **	**0.36** **
	[4.04]	[5.05]	[2.28]
	Panel B: Volatility		
HML			
Stdev	2.69	3.13	2.43
Sharpe	0.56	0.19	0.04
iHML			
Stdev	2.53	2.67	2.43
Sharpe	0.67	0.35	0.17
HML-T			
Stdev	2.66	2.46	2.00
Sharpe	0.80	0.78	0.55
iHML-T			
Stdev	2.72	2.48	2.35
Sharpe	0.84	0.95	0.53

2.9 Appendix

Figure A2.1. Book-to-Market Ratios

The figure shows the trend of book-to-market ratios for tech and non-tech (and NYSE) stocks. Panel A shows the time series of the book-to-market ratios at the 30th percentile (red/pink lines) and 70th percentile (black/grey lines). Solid lines are for tech stocks. Dashed lines are for non-tech and NYSE stocks. Panel B shows the allocation of tech stocks (in percentage) based on the NYSE breakpoints of book-to-market ratios. Sample period is from July 1968 to December 2019.

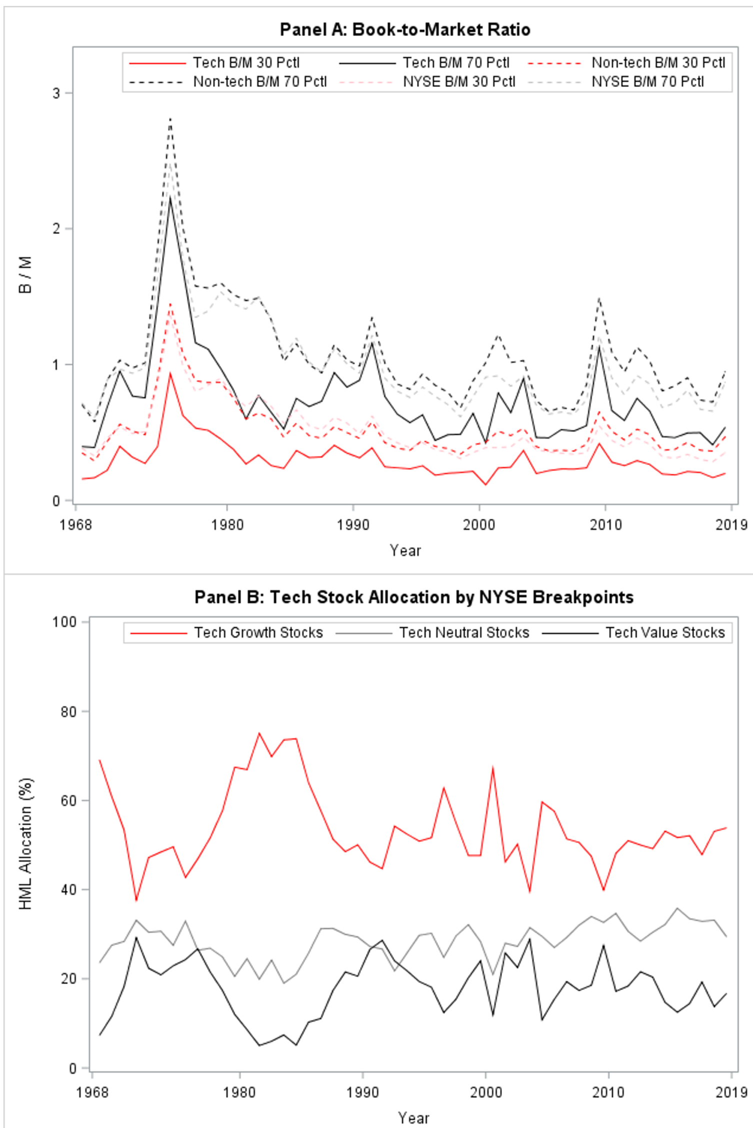


Table A2.1

List of Tech Industries

The table reports the classification of the tech industry at the 4-digit NAICS from the US Bureau of Labor Statistics by Hecker (2005). NAICS industry codes are adjusted to the 2017 NAICS revision. Level 1 tech classification is shown in the table.

NAICS	Industry
3254	Pharmaceutical and Medicine Manufacturing
3341	Computer and Peripheral Equipment Manufacturing
3342	Communications Equipment Manufacturing
3344	Semiconductor and Other Electronic Component Manufacturing
3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
3364	Aerospace Product and Parts Manufacturing
5112	Software Publishers
5179	Other Telecommunications
5182	Data Processing, Hosting, and Related Services
5191	Other Information Services
5413	Architectural, Engineering, and Related Services
5415	Computer Systems Design and Related Services
5417	Scientific Research and Development Services

Table A2.2

Cash Flow and Operating Performance

The table reports proxies for cash flows by gross profitability, long-term EPS growth forecasts, and SG&A intensity in each B/M-sorted portfolio. H, N, and L indicate high, neutral, and low B/M portfolios (top 30%, middle 40%, and bottom 30%), respectively. Gross Profitability is the mean of gross profitability defined by sales minus costs of goods sold divided by total assets (Novy-Marx (2013)). EPS Growth is the median of analysts' growth forecasts in long-term EPS from IBES. SG&A Intensity is the mean of SG&A expenses scaled by total assets. All measures are winsorized by 2 percent on both ends. T-statistics are reported in brackets. Sample period is from 1968 to 2019 for Panel A and C. Subsample in intersection with IBES coverage is used for Panel B from 1981 to 2019.

Panel A: Gross Profitability

Portfolio	Tech		Non Tech		**Tech Minus Non Tech**	
			Year 1 (T : T+1)			
H	34.8%	[37.00]	24.0%	[26.58]	**10.8%**	[12.08]
N	39.3%	[36.01]	28.0%	[35.73]	**11.4%**	[17.41]
L	42.2%	[31.04]	38.4%	[80.87]	**3.8%**	[3.81]
			Year 3 (T+2 : T+3)			
H	37.4%	[42.96]	25.2%	[25.93]	**12.3%**	[14.10]
N	39.9%	[39.88]	27.9%	[37.39]	**12.0%**	[19.38]
L	42.2%	[33.87]	37.8%	[82.85]	**4.4%**	[4.86]
			Year 5 (T+4 : T+5)			
H	38.5%	[54.81]	25.6%	[26.36]	**12.9%**	[15.47]
N	40.5%	[45.38]	28.0%	[37.12]	**12.5%**	[23.17]
L	42.5%	[35.87]	37.6%	[79.23]	**4.9%**	[6.04]

Panel B: EPS Growth (Long-term Forecasts)

			Long-term Growth			
H	16.8%	[27.06]	12.3%	[38.29]	**4.5%**	[11.03]
N	19.7%	[32.07]	13.4%	[58.47]	**6.2%**	[14.86]
L	24.1%	[32.83]	17.1%	[47.00]	**7.0%**	[16.03]

Panel C: SG&A Intensity

			Year 1 (T : T+1)			
H	15.8%	[9.61]	13.7%	[13.28]	**2.1%**	[2.40]
N	9.5%	[11.81]	7.9%	[12.09]	**1.6%**	[4.07]
L	8.0%	[11.98]	5.7%	[15.75]	**2.3%**	[4.20]
			Year 3 (T+2 : T+3)			
H	33.3%	[42.80]	22.3%	[33.25]	**11.1%**	[11.69]
N	34.1%	[51.70]	22.2%	[41.36]	**11.9%**	[15.21]
L	39.3%	[57.04]	29.0%	[71.09]	**10.3%**	[20.97]
			Year 5 (T+4 : T+5)			
H	32.7%	[47.99]	22.2%	[33.65]	**10.4%**	[11.78]
N	33.4%	[54.00]	22.2%	[39.91]	**11.2%**	[15.95]
L	38.0%	[57.88]	28.5%	[72.69]	**9.4%**	[19.87]

Table A2.3

Value Premium

The table reports the monthly return (%) of HML portfolios. HML is based on the methodology of Fama and French (1993). HML-T is the industry-adjusted HML by applying tech (non-tech) breakpoints to tech (non-tech) stocks. The tech industry classification is defined by the U.S. Bureau of Labor Statistics (BLS) but I arbitrarily remove pharmaceutical and aerospace industries from the BLS tech classification. EW represents the portfolios with equal weights. Alpha is the CAPM alpha. Stdev is the standard deviation of monthly returns. Sharpe is the annualized Sharpe ratio. T-statistics are reported in brackets. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Sample period is from July 1968 to December 2019.

Panel A: HML Return

	1968-1991	1991-2019	2001-2019
HML	**0.44*** **	**0.17**	**0.03**
	[2.69]	[1.00]	[0.17]
CAPM Alpha	0.51***	0.29*	0.00
	[3.40]	[1.71]	[-0.01]
HML-T	**0.59*** **	**0.44*** **	**0.28***
	[3.65]	[2.71]	[1.82]
CAPM Alpha	0.65***	0.55***	0.27*
	[4.31]	[3.44]	[1.76]
Tech Subsample	0.69***	0.76***	0.49***
	[3.01]	[4.09]	[2.60]
Non-tech Subsample	0.57***	0.38**	0.24
	[3.48]	[2.23]	[1.46]
HML-T (EW)	**0.73*** **	**0.61*** **	**0.38** **
	[4.53]	[3.65]	[2.34]
CAPM Alpha	0.81***	0.78***	0.45***
	[5.54]	[4.85]	[2.75]
Tech Subsample	0.83***	0.99***	0.69***
	[3.87]	[4.74]	[3.83]
Non-tech Subsample	0.71***	0.52***	0.31*
	[4.29]	[3.05]	[1.73]
HML-T minus HML	0.15**	0.27***	0.25***
	[2.48]	[4.12]	[3.48]
HML-T (EW) minus HML	0.29***	0.45***	0.36***
	[3.23]	[4.49]	[3.38]

Panel B: HML Volatility

HML				
	Stdev	2.69	3.13	2.43
	Sharpe	0.56	0.19	0.04
HML-T				
	Stdev	2.68	2.99	2.26
	Sharpe	0.76	0.51	0.42
HML-T (EW)				
	Stdev	2.68	3.10	2.42
	Sharpe	0.95	0.68	0.55

Table A2.4

HML-T by Within Industry Sorts

The table reports HML portfolio returns by different approaches. Industries are defined at 2-digit NAICS into 19 industries. The tech industry is further defined at 4-digit NAICS by the BLS' classification. HML is based on the methodology of Fama and French (1993). HML Within-Industry (19 Industries) is the HML portfolio constructed by sorting B/M ratios within 19 main industries. HML-T Within-Industry (Tech + 19 Industries) is an alternative HML-T by separately sorting B/M ratios within tech and each of the other 19 non-tech industries. HML-T Within-Industry (Tech + Non-tech) is the baseline HML-T by sorting B/M ratios within tech and non-tech industries. Panel A shows raw returns. Panel B shows alphas to the CAPM. All portfolios are value-weighted. T-statistics are in brackets. Sample period is from July 1968 to December 2019. *, ** and *** indicate significance at the 10%, 5%, and 1% levels.

Panel A: Raw Return

	1968-1991		1991-2019		2001-2019	
	Return		Return		Return	
HML	0.44	[2.69]	0.17	[1.00]	0.03	[0.17]
HML Within Industry (19 Industries)	0.42	[3.05]	0.37	[3.13]	0.25	[1.93]
HML-T Within Industry (Tech + 19 Industries)	0.42	[3.28]	0.48	[4.37]	0.31	[2.49]
HML-T Within Industry (Tech + Non-tech)	0.62	[3.86]	0.56	[4.18]	0.32	[2.39]

Panel B: CAPM Alpha

	1968-1991		1991-2019		2001-2019	
	Alpha		Alpha		Alpha	
HML	0.51	[3.40]	0.29	[1.71]	0.00	[-0.01]
HML Within-Industry (19 Industries)	0.47	[3.60]	0.42	[3.55]	0.22	[1.70]
HML-T Within-Industry (Tech + 19 Industries)	0.46	[3.81]	0.51	[4.57]	0.25	[2.03]
HML-T Within Industry (Tech + Non-tech)	0.68	[4.54]	0.63	[4.74]	0.28	[2.09]

Table A2.5

Alphas of 2-by-3 Size-B/M Sorted HML-T Portfolios

The table reports the CAPM alphas of 2-by-3 size-B/M sorted portfolios. Alphas are the intercepts by regressing excess returns of size-B/M sorted portfolios on the market excess return. HML-T is the industry-adjusted HML by applying (non-tech) breakpoints to tech (non-tech) stocks based on the tech classification from BLS. H, N, and L indicate high, neutral, and low B/M portfolios (top 30%, middle 40%, and bottom 30%), respectively. S and B indicate small and big portfolios (top 50% and bottom 50%), respectively. Excess returns are value-weighted portfolio returns in excess of the one-month Treasury bill rate, which is obtained from Ken French's website. T-statistics are reported in brackets. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Sample period is from July 1991 to December 2019.

Panel A: HML-T

	Value-weighted				Equal-weighted			
	L	N	H	**HML-T**	L	N	H	**HML-T**
S	-0.67	0.22	0.45	**1.12**	-0.44	0.36	0.79	**1.22**
	[-2.69]	[1.13]	[2.12]	**[7.48]**	[-1.42]	[1.70]	[3.30]	**[7.34]**
B	0.01	0.04	0.15	**0.14**	-0.19	0.18	0.25	**0.43**
	[0.16]	[0.56]	[1.12]	**[0.86]**	[-1.41]	[1.47]	[1.53]	**[2.88]**
				0.63				**0.83**
				[4.74]				**[5.94]**

Panel B: Tech Subsample

	Value-weighted				Equal-weighted			
	L	N	H	**HML-T**	L	N	H	**HML-T**
S	-0.69	0.27	0.80	**1.49**	-0.22	0.47	1.13	**1.35**
	[-1.78]	[0.75]	[2.54]	**[7.14]**	[-0.50]	[1.23]	[3.33]	**[5.87]**
B	0.07	0.11	0.47	**0.40**	-0.26	0.24	0.45	**0.71**
	[0.48]	[0.73]	[2.05]	**[1.60]**	[-0.92]	[1.10]	[1.95]	**[3.37]**
				0.95				**1.03**
				[5.45]				**[5.64]**

Panel C: Non-Tech Subsample

	Value-weighted				Equal-weighted			
	L	N	H	**HML-T**	L	N	H	**HML-T**
S	-0.63	0.27	0.38	**1.01**	-0.50	0.35	0.66	**1.17**
	[-2.87]	[1.53]	[1.84]	**[6.22]**	[-1.78]	[1.87]	[2.98]	**[6.50]**
B	0.01	0.05	0.09	**0.08**	-0.15	0.15	0.19	**0.34**
	[0.12]	[0.50]	[0.55]	**[0.49]**	[-1.28]	[1.12]	[1.07]	**[2.34]**
				0.54				**0.76**
				[4.02]				**[5.29]**

Table A2.6

List of Anomalies with Alpha Turned (In)Significant

The table reports a detailed list of anomalies with alphas turned (in)significant in the FF3Tech model as shown in Panel A of Table 2.7. Alphas are the intercepts by regressing each anomaly on FF3 or FF3Tech factors. Anomaly return data (monthly, %) come from Jensen, Kelly, and Pedersen (2022). Topic and Reference refer to the categorization and previous studies of the anomalies, respectively, as indicated in Jensen, Kelly, and Pedersen (2022). Panel A and B report the result of anomalies constructed by value weights and equal weights, respectively. Sample period is from July 1991 to December 2019.

Panel A: Anomaly with Alpha Turned Not Significant at 1 Percent Level

Anomaly	Variable	Topic	FF3 Alpha	T-stat	FF3Tech Alpha	T-stat	Change in Alphas	Reference
Net payout yield	eqnpo_me	Value	0.39	2.85	0.13	0.90	-0.25	Boudoukh et al. (2007)
Downside Beta	betadown_252d	Risk	0.54	2.93	0.34	1.76	-0.20	Ang et al. (2006)
CAPEX growth	capx_gr1	Investment	0.30	2.65	0.10	0.87	-0.19	Xie (2001)
Mispricing factor: Management	mispricing_mgmt	Investment	0.45	3.99	0.27	2.30	-0.18	Stambaugh and Yuan (2017)
Return volatility	rvol_21d	Risk	0.67	3.58	0.50	2.50	-0.18	Ang et al. (2006)
Change in net operating assets	noa_gr1a	Investment	0.38	4.03	0.21	2.08	-0.18	Hirshleifer et al. (2004)
Change in long-term net operating assets	lnoa_gr1a	Investment	0.28	2.86	0.11	1.05	-0.17	Fairfield et al. (2003)
Net equity issuance	eqnetis_at	Value	0.51	3.95	0.35	2.51	-0.17	Bradshaw et al. (2006)
Idiosyncratic volatility from CAPM	ivol_capm_252d	Risk	0.60	3.29	0.44	2.24	-0.16	Ali et al. (2003)
Idiosyncratic volatility from FF3 model	ivol_ff3_21d	Risk	0.56	3.53	0.40	2.34	-0.16	Ang et al. (2006)
Years 6-10 lagged returns, nonannual	seas_6_10na	Risk	0.46	3.72	0.30	2.31	-0.16	Heston and Sadka (2008)
Idiosyncratic volatility from CAPM	ivol_capm_21d	Risk	0.61	3.64	0.45	2.53	-0.15	Ali et al. (2003)
Net stock issues	chcsho_12m	Value	0.36	3.15	0.22	1.86	-0.14	Pontiff and Woodgate (2008)
Cash flow volatility	ocfq_saleq_std	Risk	0.32	3.07	0.25	2.30	-0.08	Huang (2009)
Market correlation	corr_1260d	Seasonality	0.39	2.69	0.32	2.13	-0.07	Asness et al. (2020)
Profit margin	ebit_sale	Profitability	0.31	2.76	0.24	2.03	-0.07	Soliman (2008)
Growth in book debt	debt_gr3	Debt Issuance	0.21	2.79	0.15	1.98	-0.06	Lyandres et al. (2008)
Quality minus Junk: Growth	qmj_growth	Quality	0.30	2.71	0.29	2.57	-0.01	Asness et al. (2019)

Panel B: Anomaly with Alpha Turned Significant at 1 Percent Level

Anomaly	Variable	Topic	FF3 Alpha	T-stat	FF3Tech Alpha	T-stat	Change in Alphas	Reference
# consecutive quarters with rising earnings	ni_inc8q	Quality	0.15	1.50	0.27	2.64	0.12	Barth et al. (1999)
Price momentum t-12 to t-1	ret_12_1	Momentum	0.64	2.57	0.77	2.97	0.13	Jegadeesh and Titman (1993)
Tax expense surprise	tax_gr1a	Profit Growth	0.22	2.21	0.38	3.70	0.17	Thomas and Zhang (2011)
R&D capital-to-book assets	rd5_at	Leverage	0.31	1.90	0.48	2.74	0.18	Li (2011)
Cash-to-assets	cash_at	Leverage	0.22	1.66	0.50	3.27	0.28	Palazzo (2012)
Liquidity of market assets	aliq_mat	Leverage	0.17	1.94	0.45	4.53	0.28	Ortiz-Molina and Phillips (2014)

Chapter 3

The Value of Corporate Adaptation in Bad Times: Evidence from Covid Crisis Work-from-Home Announcements

ABSTRACT

We identify voluntary corporate work-from-home announcements during the Covid-19 crisis by scraping listed-company websites. Market reactions provide new information about the value and risk implications of corporate adaptation to crises. Event studies show three-to-five percent abnormal returns over five days following work-from-home announcement. Factor regressions establish significant declines in Covid-risk exposure relative to characteristic-matched samples. We conclude that markets actively processed information about corporate adaptation to Covid-19, beyond previous assessments of *ex ante* corporate susceptibility. We develop methodological extensions for clustered event windows, show faster market reaction to Bloomberg announcements, and confirm the work-from-home proxies that predicted early adaptation.

3.1 Introduction

A corporation's ability to adapt to new conditions – also called flexibility or resilience – depends on its assets, employees, financing, and strategy, and has long been proposed as a source of value and risk-mitigation (e.g., Stigler (1939), Pindyck (1982), Trigeorgis (1996), Graham and Harvey (2001)).[1] Because both risk and the market price of risk tend to be high in bad times, adaptation in crises is particularly important.[2] The Covid-19 pandemic crystalized the criticality of corporate flexibility and resilience, especially work-from-home capability (e.g., Papanikolaou and Schmidt (2022), Pagano, Wagner, and Zechner (2021), Barry et al. (2022)).[3]

We provide new evidence about the financial-market value of corporate adaptation using a novel empirical identification strategy based on "information shocks." Early in the pandemic, we scraped company websites to obtain voluntary corporate announcements of work-from-home policies, before mandatory lockdowns required remote work. Using event study methods, cumulative abnormal returns in the five days following announcement reached three-to-five percent of firm value. Further, the risk of announcers fell relative to comparable firms, measured by both abnormal default probabilities and exposure to Covid-19 risk using the factor of Papanikolaou and Schmidt (2022). We conclude that financial markets perceived higher value and less risk for firms adaptating to Covid-19 by voluntarily announcing a work-from-home transition.

[1]See also Brennan and Schwartz (1985), McDonald and Siegel (1985), Triantis and Hodder (1990), Chen, Kacperczyk, and Ortiz-Molina (2011), Carlson, Dockner, et al. (2014), Reinartz and Schmid (2016), and Gu, Hackbarth, and Johnson (2018).

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

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

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

We use cross-sectional comparisons as in previous studies, but also uniquely exploit the information-shock nature of announcements of corporate adaptation. Cross-sectionally, we compare firms announcing work-from-home to non-announcing firms, revealing the *ex ante* characteristics that most closely predicted observable adaptation. The labor-suitability measures of DN and PS strongly foretold actual work-from-home adoption, validating the relevance of those variables for real corporate decisions and also confirming the integrity of our announcement data.

We add to cross-sectional comparisons using event studies. Unlike comparisons of firms with different characteristics, an event study uses matching and other control methods to compare firms with *similar observable characteristics*, but *different observable actions*.[4] In our case, the observable action is the voluntary announcement of a work-from-home policy. In short windows immediately following announcement, the value of announcers increased, and risk decreased, relative to controls. We thus add to prior literature investigating corporate

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

flexibility or resilience as a firm characteristic by showing positive market reaction both statistically and economically to an observable corporate action – adaptation to work-from-home.

To help interpret our results, we emphasize several points. First, empirical identification does not require that the control firms (characteristic-matched non-announcers) never adapted to work-from-home. Identification is based on market expectations in the short windows following announcement, and in those windows the observable actions of the sample firms and matches were different.[5] Second, event window price and risk responses depend on forward-looking expectations over many possible future aggregate states of the world. Pagano, Wagner, and Zechner (2021) emphasize that the most disastrous pandemic scenarios were important to initial pricing even though those greatest fears were not realized. Event study methods are well-suited to this setting. Event window prices incorporate assessments of the value of adaptation in all future states, including the worst disasters. Other indicators, such as realized operating performance for example, can only show what happened over the one path that occurred.

One might wonder what prevented non-announcers from imitating announcers to obtain a similar financial-market benefits. Work-from-home policy announcements are not cheap talk (i.e., costless and unverifiable statements without direct payoff implications (Crawford and Sobel (1982))). Remote-work policies are real decisions with implications for the productivity of hundreds or thousands of employees. Theoretically, under incomplete information and maximization of intrinsic asset value, corporate actions can reveal to markets information about underlying firm assets and real options (Lucas and McDonald (1990) and Carlson,

[5]Surveys indicate that remote-work transitions were more successful than initially anticipated (Barrero, Bloom, and Davis (2021)) and remote-work technology diffused quickly through the economy (Bick, Blandin, and Mertens (2021)).

Fisher, and Giammarino (2006)). Under the difficult circumstances of the pandemic, firms announcing voluntary transition to work-from-home credibly demonstrated an important adaptation.

Additional results confirm the validity and interpretation of our results. First, announcement effects are larger for firms in non-essential industries, where adaptation to remote work should be more valuable. Second, work-from-home announcements covered by Bloomberg realized abnormal returns more quickly, consistent with prominent news dissemination increasing the speed of price incorporation (Fedyk (2021)). Third, we test a variety of additional variables that could predict work-from-home potential including intangible capital (Peters and Taylor (2017)), organizational capital (Eisfeldt and Papanikolaou (2013)), and other firm characteristics. ESG score (Albuquerque et al. (2020) and Ding et al. (2021)) adds some ability to predict work-from-home announcement beyond labor-suitability, but does not alter inference about announcement effects. Finally, operating performance of announcers and their matches exceeds other firms during the pandemic, and announcers show significantly lower declines in employment and R&D relative to characteristic-based matches. These results corroborate that remote-work adaptability mitigated pandemic risk, while also offering opportunity to discuss identification differences between event studies and comparisons of operating performance.

We emphasize relation to several papers. Pagano, Wagner, and Zechner (2021) ("PWZ") use Covid-19 to show how learning about a disaster and the eventual unfolding of events drive time-variation in the price of disaster risk. PWZ thus emphasize learning about aggregate disaster risk, while we show that markets learned from individual firms' announcements about adaptation to work-from-home. Barry et al. (2022) survey CFOs and find that corporate flexibility, particularly in the workplace, affects business plans and is important. We confirm the significance of workplace flexibility to financial-market pricing. Recent measures of labor-suitability for remote work, such as the DN and PS estimates, are keystones for current and future research. We provide direct evidence of the validity of such measures for predicting actual work-from-home policies. Methodologically, we extend the single-day clustered event-study approach of Kolari and Pynnönen (2010) to imperfect clustering and multi-day event windows, accounting for cross-serial correlations. Finally, prior research addresses the pre-existing characteristics that made some firms more or less "immune" to the effects of Covid-19 (Ding et al. (2021)). We add to this literature by showing market response to announcements of corporate *actions*. Work-from-home announcements demonstrate corporate adaptation, distinct from assessments of *ex ante* corporate susceptibility.

One concern a reader might have is the external validity of our finding given that the pandemic was a unique event. While Covid-19 crisis may not happen again, more crises will occur in future. Firms' adaptation to new economic environment has always been critical during such events. Hence, understanding and quantifying the value of corporate flexibility and quick adaptation during crises is of general and timeless interest and particularly important for firms making ex-ante decisions whether and how to prepare for future crises of any sort. We show this for one crisis that allows a meaningful identification, but our results are generalizable to any crises and any form of corporate flexibility to adapt quickly. Furthermore, we provide first quantitative estimate, which is economically meaningful and a useful input in firms' investment decisions affecting corporate adaptability of any type.

3.2 Work-from-Home Announcements

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

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

To elaborate further, Ramelli and Wagner (2020) give a timeline of key events. They recognize January 20 as the outbreak beginning, when Chinese authorities confirmed human-to-human transmission. The first conference call that explicitly discussed the coronavirus was on January 22. Chinese authorities placed Wuhan under lockdown on January 23.[6] A month later, on February 23, Italy imposed a local lockdown. Google search for "Covid-19" rose significantly and earnings calls mentioning Covid-19 rose from thirty to nearly fifty percent. Ramelli and Wagner define the Covid-19 "fever" period starting Monday, February 24 and ending Friday, March 20. They choose March 20 as the final day because the Federal Reserve announced major interventions in corporate credit market on March 23. We end our sample period for announcements one day earlier, on March 19, because California announced the first U.S. state-imposed lockdown on the evening of March 19.[7] Work-from-home announce-

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

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

ments during our sample period were voluntary and provided new information to capital markets.

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

In more detail, Google asserts that its web crawlers pay "special attention" to changes in existing sites, which helps to more accurately detect announcements of corporate responses to Covid-19. We accessed Google's search data in early June 2020 and compiled our initial dataset of WFH announcements. Following Loughran and McDonald (2011) and others, we use a bag-of-words to parse web content. Our words include "work from home", "wfh", "working from home", "work-from-home", "home working", "remote work", "remote working", "work remotely", "work from anywhere", "working from anywhere", and "work anywhere". Manual verification involved checking for false negatives using the Google web interface, narrowing date ranges and confirming date-time stamps, and ensuring that content describes a new WFH policy. We record the first date of a new WFH policy.

For 27 companies, a website announcement regarding remote work was insufficiently clear that we emailed the companies (up to three times) to clarify whether their announcement reflected work-from-home adoption. We received seven positive responses and categorized the remaining not as announcements. Despite our best efforts, our data is imperfect and would not reflect, for example, corporate remote-work announcements in a private forums such as email or password-protected work hub. Nonetheless, our efforts reflect well the information available to markets, and in particular the effort a thorough investor might make gathering information related to companies' work-from-home policies by utilizing company websites and Google search.

Figure 3.1 shows representative WFH announcements. On March 2 Twitter started "strongly encouraging employees to work from home" and on March 11 required that employees "must work from home".[8] We record Twitter as a WFH firm starting from March 2. By March 19 when the first state-wide lockdown was implemented in California, 273 firms had announced adopting work-from-home. Our simplest dummy variable, WFH_i, indicates announcing a work-from-home policy within our search window.

Firms were also affected by government orders to close on-site operations of non-essential businesses. Only essential businesses (sometimes called life-sustaining) could maintain in-person operations. The list of critical businesses was originally guided by the Department of Homeland Security's Cybersecurity and Infrastructure Security Agency and included medical supply chains, energy, food, industrial manufacturing, and emergency services. We follow the list of life-sustaining business classifications issued by Pennsylvania. We classify firms as essential if belonging to an industry on this list, and non-essential otherwise. Essential-industry classification is relatively consistent across states (Song et al. (2021)). Pennsylvania is one of few states that provided a systematic categorization based on NAICS codes,[9] while other states gave descriptive guidance.[10]

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

[9] See https://siccode.com/page/coronavirus-essential-businesses-by-naics-code.

[10] See for example California: https://covid19.ca.gov/essential-workforce.

3.2.1 Work-from-home Suitability

We use measures of labor-suitability to remote-work developed by Dingel and Neiman (2020)("DN") and Papanikolaou and Schmidt (2022)("PS"). DN use occupation characteristics from the O*NET database to identify occupations adaptable to remote work. They calculate the percentage share of suitable occupations for 2-digit NAICS industries. PS use the American Time Use Survey (ATUS) to identify occupations that had demonstrated the capability for "telecommuting" in years prior to 2020. Our PS measure is the percentage of such occupations for 4-digit NAICS industries.[11] The DN and PS measures of labor suitability capture the standard primary data sources, O*NET and ATUS, used in the literature. For example, Pagano, Wagner, and Zechner (2021) also use measures of labor suitability to work-from-home based on the O*NET and ATUS databases.[12]

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

Table 3.1 provides summary statistics. Panel A shows properties over the cross-section of firms in our sample. Since WFH is an indicator, its mean reflects that 11 percent of firms in the sample announced remote-work policies in our sample period. The PS share of labor suitable for telecommuting averages 27 percent, varying from 5 percent at the 10^{th} percentile

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

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

to 55 percent at the 90^{th} percentile. DN shows a higher mean of 44 percent also with large cross-sectional variation. Intangible capital IK and organizational capital OK range from close to zero at the 10^{th} percentile to above one at the 90^{th} percentile. The remaining variables are standard controls.

Panel B shows the correlation matrix between WFH and the labor- and capital-type related variables. WFH correlates positively with both PS and DN, and the latter two variables have correlation coefficient of 0.42. IK and OK correlate positively with each other but not strongly with WFH.

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

3.2.2 Predictors of Work-from-home Announcements

To predict observable work-from-home adoption, we estimate a logit model for the work-from-home decision ($WFH = 1$):

$$p\left(WFH_i = 1\right) = \frac{1}{1 + e^{x_i + v_i}}, \tag{3.1}$$

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

Table 3.2 shows the results. The first column includes only controls, and among these $LnME$ and market beta significantly predict the WFH decision. Larger, lower market risk firms were more likely to voluntarily adopt remote work. The remaining columns investigate PS, DN, IK, and OK individually, and then all together, both with and without industry fixed effects. PS is a strong positive predictor of work-from-home announcements (column 2). The fitted likelihoods in the lower part of the table indicate that increasing PS from the 10th percentile to the 90th percentile increases the likelihood of remote-work announcement from 6 to 19 percent. Column 3 shows similar results for DN. Neither IK nor OK significantly predicts WFH announcements (columns 4 and 5). Column 6 includes all variables together without industry fixed effects, showing PS, DN, $LnME$, and market beta to retain predictive power.

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

We also report the Bayesian Information Criterion (BIC), commonly used in model selection. We compared the BIC for all possible combinations of explanatory variables. From the 1534 possibilities,[13] we select the model minimizing BIC, shown in column 11, which uses PS and $LnME$ without industry fixed effects. We use this model to calculate propensity score for one of our benchmarks in the following section.

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

The results in this section serve two purposes. First, the DN and PS measures of labor-suitability for remote work are keystones of current and future research, appearing for example in Hensvik, Le Barbanchon, and Rathelot (2020), Pagano, Wagner, and Zechner (2021), Bick, Blandin, and Mertens (2021), Bai et al. (2021), and Barry et al. (2022). We show that these variables predict actual work-from-home adaptations, which validates their practical relevance for an important corporate decision and also confirms the integrity of our announcement data. Second, identifying the characteristics most closely associated with actual remote-work decisions allows us to create matched samples of firms with similar *ex ante* announcement likelihood as our WFH firms, but that did not themselves announce. These control firms provide a useful benchmark for event studies.

3.3 Market Reaction to WFH Announcements

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

3.3.1 Event Study Methodology

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

$$R_{it} = const + \beta_{mkt} R_{mkt,t} + \beta_{industry} R_{industry,t} + a_1 WFH_{i,0,4} + a_2 WFH_{i,5,9} + \epsilon_{i,t}, \qquad (3.2)$$

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

Section 4.2 showed that key drivers of work-from-home announcements are firm size and the PS measure of labor suitability to remote work. We control for these characteristics using panel regressions on the return differences:

$$R_{i,t} - R_{i,t}^{benchmark} = const + \beta_{mkt} R_{mkt,t} + a_1 WFH_{i,0,4} + a_2 WFH_{i,5,9} + \epsilon_{i,t}, \qquad (3.3)$$

where $R_{i,t}^{benchmark}$ is one of several benchmarks, including quintile portfolios by size, industry-size, and PS-size, with independent sorts. We also use a propensity-score benchmark, derived from the work-from-home logit specification that minimizes the BIC criterion (Table 3.2, column 11). At the beginning of the sample period, for each work-from-home firm we rank the closest matches by propensity score for all firms belonging to the same industry-size quintile. The benchmark comprises the top five matches that have not themselves previously announced, equally weighted. We match with replacement, so a firm can be used as a benchmark more than once, which improves match accuracy. If a benchmark firm announces a work-from-home policy, it is dropped as a match for all sample firms and replaced with the next closest propensity-score match from the original ranking.

We also extend the scaled abnormal returns event-study methodology of Kolari and

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

3.3.2 Valuation Effects

Table 3.3 shows the panel regressions from equation (3.2). In Panel A, using market returns, industry returns, or both as benchmarks, announcement effects are up to one percent per day in the five days beginning with the announcement day, or five percent cumulatively. The coefficients are statistically significant at the one- or five-percent level in all cases. The abnormal returns are not significantly different from zero in the following five days. Panels B (for essential firms) and C (for non-essential firms) show that the announcement effects concentrate somewhat more heavily in non-essential versus essential businesses. Point estimates of cumulative abnormal returns over the announcement window range from 3.5-4 percent for essential firms, and from 3.5-6 percent for non-essential firms, in all cases again statistically significant at the one- or five-percent level.

Table 3.4 shows results of additional benchmarking using observable firm characteristics. Benchmarking to the market in column 1 gives similar announcement effects to Table 3.3. Benchmarking using observable characteristics in columns 2-5 reduces the observed announcement effects to varying degrees, to a range of fifty to eighty basis points per day, or 2.5-4% cumulatively. Despite the marginally smaller economic magnitudes of the announcement effects, t-statistics increase, in all cases significant at the 1% level. The improvement in power is natural, since benchmarking with observable characteristics reduces noise giving smaller standard errors. Economically, the marginally lower announcement effects in columns 2-5 allow us to infer that non-announcers with characteristics similar to announcers experienced modest gains in the announcement windows. This could be interpreted purely as a random effect of better benchmarking. Alternatively, a dynamic theory should predict that as firms announced voluntary work-from-home, the market might favorably update views on the likelihood of non-announcers with similar characteristics adapting. While interesting, inference about such cross-learning would be highly demanding of the data, and we leave further consideration of such a theory to future research. Panels B and C once again show that the announcement effect point estimates are somewhat larger for non-essential (3-5% cumulatively) versus essential firms (2-3.5%).

Table 3.5 shows results for our extension of the clustered-events scaled abnormal returns methodology of Kolari and Pynnönen (2010), building on Brown and Warner (1980) and Patell (1976). We benchmark the returns by size, industry-size, and PS-size quintiles as well as propensity score as indicated in panel titles, and further control for market and Fama-

French 3- and 5-factors as indicated in column headers. We calculate the scaled abnormal returns during pre-event window of 10 days prior to the WFH announcement, event window of 5 days from the announcement starting on day zero, and 5-days post-event. The first three columns with CAPM risk-adjustment show significantly positive scaled abnormal returns in the event window (second column), and returns indistinguishable from zero in the pre- and post-event windows (first and third columns) with the exception of one case at the ten percent level. The remaining columns with FF3 and FF5 risk-adjustment show similar results, with slightly smaller point estimates for the announcement-window scaled abnormal returns, but comparable t-statistics due to smaller standard errors.

Figure 3.2 displays the scaled abnormal returns in event time for the benchmarks based on industry-size quintile (Panels A-C) and propensity score (Panels D-F).[14] By row the panels show performance evaluation for the market-model, FF3, and FF5. The scaled abnormal returns spike following announcement, and slowly fade through the event window. The blue line, which averages daily abnormal returns within the three separate windows, visually displays positive average abnormal returns during the five-day event window with no pre- or post-trend.

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

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

3.3.3 Changes in Risk

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

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

$$\begin{aligned} R_t &= const + \beta_{mkt} R_{mkt,t} + \beta_{PS} R_{PS,t} \\ &\quad + post_t \left(\Delta const + \Delta\beta_{mkt} R_{mkt,t} + \Delta\beta_{PS} R_{PS,t} \right) + \epsilon_t, \end{aligned} \tag{3.4}$$

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

Table 3.6 shows the regression results. Panel A uses only the market factor. The first column shows that WFH announcers experienced a highly significant decline in market risk from the pre- to post-announcement periods ($\Delta\beta_{mkt} \approx -0.26$, $t \approx -3.0$). Matches and unmatched firms both experienced small increases in market beta over the same period, resulting in significantly negative differences in $\Delta\beta_{mkt}$, shown in the final two columns. Market risk declined from pre- to post-announcement for work-from-home firms, absolutely and relative to other firms.

Panel B also includes exposure to the PS factor, which is directly targeted at Covid-19 risk. These results show a large decline in PS risk for WFH firms from pre- to post-announcement ($\Delta\beta_{PS} = -0.23$, $t = -5.16$), while matched firms have essentially no change in PS risk and the exposure of the portfolio of unmatched firms increases. The differences-in-differences of PS loadings shown in the final two columns are therefore negative and also highly statistically significant ($\Delta\beta_{PS} = -0.24$ with $t = -3.98$ relative to matches, and $\Delta\beta_{PS} = -0.39$ with $t = -4.83$ relative to unmatched). Figure 3.3 displays the PS loadings, differences, and the differences-in-differences in event time, providing a visual depiction of the result. Consistent with the hypothesis of corporate adaptation in a crisis mitigating risk, WFH announcers experienced significant declines in exposure to the Covid-19 risk factor of

PS, absolutely and relative to other firms.

Abnormal changes in default probabilities offer a different way to look at WFH risk mitigation that does not rely on a proxy for Covid-19 risk. For default probabilities, we use data from the Risk Management Institute (RMI) of the National University of Singapore, which have been successfully used in previous studies (e.g., Gallagher et al. (2020)). The RMI database contains forward looking default probabilities estimated from the model of Duan, Sun, and Wang (2012) for various maturities updated on a daily basis. We use default probabilities for maturity of 12 months. We repeat regression (3.3) using changes in WFH-announcer default probabilities relative to benchmarks on the left-hand-side. On the right-hand-side we use as a proxy for average change in default risk the equal-weighted change in default probabilities across all firms in our sample, including non-announcers.

Table 3.7 shows results. In column 1, benchmarked only to the market, announcers' abnormal default probabilities are -0.6 basis points per day over the 5-day event window, i.e, 3 basis points cumulative, but not statistically significant. Benchmarking by firm characteristics in columns 2-5 gives stronger results in both magnitude and significance, with default probabilities reduced by 0.7-1.5 basis points per day or 3.5-7.5 basis points cumulative over the 5-day event window, significant at the ten- and one-percent levels. For essential firms in Panel B, the results are weaker. For non-essential firms in panel C, all benchmarks show strong reduction in default probabilities with magnitudes ranging from 1.1-2.9 basis points per day, i.e., 5.5-14.5 basis points over the entire window, significant at the five- and one-percent levels. The cumulative magnitude of up to 14.5 basis points over a five day period may seem small, but the average default probability of firms in our sample is typically in the range of 1%, so an abnormal decline of 5.5-14.5 basis points is economically meaningful.

We conclude that financial markets rewarded corporate announcements of adaptation to remote work. Announcing firms experienced positive abnormal stock returns, declines in exposure to market risk and the Covid-19 risk factor of PS, and declines in default probabilities relative to controls. Significant prior research has investigated the value of corporate flexibility and resilience using pre-existing firm characteristics and cross-sectional analyses. Our study shows positive market responses, in both value and risk, to corporate *actions*, specifically announcements of adaptation to remote-work in the Covid-19 crisis. We thus use unique data and empirical identification to provide new evidence on the importance of corporate flexibility and resilience.

3.4 Additional Results

We provide additional tests that build on the finding of positive market reaction to corporate work-from-home announcements. The online appendix provides variety of robustness tests.

Our announcement data is built by scraping company websites for changes in content related to remote-work transitions. Financial media often cover important company news, and their reporting is more readily accessible to investors than monitoring company websites. Financial media coverage of companies' adaptations to remote work may therefore influence the existence, size, and speed of announcement effects. We investigate the impact of coverage by Bloomberg, which is especially relevant to professional investors. Recent literature finds that prominent news dissemination on Bloomberg increases the immediacy of price effects (Fedyk (2021)).

We hypothesize two primary impacts of Bloomberg coverage. First, announcement effects may be larger since editorial policy should prioritize important news, and because reporting may enhance news awareness among investors within our announcement windows. Second, Bloomberg coverage reaches investors quickly and synchronously, whereas announcements appearing on company websites but not Bloomberg must reach investors by other means, suggesting slower diffusion of information through markets and slower incorporation of the news into prices. We therefore hypothesize that for announcements covered by Bloomberg we can identify faster (more front-loaded) realization of abnormal returns within the announcement windows. These hypotheses about the size and speed of announcement effects are distinct and require separate identification.

One additional point of interest is whether we can identify announcement effects at all for remote-work transitions not covered by Bloomberg. Most event studies in prior literature focus on items routinely reported in financial media such as earnings announcements and mergers. We are unaware of any prior study that has shown announcement effects for events scraped from company websites, but not reported by major financial media such as Bloomberg. Of course we cannot guarantee that an announcement not reported by Bloomberg did not receive coverage through other media, but ruling out Bloomberg reporting is an important restriction. The work-from-home announcements not covered by Bloomberg may provide important new stylized facts about market efficiency and the diffusion of information *not* transmitted by the media.

For each WFH announcement in our sample, we conduct a Bloomberg search for coverage in a window of +/- three days around appearance on the company website.[15] Of the original 273 WFH announcements, Bloomberg covered 68, or approximately 25%. Substantial Bloomberg reporting on work-from-home transitions provides *prima facie* evidence of

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

the significance of such news to investors, consistent with the announcement effects we have already documented.

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

To investigate the effects of Bloomberg vs. website-only coverage, we first run the panel regressions:

$$
\begin{aligned}
R_{it} - R_{it}^{benchmark} &= const + \beta_{mkt} R_{mkt,t} + a_{BB,04} BB_{04,it} + a_{WS,04} WS_{04,it} \\
&\quad + a_{BB,59} BB_{59,it} + a_{WS,59} WS_{59,it} + \epsilon_{it}, \qquad (3.5)
\end{aligned}
$$

where $BB_{04,it}$ and $BB_{59,it}$ are announcement-window indicators for observations covered by Bloomberg, and $WS_{04,it}$ and $WS_{59,it}$ are indicators for the remaining observations (i.e., those appearing on a corporate website but *not* on Bloomberg). The coefficients on $BB_{04,it}$ and $BB_{59,it}$ are daily total Bloomberg effects. Marginal Bloomberg effects are denoted $(a_{BB} - a_{WS})_{04} \equiv a_{BB,04} - a_{WS,04}$ for the event window, and similarly for the post-event (days 5-9) and combined (days 0-9) windows.

Our second regression specification refines regression (3.5) by breaking the day 0-5 announcement window into two pieces, days 0-1 and 2-4. We are interested in the speed of price responses, which corresponds to the front-loading of announcement effects early in the event window. We define the transformed variable $\phi \equiv a_{01}/a_{04}$, measuring the average announcement effect in the first two days relative to the entire five-day window.[16]

If $\phi > 1$ the announcement effects are front-loaded, i.e., larger per day in the 0-1 window than the 0-4 average. The parameter thus captures the relative rate at which the total five-day announcement effects are realized early in the window. We allow the parameter to differ between announcements covered by Bloomberg and those appearing on the corporate website only, and test whether Bloomberg coverage increases the speed of price response, i.e., $\phi_{BB} > \phi_{WS}$.

Table 3.8 presents results, with Panel A showing the specification (3.5) which focuses on announcement effect magnitudes and Panel B showing results for refined announcement windows and the speed parameters ϕ_{BB} and ϕ_{WS}. In Panel A, the event-window effects (days 0-4) are uniformly positive and statistically significant for both Bloomberg and website-only announcements, relative to all benchmarks. In the post-event windows (days 5-9) none of the abnormal returns are significant. Our primary result of positive work-from-home announcement effects thus holds in both subsamples, showing robustness. Moreover, we are unaware of any prior study demonstrating significant announcement effects for information posted only on corporate websites, but not transmitted broadly through financial media. The significance of both types of announcements provides a unique opportunity to study the differences in these two subsamples.

[16] The Appendix provides estimation and inference details.

The hypothesis tests in Panel A reject equal announcement effects in the 0-4 day event window. The Bloomberg announcement effects (1-1.5%/day) are significantly larger than website-only (0.5-0.9%/day). We do not know when the announcements are fully reflected in prices, but the lack of significant effects in the 5-9 day windows suggests that little information remains after five days. Over the longer 0-9 day window average return differences between Bloomberg and website-only announcements are statistically indistinguishable. This confirms the importance of the "information shock" in corporate announcements. In short windows immediately following announcement, the signal-to-noise ratio about the announcement is high. Over longer windows, confounding information makes inference more difficult and reduces statistical power.[17] Thus, if corporations did not announce their remote-work decisions, but investors had to learn over time which firms adapted by watching real performance or other signals, we would have little hope of distinguishing whether investors valued actual firm actions to adapt to a crisis. We could only see whether *ex ante* characteristics associated with adaptibility, flexibility, or resilience affected pricing. Our study is thus different, showing market reaction to corporate actions – announcements of adaptation to Covid-19 by transition to remote work – controlling for *ex ante* characteristics.

Panel B compares the speeds of information transmission to prices for Bloomberg and website-only announcements. The proportion of information arriving in days 0-1 is particularly relevant because the vast prior literature on event studies shows that for widely followed events such as earnings announcements and mergers, most of the price impact occurs on the day or day after announcement. The work-from-home announcements covered by Bloomberg are qualitatively similar, with speed parameter $\phi_{BB} \approx 2$, statistically significantly greater

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

than one, implying higher news impact on returns in the 0-1 window than in days $2-4$. The point estimate of the proportion of the total announcement effect realized in the first two days is given by $2\phi/5 \approx 4/5 = 80\%$, which is large, leaving the remaining 20% distributed over the final three days.[18] The website-only announcements appear qualitatively different, and in particular price reaction is not front-loaded. The speed coefficients ϕ_{WS} either cannot be distinguished from one or are significantly lower than one. Finally, we formally test for differences in the speed of price incorporation and find that Bloomberg coverage uniformly results in a significantly faster price response than website-only announcements, across all specifications.

To interpret the results on speed of price impact, we note that while widely broadcast news should be expected to have strongest impact almost immediately and then decline, news that are published on corporate websites may be different. The mechanisms of information transmission may involve search costs, one-to-one propagation, or roles for experts that could lead to slowly diffusing price reaction to announcements. We leave further empirical and theoretical investigation of the potentially different mechanisms of information transmission and their price impact profiles to future research.

3.4.1 ESG Scores

Prior literature has proposed that firms with stronger ESG profile were more resilient in the Covid-19 crisis (Albuquerque et al. (2020) and Ding et al. (2021)). ESG might additionally relate to our work-from-home announcements. For example, firms with greater concern for employee health or public health (social good), or with better ability to make decisions in

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

a crisis (governance), might have been more likely to quickly transition to remote work. We therefore test whether ESG scores help to predict our work-from-home announcements.

We re-run the logit regression (3.1) for the work-from-home announcements. The base specification is the model from Table 2 with the lowest BIC (column 11), and we add ESG information to the predictors. We use ESG data from Refinitiv, which has the best coverage of our sample firms. To avoid dropping 657 observations with no ESG score, we use an indicator variable $\mathbb{1}_{ESG}$ equal to one for non-missing observations and zero otherwise. The variable ESG is the Refinitiv ESG score with missing data zero-filled. Using these two variables together, the indicator allows an arbitrary shift of the difference between missing and non-missing data, providing flexibility. The indicator uses an additional degree of freedom, however, which the BIC criterion accounts for.

Table 3.9 shows results. Panel A provides the logit regressions, in the first three columns ESG by itself, with size, and with size and PS together. The zero-filled ESG is highly significant by itself, with a coefficient of 0.65 and a t-statistic exceeding eight. Adding size as a control reduces the coefficient to 0.23 and a t-statistic of about 2.2. The apparent substitution between ESG and size suggests that larger firms have higher ESG scores, likely in part because smaller firms are more likely to have missing ESG values and be zero-filled. Adding PS in column (3) raises the ESG coefficient to 0.33 ($t = 3.1$). The PS coefficient is 0.44 with $t = 5.8$, both slight increases from the model without ESG (Table 3.2, column 11). ESG and PS are thus complements, with each raising the economic and statistical significance of the other. In columns 4-6, the non-missing indicator is significant and positive by itself, but becomes insignificant in specifications with the other variables. Neither size nor PS are meaningfully impacted by including $\mathbb{1}_{ESG}$. Columns 7-9 show ESG and the non-missing indicator together. With all variables (column 9), the non-missing indicator is insignificant with a point estimate close to zero, and all other variables are very similar to specification (3) without the non-missing indicator. Thus the dummy variable for missing values is superfluous, and zero-filling missing ESG values appears to fit the data.[19]

The BIC criterion adds nuance. Compared to the best model without ESG (Table 3.2, column 11, BIC = 1195), the only specification in Panel A that improves BIC is column (3), which adds ESG but not the missing data dummy (BIC = 1193). Further adding the missing data indicator in (9), BIC worsens to 1201. ESG score thus provides enough information to justify one additional parameter, but not two.

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

In Panels B and C, we take specification (3) from Panel A as our propensity score benchmark, thereby including ESG information, and carry out the panel regression for announcement effects (compare to Table 3.4 without ESG) and the scaled abnormal returns event study (compare to Table 3.5). Both Panels B and C show that the announcement effects are robust and largely unchanged compared to prior results that did not incorporate ESG in benchmarking. The event-window abnormal returns are positive and significant in all cases, with no significant pre- or post-event drift.

[19] A caveat is that a researcher could not have known without regression (9) that zero-filling missing ESG data would be appropriate. Without this analysis both variables are necessary to fairly represent the full sample including missing data.

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

3.4.2 Operating Performance

We compare the pre- and post-pandemic operating performance of WFH firms, their propensity score matches, and other firms. Previously, Papanikolaou and Schmidt (2022) show stock returns for high- and low-PS firms. Their PS-measure distinguishes WFH firms and their matches from other firms, and operating-performance analysis of these groups through the pandemic is new to the literature. We discuss the relation between the event-study and operating-performance results, including differences in identification.

For each sample firm, beginning in 2019Q1 we calculate quarterly the year-over-year growth in sales, operating profits, total assets, and R&D expenses. Figure 3.4 plots the average growth rate of each variable by calendar quarter for the baseline group of non-WFH, non-matched firms (black line). The figure also shows the difference in average growth rates between WFH firms and the baseline (blue) and matches and the baseline (yellow). Baseline revenue and profit growth began falling in the first quarter of 2020, sharply declined in Q2, and recovered considerably in the following quarters.[20] Baseline 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 outperform during 2020, with relative growth in the displayed variables moderating or reversing in 2021. In several

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

quarters, the Covid-19 outperformance of WFH firms and their matches relative to baseline is statistically significant.[21]

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

$$
\begin{aligned}
Y_{i,t} = &\alpha + \beta_0 \times WFH_i + \beta_1 \times Match_i + \beta_2 \times Covid_t \\
&+ \beta_3 \times WFH_i \times Covid_t + \beta_4 \times Match_i \times Covid_t \\
&+ LnME_{i,t} + FE^{ind} + FE^{Q} + \epsilon_{i,t},
\end{aligned}
\tag{3.6}
$$

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

Table 3.10 shows results. The WFH and $Match$ indicators are statistically indistinguishable from zero, consistent with no pre-Covid differences from baseline. The $Covid$ indicator captures baseline performance declines during the Covid period. Baseline declines range from 4.5% (assets) to more than 10% (sales), all highly economically significant and also statistically significant. The interactions coefficients show that WFH firms outperformed the baseline during the Covid period for all growth rates, with statistical significance in four of the five cases. The amounts are economically important, reversing approximately 25-50% of the Covid underperformance (e.g., for sales mitigating 4.4% of the baseline 10.4% decline). The interaction coefficients of matches are all positive, but smaller than for WFH and only

[21] See, for example, revenue and gross profit growth in Q2 and Q3, total asset growth in Q1-Q4 for WFH, and R&D growth in Q42020-Q22021 for WFH.

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

A more demanding test directly compares WFH announcers and matches, as shown in the final row of Table 3.10. In two cases the performance of WFH announcers and matches can be statistically distinguished. First, WFH firms had smaller declines in labor growth than matches, offsetting 2% of the overall 4.6% fall in employment for matches (baseline -6.4% + 1.8%), statistically significant at the 1% level. Adaptation to remote-work directly demonstrates labor flexibility, and the predictive power of WFH announcement on employment growth shows significant real impact. WFH announcers also experienced significantly better R&D growth ($t = 1.93$) relative to matches. Baseline R&D growth is -8.1% during Covid-19. Matches do marginally but insignificantly better (-8.1+1.6=-6.5%), and WFH firms experience a decline of only 3.5% (6.5-3). Therefore, in the two important cases of employment and R&D, WFH announcers experienced significantly smaller declines during Covid-19 than their matches with similar *ex ante* characteristics.

An important question remains: If the event studies identify a statistically significant increase in value from remote-work adoption, should it bother us that we do not see a statistically significant increase in a seemingly value-relevant variable such as operating profits? We discuss several points.

First, event study identification relies on large announcement effects relative to other random valuation fluctuations in the event window. The announcement effect is a one-time occurence, and larger event windows eventually dilute information content. Similarly, operating performance over long time periods is driven by many random factors, and the effect of any one event, such as announcement of work-from-home, may be difficult to detect. Despite the apparent challenge of many confounding events in annual operating performance, we find significant differences in WFH announcer vs. matched-firm employment and R&D growth during the Covid period.

Second, small changes in earnings growth can be consistent with large changes in valuation. For example, a 1% difference in earnings growth is well within the range that could not be statistically distinguished from zero based on the standard errors in Table 3.10. Following from the Gordon growth model, a transitory 1% increase in growth produces only a 1% value increase. However, a persistent 1% increase in growth can have much larger effect.[22] Further, the ability of work-from-home announcers to mitigate declines in employment and R&D during Covid-19 is at least suggestive of lower risk and the possibility of relatively better long-run cash flow growth.

Third, we demonstrate declines in risk for WFH announcers relative to matched firms following announcement. Independent of changes in future expected cash flows, declines in priced risks imply lower costs of capital and higher valuations.

Finally, announcement effects are summations, over all future states of the world, of the value of a firm that has taken a specific action versus an otherwise *ex ante* observationally equivalent firm that did not take that action (Carlson, Fisher, and Giammarino (2006)). As pointed out by Pagano, Wagner, and Zechner (2021), in the depths of the pandemic when our announcements took place, many future states of the world were bleak. Uncertainty

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

abounded about whether vaccines would be produced and effective, and how firms would adapt. Our WFH firms were among the first to demonstrate any concrete adaptation to Covid-19 by voluntarily transitioning to work-from-home. Given the well-documented uncertainty and concern, adaptation should have had very high value, reflected in the initial price response. Pagano, Wagner, and Zechner (2021) discuss that over time the worst disasters became less likely. Additionally, surveys indicate that remote-work transitions were more successful than initially anticipated and that remote-work technology diffused rapidly through the economy (Barrero, Bloom, and Davis (2021) and Bick, Blandin, and Mertens (2021)). Neither eventuality was known when the WFH announcements took place. Thus, while remote-work announcements generated strong immediate valuation differences, we can surmise that learning about lesser pandemic severity and the diffusion of remote-work technology could gradually weaken the initial valuation differences between WFH announcers and their matches. This does not diminish the importance of the initial announcement effects, as those reflect the value of adaptation during the worst times of the crisis. These are ideal conditions to establish a positive value for corporate adaptation using an event study.

In contrast to an event study, where valuation effects reflect sums over many different future states of the world, realized operating performance reflects only the one path that actually occurred. Thus, the value of corporate adaptation in an event study differs fundamentally from analysis of post-event operating performance. The operating performance results nonetheless provide useful corroborating evidence. WFH announcers experienced lower pandemic-period declines in employment and R&D than matches, consistent with pandemic-risk mitigation. Further, both WFH announcers and their matches significantly outperformed other firms during the pandemic in multiple dimensions of operating performance.

3.5 Conclusion

Considerable prior literature has emphasized the value of corporate flexibility and resilience, especially in bad times (Stigler (1939), Pindyck (1982), Trigeorgis (1996), Graham and Harvey (2001), Pagano, Wagner, and Zechner (2021), Papanikolaou and Schmidt (2022), Barry et al. (2022)). Many prior studies examine the corporate characteristics associated with flexibility and resilience. As opposed to characteristics, we study a specific corporate *action* demonstrating adaptation to a crisis, the voluntary announcement of remote-work transition during the Covid-19 pandemic.

We develop the first event study aimed at measuring the response to observable corporate adaptation, controlling specifically for observable firm characteristics in order to isolate effects of the announced action. We provide the first evidence of an increase in valuation and decline in risk following corporate adaptation. Our results thus broaden the study of corporate flexibility and resilience to include corporate actions alongside corporate characteristics.

Our primary data is scraped from corporate websites, and to our knowledge our study is the first to demonstrate announcement effects from corporate website postings. We show that Bloomberg coverage increased the size and speed of price responses, but that website-only announcements were still significant. Our findings on slower diffusion of price response for website-only announcements may stimulate interest in organic channels of information diffusion in financial markets, as compared with announcements broadcast widely through financial media.

Event studies have been important to empirical study of financial markets for decades (Ball and Brown (1968), Fama et al. (1969), Brown and Warner (1980)), and continue to be important (Kogan et al. (2017)). We apply event studies to a new topic, the study of corporate flexibility and resilience, extend methodology to clustered events not all occurring on the same date, and incorporate a fundamentally new type of announcement scraped from corporate websites.

Remote work has become widespread throughout the economy. Early in the pandemic, the success of remote work was far from certain. Financial markets responded strongly and positively to news of corporate adaptation, and work-from-home announcers benefitted from valuation increases and risk decreases. In future crises, corporate resilience will be equally important. Our results demonstrate concrete rewards for firms prepared to adapt to crises.

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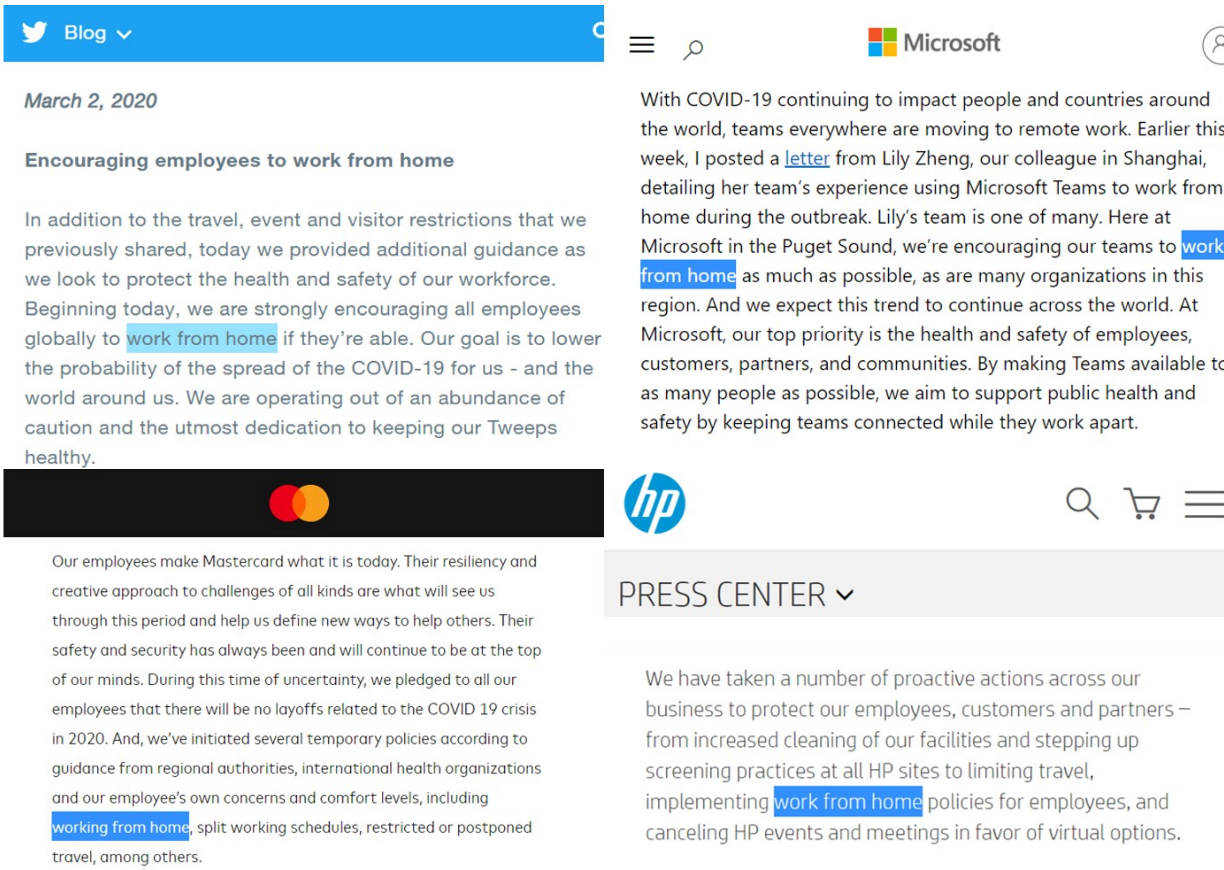
3.7 Figures

Figure 3.1. Representative Work-from-Home Announcements

This figure shows work-from-home announcements for four sample companies (Twitter Inc., Mastercard Inc., Microsoft Corporation, and Hewlett-Packard Company).



Blog

March 2, 2020

Encouraging employees to work from home

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

Microsoft

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

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

PRESS CENTER

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

Figure 3.2. Scaled Abnormal Announcement Returns

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

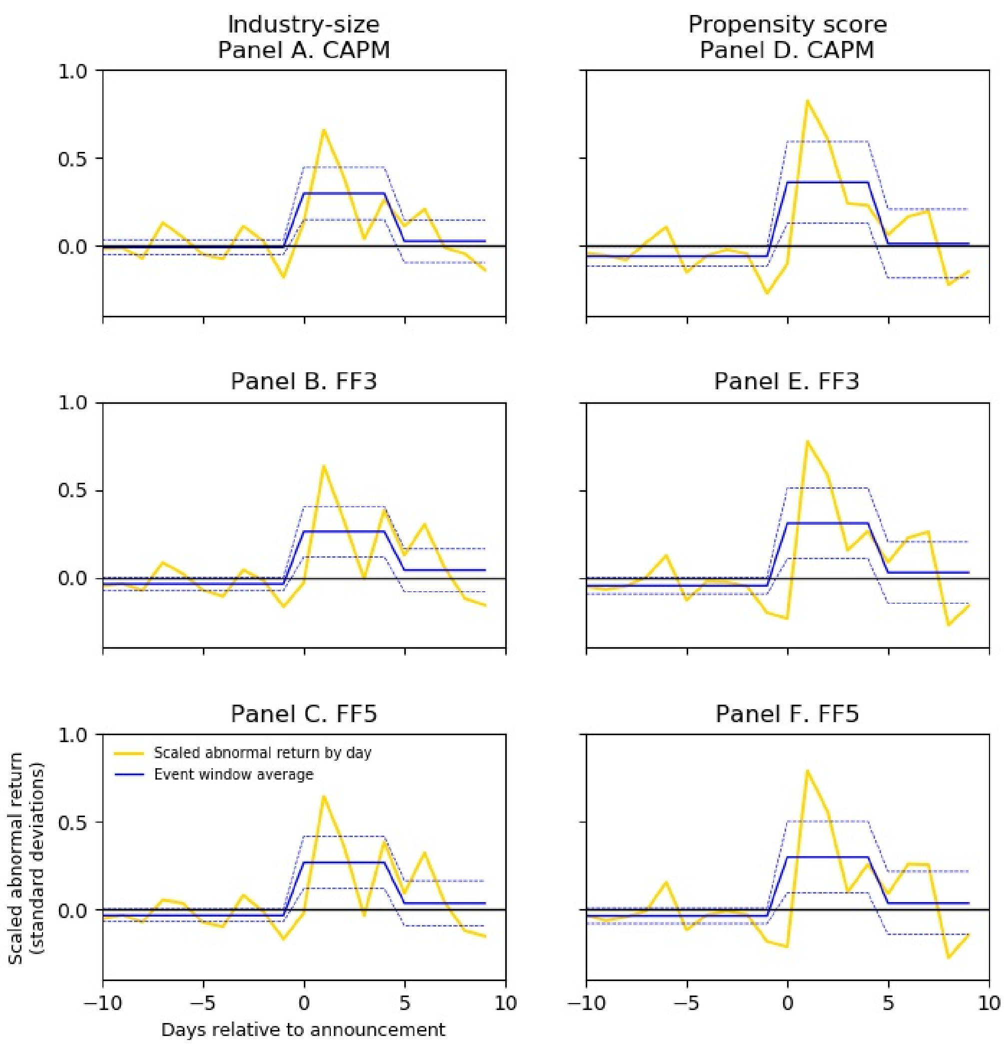


Figure 3.3. PS Loading Changes: WFH vs. Benchmarks

Panel A shows PS-factor loadings for WFH, Matched, and Unmatched portfolios before and after the Covid-fever period. Panel B shows changes from before to after the fever period (post-pre). Panel C shows differences between WFH and Matched, and WFH and Unmatched portfolio loadings. Panel D shows differences-in-differences: post- minus pre-fever differences in loadings for WFH vs. Match and WFH vs. Unmatched portfolios. The underlying regressions, time period, and standard-errors are given in the notes to table 3.6. Shaded areas indicate 90% confidence intervals. The WFH portfolio consists of work-from-home announcers (restricted to those with propensity-score matches). The Matched portfolio consists of propensity-score matches and the Unmatched portfolio consists of firms without voluntary work-from-home announcement that are also not used as matches. Portfolios are value-weighted.

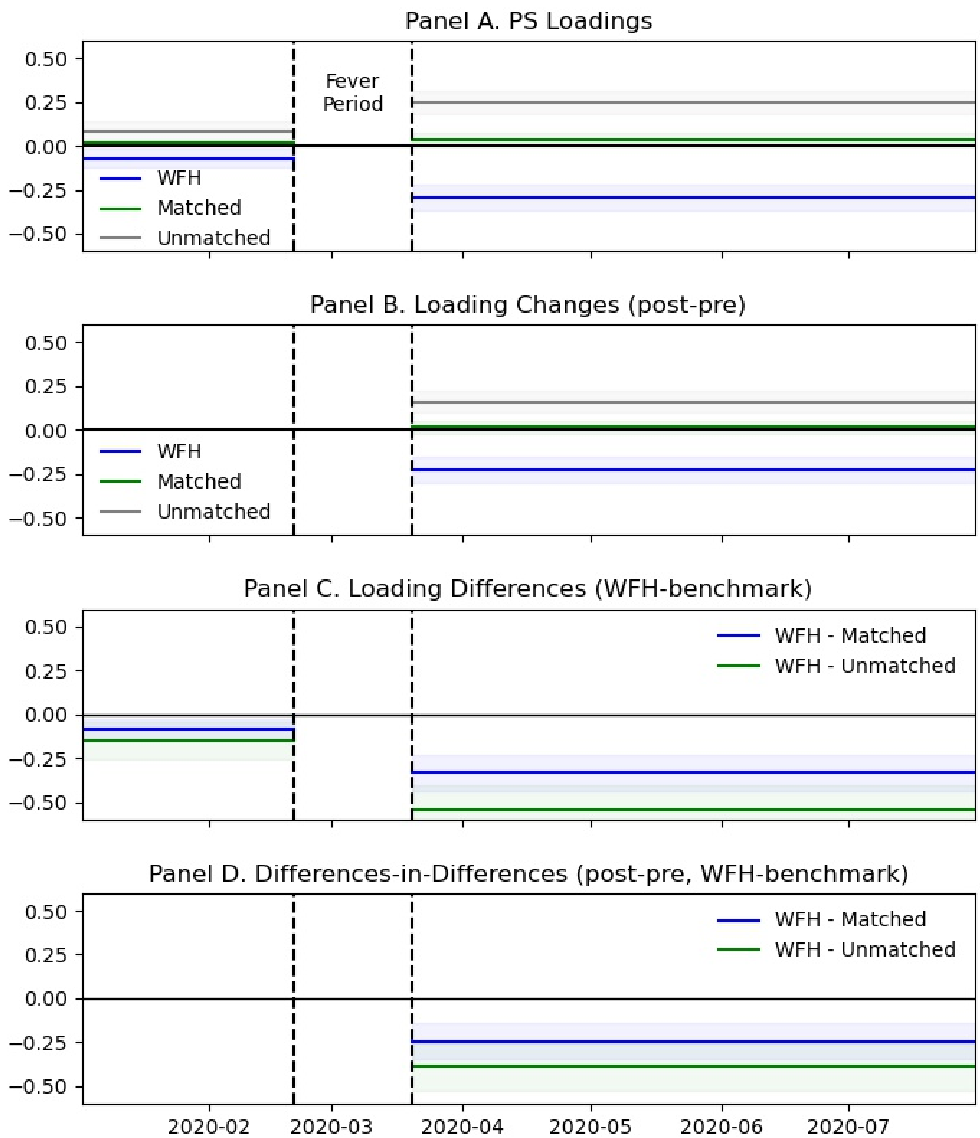
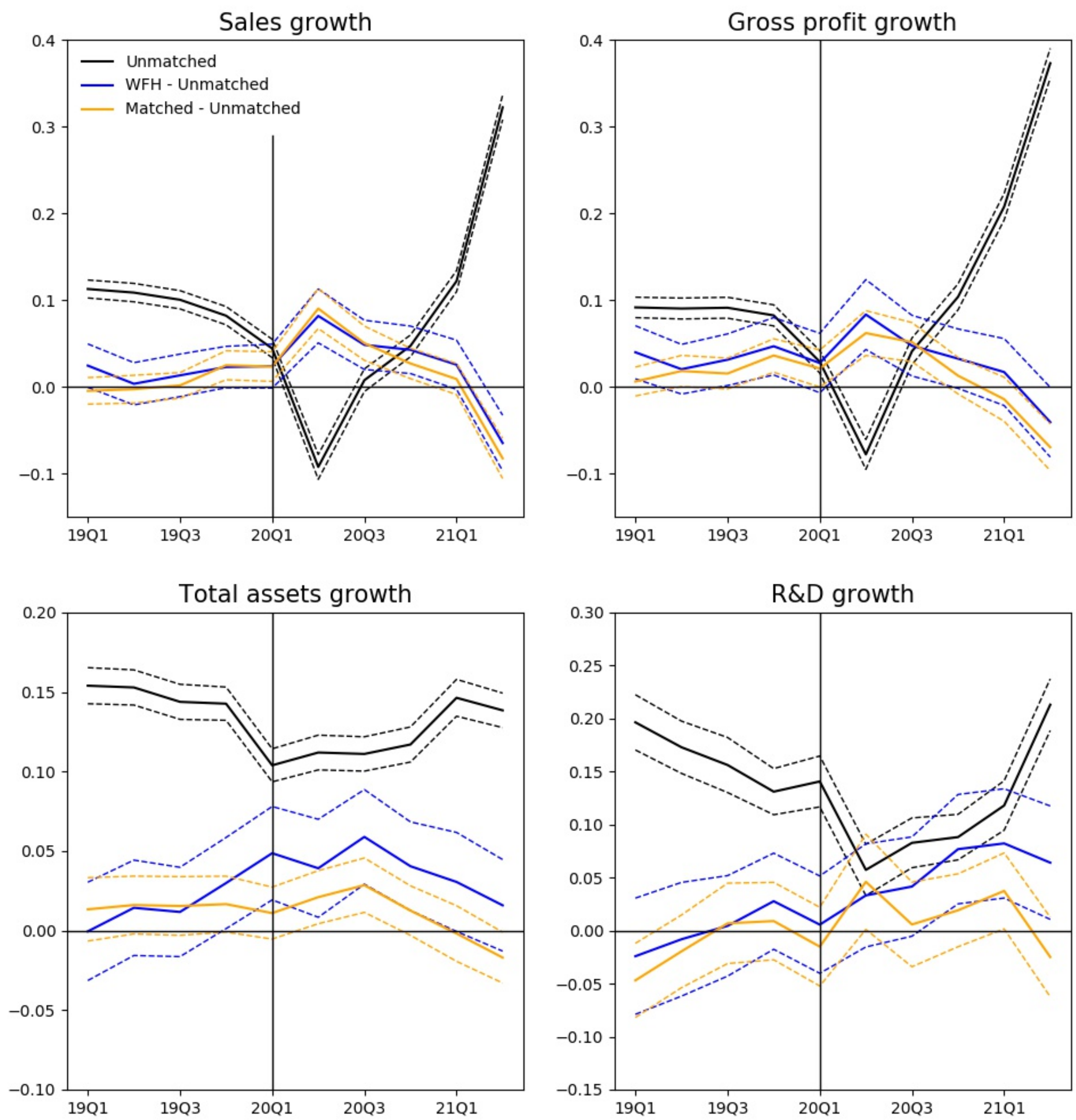


Figure 3.4. Operating Performance

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



3.8 Tables

Table 3.1

Summary Statistics

Panel A shows summary statistics: WFH (dummy variable for firms' voluntary WFH announcement), PS (industry's WFH labor share by Papanikolaou and Schmidt (2022)), DN (industry's WFH labor share by Dingel and Neiman (2020)), IK (intangible capital by Peters and Taylor (2017)), OK (organizational capital by Eisfeldt and Papanikolaou (2013)), LnME (log of capitalization), LnEmp (log of the number of employees), BM (book-to-market ratio), Profitability (gross profitability), Investment (asset growth/total assets) and Beta (market beta). Panel B shows the correlation matrix. Panel C shows subsamples of the non-WFH firms and WFH firms. Each row is based on non-missing observations in full sample of 2549 firms.

Panel A. Summary Statistics

	Mean	St. Dev.	Min	P10	Median	P90	Max
WFH	0.11	0.31	0.00	0.00	0.00	1.00	1.00
PS	0.27	0.18	0.00	0.05	0.23	0.55	0.76
DN	0.44	0.27	0.04	0.19	0.25	0.80	0.83
IK	0.49	0.84	0.00	0.01	0.27	1.13	18.80
OK	0.81	1.17	0.00	0.00	0.45	2.01	16.75
lnME	20.90	1.93	14.68	18.49	20.87	23.43	27.38
lnEmp	7.56	2.12	1.39	4.78	7.65	10.28	14.65
BM	0.64	0.59	0.00	0.13	0.53	1.22	9.73
Profitability	0.25	0.32	-2.07	0.02	0.23	0.59	3.31
Investment	0.25	1.32	-0.78	-0.09	0.05	0.56	31.14
Beta	1.13	0.70	-8.01	0.36	1.08	1.98	5.24

Panel B. Correlation Coefficients

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

Panel C. Summary Statistics for WFH and Non-WFH firms

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

Table 3.2

Likelihood of Firms' Voluntary Work-from-home Decisions

This table shows the results of estimating the logit model $p\left(WFH_i = 1\right) = \frac{1}{1+e^{x_i+v_i}}$, where WFH_i indicates firms that announced a voluntary work-from-home regime by March 19, 2020 and x_i is one or all of four main explanatory variables: PS, DN, IK, and OK, except in column 1. Regressions include a set of control variables v_i: $LnME$, $LnEmp$, BM, $Profitability$, $Investment$ and β^{mkt}. The logit model is estimated from cross section of firms with explanatory variables from year 2018. Second half of the table (Fitted likelihoods) reports the fitted likelihood of $WFH = 1$ for low and high value of the main explanatory variable. Fitted likelihoods in columns 6 and 10 are calculated for low and high of PS. Low and high values correspond to 10th and 90th percentile of the main explanatory variable, respectively. Industry fixed effects are at 2-digit NAICS. The DN variable is defined at the level of 2-digit NAICS industries and hence we omit it from regressions with industry fixed effects. The sample is composed of 1889 firms belonging to 2-digit NAICS industries with at least one WFH firm, and having non-missing values of all regressors. In this and subsequent tables, ***, **, and * indicate 99%, 95%, and 90% significance, respectively.

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

Table 3.3

Announcement Effects Panel Regressions

The table shows the results of regressing daily stock returns on a constant, $WFH_{0,4}$ indicating the five-day window from firm's announcement as day zero, $WFH_{5,9}$ indicating the subsequent five-day window, the market return R_{mkt}, and the industry return $R_{industry}$, as specified in equation 3.2. Columns 4-6 include industry fixed effects at NAICS 2-digit level. Standard errors (Driscoll and Kraay (1998) with 10 lags) for market and industry returns are in parentheses and the equivalently calculated t-statistics for the indicator variables and constant in brackets. Significance stars are omitted for market and industry returns. The table is based on the full sample of 2549 firms, with 1663 essential and 886 non-essential firms, from July 1, 2019 to April 1, 2020 (i.e., the end of the fever period on March 19 plus the 10-day announcement window).

				Industry fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All firms						
const	-0.000	0.000	0.000			
	[-0.10]	[0.78]	[0.42]			
$WFH_{0,4}$	0.010***	0.007**	0.008***	0.010***	0.007**	0.008***
	[3.06]	[2.38]	[2.62]	[3.15]	[2.34]	[2.61]
$WFH_{5,9}$	0.003	0.003	0.002	0.003	0.002	0.002
	[0.90]	[0.99]	[0.81]	[0.92]	[0.98]	[0.82]
R_{mkt}	1.09		0.22	1.09		0.22
	(0.035)		(0.032)	(0.035)		(0.031)
$R_{industry}$		0.98	0.81		0.98	0.81
		(0.026)	(0.030)		(0.026)	(0.029)
R^2	0.244	0.266	0.267	0.243	0.266	0.267
Panel B. Essential Firms						
const	-0.000	0.000	0.000			
	[-0.11]	[0.65]	[0.47]			
$WFH_{0,4}$	0.008***	0.007***	0.007***	0.008***	0.007***	0.007***
	[3.30]	[2.81]	[2.95]	[3.40]	[2.79]	[2.94]
$WFH_{5,9}$	0.002	0.000	0.000	0.002	0.000	0.000
	[0.62]	[0.13]	[0.11]	[0.65]	[0.12]	[0.10]
R_{mkt}	1.08		0.14	1.08		0.14
	(0.031)		(0.038)	(0.031)		(0.038)
$R_{industry}$		0.96	0.85		0.96	0.86
		(0.025)	(0.036)		(0.024)	(0.035)
R^2	0.225	0.251	0.252	0.225	0.251	0.252
Panel C. Non-essential Firms						
const	-0.000	-0.001	-0.001			
	[-0.17]	[-0.68]	[-0.53]			
$WFH_{0,4}$	0.012***	0.007**	0.009**	0.012***	0.008**	0.009**
	[2.67]	[2.00]	[2.43]	[2.76]	[2.01]	[2.47]
$WFH_{5,9}$	0.005	0.005	0.004	0.005	0.005	0.004
	[1.02]	[1.56]	[1.17]	[1.05]	[1.60]	[1.20]
R_{mkt}	1.11		0.36	1.11		0.36
	(0.044)		(0.038)	(0.044)		(0.038)
$R_{industry}$		1.01	0.71		1.01	0.71
		(0.032)	(0.053)		(0.032)	(0.053)
R^2	0.285	0.300	0.303	0.285	0.299	0.303

Table 3.4

Announcement Effects Relative to Matches

The table shows the results of regressing daily stock returns of WFH firms relative to a benchmark on a constant, the variables $WFH_{0,4}$ and $WFH_{5,9}$ (defined in Table 3.3) and the market return R_{mkt} as in equation 3.3. The benchmark adjusted return on the left-hand side is the return difference between the WFH firm and the benchmark indicated in the columns. The benchmark in column 1 is value-weighted market return, in columns 2-4 the average return of firms in the same quintile by Size, Industry-size, and PS-size, respectively, and in column 5 the average return of the five closest matches by propensity score. Standard errors (Driscoll and Kraay (1998) with 10 lags) are in parentheses and t-statistics in brackets. Significance stars are omitted for market returns. Columns 1-4 use the full sample of 273 WFH firms, 145 essential. Column 5 requires non-missing PS to calculate propensity score (229 WFH, 130 essential). The panel is from July 1, 2019 to April 1, 2020 (i.e., the end of the fever period March 19 plus 10-day announcement window).

	Market	Size	Industry -size	PS -size	Propensity score
Panel A. All Firms					
const	-0.001	0.000	0.000	0.000	-0.000
	[-1.58]	[0.87]	[0.33]	[0.67]	[-0.88]
$WFH_{0,4}$	0.009***	0.006***	0.006***	0.005***	0.008***
	[2.64]	[6.69]	[13.10]	[6.63]	[10.60]
$WFH_{5,9}$	0.004	0.001	0.001	0.001	0.000
	[1.07]	[0.55]	[0.58]	[0.44]	[0.20]
R_{mkt}	0.05	-0.06	-0.03	-0.04	-0.02
	(0.026)	(0.009)	(0.007)	(0.007)	(0.010)
R^2	0.004	0.003	0.002	0.002	0.002
Panel B. Essential Firms					
const	-0.001	0.000	0.000	0.000	-0.000
	[-1.47]	[0.78]	[0.46]	[0.56]	[-0.04]
$WFH_{0,4}$	0.008***	0.004**	0.006***	0.005***	0.007***
	[2.87]	[2.10]	[6.85]	[3.35]	[7.63]
$WFH_{5,9}$	0.002	-0.000	-0.000	-0.000	0.001
	[0.70]	[-0.01]	[-0.03]	[-0.02]	[0.37]
R_{mkt}	0.06	-0.05	-0.04	-0.04	-0.03
	(0.031)	(0.011)	(0.011)	(0.011)	(0.014)
R^2	0.004	0.002	0.002	0.002	0.002
Panel C. Non-essential Firms					
const	-0.001	0.000	-0.000	0.000	-0.000
	[-1.30]	[0.44]	[-0.04]	[0.30]	[-1.24]
$WFH_{0,4}$	0.011**	0.008***	0.007***	0.006***	0.010***
	[2.31]	[6.31]	[6.77]	[5.33]	[6.18]
$WFH_{5,9}$	0.006	0.003	0.003	0.002	-0.000
	[1.35]	[0.94]	[1.12]	[0.87]	[-0.03]
R_{mkt}	0.04	-0.07	-0.02	-0.05	-0.01
	(0.023)	(0.013)	(0.009)	(0.008)	(0.011)
R^2	0.005	0.005	0.002	0.003	0.003

Table 3.5

Event Studies of Scaled Abnormal Returns

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

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

Table 3.6

Changes in Systematic Risk

The table shows the exposure and the change in exposure of different portfolios (columns) to market return (panel A) and to the PS-factor and market (panel B) before and after the fever period as specified in regression 3.4. β and β_{PS} are coefficients of market return and the PS factor, respectively. $\Delta const$ is coefficient of a dummy variable indicating post-fever period, i.e., from March 20, 2020. $\Delta\beta$, and $\Delta\beta_{PS}$ indicate the change in the respective coefficients after the fever period. The regressions are estimated from beginning of January to end of July 2020 (skipping the fever period February 23 to March 19, 2020). t-statistics based on standard errors adjusted for autocorrelation and heteroscedasticity using Newey and West (1987) with 10 lags are reported in brackets. The WFH portfolio consists of work-from-home announcers with valid propensity-score matches. The Matched portfolio consists of propensity-score matches and the Unmatched portfolio consists of non-announcing, unmatched firms. Portfolios are value-weighted. The last two columns show long-short portfolios with a long position in the WFH portfolio and a short position either in the Matched portfolio or the Unmatched portfolio as indicated.

	Portfolios			Differences	
	WFH	Matched	Unmatched	WFH-Matched	WFH-Unmatched
Panel A. Market Factor					
const	0.001	0.0	-0.001**	0.001	0.002
	[1.21]	[1.0]	[-2.1]	[0.75]	[1.62]
β	1.145***	0.929***	1.0***	0.216*	0.145
	[14.14]	[19.42]	[14.59]	[1.73]	[1.01]
$\Delta const$	0.0	0.0	0.001	0.001	-0.001
	[0.07]	[-1.42]	[1.44]	[0.47]	[-0.56]
$\Delta\beta$	-0.262***	0.085	0.091	-0.348**	-0.353**
	[-3.04]	[1.53]	[1.27]	[-2.57]	[-2.36]
R^2	0.882	0.982	0.945	0.097	0.119
Panel B. Market and PS Factors					
const	0.001	0.0	-0.001	0.0	0.001
	[0.78]	[1.46]	[-1.45]	[0.29]	[1.08]
β	1.111***	0.938***	1.04***	0.173*	0.071
	[19.59]	[21.74]	[24.9]	[1.81]	[0.8]
β_{PS}	-0.07**	0.019**	0.082**	-0.089**	-0.152**
	[-2.23]	[2.4]	[2.45]	[-2.3]	[-2.36]
$\Delta const$	0.0	-0.001	0.001	0.001	-0.001
	[0.09]	[-1.64]	[1.52]	[0.6]	[-0.59]
$\Delta\beta$	-0.125*	0.063	-0.034	-0.189*	-0.092
	[-1.95]	[1.19]	[-0.77]	[-1.68]	[-0.96]
$\Delta\beta_{PS}$	-0.227***	0.017	0.163***	-0.244***	-0.39***
	[-5.16]	[0.79]	[4.21]	[-3.98]	[-4.83]
R^2	0.961	0.983	0.984	0.575	0.761

Table 3.7
Default Probabilities

The table shows the results of regressing 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 Table 3.3), and average daily change in default probabilities across the market $PrDef_{mkt}$, following the structure of equation (3.3). To calculate default probabilities relative to benchmarks we use the benchmarks indicated in the columns. The benchmark in column 1 is daily average change in default probabilities across the market, in columns 2-4 the average change in default probabilities of firms in the same quintile by Size, Industry-size, and PS-size, respectively, and in column 5 the average change in default probabilities of the five closest matches by propensity score. Standard errors (Driscoll and Kraay (1998) with 10 lags) are in parentheses and t-statistics in brackets. Significance stars are omitted for $PrDef_{mkt}$. Columns 1-4 use the sample of 272 WFH firms with available default probability data, 145 essential. Column 5 additionally requires non-missing PS to calculate propensity score (229 WFH, 130 essential). The panel is from July 1, 2019 to April 1, 2020 (i.e., the end of the fever period March 19 plus 10-day announcement window).

	Market	Size	Industry -size	PS -size	Propensity score
Panel A. All Firms					
const	-0.000	0.001	0.001	0.001	0.001
	[-0.58]	[1.09]	[1.13]	[1.03]	[1.43]
$WFH_{0,4}$	-0.006	-0.007*	-0.013***	-0.010***	-0.015***
	[-1.35]	[-1.85]	[-3.94]	[-2.72]	[-3.85]
$WFH_{5,9}$	0.002	-0.005	0.001	-0.003	0.006
	[0.35]	[-1.55]	[0.32]	[-0.64]	[0.95]
$PrDef_{mkt}$	-0.68	-0.50	-0.25	-0.39	-0.17
	(0.024)	(0.024)	(0.036)	(0.021)	(0.050)
R^2	0.225	0.227	0.062	0.108	0.015
Panel B. Essential Firms					
const	-0.000	0.001	0.001	0.001	0.001
	[-1.40]	[0.98]	[1.26]	[0.91]	[1.28]
$WFH_{0,4}$	-0.000	-0.005	-0.014***	-0.010**	-0.006
	[-0.01]	[-1.47]	[-4.23]	[-2.43]	[-1.08]
$WFH_{5,9}$	0.000	-0.005	0.001	-0.001	0.001
	[0.02]	[-1.56]	[0.24]	[-0.17]	[0.18]
$PrDef_{mkt}$	-0.79	-0.58	-0.31	-0.43	-0.23
	(0.018)	(0.022)	(0.039)	(0.025)	(0.051)
R^2	0.414	0.335	0.103	0.148	0.032
Panel C. Non-essential Firms					
const	-0.000	0.001	0.001	0.001	0.001
	[-0.04]	[1.16]	[0.90]	[1.09]	[1.46]
$WFH_{0,4}$	-0.014***	-0.011**	-0.013***	-0.011**	-0.029***
	[-3.36]	[-2.32]	[-3.70]	[-2.18]	[-6.40]
$WFH_{5,9}$	0.005	-0.005	0.003	-0.005	0.014
	[0.71]	[-1.13]	[0.53]	[-1.04]	[1.11]
$PrDef_{mkt}$	-0.56	-0.41	-0.17	-0.36	-0.09
	(0.032)	(0.029)	(0.033)	(0.028)	(0.050)
R^2	0.118	0.140	0.030	0.076	0.006

Table 3.8

Bloomberg Announcement Effects: Size and Speed

Panel A shows the results of regressing daily stock returns of WFH firms relative to benchmarks on a constant, the market return, announcement-window indicators $BB_{04,it}$ and $BB_{59,it}$ for announcements reported by Bloomberg, and indicators $WS_{04,it}$ and $WS_{59,it}$ for announcements not covered by Bloomberg, as specified in equation 3.5. The panel reports the estimated coefficients $a_{BB,04,}$, $a_{BB,59}$, $a_{WS,04}$ and $a_{WS,59}$ of the announcement-window indicators and omits reporting the constant and market-return coefficient. The Bloomberg marginal effects section reports the marginal effects of Bloomberg relative to website-only announcements, i.e., $a_{BB} - a_{WS}$. Panel B shows results of regressions that additionally include the interactions with the indicators $(BB_{01} - 2/3BB_{24})$ and $(WS_{01} - 2/3WS_{24})$ as specified in regression equation 3.17 in the Appendix to estimate the speed parameters ϕ_{BB} and ϕ_{WS}. The panel omits coefficients for the constant, market return and days 5-9 announcement indicators. The Bloomberg marginal effects section reports the difference in the speed parameters ϕ_{BB} and ϕ_{WS}. Benchmarks (column headings) are defined in Table 3.4. t-statistics (Driscoll and Kraay (1998) with 10 lags) are in brackets. The panel is from July 1, 2019 to April 1, 2020 (i.e., the end of the fever period March 19 plus 10-day announcement window).

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

Table 3.9

ESG and Work-from-home: Announcement Decisions and Returns

Panel A shows results of estimating the logit model from equation 3.1 adding two ESG variables to those considered in Table 3.2. The variable ESG is ESG score with missing values filled to the value zero, and 1_{ESG} is an indicator for nonmissing ESG score. The fitted likelihoods are for the 10th and 90th percentiles of the ESG variable, except for columns 4-6, where Low is for $1_{ESG} = 0$ and High for $1_{ESG} = 1$. Panel B reports panel-regression announcement effects (equivalent to Table 3.4) for the ESG-propensity-score benchmark based on the BIC-minimizing logit model in column 3 of Panel A. Panel C shows the scaled abnormal returns (equivalent to Table 3.5) for the ESG-propensity-score benchmark. ESG data is from Refinitiv.

Panel A. Likelihood of Voluntary WFH Decisions

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

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

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

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

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

Table 3.10

Operating Performance: WFH Announcers and Matches

This table reports the results of estimating regression of the form: $Y_{i,t} = \alpha + \beta_0 \times WFH_i + \beta_1 \times Match_i + \beta_2 \times Covid_t + \beta_3 \times WFH_i \times Covid_t + \beta_4 \times Match_i \times Covid_t + LnME_{i,t} + FE^{ind} + FE^{Q} + \epsilon_{i,t}$, where $Y_{i,t}$ is year-to-year growth in one of these variables: sales, gross profits, total assets, R&D and number of employees. WFH_i and $Match_i$ are (time-constant) dummy variables indicating WFH announcers and their final matches by propensity score, respectively. $Covid_t$ is a dummy variable indicating whether the firm's fiscal-quarter end (fiscal-year end for the number of employees) falls into the Covid-19 period designated as the calendar year 2020. $LnME$ is log market capitalization. Each column is based on non-missing observations of the corresponding variable of full sample of 2549 firms. The data is at quarterly frequency except for the number of employees which is at annual frequency. To avoid a potential seasonality, we calculate the growth in the quarterly variables as year-to-year growth rate, i.e., by comparing the same quarters in two consecutive years, e.g., $Y_{i,2019Q1} = \frac{Sales_{i,2019Q1} - Sales_{i,Q2018Q1}}{Sales_{i,2018Q1}}$. Regressions include industry fixed effects at 2-digit NAICS and, except for the last column, quarter fixed effects. Standard errors are clustered at 2-digit NAICS industries. The panel of firms spans the period from Q1 2019 to Q4 2020.

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

3.9 Appendix

3.9.1 Matching Details

We match by propensity score using the regression (3.1) specification that minimizes BIC in Table 3.2, column 11:

$$p\,(WFH_i = 1) \quad = \quad \frac{1}{1 + e^{PS_i + ME_i}}, \tag{3.7}$$

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

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

Event Study Details: Scaled Abnormal Returns

We extend the event-study methodology of Kolari and Pynnönen (2010) by explicitly considering event windows that span multiple days, and event windows that cluster in time but need not be exactly identical across all observations. This allows to explicitly account for cross-correlation, serial correlation, and cross-serial correlation of the event returns.[23] The scaled abnormal returns test statistic is defined as:

$$t = \frac{\bar{A}\sqrt{N \times W}}{\sqrt{var\left(\bar{A}\right)}}, \tag{3.8}$$

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

$$\bar{A} \;=\; \frac{1}{N \times W} \sum_{i=1}^{N} \sum_{\tau=1}^{W} A_{i,\tau,t}, \tag{3.9}$$

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

$$R_t^{i,WFH} - R_t^{i,benchmark} = const^i + \beta^i R_{mkt,t} + \epsilon_t^i, \tag{3.10}$$

using one of four different benchmarks $R_t^{i,benchmark}$: size quintile, industry-size quintile, PS-size quintile and five closest matches by propensity score. We also use FF3 and FF5 factors as control variables in regression 3.10. The regressions are estimated for each firm over an estimation period of 60 days before the WFH announcement.

The abnormal daily event return $\epsilon_{\tau,t}^i$ is the difference between the dependent variable and

[23] In a follow-up paper Kolari, Pape, and Pynnonen (2018) extend their framework to partially overlapping event windows and account for cross-correlation, but not cross-serial correlation and their treatment of serial correlation is implicit by summing up returns to cumulative returns.

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

$$A_{i,\tau,t} = \frac{\epsilon_{\tau,t}^{i}}{\sigma_{\epsilon,i}\sqrt{1+d}}, \tag{3.11}$$

where $\sigma_{\epsilon,i}$ is the standard deviation of the residuals over the estimation period and d_t is the correction term of the form $x_t' \left(X'X\right)^{-1} x_t$ due to the estimation of the regression parameters in the estimation period with $x_t = [1\ R_{mkt,t}]'$ and X being the matrix of the explanatory variables during the estimation period (see Kolari and Pynnönen (2010)).

The variance of the average abnormal daily event return is:

$$\begin{aligned} var\left(\bar{A}\right) &= var\left(\frac{1}{W \times N}\sum_{i=1}^{N}\sum_{\tau=1}^{W} A_{i,\tau,t}\right) \\ &= \left(\frac{1}{W \times N}\right)^{2} var\left(\sum_{i=1}^{N}\sum_{\tau=1}^{W} A_{i,\tau,t}\right) \\ &= \left(\frac{1}{W \times N}\right)^{2} \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{\tau_1=1}^{W}\sum_{\tau_2=1}^{W} cov\left(A_{i,\tau_1,t_1}, A_{j,\tau_2,t_2}\right). \end{aligned} \tag{3.12}$$

We rewrite the last expression as:

$$\begin{aligned} var\left(\bar{A}\right) = \left(\frac{1}{W \times N}\right)^{2} \Bigg[&\sum_{i=1}^{N}\sum_{\tau=1}^{W} cov\left(A_{i,\tau,t}, A_{i,\tau,t}\right) \\ &+ \sum_{i=1}^{N}\sum_{\tau_1=1}^{W}\sum_{\tau_2 \neq \tau_1} cov\left(A_{i,\tau_1,t_1}, A_{i,\tau_2,t_2}\right) \\ &+ \sum_{i=1}^{N}\sum_{j \neq i}\sum_{\tau_1=1}^{W}\sum_{\tau_2=1}^{W} cov\left(A_{i,\tau_1,t_1}, A_{j,\tau_2,t_2}\right) \Bigg]. \end{aligned} \tag{3.13}$$

The first summation term (first line) are variances of individual scaled abnormal daily event returns. The second summation term (second line) are autocovariances, i.e., covariance of individual scaled abnormal daily event return of the same stock on different event days τ_1 and τ_2. The third summation term (third line) are cross-covariances including cross (serial) covariances, i.e., covariances of abnormal daily event returns of different stocks on the same or different *calendar* days.

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

$$\begin{aligned} var\left(\bar{A}\right) \;=\; & \left(\frac{1}{W \times N}\right)^2 \left[\sum_{i=1}^{N}\sum_{\tau=1}^{W} var\left(A_{i,\tau,t}\right)\right. \\ & + \sum_{i=1}^{N}\sum_{\tau_1=1}^{W}\sum_{\tau_2 \neq \tau_1} cov\left(A_{i,\tau_1,t_1}, A_{i,\tau_2,t_2}\right) \\ & + \sum_{i=1}^{N}\sum_{j \neq i}\sum_{\tau_1=1}^{W}\sum_{\tau_2=1}^{W} cov\left(A_{i,\tau_1,t}, A_{j,\tau_2,t}\right) \\ & \left. + \sum_{i=1}^{N}\sum_{j \neq i}\sum_{\tau_1=1}^{W}\sum_{\tau_2=1}^{W}\sum_{k=-W+1,k\neq 0}^{W-1} cov\left(A_{i,\tau_1,t}, A_{j,\tau_2,t-k}\right)\right]. \end{aligned} \tag{3.14}$$

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

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

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

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

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

$$\begin{aligned} var\left(\bar{A}\right) &= \left(\tfrac{1}{W\times N}\right)^2 \sigma_A^2 \Big[\quad (W\times N) \\ &\quad + \sum_{i=1}^{N} \sum_{k=-W+1,k\neq 0}^{W-1} (W-k)\, AC_{i,k} \\ &\quad + \sum_{i=1}^{N} \sum_{j\neq i} \sum_{\tau_1=1}^{W} \sum_{\tau_2=1}^{W} \rho_{i,j} \mathbf{1}_{\{\tau_1 \& \tau_2 \text{ are on the same } t\},i,j,\tau_1,\tau_2} \\ &\quad + \sum_{i=1}^{N} \sum_{j\neq i} \sum_{\tau_1=1}^{W} \sum_{\tau_2=1}^{W} \sum_{k=-W+1,k\neq 0}^{W-1} CSC_{i,j,k} \mathbf{1}_{\{\text{cross lag=k}\},i,j,\tau_1,\tau_2} \Big], \end{aligned} \tag{3.15}$$

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

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

3.9.2 Announcement Speed Regression

The announcement speed parameters and regression results in Table 3.8, Panel B, can equivalently be derived from two different regressions. First, refining regression (3.5) to break the 0-4 event window into periods of days 0-1 and 2-4 gives a linear regression:

$$
\begin{aligned}
R_{it} - R_{it}^{benchmark} &= const + \beta_{mkt} R_{mkt,t} + a_{BB,01} BB_{01,it} + a_{WS,01} WS_{01,it} \\
&\quad + a_{BB,24} BB_{24,it} + a_{WS,24} WS_{24,it} \\
&\quad + a_{BB,59} BB_{59,it} + a_{WS,59} WS_{59,it} + \epsilon_{it}. \qquad (3.16)
\end{aligned}
$$

Consider the parameter transformations $a_{04} \equiv 0.4a_{01} + 0.6a_{24}$ and $\phi \equiv a_{01}/a_{04}$. We can rewrite a regression equivalent to (3.16) in the transformed parameters by taking linear combinations and interactions of the original regressors:

$$
\begin{aligned}
R_{it} - R_{it}^{bench} &= const + \beta_{mkt} R_{mkt,t} + a_{BB,04} BB_{04,it} + a_{WS,04} WS_{04,it} \\
&+ (\phi_{BB} - 1) a_{BB,04} BB_{04,it} \left(BB_{01} - (2/3) BB_{24} \right) \\
&+ (\phi_{WS} - 1) a_{WS,04} WS_{04,it} \left(WS_{01} - (2/3) WS_{24} \right) \\
&+ a_{BB,59} BB_{59,it} + a_{WS,59} WS_{59,it} + \epsilon_{it}. \qquad (3.17)
\end{aligned}
$$

Table 3.8 presents regression results and test statistics from the regression (3.17). The interpretation of the parameters $\phi \equiv a_{01}/a_{04}$ is the average announcement effect in days 0-1 divided by the average announcement effect in days 0-4, i.e., the relative speed at which the total five day announcement effects are realized in the first two days. If $\phi > 1$ the announcement effects are front-loaded. The Internet Appendix provides parameter estimates for the equivalent regression (3.16).

Chapter 4

Disruptive Technologies and Industrial Revolution in Retailing

ABSTRACT

I study firm performance in adopting new technologies in the retail industry. I use the textual analysis on 10-Ks and identify the key disruptive technologies implemented by retailing firms. These technologies, including "search engine," "cloud computing," "social networking," and "mobile commerce" are directly linked to sales strategies that enable retailing firms to achieve a greater production (i.e., sales) scale beyond the bottleneck of production sites. Using the yearly stamps of technology adoptions, I find that retail firms experience a four-percentage-point increase in annual sales and gross profits growth over the three years following technology adoptions. Stock performance positively responds to technology adoptions, yielding an extra return of 7.5% p.a. over the following three years. Overall, this paper highlights the role of new technologies that reshape retail operations and unveil the industrial revolution in the retail industry.

4.1 Introduction

A hundred years ago, Ford Motor Company successfully launched its first car manufactured by the assembly line. This innovation marked a symbol of mass production and unleashed an era of the modern industrial revolution in manufacturing. Using new technologies to reach large-scale production has become a norm over the last century. On the other side of sectors in the economy, however, retailing has a bottleneck for mass production (i.e., sales) due to the nature of the industry. Traditionally, retailing is labor-intensive, and its production capacity is subjective to the size of production sites. Take Walmart, for example. Each store was constrained by space for storage and selling. The conventional way to grow was to expand the size of sites or open up new locations. Nonetheless, the fixed cost that underlines an expansion is usually too large to achieve a pervasively large production in the retail industry.[1] Productivity growth was also shown to be relatively slow before the 1990s.[2]

Until recently, IT-based technologies have been argued to be pivotal in helping the service/retail industry scale production across locations (Hsieh and Rossi-Hansberg (2023)).[3] In Hsieh and Rossi-Hansberg (2023)'s model, adopting fixed-cost-intensive technologies can help these firms lower the marginal production cost and expand into new markets through the industrial revolution.[4] Moreover, IT investment is correlated with productivity and growth in retailing (Doms, Jarmin, and Klimek (2004) and Gordon and Sayed (2020)), and E-commerce

[1] Though some retail firms manage to increase the efficiency of operations at a site, the growth strategy through efficiency improvement within a store plays less of a role since within-store productivity growth accounts for a minor fraction of the retailing productivity growth (Foster, Haltiwanger, and Krizan (2006)).

[2] See Sieling, Friedman, and Dumas (2001), Doms et al. (2004), and Gordon and Sayed (2020).

[3] Also see Caroli and Van Reenen (2001), Hobijn and Jovanovic (2001), Rosenberg and Trajtenberg (2004), Syverson (2017), and Aghion et al. (2023) that discuss the economic implications of the IT advancements.

[4] The authors show that the retail industry grew at the second fastest speed, next to the finance industry, over the last four decades.

has been reshaping the retail landscape since the late 1990s (Hortaçsu and Syverson (2015)).[5] In this paper, I build on Hsieh and Rossi-Hansberg (2023) and ask what technologies retail firms implement in the wave of the industrial revolution and how much retail firms grow by adopting new technologies.

Conventionally, it is challenging to identify the new technologies in which retail firms invest. Firms' investment in technologies is not explicitly reported in financial reports or systematically recorded in a standard database. One popular measure for innovations is through patents, but retail firms rarely patent. Traditional accounting measures such as R&D cannot explicitly indicate what a firm does to advance its business frontiers. Previous work that investigates the relations between IT and productivity growth can only be done broadly at the industry level or in case studies.

Regarding an appropriate measure, I propose to use a text-based measure that captures the intensity of new technologies at the firm level. I build on the innovative work of Bloom et al. (2021) that identifies 29 disruptive technologies into a list of 221 bigrams.[6] I construct a technology-intensity measure, $Tech$, as the percentage of words in 10-Ks that appear on Bloom et al. (2021)'s bigram list.[7] In other words, $Tech$ is a time-varying variable that captures how much a firm emphasizes its involvement in the disruptive technologies demonstrated in the annual report. $Tech$ can also indicate the yearly stamp when a firm adopts new technologies. Through the $Tech$ measure, I can explicitly identify the new technologies

[5] Also see Basker (2012) and Brynjolfsson, Hu, and Smith (2010).

[6] Bloom et al. (2021) use a supervised approach through machine learning and human audits to reduce dimensions from patents and document 29 disruptive technologies. One of the advantages is that the language of the bigrams is classified by algorithm from technical terms into business terms used by investors and executives. Accordingly, the bigram list provides a sound basis for textual analysis of the 10-Ks.

[7] The bag-of-words methodology has been commonly used in the finance and accounting literature, such as Loughran and McDonald (2011, 2014, 2015), Li, Lundholm, and Minnis (2013), Bodnaruk, Loughran, and McDonald (2015), and Kim, Wang, and Zhang (2019).

implemented by retail firms and exploit a firm's performance in an event study.

Armed with the list of disruptive technologies, I find that the new technologies retail firms most often use are "search engine," "cloud computing," "social networking," and "mobile commerce" in 2019.[8] These technologies are directly linked to sales strategies that can help retail firms achieve greater production (i.e., sales) scale beyond the limitation of production sites. The mean percentage (frequency) of $Tech$ bigrams is 0.01% (2.4) per 10-K filing. Equivalently, a retail firm mentions 2.4 bigrams, on average, of disruptive technologies in an annual report. Moreover, the trend of using new technologies increased from 15% of retail firms in 2002 to more than 60% in 2019. The result indicates that the industrial revolution for retailing has been taking place.

I begin by investigating firm performance in adopting new technologies in simple OLS regressions. I primarily focus on the firm's sales growth and stock returns. I find that the $Tech$ intensity is statistically and economically associated with sales growth and stock returns at the 1% level after controlling for the fixed effects and the standard firm characteristics, including R&D and SG&A. The result suggests that $Tech$ intensity can explain the variation in firm performance and that the role of the $Tech$ intensity is not absorbed by classic intangible measures such as R&D and SG&A.

Next, I examine how much growth a firm can gain by adopting new technologies in event analysis. Since $Tech$ is a time-varying variable that can indicate the yearly stamp of adopting new technologies, I use a firm's first year of technology adoptions as event year 0 and calculate a firm's performance over a six-year window following an event. Put differently, the identified performance effect should be evident after a technology adoption. Indeed, I

[8] In contrast, the most popular technologies in 2002 were "search engine," "video game," and "digital video".

find that the average sales growth jumps from 5.5% to 9.5% during the three-year period after adoption. The difference of the 4 percentage points is statistically significant at the 1% level. In the second three-year period, the average sales growth is only marginally higher by around 1.5% insignificantly. Furthermore, stock returns (in excess of the market return) are also higher over the six-year period following an event. Before adoption, the stock return is around –0.2% per month. Following adoption, the stock return increases by 0.65% (t=2.06) and 0.89% (t=3.03)in the first and second three-year periods, respectively. In sum, my result suggests that sales and stock return positively respond to the news about disruptive technologies that are the critical driver for a firm's growth.

Overall, in this paper, I identify the key technologies implemented by retail firms in response to the call from Hsieh and Rossi-Hansberg (2023). Using a new text-based measure at the firm level, I quantify the effect of adopting new technologies on firms' operating and stock performances in an event study. My results highlight the role of new technologies that reshape retailing operations and unveil the industrial revolution in the retail industry.

This paper contributes to the vast literature on how technological changes affect the real economy (e.g., Caroli and Van Reenen (2001), Hobijn and Jovanovic (2001), Rosenberg and Trajtenberg (2004), Syverson (2017)) and, especially, the retail industry (e.g., Hortaçsu and Syverson (2015), Gordon and Sayed (2020), Hsieh and Rossi-Hansberg (2023)). I propose a text-based measure to identify the key technologies for the retail industry and contribute to the emerging literature on innovations by linking technological advancements to firm performance (e.g., Hsu (2009), Hirshleifer, Hsu, and Li (2013, 2018), Kogan et al. (2017), Stoffman, Woeppel, and Yavuz (2022)). In short, this paper identifies the new technologies adopted by retail firms and quantifies how these technologies affect firm performance in the event study.

The article proceeds as follows: Section 4.2 describes the data and methodology, Section 4.3 examines the relation between new technologies and firm performance, and Section 4.4 concludes.

4.2 Data and Methodology

I obtain return data from CRSP, accounting data from Compustat, and 10-K data from SEC EDGAR. Compustat data available of fewer than two years are excluded from the sample. My sample includes all common stocks (share codes 10 and 11) traded on NYSE/AMEX/NASDAQ (exchange codes 1, 2, and 3). To classify retail firms, I employ the NAICS codes at the 2-digit level for defining the retail industry (NAICS codes 44 and 45) from Compustat. The final sample is in the universe of CRSP/Compustat/EDGAR and includes 2,684 firm-year observations from 2002 to 2019.

To identify the technologies employed by firms, I use textual analysis methodology to construct a text-based technology measure from the 10-K filings. Conventionally, it is challenging to capture how retail firms invest in new technologies for several reasons. Firstly, firms' investment in technologies is not explicitly reported in financial statements, nor is their investment systematically recorded in any database. Second, an emerging body of studies uses patents to measure firms' innovations.[9] However, retail firms rarely invest in and apply for patents, while patenting is more common for the IT, manufacturing, or pharmaceutical industries. Lastly, although traditional measures of intangible capital such as R&D or SG&A

[9]See, for example, Hsu (2009), Hirshleifer, Hsu, and Li (2013, 2018), Kogan et al. (2017), and Stoffman, Woeppel, and Yavuz (2022).

are associated with firms' investment in research and frontier developments, it is unclear how and to what extent firms develop and advance in their businesses. For these reasons, I turn to the text-based method to investigate retail firms' technology investments.

I download 10-Ks from the SEC EDGAR database. I parse the documents and focus on Part 1 and Part 2 (until Management's Discussion and Analysis) of 10-Ks, which constitute the main text discussions of firms' businesses and operations.[10] Building on the recent innovative work of Bloom et al. (2021), I use Bloom et al. (2021)'s list of disruptive technologies to identify retail firms' technology involvements. Bloom et al. (2021) pioneer to document an essential list of the 29 disruptive technologies originally from patents.[11] The list provides a unique set of 221 bigrams of disruptive technologies.[12] These bigrams are identified by a rigorous supervised approach through machine learning, embedding vector algorithms, and human audits. One of the major advantages is that the language of the bigrams is extracted into a business vocabulary which is commonly used in earnings calls and by executives and investors. Therefore, these bigrams are also the language communicated in annual reports.

Based on Bloom et al. (2021)'s bigram list of disruptive technologies, I construct a technology-intensity measure, $Tech$, as the percentage of words in each 10-K that appear on Bloom et al. (2021)'s bigram list in the form of Equation 4.1. Namely, $Tech$ captures how much a firm emphasizes its involvement in the disruptive technologies shown in the annual report. This bag-of-words methodology has been commonly applied in the finance and accounting literature since the seminal work of Loughran and McDonald (2011).[13]

[10] I follow the standard procedures to clean, tokenize, and stem the text.

[11] These 29 technologies are argued to "cover a significant part of recent innovative activity" and have "significant implications for businesses and jobs."

[12] The top three bigrams include mobile devices, machine learning, and cloud computing. See the detailed list in Bloom et al. (2021).

[13] See, for example, Li, Lundholm, and Minnis (2013), Loughran and McDonald (2014, 2015), Bodnaruk,

$$Tech_{i,t} = \frac{\sum_{n=1}^{N} Count(x_n)_{i,t}}{TotalWords_{i,t}}, \tag{4.1}$$

where i is a company's annual 10-K filing and t is a year. $Count()_{i,t}$ is a count function for each bigram x_n. N is the number of bigrams from Bloom (2022)'s list of disruptive technologies. $TotalWords_{i,t}$ is the number of words in a firm's 10-K.

Table 4.1 reports the summary statistics of the key variables. The mean percentage (raw count) of $Tech$ bigrams is 0.01% (2.4) per 10-K document; in other words, a retail firm mentions disruptive technologies by 2.4 times on average in each document.[14] $Tech$ is strongly left-skewed. Around one-third of the firms are involved in at least one disruptive technology in the full sample.[15] The top 10% of retail firms mention at least four times of disruptive technologies. Noticeably, R&D intensity (R&D scaled by total assets) is even more extremely left-skewed, indicating that the retail firms rarely invest in R&D.[16]

Figure 4.1 shows the trend of using the disruptive technologies among retail firms. In 2002, less than 20% of retail firms were involved in disruptive technologies. The top 3 popular disruptive technologies were search engines, video games, and digital videos.[17] After 2010, the percentage of retail firms that adopted new technologies more than doubled to 40%. The scope of technology bigrams expanded from 12 in 2002 to 23 in 2010. Noticeably, social networking emerged rapidly as the second most popular technology. Mobile commerce and smartphone also appeared, whereas video game and digital video lost ground. In 2019,

Loughran, and McDonald (2015), and Kim, Wang, and Zhang (2019).

[14] The correlation between $Tech$ % and raw count of tech bigrams is 98% (unreported in the table).

[15] Specifically, 35% of firms mentioned at least one disruptive technology in the full sample.

[16] Note that R&D intensity is 0% correlated with $Tech$ (unreported in the table).

[17] The size of words represents the relative frequency of words mentioned in each year.

more than 60% of retail firms adopted at least one technology. There was a massive rise in technology innovations implemented by retail firms, ranging from smartphones and clouds to electric vehicles and artificial intelligence. Search engines, cloud computing, and social networking were at the top of the list.

4.3 Performance

In this section, I present empirical results of how disruptive technologies affect firms' performance in OLS regressions and event studies. I primarily focus on firms' operating and stock market performances.

4.3.1 Operating Performance

I begin by investigating whether firms with higher technology intensity perform better in a panel regression as the following form:

$$Y_{it} = \alpha + \beta Tech_{i,t} + \gamma Z_{i,t-1} + \nu_i + \tau_t + \epsilon_{i,t}, \tag{4.2}$$

where i is a company and t is a year. The dependent variable Y_{it} measures company performance. $Tech_{i,t}$ is a technology-intensity measure which is the variable of interest, $Z_{i,t-1}$ is a vector of company control variables, ν_i are industry fixed effects, and τ_t are year fixed effects. The vector of company control variables includes lagged values of market equities, book-to-market ratios, leverage (total debts to total assets), gross profitability (sales minus costs of goods sold scaled by total assets), R&D intensity (R&D expenses scaled by total assets), and SG&A intensity (SG&A expenses scaled by total assets). Standard errors are heteroscedasticity robust and clustered by company.

Table 4.2 presents the result for ordinary least squares (OLS) estimation of Equation 4.2 using sales growth and gross profit growth as dependent variables indicated in column headers.[18] The variable of interest is the technology intensity $Tech$. I first examine whether sales growth is higher for the firms with higher technology intensity in Columns 1 to 4. The coefficients on $Tech$ are all positive and statistically significant at the 1% level in four models with different sets of controls. Interestingly, adding $R\&D$ and $SG\&A$ as controls in Column 3 only marginally reduces the coefficient $Tech$ by 0.39, indicating that the tech intensity contains the information that cannot be explained by intangible capital in $R\&D$ and $SG\&A$. The economic magnitude is also meaningful. Take column 4, for example, in which all control variables are included, a standard deviation increase in $Tech$ is associated with a 0.6% (9.9%*0.06) increase in sales growth, which is equivalent to 4.3% (0.6/13.82) of the standard deviation of sales growth.

Similarly, gross profit growth is higher for the firms with higher technology intensity as shown in Columns 5 to 8.[19] $Tech$ is statistically positively associated with gross profit growth at the 1% level in Columns 5 and 6 and at the 5% level in Columns 7 and 8 in which $R\&D$ and $SG\&A$ are included. The economic magnitude is similar to sales growth, implying that the costs of goods sold grow proportionally with sales. Put differently, using disruptive technology neither increases nor decreases production costs.

Next, I examine the operating performance in an event study. By construction, $Tech$ measure is retrieved from a firm's disclosure of its technology usage. As a result, the year of the technology disclosure serves to be informative as a start of a technology-adoption event.[20]

[18] In Appendix A4.1, I examine a predictive regression by using $Y_{i,t:t+2}$ (the average of years 0 and 1) as a dependent variable instead. The result remains qualitatively similar.

[19] The number of observations for gross profit growth is fewer than that for sales growth by two because negative gross profits are excluded when calculating the growth rate

[20] Implicitly, I assume that the first year of the technology disclosure marks the beginning of an event on

I hypothesize that a firm has a better operating performance following a technology-adoption announcement. I run a regression for event analysis in the following form:

$$Y_{i,t-3:t+6} = \alpha + \beta_1 Ann_{i,t:t+3} + \beta_2 Ann_{i,t+3:t+6} + \gamma Z_{i,t-1} + \nu_i + \tau_t + \epsilon_{i,t}, \tag{4.3}$$

where i is a company and t is the first year of a firm's technology-adoption announcement (first year = t+0). The event window is from three years prior to the announcement (t-3:t) to six years post the announcement (in sub-periods of t:t+3 and t+3:t+6). The dependent variable $Y_{i,t}$ measures company performance. $Ann_{i,t}$ is year dummies that capture the periods surrounding a technology-adoption announcement. The other variables are the same as in Equation 4.2. Standard errors are heteroscedasticity robust and clustered by company.

Table 4.3 presents the event result for Equation 4.3 using sales growth and gross profit growth as dependent variables. The variables of interest are $Ann_{i,t:t+3}$ and $Ann_{i,t+3:t+6}$ that capture a firm's post-event performance relative to its pre-event performance.[21] I first examine whether sales growth is higher following a technology adoption in Columns 1 to 4. The coefficients on $Ann_{i,t:t+3}$ are all positive and statistically significant at the 1% level in four models with different control variables. The estimates indicate that sales growth in the first three years after tech adoptions is around 4 percentage points (from 3.88 (t=3.30) to 4.49 (t=3.53)) higher than the pre-adoption performance. Put differently, a technology adoption contributes extra sales growth by 4 percentage points. The economic magnitude is sizeable and meaningful. Further, in years 4 to 6, the $Ann_{i,t+3:t+6}$ estimates show that sales growth is around 0.91-1.91 percentage points higher but statistically insignificant.

Columns 5 to 8 show the results for gross profit growth. Gross profit growth is similar to

technology adoption.

[21] The yearly result is in Appendix A4.2.

(or slightly larger than) sales growth. In the first three years of technology adoption, gross profit growth is about 4 percentage points (from 3.98 (t=3.14) to 4.80 (t=3.53)) higher than the pre-adoption performance. Moreover, in years 4 to 6, sales growth is 2.55 (t=2.00 in Column 5) and 2.30 (t=1.82 in Column 7) percentage points higher, statistically significant at the 5% and 10%, respectively. Nonetheless, the coefficients in the years 4 to 6 are positive but not statistically significant in Columns 6 and 8 when intangible variables are added as controls.

Figure 4.2 addresses the parallel trends in an event. The identified performance effect should only be evident after a technology adoption (from year t+0) rather than before an adoption. Indeed, Panel A of Figure 4.2 shows no pre-trend for sales growth in the event. The average of sales growth before a technology adoption is around 5.5%. Following the first year of technology adoption, sales growth jumps to 10%, 11%, and 7.5% in years t+0, t+1, and t+2, respectively. The change in the sales growth rate in response to a technology adoption mirrors a 4-percentage-point difference shown in $Ann_{i,t:t+3}$ of Table 4.3. In addition, the average sales growth decreases to 7% in years t+3, t+4, and t+5. This (insignificant) 1.5 percentage-point change corresponds to the estimate of $Ann_{i,t+3:t+5}$. Similarly, Panel B shows no pre-trend for gross profit growth either. The change in the gross profit growth in response to a technology adoption also mirrors a 4-percentage-point difference shown in $Ann_{i,t:t+3}$.

Overall, the results indicate that disruptive technologies are essential drivers for operating performance among retail firms. Firms that adopt new technologies experience higher sales growth and gross profit growth.

4.3.2 Stock Performance

In this section, I examine whether firms' stock performance is associated with disruptive technologies. I begin with an OLS regression to test whether a firm's technology adoption can predict future stock returns in the following form:

$$R_{i,t+1} = \alpha + \beta Tech_{i,t} + \gamma Z_{i,t-1} + \nu_i + \tau_t + \epsilon_{i,t}, \tag{4.4}$$

where i is a company and t is a year. $Tech_{i,t}$ is a technology-intensity measure which is the variable of interest. Year t is the end of the calendar year. The dependent variable $R_{i,t+1}$ measures future monthly excess return (in excess of the market return) in year t+1.[22] Other variables are the same as discussed above. Standard errors are heteroscedasticity robust and clustered by company.

Table 4.4 presents the result for Equation 4.4. The coefficients on $Tech$ are all positive and statistically significant at the 1% level in four models, indicating that the future stock performance is strongly related to the technology intensity. Adding $R\&D$ and $SG\&A$ as controls only slightly reduces the coefficient on $Tech$. The result again suggests that the tech intensity contains the information that cannot be explained by intangible capital. Moreover, among the control variables, $BEME$ and $R\&D$ are also statistically significant at the 5% level. Consistent with the literature on the value and R&D effect, value stocks and high R&D stocks earn higher returns than growth stocks and low R&D stocks, respectively.

Next, I examine the stock performance by using technology adoption as an exogenous event. Technology adoption is a positive cash flow channel that can drive sales growth for

[22]Specifically, the time frame of stock returns begins from July of calendar year t+1 to June of calendar year t+2, for each technology-intensity observation retrieved from annual 10-Ks. Consistent with the finance literature, this time setting allows the market to incorporate the information from annual accounting reports.

retail firms. Accordingly, I hypothesize that stock return is higher following a technology adoption.

Table 4.5 presents the event result for Equation 3.2 using monthly excess return as a dependent variable. The variables of interest are $Ann_{i,t:t+3}$ (from year 0 to 3) and $Ann_{i,t+3:t+6}$ (from year 3 to 6)) that capture a firm's post-adoption performance relative to its pre-adoption performance (from year -3 to 0). The coefficients on $Ann_{i,t:t+3}$ are all positive and statistically significant at the 5% level in four models. Following a technology adoption, the monthly stock return increases by around 0.65%, on average, in years 1 to 3. Moreover, in years 4 to 6, the monthly stock returns are persistently higher by around 0.88% on average. The magnitude is statistically and economically significant. In other words, firms that adopted new technologies experienced higher stock returns by almost 8% and 10% annually in the first and second three-year periods, respectively.

Lastly, Figure 4.3 shows no pre-trend for stock returns in an event. The average monthly excess returns prior to technology adoption is around -0.2%. After firms adopt new technologies, monthly returns increase to around 0.4% in the first three years and 0.6% in the subsequent three years. Overall, stock returns positively respond to the news about disruptive technologies that are the essential drivers for cash flow growth.

4.4 Conclusion

The recent new technologies have facilitated the growth and productivity of retailing firms since the 1990s. In this paper, I investigate the firm performance in adopting new technologies in the retail industry. Using the textual analysis, I identify the key disruptive technologies retailing firms implement in the recent wave of technological innovations. These technologies, such as “search engine,” “cloud computing,” “social networking,” and “mobile commerce” are directly linked to sales strategies that can help retail firms achieve greater production (i.e., sales) scale beyond the bottleneck of production sites.

The documentation of new technologies provides a unique yearly stamp that enables an event study of technology adoption. I show that a retail firm experiences a 4 percentage point increase in sales and gross profit growth over the 3-year period following a technology adoption. Also, stock performance positively responds to technology adoption, yielding an extra return of almost 8% per annum over the following 3-year period. The results suggest that a firm’s operating and stock performances positively respond to the news about new technologies that are the critical driver for a firm’s growth. Overall, this paper highlights the role of new technologies that have reshaped retail operations and unveiled the industrial revolution in the retail industry.

4.5 References

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4.6 Figures

Figure 4.1. Disruptive Technologies in Retail Industry

The figures show the trend of using the disruptive technologies among retail firms. The upper figure plots the time series of the retail firms (%) that adopted new technologies. The lower figure plots the main technologies that were adopted in 2002, 2010 and 2019 (from left to right). The size of words represents the relative importance of the technologies in each year (i.e., the number of firms that adopt the technologies). The technology word counts are constructed by scraping the technical bigrams from 10-K reports based on the Bloom et al. (2021)'s list of the disruptive technologies. Sample period is from 2002 to 2019.

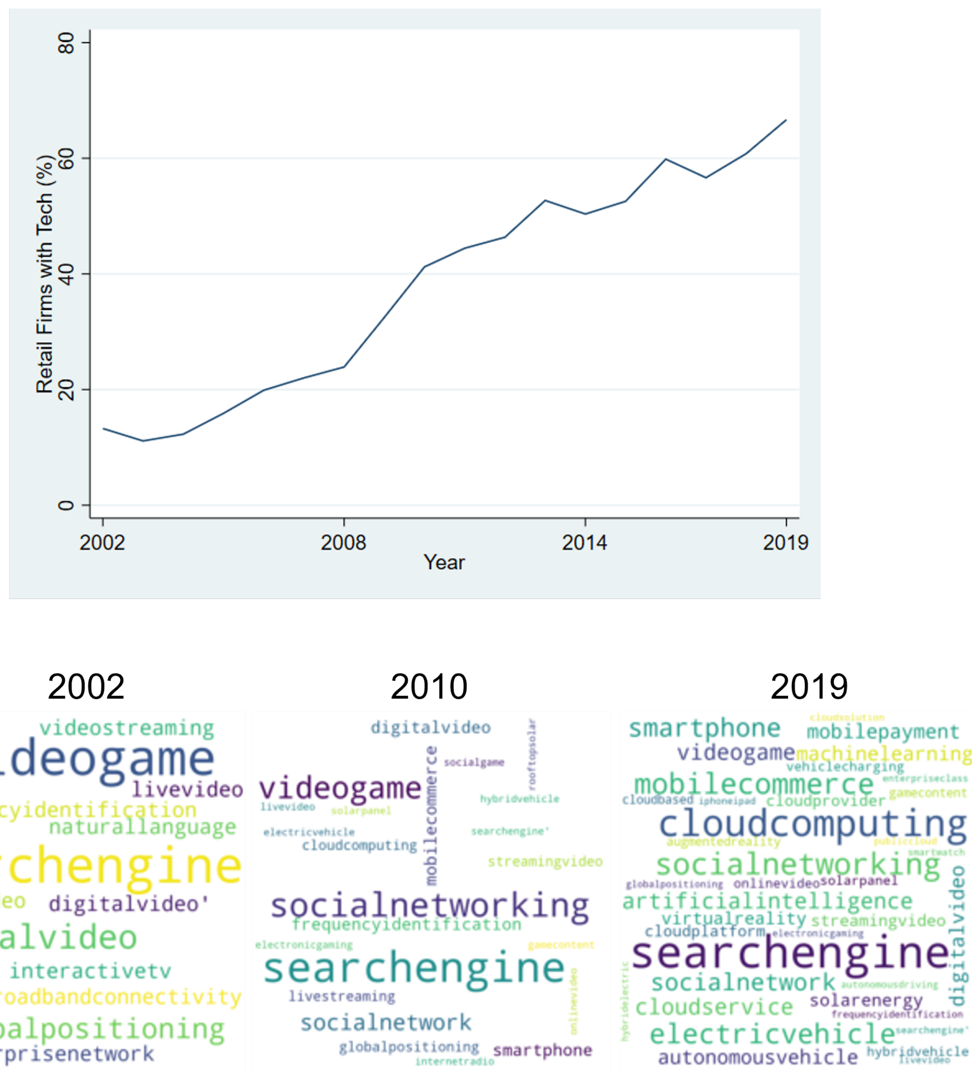


Figure 4.2. Event Pre-trend: Operating Performance

The figure shows the dynamics of operating performances on the technology adoption. Year 0 represents the first year of the technology adoption in which a firm disclosed disruptive technologies on its 10-Ks. Panel A reports sales growth, and Panel B reports gross profit growth. Sample period is from 2002 to 2019.

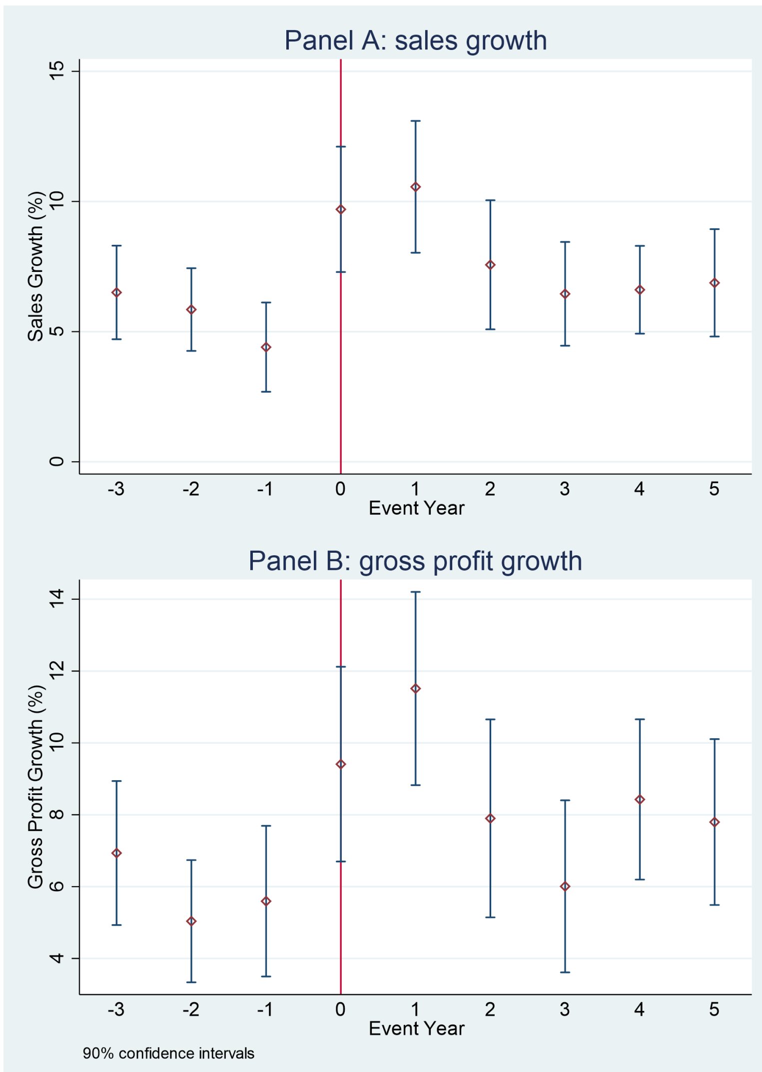
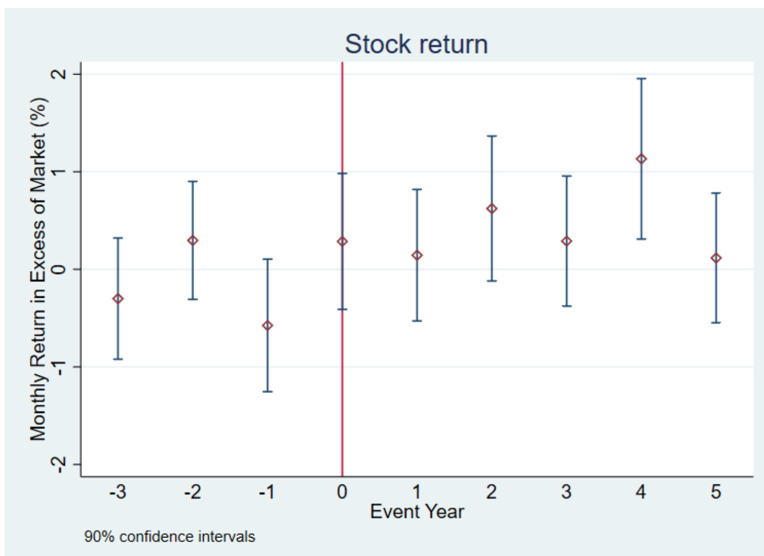


Figure 4.3. Event Pre-trend: Stock Return

The figure shows the dynamics of stock returns on the technology adoption. Year 0 represents the first year of the technology adoption in which a firm disclosed disruptive technologies on its 10-Ks. Sample period is from 2002 to 2019.



4.7 Tables

Table 4.1

Summary Statistics

This table presents summary statistics at the company-year level. Technology measure is constructed by scraping the technical bigrams from 10-K reports based on the Bloom et al. (2021)'s list of the disruptive technologies. The main variable is the percentage of the technology word count in a company's 10-K report.

	mean	sd	p1	p10	p25	p50	p75	p90	p99
Tech count	2.42	15.44	0.00	0.00	0.00	0.00	1.00	4.00	31.00
Tech (%)	0.01	0.06	0.00	0.00	0.00	0.00	0.01	0.02	0.19
Sales growth (%)	6.86	13.82	-23.49	-6.69	-0.33	5.26	11.94	22.12	51.74
Gross profit growth (%)	7.44	16.07	-26.46	-8.19	-0.47	5.76	13.42	24.48	63.19
Employees growth (%)	5.20	15.72	-24.79	-9.09	-2.50	2.92	9.84	20.93	60.69
Operating expense growth (%)	7.62	14.90	-22.47	-6.20	0.29	5.44	12.07	22.45	67.55
LnME	13.55	2.08	8.74	10.86	12.28	13.49	14.92	16.28	18.75
BEME	0.76	1.23	-0.45	0.12	0.27	0.50	0.87	1.58	5.73
Leverage	17.36	19.70	0.00	0.00	0.57	12.28	27.09	42.32	83.68
Profitability	12.56	13.19	-23.56	1.40	6.58	12.51	18.94	25.98	43.08
R&D/Total assets (%)	0.22	1.63	0.00	0.00	0.00	0.00	0.00	0.00	10.41
SG&A/Total assets (%)	54.84	26.18	7.39	28.35	37.29	50.29	68.01	87.13	142.19

Table 4.2

OLS: Technology and Operating Performance

This table presents results for regressions of sales growth on technology measures. The dependent variable is annual sales growth (in %). *Tech* measure is defined as the percentage of technology word count in a company's 10-K report based on the Bloom et al. (2021)'s list of the disruptive technologies. T-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Sales G	(2) Sales G	(3) Sales G	(4) Sales G	(5) GrProfit G	(6) GrProfit G	(7) GrProfit G	(8) GrProfit G
Tech	9.71***	10.36***	9.32***	9.90***	9.32***	9.62***	8.88**	9.08**
	(3.15)	(3.30)	(2.87)	(2.96)	(2.63)	(2.67)	(2.33)	(2.37)
LnME		0.46*		-0.07		0.75**		0.15
		(1.75)		(-0.29)		(2.41)		(0.54)
BEME		-2.58***		-2.82***		-3.33***		-3.59***
		(-5.05)		(-5.05)		(-5.24)		(-5.28)
Leverage		-0.03*		-0.04**		-0.04*		-0.05***
		(-1.75)		(-2.53)		(-1.94)		(-2.66)
Profitability		0.02		0.05		-0.12**		-0.09
		(0.60)		(1.17)		(-2.23)		(-1.60)
R&D			1.15***	1.08***			1.43***	1.17***
			(5.57)	(5.24)			(4.79)	(3.47)
SG&A			-0.07***	-0.08***			-0.07***	-0.09***
			(-4.29)	(-4.06)			(-4.61)	(-4.55)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2684	2684	2684	2684	2682	2682	2682	2682
Adj R-squared	0.06	0.13	0.10	0.16	0.06	0.13	0.09	0.16

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3

Event: Technology and Operating Performance

This table presents results for regressions of sales growth on technology measures. The dependent variable is annual sales growth (in %). $Ann_{t:t+n}$ is year dummies that capture the period surrounding a technology-adoption announcement. T-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sales G	Sales G	Sales G	Sales G	GrProfit G	GrProfit G	GrProfit G	GrProfit G
Ann t+0:t+3	4.49***	4.14***	4.28***	3.88***	4.80***	4.24***	4.57***	3.98***
	(3.53)	(3.51)	(3.38)	(3.30)	(3.53)	(3.34)	(3.35)	(3.14)
Ann t+3:t+6	1.91	1.22	1.67	0.91	2.55**	1.66	2.30*	1.35
	(1.57)	(1.08)	(1.39)	(0.81)	(2.00)	(1.35)	(1.82)	(1.12)
LnME		0.45		0.08		0.62		0.17
		(1.37)		(0.21)		(1.64)		(0.40)
BEME		-3.38***		-3.72***		-4.24***		-4.71***
		(-5.48)		(-5.54)		(-6.38)		(-6.61)
Leverage		-0.04*		-0.05**		-0.03		-0.05*
		(-1.95)		(-2.34)		(-1.32)		(-1.81)
Profitability		0.02		0.02		-0.11*		-0.11*
		(0.26)		(0.40)		(-1.75)		(-1.92)
R&D			0.88***	0.76**			0.92**	0.54
			(2.85)	(2.33)			(2.10)	(1.22)
SG&A			-0.06**	-0.07***			-0.07***	-0.09***
			(-2.52)	(-2.73)			(-2.98)	(-3.47)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1317	1317	1317	1317	1316	1316	1316	1316
Adj R-squared	0.06	0.14	0.08	0.16	0.06	0.15	0.08	0.17

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4

OLS: Technology and Stock Performance

This table presents results for regressions of future excess returns on technology measures. The dependent variable is future excess returns (in % monthly). *Tech* measure is defined as the percentage of technology word count in a company's 10-K report based on the Bloom et al. (2021)'s list of the disruptive technologies. T-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Return	(2) Return	(3) Return	(4) Return
Tech	13.37***	13.25***	13.34***	13.23***
	(14.27)	(12.82)	(14.55)	(12.76)
LnME		0.02		-0.01
		(0.32)		(-0.25)
BEME		0.30**		0.29**
		(2.43)		(2.31)
Leverage		0.00		0.00
		(0.49)		(0.35)
Profitability		-0.01		-0.01
		(-0.91)		(-0.70)
R&D			0.08***	0.09**
			(3.04)	(2.41)
SG&A			-0.00	-0.00
			(-0.94)	(-0.86)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	30932	30932	30932	30932
Adj R-squared	0.01	0.01	0.01	0.01

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.5

Event: Technology and Stock Performance

This table presents results for regressions of future excess returns on technology measures. The dependent variable is future excess returns (in % monthly). $Ann_{t:t+n}$ is year dummies that capture the period surrounding a technology-adoption announcement. T-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Return	(2) Return	(3) Return	(4) Return
Ann t+0:t+3	0.65**	0.67**	0.63**	0.65**
	(2.06)	(2.12)	(2.01)	(2.06)
Ann t+3:t+6	0.86***	0.91***	0.85***	0.89***
	(2.84)	(3.09)	(2.79)	(3.03)
LnME		0.11		0.08
		(1.43)		(0.87)
BEME		0.29		0.25
		(1.50)		(1.26)
Leverage		0.00		0.00
		(0.69)		(0.52)
Profitability		-0.02		-0.02
		(-0.65)		(-0.64)
R&D			0.04	0.02
			(0.40)	(0.22)
SG&A			-0.01	-0.01
			(-1.28)	(-1.05)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	14751	14751	14751	14751
Adj R-squared	0.01	0.01	0.01	0.01

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.8 Appendix

Table A4.1

OLS: Technology and Operating Performance

This table presents results for regressions of sales growth on technology measures. The dependent variable is annual sales growth (in %). *Tech* measure is defined as the percentage of technology word count in a company's 10-K report based on the Bloom et al. (2021)'s list of the disruptive technologies. T-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sales G	Sales G	Sales G	Sales G	GrProfit G	GrProfit G	GrProfit G	GrProfit G
Tech	10.01***	10.21***	9.66***	9.84***	11.25***	10.84***	10.87**	10.45***
	(3.24)	(3.98)	(3.15)	(3.60)	(2.83)	(2.99)	(2.59)	(2.73)
LnME		0.45*		-0.01		0.80***		0.31
		(1.72)		(-0.05)		(2.65)		(1.12)
BEME		-2.37***		-2.54***		-2.48***		-2.67***
		(-4.90)		(-4.82)		(-4.56)		(-4.62)
Leverage		-0.03*		-0.04**		-0.04**		-0.05**
		(-1.87)		(-2.51)		(-2.06)		(-2.58)
Profitability		0.02		0.05		-0.13**		-0.09
		(0.55)		(1.24)		(-2.29)		(-1.61)
R&D			1.16***	1.10***			1.44***	1.18***
			(4.94)	(4.79)			(4.52)	(3.24)
SG&A			-0.06***	-0.06***			-0.06***	-0.07***
			(-3.79)	(-3.66)			(-3.68)	(-3.61)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2573	2573	2573	2573	2572	2572	2572	2572
Adj R-squared	0.06	0.13	0.10	0.17	0.06	0.13	0.10	0.16

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4.2

Event Study: Technology and Revenue Growth by Year

This table presents results for regressions of sales growth on technology measures. The dependent variable is annual sales growth (in %). $Ann_{t:t+n}$ is year dummies that capture the period surrounding a technology-adoption announcement. (2021)'s list of the disruptive technologies. T-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sales G	Sales G	Sales G	Sales G	GrProfit G	GrProfit G	GrProfit G	GrProfit G
Ann t+0:t+1	5.11***	4.72***	5.16***	4.79***	4.64***	4.15***	4.70***	4.27***
	(3.53)	(3.36)	(3.50)	(3.36)	(2.76)	(2.61)	(2.74)	(2.64)
Ann t+1:t+2	5.55***	5.23***	5.34***	4.92***	6.48***	5.90***	6.24***	5.53***
	(3.41)	(3.40)	(3.30)	(3.22)	(3.68)	(3.56)	(3.57)	(3.37)
Ann t+2:t+3	2.77*	2.43	2.31	1.90	3.12*	2.51	2.63	1.99
	(1.73)	(1.65)	(1.46)	(1.30)	(1.74)	(1.50)	(1.46)	(1.19)
Ann t+3:t+4	2.06	1.45	1.83	1.07	1.62	0.81	1.37	0.39
	(1.42)	(1.03)	(1.28)	(0.77)	(0.94)	(0.46)	(0.80)	(0.23)
Ann t+4:t+5	1.90	1.34	1.73	1.13	3.52**	2.65*	3.34**	2.45*
	(1.49)	(1.11)	(1.37)	(0.94)	(2.30)	(1.94)	(2.18)	(1.80)
Ann t+5:t+6	1.74	0.79	1.39	0.41	2.62	1.61	2.26	1.26
	(1.14)	(0.56)	(0.92)	(0.29)	(1.58)	(1.01)	(1.37)	(0.80)
LnME		0.45		0.07		0.62		0.16
		(1.36)		(0.19)		(1.63)		(0.38)
BEME		-3.38***		-3.73***		-4.25***		-4.71***
		(-5.49)		(-5.55)		(-6.34)		(-6.56)
Leverage		-0.04**		-0.05**		-0.03		-0.05*
		(-1.99)		(-2.37)		(-1.37)		(-1.85)
Profitability		0.02		0.02		-0.11*		-0.11*
		(0.25)		(0.40)		(-1.74)		(-1.91)
R&D			0.92***	0.80**			0.96**	0.58
			(3.01)	(2.46)			(2.17)	(1.29)
SG&A			-0.06**	-0.07***			-0.07***	-0.09***
			(-2.51)	(-2.73)			(-2.96)	(-3.47)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1317	1317	1317	1317	1316	1316	1316	1316
Adj R-squared	0.06	0.14	0.08	0.16	0.06	0.15	0.08	0.17

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 5

Conclusion

This thesis contributes to our understanding of the asset pricing implications of technologies and corporate adaptation. Chapter 2 investigates the recent decline in the value premium by studying the role and impact of technology stocks. Through variance and return decompositions, I find that the tech component explains 45% of the time variation in the value premium and materially reduces the value premium in the recent data. Since the book-to-market ratios are argued not comparable across tech and non-tech industries, using the standard NYSE breakpoints to form portfolios will disproportionately allocate tech stocks to the growth portfolio. The rapidly growing market capitalization of tech stocks over the past thirty years has made this classification effect of first-order importance, leading to a small and insignificant value premium in the recent data. Instead, I propose to compare tech (non-tech) stocks with their relevant tech (non-tech) industry peers. Using the tech (non-tech) breakpoints to allocate tech (non-tech) stocks can cater to their unique growth and valuation properties and, thus, better capture the value effect. Overall, the value premium can be recovered once investors meaningfully adjust the industry composition of tech stocks in forming portfolios.

Chapter 3 examines corporations' ability to adapt to the Covid crisis and shows that market reactions provide new information about the value and risk implications of corporate adaptation. Using voluntary work-from-home announcements as an information shock, our event studies show up to 5 percent abnormal returns over five days following the WFH announcement. We also find significant declines in risk exposure relative to the matched firms. Overall, this chapter provides new evidence that financial markets perceived higher value and less risk for firms adapting to Covid by voluntarily announcing a work-from-home transition. The results confirm the long-standing view that corporate adaptation adds value and mitigates risk.

Finally, Chapter 4 studies the firm performance of adopting new technologies in the retail industry. I use textual analysis to identify new technologies from the 10-Ks and examine how much growth a firm can gain by adopting new technologies. Event studies show that firms experience an increase in sales and gross profit growth by 4 percentage points per annum over three years following adoption of new technologies. The tock performance also positively responds to technology adoptions by 8% per annum over the three-year period. Overall, the results suggest that operational performance and stock return positively respond to the news about disruptive technologies that are the critical driver for a firm's growth. This chapter highlights the impact of new technologies on firm operations and performance.