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Abstract

We examine firm value and performance implications of the growing trend of non-technology companies adopting digital technologies, using a measure based on the disclosure of digital words in the business description section of 10-Ks. Digital adoption is associated with a market-to-book ratio 8-26% higher than industry peers. Part of the differences in market-to-book is explained by accounting capitalization restrictions, which we estimate to explain roughly 15% of the differences. Portfolios formed on digital disclosure earn a DGTW-adjusted return of 36% over a 3-year horizon and a monthly alpha of 57-basis-points. We also find significant increases in asset turnover conditional on digital activities, while also finding significant declines in margins and sales growth.

Keywords: Digital Adoption; Valuation; Return Predictability

JEL Classification: G32, G14, O13, M41

Data Availability: Data are available from the public sources cited in the text.

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I INTRODUCTION

The new wave of data-driven digital technologies, such as analytics, artificial intelligence, big data, cloud computing, and machine learning, has brought substantial changes in recent years to how companies are organized, invest, and operate. In 2016 alone, a McKinsey survey estimates, large technology companies have invested a total of 20 to 30 billion USD in artificial intelligence (AI) (Bughin et al. 2017). While initial investments in new digital technologies were concentrated in tech firms, recent developments, especially in cloud computing, have also enabled non-tech firms to invest in these technologies at scale. While, in the past, firms seeking to adopt digital technology had to invest in data infrastructure and hardware, cloud-computing technologies provide firms with an alternative option of renting data infrastructure from service providers such as Amazon Web Services (AWS). As a result, digital technologies have become easier to scale-up at a lower cost (Brynjolfsson et al. 2017). Recent anecdotal evidence suggests that some non-technology (non-tech) firms have responded by actively adopting digital technologies at a large-scale (Bass 2018). For example, many car manufacturers have increased investment in self-driving and autonomous technologies, and retail firms are making investments in digital marketing and data analytics.

Our objective in this paper is to identify, characterize and examine the economic performance of firms from non-technology industries that are among the first movers in adopting new digital technologies relating to analytics, automation, artificial intelligence, big data, cloud computing and machine learning. To measure digital adoption, we construct a dictionary of digital terms[1], and obtain word counts of digital terms in firms' 10-K reports to proxy for the extent of digital activity in firms.

We provide novel large-sample empirical findings, consistent with anecdotal evidence, of an increasing trend in digital technology adoption by non-tech firms in recent years. Our sample consists of all US-listed non-tech firms, which are identified

1. We define the digital terms in Appendix A.

by their industry classification[2], for the fiscal years 2010-2019. Based on our measurement from the business description of the 10-Ks, we find that companies are indeed disclosing more about digital activities. For instance, the proportion of firms in our sample disclosing at least one digital label increased from 8% in 2010 to 25% in 2019.

We find that our proxy for digital activities[3] captures significant changes in firm characteristics when firms go digital. We illustrate this by examining the stock return co-movement of digital firms with a tech portfolio and a non-tech portfolio. We find that relative to industry peers, firms that go digital exhibit greater co-movement with the tech portfolio by 15-46% (i.e., a firm in the top tercile of digital disclosure has a β_{Tech} that is 0.042 higher than the sample average of 0.09, or 46%). In addition, firms that engage in digital activities also exhibit less co-movement with the non-tech portfolio by 4-13%. This implies that non-tech firms become more tech-like than their industry peers once they adopt digital technologies. Moreover, we find that the co-movement differences between non-tech firms that go digital and their peers change over time. In our analysis of the changes between current and 3-years-prior co-movement, we find that firms that go digital are associated with increases in co-movement with the tech portfolio by 13-40% (that is, a firm in the top tercile of digital disclosure increases β_{Tech} by 0.036 relative to the sample average of 0.09, or 40%) and decreases in co-movement with the non-tech portfolio by 1.7-5%. Combined, our analysis on co-movement suggests that our measure of digital activities identifies firms that gradually differentiate from non-tech firms and become more like tech firms.

Next, we examine the profile of firms that go digital. Our results suggest that firms that adopt digital activity are larger, younger and expend more on SG&A. Past digital activities also significantly predict current digital activity, which suggests going digital is a persistent process. Moreover, we also find that firms in industries with higher

2. Appendix B presents the list of industry codes that are used to identify Tech firms. Non-tech firms are those that are not in these industries.

3. For a full discussion of how we measure digital activities from the 10-Ks, see Section 3 on the text extraction and quantization procedure.

digital activity also tend to be more likely to engage in digital activities, consistent with industry-wide complementarities in digital technologies.

Building on the technology adoption literature, we examine whether digital activities increase firm value. Prior studies such as Brynjolfsson et al. (2017) and Cockburn et al. (2017) have argued that digital technologies increase the growth opportunities and productivity of firms. Consequently, markets should place a higher valuation on non-tech firms that engage in digital activities due to potential future gains in performance. On the other hand, prior work has also suggested that there are various frictions associated with new technologies that may delay or limit the benefits of new technologies (Bresnahan and Greenstein 1996; Brynjolfsson et al. 2017). Consistent with digital technologies providing net benefits to firms, we find that the market-to-book ratio of non-tech firms that engage in digital activities is significantly higher than their industry peers. Specifically, we estimate that a firm that adopts digital activities has a 8-26% higher market-to-book than its peers (that is, a firm in the top tercile of digital disclosure exhibits a market-to-book that is by 0.795 higher relative to the sample average of 3, or 26%)[4]. The difference widens over subsequent years, as we find significant monotonic increases in market-to-book over a 3-year period. In particular, firms that go digital increase market-to-book by 7-21%, relative to industry peers (that is, a firm in the top tercile of digital disclosure increases market-to-book by 0.645 relative to the sample average of 3, or 21%), over the following 3 years.

We recognize that accounting rules for capitalization could play a role in explaining some of the market-to-book results as digital investments are likely not capitalized thus affecting the book value of equity. We study how capitalization restrictions influence the market-to-book increases that we find in digital firms in two ways. First, we address the capitalization restrictions by controlling directly for the expenditures relating to

4. In the rest of the text, we also use the bottom tercile and top tercile estimates to compute the economic ranges. Specifically, we impute the top (bottom) range by multiplying the coefficient estimate by 3 (1), and compare the range to the sample average to obtain the range in percentage terms.

the intangibles (SG&A and R&D). With these controls, we find that level differences in market-to-book remain statistically significant but falls in magnitude to about 4-14%, while we also find that magnitudes of the changes in market-to-book are relatively unchanged with the addition of these controls. Second, we control for capitalization restrictions more formally, by correcting market-to-book for accounting conservatism following McNichols et al. (2014). We implement this version of market-to-book for a sub-sample of firms with sufficient investment histories and we show that correcting for accounting conservatism reduces the level differences of digital firms' market-to-book relative to industry peers by 15%, and the changes in market-to-book by roughly a third. Specifically, without the conservatism correction, digital firms exhibit a 14-44% higher market-to-book and a 7-21% increase in market-to-book over three years. And with the conservatism correction, the same firms exhibit a 12-37% higher market-to-book and a 5-14% increase in market-to-book over three years.

Additionally, we examine the valuation benefits of going digital in the cross-section of firms. We find that firms that are larger, with higher CapEx and SG&A tend to experience higher valuations for going digital. The first result suggests that digital technologies help companies increase the benefits of scale (Hitt 1999; Baker and Hubbard 2004), while the last two results suggests that digital investment complements other forms of investment (Cockburn et al. 2017). Moreover, consistent with industry-wide complementarities in digital adoption (Dranove et al. 2014), firms that are in industries that are also going digital tend to receive higher valuations from investors.

We corroborate our market-to-book results with an analysis of the Earnings Response Coefficient (ERC) and the Sales Response Coefficient (SRC)[5], conditional on digital activity. If firms that go digital are more highly valued by investors, we expect that their ERCs and SRCs would increase as investors would increase their pricing

5. We study the SRC, as the valuation of sales, unlike book equity and earnings, is not confounded by capitalization restrictions. Thus, examining the effects of digital activities on the SRC is a relatively clean way of studying whether digital activities do indeed increase firm valuations.

multiples on earnings and sales. Consistent with this prediction, we find that ERCs for firms that go digital are substantially higher than those of their peers. Specifically, such a firm exhibits a 21-63% higher annual ERC and a 12-37% higher decile-based ERC than its industry peers. Similarly, we find that SRCs for firms that go digital are also substantially higher compared to peers. In particular, a digital firm exhibits 84-250% higher annual SRC and a 50-150% higher decile-based SRC compared to its industry peers. The SRC results are especially noteworthy, as inferences based on the sales-based valuation metric are not confounded with earnings impact of expenses on digital efforts that cannot be capitalized per accounting rules.

As we find a persistent *future* increase in market-to-book for non-tech firms that go digital, our findings suggest that markets slowly incorporate the value implications of digital activities into prices. This implies that the value implications of digital activities are not fully priced at the point of disclosure. Hence, digital activities should positively predict returns. We conduct several return predictability tests to investigate this conjecture, and in general, we find that digital disclosure predicts future returns. In particular, we find that for long-short value-weighted portfolios formed on digital disclosure, these portfolios earn, on average, a 36% DGTW-adjusted return[6] over three years[7]. Additionally, in calendar portfolio tests, we find that after controlling for market, size, value, investment, profitability and momentum risk factors, the portfolios formed on 10-K digital disclosure earn a monthly alpha of 57 basis points, or 7% on an annualized basis. These results add support to the claim that digital activities are not efficiently priced by markets, and from a managerial standpoint, these results suggest that managers could do better by providing greater disclosure about digital activities.

Next, we examine whether the increase in valuations is validated by increases in future financial performance measured by asset turnover, profit margins, sales growth

6. Abnormal returns are estimated by deducting the firm's raw returns from the corresponding firm's size, book-to-market and momentum quintile portfolio returns, following Daniel et al. (1997)

7. These portfolios hold firms that are in the top tercile of digital disclosers in the long position and firms that do not disclose digital terms in the short position.

and return-on-assets (ROA). Consistent with productivity gains from data-driven technologies (Tambe 2014), we find that there are significant improvements in asset turnover following the disclosure of digital activities as digital firms exhibit higher asset turnover of 2.5-7.6% relative to industry peers. Additionally, we also show that asset turnover continues to increase over the following 3 years, as firms that engage in digital activity increase asset turnover by 1.4-4% compared to industry peers over the 3-years after digital disclosure, which is consistent with digital technologies improving long-term productivity in firms.

On the other hand, we find significant declines in profit margins and sales growth after the firm engages in digital activity, as digital firms exhibit lower profit margins and sales growth of 7-21% and 9-27% respectively. Moreover, we find that the differences in margins and sales growth also widens over a 3-year span. Additionally, we find no evidence of changes in ROA for firms that engage in digital activities. We provide three interpretations of these results — (1) they could reflect the fact that digital investments are costly in the short run but will hopefully pay off in the long run, and (2) the benefits of going digital are quickly eroded through market competition, as firms tend to go digital when faced with greater market pressures (as indicated by the negative association between prior market returns and digital activity). (3) Companies may not have the right complementary managerial human capital to effectively enact new digital technologies. In particular, we find evidence consistent with the managerial-based explanation, as we find that firms that go digital with tech-savvy managers exhibit 2.6% higher ROA relative to those that do not have such managers.

One limitation of the paper is that our findings are associative, and thus we cannot attribute causality to our results. We acknowledge three potential issues relating to selection bias, specifically, (1) better performing firms selecting into digital adoption, (2) firms selectively disclosing only successful digital activities and (3) mis-classified non-tech digital firms. We argue that the first concern is unlikely as we find that past performance is generally unrelated to digital activity. We argue that the second effect is unlikely as we find only limited improvements to accounting performance for digital firms. We evaluate the third concern by examining our results after dropping potentially mis-classified non-tech firms and we find no changes to our main inferences.

Our findings relate to two strands of research. First, we are among the first studies, to our knowledge, that provide large-sample empirical evidence at the firm level of the impact of AI and other digital technologies. Our proxy for digital activity is created using publicly available data for a wide range of publicly listed firms and is easily replicable. We contribute by providing novel and wide-ranging firm-level evidence on the valuation impact of such digital activities. Second, we contribute to the literature on valuation by introducing a new source of non-financial information that significantly drives prices. In particular, we find that markets are sluggish at responding to the value implications of digital technologies, as portfolios formed on the disclosure of digital activities earn statistically significant positive returns.

II LITERATURE REVIEW

Digital Technology Adoption and Firm Value

The adoption of digital technology potentially enhances firm value in two ways. First, digital technologies can increase firm value by increasing productivity. For example, during the information technology (IT) revolution in the 1990s, several large and diversified organizations benefited from IT adoption by improving inventory management (Brynjolfsson and Hitt 2000). IT adoption also allows firms to produce more (Brynjolfsson and Hitt 1996) and expand more effectively (Hitt 1999). Moreover, recent studies that explore the consequences of adopting digital technologies, such as data analytics, suggest that these technologies will also improve firm productivity (e.g., Tambe 2014). In addition, studies on FinTech have also found that adopting these technologies leads to improvements in productivity for financial services firms (Philippon 2016).

Second, another value-enhancing aspect of digital technologies is that they potentially increase the value of existing investments within the firm. Recent studies that explores the potential productivity benefits of AI have argued that these technologies are general purpose technologies (GPT), which act as complements to other existing investments (Cockburn et al. 2017) and thus, increases the value of existing resources.

Frictions in Adopting New Technology

Although technology adoption potentially introduces many benefits to the firm, these take long to be realized, lowering their value, especially in the short term. In the late 1980s, the benefits of IT adoption took so long to realize that they were not evident in the data, leading Robert Solow to coin the famous "Solow's paradox"—the observation that you can see the computer age everywhere but in the productivity statistics.

There are several reasons that explains why the benefits of IT adoption take long to realize. First, adopting technologies requires developing complementary organizational capabilities (Bresnahan and Greenstein 1996), which may be difficult to implement without sufficient managerial expertise. Bloom et al. (2012) illustrate this point as they show that managerial capabilities explains the US-Europe productivity gap in IT adoption. Specifically, the authors find that US firms have better "people-management" practices[8] that allow US firms to more effectively implement the necessary organizational changes that complement IT adoption. Notably, these findings also generalize to the adoption of digital technologies. Organizational changes are also required to generate value from these technologies as these technologies require employees with data expertise and the creation of new organizational structures that emphasize knowledge sharing (Cockburn et al. 2017). These changes are difficult to implement quickly and could explain why we do not observe immediate changes in

8. For example, better reward-punishment practices, performance evaluations

firm performance from digital technology adoption (Brynjolfsson et al. 2017).

Second, new technology adoption incurs high fixed costs of implementation and also of creating new markets. Consistent with this view, several empirical studies show that the benefits of technology adoption are higher for firms in geographical regions or industries that have already adopted the technology (e.g., the case of electronic medical records in Dranove et al. 2014) as shared fixed costs—in the form of developing human capital and physical infrastructure—are lower for later entrants. Moreover, the cost of creating new markets is also a shared fixed cost borne by early entrants. For example, Brynjolfsson and Smith (2000) found that early internet retailers had to provide lower prices and spend more on advertising to convince consumers to trust internet retailing. Similarly, new business products and services that are based on digital technologies may be unfamiliar to consumers, and additional investments must be made by early adopters to create markets for these products and services.

In sum, prior literature outlines various frictions, which may delay or limit the benefits of adopting new technology. Hence, whether the new digital technologies provide *net value* to firms when adopted is an open empirical question.

To briefly preface our results, we find that the benefits of digital technologies tend to outweigh the costs, as we find increases in valuation across various metrics (i.e. Market-to-book, pricing of earnings and sales). Moreover, consistent with technology adoption frictions delaying the realized benefits of new technology, we find higher valuations but little evidence of firm performance changes. In addition, we present several other findings that are also consistent with the frictions outlined above – (1) Consistent with shared fixed costs, we find that non-tech firms that adopt digital technologies in industries where other companies have also adopted these technologies tend to experience higher valuations. (2) We also find that firms with tech-saavy managers tend to perform better when adopting digital technologies, which is consistent with the importance of complementary human capital assets in technology adoption.

Challenges in Empirical Research on Technology Adoption

A key empirical challenge in many studies on technology adoption is the difficulty in identifying investments in new technologies. Measures of R&D or CapEx do not suffice, as these capture the firms' total investment and not just in the new technologies. Therefore, scholars have had to rely on alternative methods of identifying new technology investment. For example, several studies on IT adoption have relied on survey data — One source was Computer Intelligence Infocorp, which tracked the stock of computer hardware across Fortune 1000 firms (e.g., Hitt 1999). Another source is the Census Bureau; however, census survey data are limited to only the industry level.

Firm-level data on digital and AI-related technologies are even more sparse. This has led to calls for new measures of digital technology adoption (Seamans and Raj 2018). We develop a new measure of digital technology based on the firm's disclosure of digital activities, which is easily replicable for a large sample of publicly listed firms.

Valuation and Non-Financial Information

The Growing Wedge Between Book and Equity Values

Following the rapid growth of the technology industry in the 1990s, several studies examined the failure of accounting systems in measuring the technology investment by firms. Specifically, scholars expressed concern that the rules on accounting for R&D expenditures reduced the value-relevance of accounting numbers because under FAS No. 2, R&D must be immediately expensed. Thus the accounting for R&D does not capture the underlying economics of the investment. To illustrate that accounting rules obscured a key source of information from markets, Lev and Sougiannis (1996) showed that R&D capitalization is value-relevant to capital markets.

A key point in Lev and Sougiannis (1996) is that the standard accounting of firm performance is unsuited to firms that engage in high levels of R&D. This fact is especially concerning in today's economy, with increasing investment in intangibles through R&D expenditures and less on fixed tangible assets. Indeed, Lev and Zarowin (1999) and Core et al. (2003) find that the value-relevance of accounting measures have decreased over time as a result of the greater importance of intangible investments. This trends suggests that there is a growing wedge between accounting and economic value, which highlight a need for more research into value-relevant, non-financial information.

Value-Relevance of Non-Financial Information

One of the first studies to investigate the value-relevance properties of non-financial information was Amir and Lev (1996). Using a sample of cellular phone companies, the authors found that non-financial metrics, such as the population size of the service area, were value-relevant to investors. In a similar spirit, Trueman et al. (2000) showed that measures of internet usage provided value-relevant information about tech companies to investors, above and beyond accounting numbers.

Furthermore, studies have conducted textual analysis of corporate disclosures to examine relationships between non-financial variables and prices, much like we do in this paper (Li 2008, 2010; Brown and Tucker 2011; Mayew and Venkatachalam 2012; Li et al. 2013). For example, Li (2010) shows that certain linguistic aspects of the qualitative disclosures in the MD&A section of the 10-K are associated with future performance and returns. In sum, these studies emphasize that disclosure of non-accounting/financial information is relevant to markets.

The findings of our study builds on the above literature that uses textual disclosures or non-financial metrics to uncover information that is useful for valuation and predicting future performance. In particular, we find that our textual-based proxy for digital activities can help predict future improvements in asset turnover, as well as return performance over a 3-year horizon.

III DATA

We construct our sample from several sources. We begin with all US incorporated or headquartered firms from the intersection of COMPUSTAT and CRSP from fiscal years 2010 to 2019 with share codes 10, 11 and 12 in CRSP. We also include earnings/sales forecasts from IBES and 10-K filings from the SEC Edgar Database.

Our analysis focuses on the digital activities of non-tech firms, so we construct a sample of non-tech firms from our initial sample of firms from the COMPUSTAT-CRSP universe. We first define technology firms as firms that operate in industries relating to computers, electronics, communications, data processing and internet services. Subsequently, we develop a parsimonious filter for technology firms by searching through the SIC, NAICS and GICS industries definitions to identify the technology industries. The list of industry codes classified as tech industries is presented in Appendix B, and we remove all firms within these industries from our analysis.

The main subject of our study is digital activities, and we proxy for these activities by identifying digital terms in the firms' disclosures. Specifically, we construct a dictionary of digital terms, revolving around 7 topics — analytics, automation, artificial intelligence (AI), big data, cloud (-computing), digitization and machine learning (ML)[9] — to count digital terms in the firms' disclosures. These terms were identified from numerous articles on the digital phenomena as well as glossaries of digital terms provided by consulting firms that specialize in digital transformation.

We analyze the business description section of the 10-K report to count mentions of digital terms. We identify the beginning and end of this section by searching for the line with either "Item 1" or "Business." and the lines with either "Item 1A" or "Risk Factors"[10]. To address concerns that the raw count of words from this section

9. We outline the specific words within these topics groups in Appendix A.

10. If the risk factor line is missing, we search for the line of the next section (i.e., unresolved staff comments, properties or legal proceedings). To address potential errors in section parsing, we drop observations with word counts above 3 standard deviations from the yearly average of word counts.

is a noisy measure of digital activity, we quantize the raw counts into terciles that are coded as follows: 0 if no digital activity is disclosed, 1, 2 and 3 if digital mentions fall in the bottom, middle and top tercile of digital mentions in the year respectively. In the subsequent tests, we use this score as our main proxy for digital activity.

Sample Statistics

We report the sample statistics for the main variables in our study in Table 1[11] and describe several key characteristics of the sample of non-tech firms below. First, the market-to-book ratio of non-tech firms in our sample, tends to be lower at a mean (median) market-to-book of approximately 3 (1.8), compared to 4.2 (2.5) for tech firms. Additionally, the sample firms are older, with a mean (median) age of 22 (19) years compared to 18 (16) years for tech firms[12].

Second, the non-tech firms in the sample do not significantly co-move with the tech portfolio, as the average beta on this portfolio is 0.09. By contrast, the sample of non-tech firms co-move strongly with the non-tech portfolio, as the average beta on this portfolio is 0.97. Taken together, these statistics suggests that there are substantial characteristic differences between non-tech and tech firms.

IV NON-TECH FIRMS AND DIGITAL ACTIVITY

Our first key finding is that non-tech firms are increasingly adopting digital technologies. To illustrate this, we aggregate the number of digital terms in the 10-K and plot the distribution over time. Figure 1 shows that the disclosure of digital activity is steadily increasing over time[13]. This trend speaks to the increasing relevance of the phenomenon and motivates our study.

11. The construction of these variables are detailed in Appendix C
12. We report the sample statistics of the the tech firms in Table A.1. in the Internet Appendix
13. Our assumption is that the number of digital words proxies for digital activity and so in Appendix D, we provide some examples of how these digital terms are used in the firms' disclosures

Next, we break down the aggregate digital terms by topic group in Panel A of Table 2 and find that the increasing trend exists across all topics. Notably, digital terms are most concentrated in "analytics", which has 1144 mentions in 10-Ks across 314 firms in 2019. The disclosure of "digitization" is also quite frequent, with 326 mentions across 179 firms in 2019. In addition, we report the digital word counts across industries in Panel B of Table 2 and find that digital disclosure is highest in the manufacturing, financial, and services industries, but is also growing across other industries.

Co-Movement with Tech and Non-Tech Portfolios

Both as a way of validating that our proxy for digital captures non-tech firms' adoption of new digital technologies and to examine how the economic characteristics of firms change when they go digital, we examine whether digital firms co-move more with tech firms and co-move less with non-tech firms.

Our measure of co-movement is estimated using the βs in the following regression:

$$R_{i,t} = \alpha + \beta_{Tech} R_{Tech,t} + \beta_{NTech} R_{NTech,t} + \epsilon_{i,t} \tag{1}$$

where daily returns, $R_{i,t}$, is regressed on the value-weighted daily returns of the tech portfolio ($R_{Tech,t}$) and the non-tech portfolio ($R_{NTech,t}$) over the fiscal period for each firm-year[14]. The estimates of interest are β_{Tech} and β_{NTech}, which measure the co-movement to the tech portfolio and non-tech portfolio, respectively.

To examine the changes in the non-tech and tech βs due to digital activities, we regress the non-tech and tech βs on the quantized score for digital activity. We also include controls for size (log of market cap) and other firm characteristics, namely, firm age, leverage ratio, market-to-book, return-on-assets, sales growth, annual market-

14. The tech portfolio consists of all firms that are classified as tech firms under the industry classification scheme in Appendix B. The returns within the portfolio are value-weighted, and we compute and portfolio returns re-balance portfolio weights at the daily-level. The non-tech portfolio is defined similarly but consists of firms that are classified as non-tech. To reduce the effects of low liquidity stocks from inducing measurement error in the return regressions, we drop penny stock entries with less than $5 in price. Also to reduce measurement error, betas estimated with less than 200 observations are dropped from the analysis.

adjusted return and the number of words in the business description section of the 10-K. To address potential measurement errors in the daily returns arising from bid-ask bounce in thinly traded and low visibility firms (Piotroski and Roulstone 2004; Crawford et al. 2012), we also control for share turnover and return volatility.

Specifically, we implement the following regression model:

$$\beta_{i,t} = \alpha + \zeta_1 Digital_{i,t} + \sum_j \gamma_j X_{j,i,t} + \xi_j + \eta_t + \epsilon_{i,t} \tag{2}$$

where $\beta_{i,t}$ is either the beta on the tech portfolio (β_{Tech}) or the beta on the non-tech portfolio (β_{NTech}). We regress the dependent variable on the digital activity proxy and the control variables ($\sum_j X_{i,j,t}$) outlined above. We also control for year and industry (Fama-French 48-industry) fixed effects and cluster standard errors at the firm level.

Panel A in Table 3 presents our results on the association between β_{Tech} and digital activity using the levels specification and 3-year changes, respectively. In Column 1 in Panel A, we report the levels specification and find that digital activity is strongly associated with greater co-movement with the tech portfolio, as digital firms exhibit 15-46% higher co-movement with this portfolio (i.e., a firm in the top tercile of digital disclosure has a β_{Tech} that is 0.042 higher than the sample average of 0.09, or 46%).

One concern is that the association between β_{Tech} and digital activity might indicate that our digital activity proxy is identifying mis-classified tech firms. Note however, that the mean β_{Tech} for tech firms is 0.72, so even though digital non-tech firms have higher β_{Tech}, these firms are still substantially different from the typical tech firm. Nonetheless, we further address this concern by examining the evolution of co-movement over previous years, conditional on current digital activity. Column 2 report the changes from 3 years-prior to current β_{Tech}, regressed on the digital activity proxy and lagged controls. Our results show that digital firms have increased co-movement by 13-40% over 3 years (that is, a firm in the top tercile of digital disclosure increases β_{Tech} by 0.036 relative to the sample average of 0.09, or 40%), which is roughly 85% of the contemporaneous difference between the β_{Tech} of digital firms and industry peers. Thus, these results suggest that our digital activity proxy is measuring activities within non-tech firms that lead these firms to become more tech-like.

Next, we examine whether firms that go digital co-move less with the non-tech firms. In Panel B, we report the association between β_{NTech} and digital activity using the levels specification in column 1 and the changes specification in column 2. Our results indicate that digital activity is associated with less co-movement with the non-tech portfolio, as digital firms exhibit 4-13% less co-movement with this portfolio. We also find that the lower β_{NTech} comes from firms that engage in digital activities becoming less like to non-tech firms over prior years. Column 2 report the changes from 3 years-prior to current β_{NTech}, regressed on the digital activity proxy and the lagged controls. Our results show that digital firms experience declines of 1.7-5% in β_{NTech} over 3 years, which is roughly 39% of the contemporaneous difference between the β_{NTech} of digital firms and industry peers. Thus, the results in this panel complement our findings for β_{Tech} and suggest that our digital activity proxy is measuring activities within non-tech firms that lead these firms to be less like their peers.

In sum, the economic significance of our co-movement results suggests that our digital activities proxy is identifying firms that are becoming substantially more (less) similar to tech (non-tech) firms over time. Thus, these results can also be viewed as a validation of our text-based digital activities proxy.

Determinants of Digital Activity

Next, we examine determinants of firm-level digital activity in the following regression model, which regresses our digital activity proxies on lagged determinant variables:

$$\begin{aligned} Digital_t = \beta_1 Digital_{t-1} + \beta_2 SIZE_{t-1} + \beta_3 MB_{t-1} + \beta_4 LEV_{t-1} + \beta_5 ROA_{t-1} \\ + \beta_6 AGE_{t-1} + \beta_7 SALES_{t-1,t-2} + \beta_8 CASH_{t-1} + \beta_9 R\&D_{t-1} + \beta_{10} Missing\ R\&D_{t-1} \\ + \beta_{11} SG\&A_{t-1} + \beta_{12} CapEx_{t-1} + \beta_{13} Returns_{t-1} + \beta_{14} Tech\ Manager_{t-1} + \xi_j + \eta_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

where our proxy for digital activity (the quantized score or an indicator for the first disclosure of digital terms in the 10-K), $Digital_t$, is regressed on lagged digital activity ($Digital_{t-1}$), and a number of determinant variables, which we describe in Appendix C. We control for year and industry (Fama-French 48-industry) fixed effects and cluster standard errors at the firm level.

Table 4 presents regression results on the determinants of digital activity. We first run a regression with the current digital activity quantized score as the dependent variable. As digital activities tend to be sticky, we run a second regression with an indicator for the firm's first digital disclosure (coded as 1 for first disclosure of digital activity and 0 otherwise) as the dependent variable and drop observations subsequent to the initial disclosure of digital activities. Columns 1 and 2 report the determinants model of the digital quantized score, but in column 2, we drop the industry fixed effects and include the lagged industry-level digital activity (total number of industry peers that have disclosed digital activities) as a determinant. We perform a similar analysis on the first digital disclosure in columns 3 and 4.

Across all columns, we find that several variables significantly explain digital engagement, namely, lagged digital activity, size, age, SG&A expenditure and the lagged industry-level of digital activity. The size and age coefficient loadings, indicate that larger but younger firms tend to adopt digital technologies. The positive coefficient on SG&A expenditure suggests that more SG&A intensive firms make digital investments, while the generally negative coefficient on R&D and CAPEX suggests that more R&D and CAPEX intensive firms are less likely to invest in digital technologies.

Notably, lagged digital activity explains a significant amount of variation in the determinants model as including this variable increases the adjusted R^2 from 0.20 to 0.72. Moreover, a firm that discloses at least 1 digital term has a 79% unconditional probability of disclosing at least 1 term in the next year, which suggests that digital activity is a fairly persistent process. Lagged industry-level digital activity also significantly determines firm-level digital activity, which suggests that there are industry-wide complementarities that increase the benefits and thus likelihood of digital adoption.

Moreover, we find that lagged performance measures at the firm-level do not predict digital activity. Although ROA is significantly positive only for the specification without industry effects (which indicates that firms in higher ROA industries tend to go digital, but firms with higher ROA relative to industry peers do not), all other metrics of performance, such as stock returns, sales growth and market-to-book exhibit statistically insignificant and negative relationships with digital activities. Notably, these results suggests that more successful firms are not more likely to adopt digital technologies, which alleviate concerns that selection biases could confound the interpretation of the valuation effects of these technologies.

V VALUATION AND PERFORMANCE IMPLICATIONS

Market Valuations And Digital Activity

We begin by examining whether the market-to-book ratio reflects digital activity. In these tests, we regress the current changes, levels, 1-3-year-ahead changes in market-to-book on our digital activity proxy and controls, in the following regression model:

$$MB_{i,t} = \alpha + \beta_1 Digital_{i,t} + \sum_j \gamma_j X_{j,i,t} + \xi_j + \eta_t + \epsilon_{i,t} \tag{4}$$

where $MB_{i,t}$ is either the level, current changes, or 1-3-year-ahead changes in market-to-book. The independent variables consist of the proxy for digital activity and a set of control variables $\sum_j X_{j,i,t}$. Additionally, we control for year and industry fixed effects and cluster standard errors at the firm level. Since capitalization restrictions on intangible investments could also increase market-to-book, in an alternative specification we also control for SG&A and R&D to examine the effects of this channel.

We use the quantized scores for digital activities, described in Section 3. Baseline control variables are size, firm age, leverage ratio, return-on-assets, sales growth, market-adjusted annual returns and the number of words in the business description section. For regressions with dependent variables in changes, we control for mean reversion by controlling for the industry median and industry-adjusted market-to-book.

Table 5 presents our market-to-book results. In Panel A, we report the current changes and level differences in market-to-book for digital firms. In column 1, we find that firms with digital activities are associated with a current increase in market-to-book of 3-10% relative to industry peers. Column 2, examines the same dependent variable but with an additional control for SG&A, and we observe similar increases in market-to-book. We examine the level differences in market-to-book in column 3, and we find that firms with digital activity are associated with a market-to-book that is 8-26% higher than their industry peers (i.e., a firm in the top tercile of digital disclosure has a market-to-book ratio that is 0.795 higher than the sample average of 3.03, or 26%). The second column on the levels analysis indicates that part of the level differences in market-to-book is due to capitalization restrictions of intangibles, as the magnitudes of the valuations differences ranges from 4-14% when intangibles are added as a control[15]. Nonetheless, we note that the level differences are still statistically and economically significant under this specification, and indicates that the differences in market-to-book is not fully driven by capitalization restrictions. We next examine the future changes in market-to-book in Panel B of Table 5. Columns 1-6 report the 1-3-year-ahead changes in market-to-book, and show that digital activity is significantly associated with monotonically increasing positive changes in market-to-book in the following 3 years. In particular, by the 3rd year, firms that go digital exhibit a 7-21% increase in market-to-book relative to industry peers (that is, a firm in the top tercile of digital disclosure increases market-to-book by 0.645 relative to the sample average of 3.03, or by 21%). As before, we also examine the same results but with controls for intangibles. Under this specification, we find that the economic magnitudes and

15. Note that this estimate could be viewed as conservative as the controls for intangibles also absorbs the effects that digital investments may have on future investment opportunities and growth.

statistical significance are relatively unchanged.

We further study the effects of capitalization restrictions on the market-to-book differences and changes, by examining the digital valuation effects on conservatism corrected market-to-book (McNichols et al. 2014). Specifically, we estimate the conservatism correction factor for a sub-sample of firms with sufficient length of investment histories, and compute an adjusted-version of market-to-book that explicitly controls for the component of market-to-book that is attributable to the missing capitalization of intangibles[16]. We present the results with this sub-sample in Table 6. In Panel A, we report the results using the unadjusted market-to-book to provide a baseline for this sub-sample of firms. Our estimates show that digital firms in this sub-sample exhibit a 14-44% higher market-to-book relative to industry peers (i.e., a firm in the top tercile of digital disclosure has a market-to-book ratio that is 1.434 higher than the sample average of 3.24[17], or 44%) and a further 7-21% increase in market-to-book over the following 3-years. We control for the capitalization effects in Panel B by using conservatism-corrected market-to-book as the dependent variable. In this specification, we find that digital firms exhibit 12-37% higher market-to-book (i.e., a firm in the top tercile of digital disclosure has a market-to-book ratio that is 0.573 higher than the sample average of 1.53[18], or 37%) and a further 5-14% increase in market-to-book over the following 3-years. Thus, our estimates suggest that roughly 15% of the level differences in market-to-book can be attributed to the capitalization restrictions, while roughly a third of the increases can be attributed to these restrictions as well.

To examine which digital firms receive higher valuations in the cross-section, in

16. This approach corrects for accounting conservatism by first estimating the conservatism correction factor, which is the ratio of the capitalized tangible and intangible assets (via the cost accounting method over the estimated useful life of assets) to capitalized tangible assets (via the straight-line depreciation method over the estimated useful life of assets). Market-to-book is then adjusted by dividing by this ratio. See Section 2 in the Internet Appendix for more details on the methodology and theory behind the computation of this conservatism correction factor.

17. This is based on the average market-to-book of this sub-sample reported in Table A.2 in the Internet Appendix.

18. See Table A.2 in the Internet Appendix for more details on the sample statistics of the conservatism-corrected market-to-book.

Table 7 we perform a regression of market-to-book on our digital proxy, interacted with various cross-sectional variables, namely: size, age, R&D, SG&A, CapEx, return-on-assets, sales growth, leverage, cash balances and the industry-level of digital adoption.

Results in Panel B of Table 7 show that firms that are larger, expend more on SG&A, CapEx and exhibit better performance (in ROA and sales growth) tend to receive higher valuations when they go digital. In particular, the positive relationship between size and digital activity suggests that digital technologies help larger companies increase the net benefits of scale, which is consistent with prior work that argues that IT technologies help companies expand and integrate more effectively (Hitt 1999; Baker and Hubbard 2004). Additionally, the finding that firms with higher SG&A and CapEx tend to receive higher valuations for digital investment suggests that digital technologies are general purpose technologies (Cockburn et al. 2017), which complement other investments. Consistent with investors pricing in higher valuations on digital activities when there are early signs of success, we find that digital firms with higher ROA and sales growth tend to receive higher valuations. On the other hand, we find that the firm-level interactions with age, R&D do not incrementally explain the higher valuations from digital activities.

For the cross-industry interaction variable, regression results in Panel B of Table 5 show that firms in industries with higher rates of digital adoption tend to receive higher valuation with greater digital activity. This result is consistent with existing work in the technology adoption literature, which argues that there are shared fixed costs for adoption technologies that are lower for later adopters (see for example, Dranove et al. 2014). Thus, for firms in industries with significant extent of digital activity, the costs of going digital is lower and is reflected in higher valuations.

Next, we supplement our market-to-book tests by examining whether the market values earnings more following digital activity. If digital activities do increase firm valuations, we should also observe increases in the earnings response coefficients (ERC) as investors foresee higher future growth opportunities for the firm and consequently value current earnings more[19]. We measure the changes in investors' valuation of earnings using the following ERC regression:

$$CAR_{i,t} = \beta_1 UE + \beta_2 Digital_{i,t} + \beta_3 UE_{i,t} \times Digital_{i,t} + \sum_s \gamma_s X_{i,s,t} \tag{5}$$
$$+ \sum_s \delta_s UE \times X_{i,s,t} + \xi_j + \eta_t + \sum_j UE \times \xi_j + \sum_t UE \times \eta_t + \epsilon_{i,t}$$

where $CAR_{i,t}$ represents the (-1,40) window[20] cumulative abnormal returns[21] around the earnings announcement and is regressed on the unexpected earnings (UE), which is defined as the actual EPS minus the most recent median IBES consensus scaled by price at fiscal year end[22], and a number of controls and interactions that incrementally explain the baseline returns-earnings relationship, which is measured by β_1, the earnings response coefficient (ERC). Our primary coefficient of interest is β_3, which measures the incremental impact of digital activity ($Digital$) on the ERC. $\sum_s X_s$ represent the list of controls in the ERC regression. Following prior literature (e.g., Collins and Kothari 1989; Easton and Zmijewski 1989), we control for several variables (and their interactions with UE) that explain variation in the ERC: market cap., leverage ratio, market beta, loss (indicator), persistence, return volatility, earnings announcement and 10-K filing lag. Additionally, we also add industry and time fixed effects (and their interactions with UE), and cluster standard errors at the firm level.

Panel A of Table 8 reports the results of ERC tests. Column 1 presents the baseline (the regression model with only controls and UE interactions) ERC coefficient and we

19. The logic underlying the valuation interpretation of the ERC stems from an accounting literature that views the ERC coefficient as capturing the market's expectation of the capitalization rate of earnings (see for example, Easton and Zmijewski 1989; Collins and Kothari 1989)

20. We chose this return window as the 99th percentile of the lag between earnings announcement and 10-K filing date is 39 days. We drop observations where the lag is greater than 40 days.

21. Abnormal daily returns are calculated by taking the raw return minus the Carhart, Fama-French four-factor expected returns (Carhart 1997), where the expected returns are estimated with the βs of the four-factor model that are estimated in a (-280,-60) window.

22. We remove consensus forecasts that are more than 100 days old at the time of the announcement and remove forecasts in which the price at the end of the fiscal period is less than 1 and unexpected earnings are greater than the price.

report an ERC coefficient of 2.661. Column 2 explores the interactive effect of digital activity, proxied by the quantized score of digital terms, on the ERC model. Consistent with our expectations, we find that the coefficient on Unexpected Earnings × Digital is statistically significant, and suggests that a digital firm exhibits ERCs that are 21-63% higher than industry peers (i.e., a firm in the top tercile of digital disclosure has an ERC that is 1.677 higher than the baseline ERC of 2.661, or 63%)[23].

As the earnings-returns relationship is characterized by non-linearities (Freeman and Tse 1992; Gipper et al. 2019), one might be concerned that the incremental increase in ERC for digital firms could be an artifact of these non-linearities. To address this potential confounding effect, we implement the same regressions, but with UE deciles which are ranked each year in columns 3-4. Like our previous results, we find that digital firms tend to have higher ERCs as the estimates suggest that a digital firm exhibits a decile-based ERC that is 12-37% higher than the baseline[24].

We recognize that the same accounting rules regarding expensing of R&D affect the ERC tests as they did the market-to-book tests. Therefore, we also examine the market response to unexpected sales or the sales response coefficient (SRC). Unlike book equity and earnings, sales are not affected by the capitalization restrictions and thus observing increases in the valuations of unexpected sales would help corroborate the claim the digital investments are indeed highly valuable to firms.

To examine the SRC, we run the same regression model as before but with unexpected sales, defined as the actual sales per share minus the most recent median IBES consensus scaled by price at fiscal year end[25]. Panel B of Table 8 report the results

23. To further control for firm-level heterogeneity in the UE and returns relationship, we also examine an alternative specification with grouped firm fixed effects (following the methodology in Gipper et al. 2019) based on 10×10 size and beta portfolios in Table A.4 in the Internet Appendix. We find similar results under this specification.

24. In addition, following the approach in Gipper et al. (2019), we also examine the fitted ERC curves for digital and non-digital firms using fractional polynomials to fit the non-linearities in the ERC. Our results, presented in Figure A.1 in the Internet Appendix shows that digital firms tend to exhibit greater return reactions to both positive and negative unexpected earnings (albeit at the more extreme end for negative earnings), consistent with these firms exhibiting a higher ERC coefficient.

25. Similarly, we remove consensus forecasts that are more than 100 days old at the time of earnings

for the SRC regressions. As before, we report the baseline SRC model in Column 1, which is 0.440. In Column 2, we explore the interactive effects of digital activities and our findings mirror the ERC results, as our estimates suggest that digital firms exhibit an SRC that is 84-250% higher than industry peers. Columns 3 and 4 implements the same regression model with yearly unexpected sales deciles and we find also find that a digital firm exhibits a decile-based SRC that is 50-150% higher than the baseline[26].

In summary, our ERC, SRC and market-to-book regressions indicate that firms that engage in digital activities are valued more highly than their peers at economically and statistically significant levels. In addition, our results on the time-series changes in market-to-book also indicates that the effects of digital activity are fairly persistent and increase for up to 3 years after the initial disclosure of digital activities.

Digital Activity and Return Predictability

The valuation tests suggest that digital activity is associated with higher market valuations, and this effect persists and grows over time. We now address the question of whether markets value digital activities fully when they are disclosed to the market.

To address this question, we examine return predictability based on digital activity disclosure. We first construct portfolios in June of each year, starting from 2011, by holding firms in the long position if they are in the top tercile of firms that disclose digital terms in the business description section of the 10-K[27], and holding firms in the short position if they have not disclosed digital terms.

We then track the performance of these long-short digital portfolios over the course of 3 years using DGTW-adjusted returns (following, Daniel et al. 1997). These risk-adjusted returns are first calculated at the firm level by deducting the corresponding

announcement and remove forecast in which the price at the end of the fiscal period is less than $1.

26. We also examine the robustness of the SRC results by implementing SRC regressions with grouped fixed effects and by examining the fitted SRC using fractional polynomials in Table A.4 and Figure A.2 of the Internet Appendix. The inferences from both sets of analysis corroborate the main results presented above.

27. We assume 10-K information to be publicly available by four months after the fiscal year end.

size, book-to-market and momentum quintile portfolios from the raw returns. We then aggregate to the digital portfolio returns by taking the weighted average of these returns based on the market capitalization of the firms at the portfolio formation date. To account for the changing risk profile of firms, we allow the benchmark portfolio to change every year in June. Furthermore, to help address survivorship bias, if a firm delists before the end of the returns horizon period we include the delisting return[28] and reinvest the proceeds in the value-weighted market portfolio, while also reinvesting the benchmark return to the end of the horizon period[29].

Our results reported in Figure 2 shows that value-weighted portfolios formed on digital disclosure consistently predict positive returns. Notably, by the end of the third year, our results indicate that an investor can earn a 36.4% risk-adjusted return. We tabulate the time-series average return performance at the full 3-year horizon in columns 1 of Table 9 and find that the long-short portfolio formed on digital disclosure exhibits statistically significant (at the 1% level) returns over 3 years. In addition, we examine the portfolio returns in the 1-3 years of the holding period separately in columns 2-4, and observe significant long-short returns for all three intervals. In particular, in the 1st year of the strategy, an investor can earn a 8.9% risk-adjusted return on a long-short strategy formed on digital disclosures and a 7.2% risk-adjusted return with a long-only strategy. One caveat to our return results is that a portion of the long-short returns comes from the short side. While this may be puzzling because digital firms form a small proportion of our sample, we note that we are considering only the universe of non-tech firms. Thus, our results also suggest that non-tech firms that fail to adopt digital technologies have performed poorly in our sample period.

To further address concerns that other forms of risk may be driving our results, we run fama-macbeth regressions of raw returns on an indicator ($Digital_{i,t}$) proxying

28. Following Shumway (1997) and Shumway and Warther (1999) we code the delisting return as -30% and -55% if the firm delists for performance reasons from NYSE and NASDAQ respectively

29. Additionally, to further account for low liquidity and high transactions costs in penny stocks, we also remove stocks with prices below $5.

for the digital long-short strategy (that is, an indicator that is coded 1 for top tercile digital disclosure, -1 for no digital disclosure and 0 otherwise), and controls for risks, namely, size ($SIZE_{i,t}$), book-to-market ($BM_{i,t}$), operating profit ($OP_{i,t}$), investment ($INV_{i,t}$), momentum ($MOM_{i,t}$), SG&A and R&D as well as portfolio year fixed effects. Specifically, we implement the following regression model:

$$R_{i,t} = \alpha + \beta_1 Digital_{i,t} + \beta_1 SIZE_{i,t} + \beta_2 BM_{i,t} + \beta_3 OP_{i,t} + \beta_4 INV_{i,t} \qquad (6)$$
$$+\beta_5 MOM_{i,t} + \beta_6 SG\&A + \beta_7 R\&D + \epsilon_{i,t}$$

We implement the regression at the portfolio year level. To address serial correlation, we apply newey-west standard error corrections with lags that corresponds to the holding period of the returns for the portfolio-year regressions. Panel B of Table 9 reports our results based on fama-macbeth regression analysis. Confirming our prior portfolio-level results, we find that the long-short strategy yields significant risk-adjusted average returns of 2.5% and 4.4% at the 2- and 3-year return horizons respectively.

We also assess whether the digital long-short strategy yields positive returns in calendar time, by turning to calendar-time portfolio regressions. We implement this by evaluating the alpha from a regression of the long-short portfolio returns on the Fama and French (2015) five factors and the momentum factor as described below:

$$R_{pt} = \alpha_p + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \beta_6 MOM_t + \epsilon_{pt} \quad (7)$$

where R_{pt} is the monthly long-short portfolio return in excess of the risk-free rate. The allocations to the long and the short side of the portfolio are based on the previously described portfolio construction methodology and are revised in June of each year. The monthly portfolio return is estimated by value-weighting the firm-level raw returns, and the weights are re-balanced monthly. MKT_t is the monthly market return in excess of the risk-free rate. SMB_t, HML_t, RMW_t and CMA_t are the size, value, profitability and investment risk-factor-mimicking monthly portfolio returns (Fama and French 2015). The coefficient of interest is α_p, the excess return on the portfolio, after controlling for exposure to the five risk factors in the regression model.

Table 10 reports our calendar portfolio regression results for the long-short, long-side and short-side portfolio returns. In the first column, we report the results for the long-short portfolios, and our results indicate that the portfolio returns a 57-basis-point alpha on average, which on an annualized basis, is approximately 7%. We examine the long-side and short-side returns in column 2 and find that the portfolios return a positive 38-basis-point alpha and a negative 19-basis-point alpha.

Taken together, our return predictability results suggest that markets are sluggish at reacting to the disclosure of digital activity. In particular, we find that trading strategies formed on the digital disclosure in 10-Ks and both disclosure mediums tend to perform well and can deliver significant risk-adjusted returns.

Digital Activity And Fundamental Performance

In this subsection, we study the changes to fundamental performance due to digital activity, to investigate whether the increased valuations are validated by improvements in fundamental performance. The framework of our tests in this subsection is similar to the design of our market-to-book tests. We regress measures of fundamental performance on the digital activity proxy and a set of controls ($\sum_j X_{i,j,t}$): size, age, leverage ratio, return-on-assets, annual market-adjusted returns, SG&A, R&D, missing R&D indicator and the number of words in the business description section of the 10-K, as well as industry and time fixed effects. Additionally, for regressions with dependent variables in changes, we control for the industry median and the industry-adjusted level of the dependent variable.

Specifically, our fundamental performance tests use the following regression model:

$$VAR_{i,t} = \beta_1 Digital_{i,t} + \sum_j \gamma_j X_{j,i,t} + \phi_s + \delta_t + \epsilon_{i,t} \tag{8}$$

where $VAR_{i,t}$, the dependent variable, is a performance measure.

We first examine asset turnover and we find that asset turnover improves following digital activity, which is consistent with prior work that find productivity benefits of digital investments (Tambe 2014). Panel A of Table 11 presents the results of regressing levels, 1-3-year-ahead changes in asset turnover in columns 1 to 4. In column 1 we find that digital firms exhibit asset turnover that are 2.5-7.6% higher than industry peers (i.e., a firm in the top tercile of digital disclosure has asset turnover that is 0.06 higher than the sample average of 0.78, or 7.6%)[30]. And over a 3-year horizon, asset turnover continues to increase for digital firms and by the 3rd year, these firms increase asset turnover by 1.5-4% relative to industry peers (that is, a firm in the top tercile of digital disclosure increases asset turnover by 0.036 relative to the sample average of 0.78, or 4%), consistent with digital technologies improving long-term productivity.

Next, we examine profit margins and sales growth. Surprisingly, we find that digital firms are associated with declines in both of these metrics. In Panel B, we find that firms that go digital are associated with 7-21% lower profit margins relative to their industry peers[31]. In the following year after the digital disclosure, profit margins continue to fall by 3-8% relative to industry peers. The profit margins result could be a consequence of the accounting system that expenses the investments in digital activities through SG&A, and other expense items that are not allowed to be capitalized as an asset[32]. In Panel C, we examine sales growth and find that digital firms exhibit 9-27% lower sales growth relative to industry peers. Columns 2-4 of the panel show that sales growth is also lower in the years following the digital disclosure,

30. We also examine the asset turnover effects of digital investments in the cross-section of firms in Table A.5 in the Internet Appendix. We find that digital firms that expend more on CapEx and are in industries that invest more in digital technologies tend to exhibit higher asset turnover, consistent with digital investments complementing other investments and industry-wide complementarities in digital investments.

31. We also examine the profit margins effects of digital investments in the cross-section of firms in Table A.5 in the Internet Appendix, and we find that digital firms that are in industries that invest more in digital technologies tend to exhibit lower profit margins. This results suggests that market competition may erode the margin-related benefits of digital investments, as other firms in the same industry who also go digital may squeeze margins for the industry overall.

32. To investigate this conjecture, we check and find that digital activities are associated with higher levels of SG&A in Table A.6 in the Internet Appendix.

as we find a 5-16% lower sales growth relative to industry peers by the 3rd year of the disclosure (i.e., a firm in the top tercile of digital disclosure has 3-year sales growth that is 0.054 lower relative to the tri-annualized sample average of 0.33, or 16%).

In Panel D of Table 11, we examine the return-on-assets of digital firms. We do not find statistically significant evidence of changes in ROA. Thus, our results indicate that digital activities, on average, have a negligible effect on overall performance in the current period, and the 3-years subsequent to the disclosure of these activities[33].

Finally, motivated by the idea that management plays a key role in technology adoption (Bloom et al. 2012), we investigate how firms with tech-saavy managers can improve performance through digital technologies. In Table 12, we re-run the ROA regressions in Panel D of Table 11 for the sub-sample of non-tech digital firms, and include a proxy for tech-saavy managers, based on executive titles in Capital IQ's People Intelligence database[34]. In Table 12, our results show that the presence of a tech-saavy manager improves performance through digital activities. In column 1 of Table 12, we find that non-tech digital firms with these managers exhibit higher ROA performance as these firms exhibit a 2.6% higher ROA compared to industry peers. Furthermore, the difference in ROA do not reverse and hold constant over a three-year period. Thus, our results in this table suggest that managerial expertise within the firm is important for integrating and generating value from new digital technologies.

33. We also examine the ROA effects of digital investments in the cross-section of firms in Table A.5 in the Internet Appendix, and we find that larger and more CapEx intensive digital firms tend to exhibit higher ROA. The first result suggests that digital technologies have significant benefits in helping companies maintain scale, and thus benefits larger firms more. The second results echos the asset turnover cross-section result described in Footnote 25 and suggests that digital investments complements other investments within the firm.

34. This is coded as 1 if the firm has a top-5 executive with a tech-related title. Examples of these titles include: "Chief Information Officer" or "Chief Technology Officer"

Discussion

Reconciling the Valuation and Fundamental Performance Results

Previously, we report mixed evidence that digital activity improves fundamental performance. In fact, we show that digital activity has negligible effects on ROA and is associated with significant decreases in profit margins and sales growth. These results are puzzling given our earlier findings on a positive association between digital activity and valuations. We offer several explanations to help reconcile this apparent puzzle.

First, we note that increases in valuation are driven by increases in the market expectation of growth opportunities and not necessarily by immediate changes in performance. Although these growth opportunities should eventually be realized in changes to future performance, it is unclear when these changes would occur, and anecdotal evidence suggests that these changes may take a long time to realize. Amazon, for example, reported its first annual profit in the seventh year (2004) after its IPO. Many other tech firms with high valuations report profits only after years of consecutive losses. Thus, our results on the changes in fundamental performance possibly reflect the fact that investment in digital technologies takes a long time to bear fruit.

Second, investment in digital technologies is costly to the firm in the short term. These investments have high start-up costs because firms must develop large databases of information, invest in human capital to maintain and exploit the data, and invest in infrastructure that links digital technologies to firms' business operations. Moreover, due to accounting rules, many of these investments are immediately expensed and cannot be capitalized. Our results on profit margins suggest that digital technologies are costly in the short run, as we report negative changes to profit margins after the disclosure of digital activities. However, if digital investments are successful, the negative effect on margins is unlikely to persist and will turn positive when digital investment starts to bear fruit. Unfortunately, we are limited by the short time-scale of our sample, and thus, this hypothesis will have to be tested in future research.

Third, some of the gains from digital investment could be eroded by market competition. In particular, for profit margins and sales growth, there may be little improvement in these performance measures if competitors are also making similar investments in digital technologies[35]. Moreover, under the market competition story, one should still observe gains in productivity-based metrics because productivity is unlikely to be affected by market pressures on price, and indeed, we find consistent associations between digital activity and both current and future changes in asset turnover.

Fourth, the gains from digital technology adoption could be limited by a lack of the necessary managerial human capital to enact digital adoption (Bloom et al. 2012). We find consistent evidence with this conjecture, as we find that firms that go digital with tech-saavy managers consistently perform better than firms without such management teams. In fact, these firms experience an immediate positive increase in ROA compared to their industry peers when going digital of 2.6%, which suggests that the presence of such managers are critical for successful implementation of new technologies.

Accounting Capitalization Rules and Digital Valuations

Another interpretation of our valuation results is that it could be driven by accounting capitalization rules that restrict the capitalization of R&D expenses. Since digital assets are likely to be in the nature of R&D that are not capitalized, investing in these activities could increase valuations as investors price in the replacement costs of the intangible assets created. We address this possibility in several ways. First, in our market-to-book tests, we control for the capitalization effect by including controls for SG&A and R&D. Our inferences with these controls are mainly unchanged, although magnitudes of level differences are somewhat smaller with the addition of

35. In particular, we find some evidence for this conjecture, as we also find declines in gross margins (defined as revenues minus cost of goods sold, scaled by sales) that persist for up to a year after the digital disclosure (see Table A.5 in the Internet Appendix). This suggests that even without factoring in the high investment in digital, market competition also erodes margins

these controls. As an alternative way of controlling for the capitalization channel, we also examine the market-to-book tests with a conservatism-corrected market-to-book (McNichols et al. 2014) for a sub-sample of firms with sufficiently long investment histories. Under this specification, we also find that our main inferences are unchanged.

Secondly, the positive increases in sales valuations that we observe in the SRC tests also indicates that the positive valuations of digital firms is not completely driven by capitalization restrictions. Since sales are unaffected by capitalization rules, examining sales valuations is a useful way of examining digital valuations without the confounding effects of these rules. Our analysis of the SRC show that digital activities increases the valuation of sales significantly, which thus indicates that increases in valuation through digital investment is not solely driven by capitalization restrictions.

Potential Selection Bias

A concern in interpreting our results is that they may be driven by three forms of selection bias. The first such concern is that our results may be driven by better performing firms that also adopt digital technologies. The higher valuations of digital firms would thus be an artifact of the higher valuations of better performing firms. We argue that this form of selection bias is unlikely, as our determinant results (Table 4) show that lagged firm-level performance is unrelated to digital disclosure.

Second, another concern related to selection bias is that our results may be driven by the selective *disclosure* of successful digital activities. That is, because we equate the disclosure of digital activities to the adoption of those activities, we may be identifying firms that have been successful at digital adoption and are therefore disclosing these activities. We argue that this is unlikely to be a contributing factor to our results because we do not observe any association between digital activities and current or 1-3-year-ahead ROA changes. This finding suggests that at the point of disclosure, the success of the digital activity is difficult to assess. Thus, it seems unlikely that firms are selectively disclosing successful digital activities.

Finally, another concern is that the non-tech digital firms in our study could be mis-classified tech firms. We address this concern in two ways. First, we drop firms that exhibit a median β_{Tech} that is in the top 2.5 percentile of the median β_{Tech} for all non-tech firms. With this sample, we find that our main inferences are unchanged. Second, we drop firms that made digital disclosures in the years before 2010, which is the year when we observe a upswing in non-tech firms starting to go digital. We find that our main inferences are unchanged with this sample[36].

VI CONCLUSION

In this paper, we develop a textual-based measure of digital activity to create a large sample of firms that are going digital. We show that this measure captures the growing trend of going digital amongst non-tech firms. We find that these non-tech firms that go digital tend to be firms that are large and young, invest more in SG&A and are in industries with higher digital activity.

We find that going digital improves valuations as the market-to-book of firms that engage in digital activities is 8-26% higher than their industry peers. While part of these level differences is attributable to capitalization restrictions on digital investments, we still observe economically and statistically significant level differences after controlling for the capitalization restrictions effect. Furthermore, we also find that digital activities increases the valuations of earnings and sales, which further corroborates the claim that digital activities increase valuations. In addition, we find that the valuation benefits of going digital accrue slowly as 3-year-ahead market-to-book of firms that go digital increases by a further 7-21% over time. Moreover, portfolios formed on digital disclosure significantly predict returns and deliver a 57 basis point alpha in a Fama-French 5 factor plus momentum model.

36. We report these analyses in Tables A.7 and A.8 in the Internet Appendix

However, we find mixed results when examining the implication of digital activities on accounting performance measures. Asset turnover improves suggesting that digital activities offer immediate gains in firm productivity and efficiency. However, ROA, profit margins and sales growth are either insignificantly or negatively associated with digital activity, which could be due to (1) the long-term nature of technological investments, (2) competitive pressures and (3) managerial ability. Notably, we find evidence of the managerial ability channel as firms with tech background managers tend to perform better when going digital. The other two channels are also intriguing possible explanations for our mixed accounting performance results, and we leave a detailed study of these possible channels for future research.

Based on our findings, we make two main conclusions. First, from an investment perspective, our results show that investors can make trade profitably from conducting research on digital activities of firms. In this study, we used a relatively parsimonious method of identifying digital activities and showed that trading profits can be made from trading on signals based on identifying such activities[37]. Thus we believe that more detailed research on digital activities in firms, could potentially uncover even greater investment opportunities for investors.

Second, from a managerial point of view, our findings highlight the importance of the disclosure of digital activities. We find that the gains of going digital are not always clear and engaging in digital activities can entail significant short-term costs. Moreover, markets tend to undervalue digital activities, perhaps due to the high uncertainty related to these activities. Thus, if managers would like to receive due credit for their digital investments, they should provide better information to investors on the success potential of their digital efforts and convince markets that going digital will succeed in the long-run.

37. However, we caution the reader that real-time profits are likely to be lower than the returns reported in this study, as trading frictions could impose additional costs for the investors.

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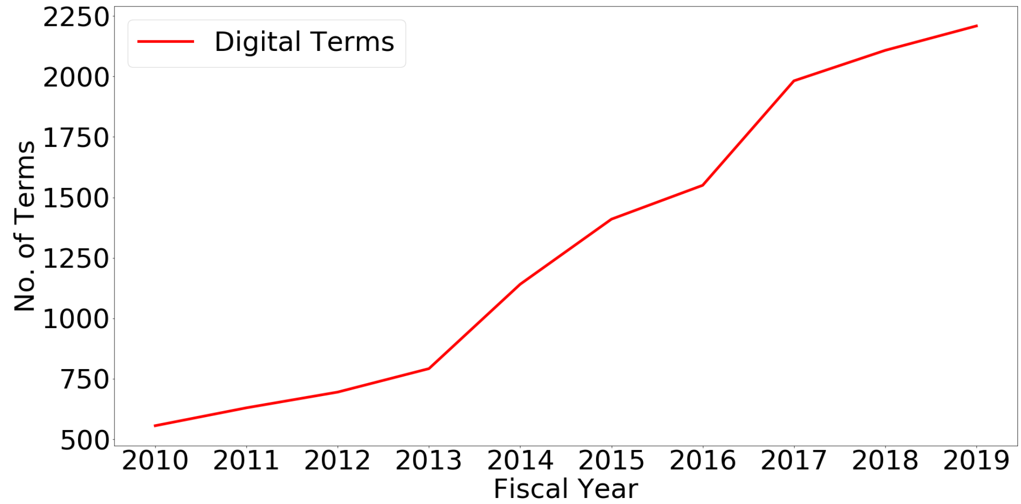
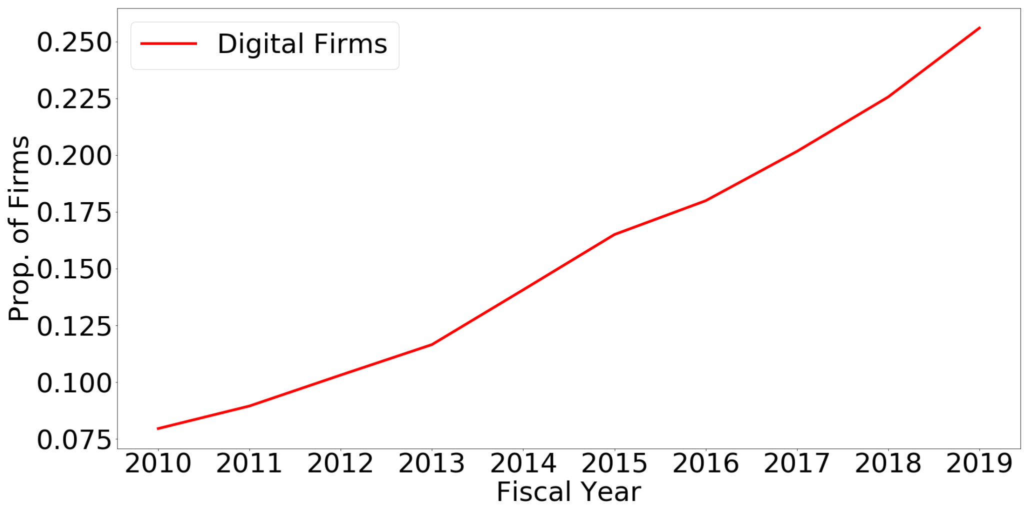


(a) Number of Digital Terms



(b) Proportion of Firms with Digital Terms

Figure 1: Number of Digital Terms over Years (a) and Proportion of Firms (b) Disclosing Digital Terms in the Business Description of the 10-Ks

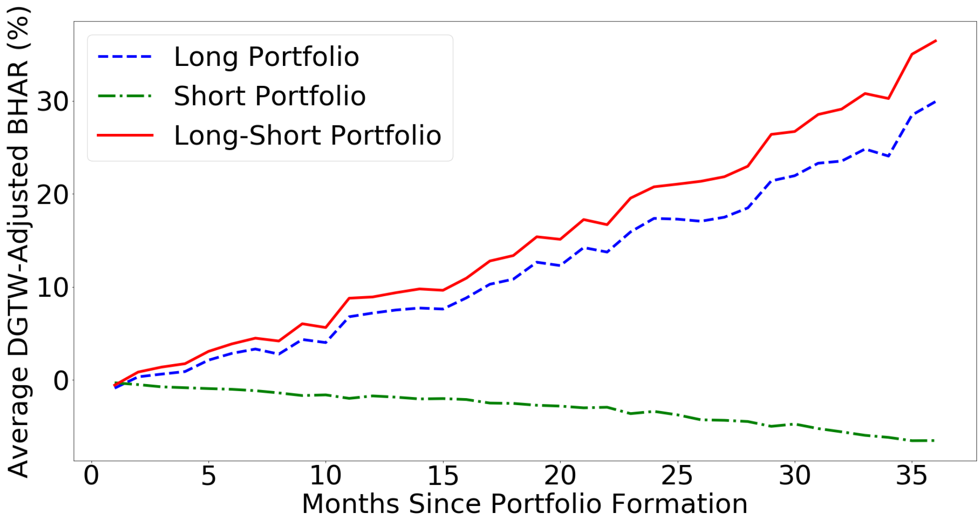


Figure 2: Average Size, Book-to-Market and Momentum (DGTW) Adjusted Returns to Value-Weighted Portfolios Formed on "Digital" Disclosure

Table 1: Summary Statistics

We report the summary statistics of the main control variables in this table for the sample of non-tech firms in fiscal years 2010-2019. We examine the statistics of the following variables: market capitalization, market-to-book, firm age, leverage ratio, market beta, beta with respect to the tech and non-tech portfolios, earnings persistence, return volatility, no. of days from fiscal year end to earnings announcement, no. of days from fiscal year end to 10-K filing, no. of days between earnings announcement and 10-K filing, 40-day cumulative abnormal returns after the earnings annoucement, unexpected earnings, unexpected sales, market-adjusted annual returns, return-on-assets, profit margins, asset turnover, 1-year sales growth, SG&A expense, R&D expense, an indicator for loss firms and an indicator for firms with technology-related top executives. Descriptions of the variables are outlined in detail in Appendix C.

	Mean	Std Dev	Median	25%	75%	N
Market Cap. (Millions)	3846	9047	619	138	2634	23108
Market-to-Book	3.03	3.51	1.81	1.12	3.4	23108
Firm Age	22	17	19	9	31	23097
Leverage Ratio	0.96	1.41	0.51	0.12	1.12	23007
β	1.01	0.56	1.01	0.68	1.35	22126
β_{Tech}	0.09	0.37	0.08	-0.13	0.3	17608
β_{NTech}	0.97	0.6	0.92	0.57	1.31	17608
Earnings Persistence	0.21	0.4	0.12	-0.06	0.45	21113
Return Volatility	0.03	0.01	0.02	0.02	0.03	22305
Days to EA	34	13	34	23	42	18960
Days to 10-K Filing	46	15	43	40	53	23108
Days Between 10-K & EA	9	12	5	0	16	18960
EA CAR(-1,40)	0	0.15	0.01	-0.07	0.08	14686
Unexpected Earnings	-0	0.01	0	-0	0	16294
Unexpected Sales	0	0.02	0	-0	0	16075
Market-Adj. Annual Returns	-0	0.56	-0.04	-0.25	0.17	22114
Return-on-Assets	0.01	0.18	0.04	0.01	0.1	21839
Profit Margins	0.14	0.2	0.11	0.04	0.25	20709
Asset Turnover	0.78	0.73	0.61	0.15	1.16	21464
Sales Growth$_{t,t-1}$	0.1	0.28	0.05	-0.02	0.16	21038
SG&A Expense	0.15	0.19	0.08	0.02	0.22	23108
R&D Expense	0.1	0.15	0.02	0	0.11	10267
Loss (Indicator)	0.23	0.42	0	0	0	23108
Tech Manager	0.04	0.19	0	0	0	23108

Table 2: Distribution of Digital Words

In Panel A, we report the distribution of individual digital words in the business description section of 10-Ks of non-tech firms by fiscal year from 2010 to 2019. The regex expressions used to identify these words are described in the Appendix A. In Panel B. we report the distribution of digital words in 10-Ks by SIC divisions-years for non-tech firms from 2010 to 2019. The industry divisions reported are Agriculture, Forestry and Fishing (0100-0999), Mining (1000-1499), Construction (1500-1799), Manufacturing (2000-3999), Transportation, Communications, Electric, Gas and Sanitary service (4000-4999), Wholesale Trade (5000-5199), Retail Trade (5200-5999), Finance, Insurance and Real Estate (6000-6799) and Services (7000-8999). The second-to-last column reports the number of firms that disclose at least one digital term in the year. The last column reports the proportion of firms that disclose at least one digital term in the year.

Panel A: Word Group-Year Distribution

	Analytics	Automation	AI	Big Data	Cloud	Digitization	ML
2010	308	35	23	12	13	109	56
2011	326	46	23	18	31	129	57
2012	360	45	19	24	55	159	33
2013	450	30	14	18	83	148	49
2014	652	31	14	44	112	233	55
2015	816	41	16	72	147	259	59
2016	881	31	36	71	168	293	70
2017	1080	56	114	117	174	317	124
2018	1088	66	125	104	224	365	136
2019	1144	69	168	98	228	326	176

Panel B: Industry-Year Distribution

	0100-0999	1000-1499	1500-1799	2000-3999	4000-4999	5000-5199	5200-5999	6000-6799	7000-8999	Total Firms	Prop. Firms
2010	1	7	0	150	6	16	16	178	182	191	0.08
2011	0	6	0	169	11	13	27	198	206	198	0.09
2012	0	3	3	182	15	15	29	189	259	227	0.103
2013	0	3	3	243	21	21	36	191	274	269	0.117
2014	1	5	5	316	34	24	65	314	377	349	0.141
2015	0	6	4	333	58	27	84	349	549	400	0.165
2016	1	10	8	397	68	25	103	378	560	426	0.18
2017	1	15	10	512	76	33	92	524	719	472	0.202
2018	0	17	22	608	101	50	84	451	775	522	0.226
2019	0	23	41	670	121	49	85	469	751	527	0.256

Table 3: Return Co-Movement with Tech and Non-Tech Portfolios

We report the coefficients of the regressions of tech and non-tech portfolio betas on the proxy for digital activities and controls in this table for the sample of non-tech firms in fiscal years 2010-2019. β_{Tech} and β_{NTech} are estimated for each fiscal year, by regressing the firm's daily returns on the tech and non-tech portfolio returns. We perform regressions using the levels specification in column 1. In column 2, we perform regressions on the past 3-year changes. Panel A reports the estimates from the tech portfolio co-movement (β_{Tech}), and panel B reports the estimates from the non-tech portfolio co-movement (β_{NTech}). In all regressions, we proxy for digital by using a quantized score of the number of digital mentions in the business description of the 10-K (coded 0 for no disclosure, 1 for bottom tercile, 2 for middle tercile and 3 for top tercile disclosure). All regressions control for SIZE, AGE, LEV, MB, ROA, SALES GROWTH, Market-Adjusted Annual Returns, Share Turnover, Return Volatility, and the number of words in the business description section as well as industry (Fama-French 48-industry) and year fixed effects. In the changes specification, control variables are lagged by 3-years. Standard errors are clustered at the firm level and are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Levels	Past 3 Year Change
Panel A: Tech Portfolio Co-Movement (β_{Tech})		
Dependent Variable	$\beta_{Tech,t}$	$\beta_{Tech,t}$ - $\beta_{Tech,t-3}$
Digital$_{i,t}$	0.014***	0.012**
	(0.004)	(0.005)
Controls	Yes	Yes
Time FE	Yes	Yes
Industry FE	Yes	Yes
Observations	16,961	12,735
Adj. R^2	0.2437	0.0948
Panel B: Non-Tech Portfolio Co-Movement (β_{NTech})		
Dependent Variable	$\beta_{NTech,t}$	$\beta_{NTech,t}$ - $\beta_{NTech,t-3}$
Digital$_{i,t}$	-0.043***	-0.017**
	(0.008)	(0.007)
Controls	Yes	Yes
Time FE	Yes	Yes
Industry FE	Yes	Yes
Observations	16,961	12,735
Adj. R^2	0.3926	0.1640

Table 4: Determinants of Digital Activity

We report the determinants of digital activity in this table for the sample of non-tech firms in fiscal years 2010-2019. In Columns 1 and 2, we use the quantized score of digital mentions in the business description of 10-Ks (coded 0 for no disclosure, 1 for bottom tercile, 2 for middle tercile and 3 for top tercile disclosure) as the dependent variable. In Columns 3 and 4, we use an indicator for first disclosure of digital terms in the business description of the 10-K as the dependent variable. For these columns, we also remove observations where the firm makes subsequent disclosure of digital terms. We also use the probit specification for columns 3 and 4, and report the margins as the coefficient estimates. Standard errors are clustered at the firm level and are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level respectively.

Dependent Variable	Quantized Score	Quantized Score	First Disclosure	First Disclosure
$\text{Digital}_{i,t-1}$	0.863***	0.885***		
	(0.008)	(0.008)		
$\text{SIZE}_{i,t-1}$	0.013***	0.014***	0.008***	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)
$\text{Market-to-Book}_{i,t-1}$	0.002	0.001	-0.000	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
$\text{Leverage}_{i,t-1}$	0.002	0.003	0.003***	0.004***
	(0.003)	(0.002)	(0.001)	(0.001)
$\text{Return-on-Assets}_{i,t-1}$	0.030	0.067***	0.001	0.021*
	(0.026)	(0.025)	(0.014)	(0.013)
$\text{AGE}_{i,t-1}$	-0.017***	-0.014***	-0.008***	-0.008***
	(0.004)	(0.004)	(0.002)	(0.002)
$\text{Sales Growth}_{i,t-1}$	-0.005	-0.011	-0.007	-0.009*
	(0.010)	(0.010)	(0.006)	(0.006)
$\text{CASH}_{i,t-1}$	0.016	0.035*	0.018*	0.027***
	(0.022)	(0.020)	(0.010)	(0.009)
$\text{R\&D}_{i,t-1}$	0.008	-0.083	-0.021	-0.037
	(0.058)	(0.052)	(0.034)	(0.033)
$\text{Missing R\&D}_{i,t-1}$	-0.006	-0.002	-0.004	-0.006**
	(0.009)	(0.007)	(0.004)	(0.003)
$\text{SG\&A}_{i,t-1}$	0.046*	0.091***	0.025***	0.060***
	(0.023)	(0.018)	(0.009)	(0.008)
$\text{CAPEX}_{i,t-1}$	-0.157**	-0.096**	-0.076**	-0.018
	(0.066)	(0.046)	(0.035)	(0.027)
$\text{Stock Returns}_{i,t-1}$	-0.005*	-0.004	-0.002	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)
$\text{Tech Manager}_{i,t-1}$	-0.001	0.004	-0.002	-0.000
	(0.017)	(0.017)	(0.007)	(0.007)
$\text{Industry Digital}_{j,t-1}$		0.001***		0.000***
		(0.000)		(0.000)
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Observations	20,560	20,560	16,968	17,247
Adj./Pseudo. R^2	0.7228	0.7190	0.1098	0.0622

Table 5: Market-to-Book

We report the coefficients of the regressions of market-to-book on the proxy for digital activities for the sample of non-tech firms in fiscal years 2010-2019. In Panel A, we report the associations between market-to-book current changes, levels and digital activity. In Panel B, we report the associations between market-to-book 1-3-year-ahead changes and digital activity. In the regressions, we proxy for digital by using a quantized score of the number of digital mentions in the business description of the 10-K (coded 0 for no disclosure, 1 for bottom tercile, 2 for middle tercile and 3 for top tercile disclosure). All regressions control for SIZE, AGE, LEV, ROA, SALES GROWTH, Market-Adjusted Annual Returns, number of words in the business description section and industry (Fama-French 48-industry) and year fixed effects. Additionally, in the changes specification, we control for the industry median and the industry median-adjustment of the dependent variable. For each dependent variable, we also run an additional specification with controls for intangible investment, namely SG&A, R&D and an indicator for missing R&D. Standard errors are clustered at the firm level and are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Current Changes and Levels

	Current Changes		Levels	
Dep. Var.	$MB_t - MB_{t-1}$	$MB_t - MB_{t-1}$	MB_t	MB_t
$Digital_{i,t}$	0.104***	0.087***	0.265***	0.143**
	(0.027)	(0.027)	(0.065)	(0.058)
Baseline Controls	Yes	Yes	Yes	Yes
Intangibles Controls	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	20,615	20,615	20,804	20,804
Adj. R^2	0.0930	0.0989	0.3722	0.4541

Panel B: Future Changes

	1 Year Ahead		2 Year Ahead		3 Year Ahead	
Dep. Var.	MB_{t+1} - MB_t	MB_{t+1} - MB_t	MB_{t+2} - MB_t	MB_{t+2} - MB_t	MB_{t+3} - MB_t	MB_{t+3} - MB_t
$Digital_{i,t}$	0.108***	0.091***	0.174***	0.145***	0.215***	0.175**
	(0.030)	(0.030)	(0.052)	(0.052)	(0.067)	(0.068)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Intangibles Controls	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,452	17,452	14,439	14,439	11,811	11,811
Adj. R^2	0.0924	0.0975	0.1232	0.1321	0.1247	0.1371

Table 6: Conservatism-Corrected Market-to-Book

We report the coefficients of the regressions of conservatism-corrected market-to-book on the proxy for digital activities for the sample of non-tech firms in fiscal years 2010-2019. In Panel A, we report the associations between unadjusted market-to-book current changes, levels and digital activity for the sample of non-tech firms with sufficient investment histories to estimate the conservatism adjustment. In Panel B, we report the associations between conservatism-corrected market-to-book 1-3-year-ahead changes and digital activity. In the regressions, we proxy for digital by using a quantized score of the number of digital mentions in the business description of the 10-K (coded 0 for no disclosure, 1 for bottom tercile, 2 for middle tercile and 3 for top tercile disclosure). All regressions control for SIZE, AGE, LEV, ROA, SALES GROWTH, Market-Adjusted Annual Returns, number of words in the business description section and industry (Fama-French 48-industry) and year fixed effects. Additionally, in the changes specification, we control for the industry median and the industry median-adjustment of the dependent variable. Standard errors are clustered at the firm level and are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Unadjusted Market-to-Book

	Current Changes	Levels	1 Year Ahead Changes	2 Year Ahead Changes	3 Year Ahead Changes
Dep. Var.	MB_t - MB_{t-1}	MB_t	MB_{t+1} - MB_t	MB_{t+2} - MB_t	MB_{t+3} - MB_t
$Digital_{i,t}$	0.157***	0.478***	0.185***	0.240**	0.228*
	(0.051)	(0.116)	(0.061)	(0.109)	(0.127)
Controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	6,368	7,114	5,664	4,663	3,833
Adj. R^2	0.0716	0.4275	0.0774	0.1164	0.1284

Panel B: Conservatism-Corrected Market-to-Book

	Current Changes	Levels	1 Year Ahead Changes	2 Year Ahead Changes	3 Year Ahead Changes
Dep. Var.	MB_t - MB_{t-1}	MB_t	MB_{t+1} - MB_t	MB_{t+2} - MB_t	MB_{t+3} - MB_t
$Digital_{i,t}$	0.036**	0.191***	0.031*	0.035	0.075*
	(0.016)	(0.051)	(0.017)	(0.028)	(0.045)
Controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	6,368	7,114	5,664	4,663	3,833
Adj. R^2	0.1290	0.2726	0.1314	0.1791	0.1616

Table 7: Cross-Sectional Market-to-Book

We report the coefficients of the cross-sectional regressions of market-to-book on the proxy for digital activities for the sample of non-tech firms in fiscal years 2010-2019. We report cross-sectional associations between market-to-book and digital activity. In the regressions, we proxy for digital by using a quantized score of the number of digital mentions in the business description of the 10-K (coded 0 for no disclosure, 1 for bottom tercile, 2 for middle tercile and 3 for top tercile disclosure). All regressions control for SIZE, AGE, LEV, ROA, CASH, SALES GROWTH, Market-Adjusted Annual Returns, number of words in the business description section, R&D, an indicator for missing R&D SG&A, CAPEX and industry (Fama-French 48-industry) and year fixed effects. We also examine the digital proxy's interaction with the following variables: SIZE, AGE, R&D, SG&A, CAPEX, ROA, SALES GROWTH, CASH, LEV and the industry-level of digital activity. Standard errors are clustered at the firm level and are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Dependent Variable	MB_t	MB_t
$Digital_{i,t}$	-1.238***	-1.492***
	(0.326)	(0.337)
$Digital_{i,t} \times SIZE_{i,t}$	0.084***	0.077**
	(0.031)	(0.031)
$Digital_{i,t} \times AGE_{i,t}$	0.049	0.052
	(0.067)	(0.067)
$Digital_{i,t} \times R\&D_{i,t}$	0.860	1.258
	(1.150)	(1.194)
$Digital_{i,t} \times SG\&A_{i,t}$	0.706**	0.617**
	(0.297)	(0.300)
$Digital_{i,t} \times CAPEX_{i,t}$	3.515**	4.246***
	(1.457)	(1.507)
$Digital_{i,t} \times ROA_{i,t}$	1.077**	1.176**
	(0.531)	(0.551)
$Digital_{i,t} \times \text{Sales Growth}_{i,t}$	0.443***	0.416**
	(0.172)	(0.173)
$Digital_{i,t} \times CASH_{i,t}$	0.789*	0.803*
	(0.438)	(0.427)
$Digital_{i,t} \times LEV_{i,t}$	0.123**	0.121**
	(0.049)	(0.049)
$Digital_{i,t} \times \text{Industry Digital}_{j,t}$		0.012***
		(0.003)
Controls	Yes	Yes
Time FE	Yes	Yes
Industry FE	Yes	No
Observations	20,754	20,754
Adj. R^2	0.4764	0.4544

Table 8: Market Response to Earnings and Sales

We report the coefficients to the ERC (Earnings Response Coefficient)/SRC (Sales Response Coefficient) regression with the proxy for digital activities in this table for the sample of non-tech firms in fiscal years 2010-2018. In Columns 1 and 2, we report the ERC/SRC regression at the using raw unexpected values, where CAR(-1,40) is regressed on unexpected earnings/sales, controls, industry and year fixed effects (for column 2), as well as their interactions with unexpected earnings/sales. In Columns 3 and 4, we report the ERC/SRC regression at the using yearly decile rankings of unexpected earnings/sales, where CAR(-1,40) is regressed on unexpected earnings/sales, controls, industry and year fixed effects (for column 4), as well as their interactions with unexpected earnings/sales. Columns 2 and 4 include our proxy for digital activities as an interaction variable. We proxy for digital activity in the regression models by the quantized score of the number of digital mentions in the business description of the 10-K (coded 0 for no disclosure, 1 for bottom tercile, 2 for middle tercile and 3 for top tercile disclosure). All regressions control for log of market cap., leverage ratio, loss (ind.), persistence, return volatility the no. of days to EA, the no. of days to 10-K filing and the number of words in the business description section. For the ease of interpretation of the unexpected earnings/sales coefficient, we mean-center all continuous control variables. Standard errors are clustered at the firm level and are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Raw Values		Yearly Deciles	
	Baseline	With Digital	Baseline	With Digital
Panel A: Unexpected Earnings				
Dependent Variable	CAR(-1,40)	CAR(-1,40)	CAR(-1,40)	CAR(-1,40)
Unexpected Earnings$_{i,t}$	2.661***	1.384	0.008***	0.009**
	(0.304)	(1.894)	(0.001)	(0.004)
Digital$_{i,t}$		0.005**		-0.003
		(0.002)		(0.005)
Digital$_{i,t}\times$Unexpected Earnings$_{i,t}$		0.559*		0.001*
		(0.292)		(0.001)
Controls	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes
Unexpected Earnings $\times$ Controls	Yes	Yes	Yes	Yes
Unexpected Earnings $\times$ Time FE	No	Yes	No	Yes
Unexpected Earnings $\times$ Industry FE	No	Yes	No	Yes
Observations	11,778	11,778	11,778	11,778
Adj. R^2	0.0330	0.0527	0.0417	0.0553
Panel B: Unexpected Sales				
Dependent Variable	CAR(-1,40)	CAR(-1,40)	CAR(-1,40)	CAR(-1,40)
Unexpected Sales$_{i,t}$	0.440***	0.754*	0.004***	0.006
	(0.103)	(0.388)	(0.001)	(0.005)
Digital$_{i,t}$		0.005***		-0.004
		(0.002)		(0.005)
Digital$_{i,t}\times$Unexpected Sales$_{i,t}$		0.373***		0.002**
		(0.122)		(0.001)
Controls	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes
Unexpected Sales $\times$ Controls	Yes	Yes	Yes	Yes
Unexpected Sales $\times$ Time FE	No	Yes	No	Yes
Unexpected Sales $\times$ Industry FE	No	Yes	No	Yes
Observations	11,589	11,589	11,589	11,589
Adj. R^2	0.0252	0.0414	0.0265	0.0403

Table 9: Portfolio Returns

We report the risk-adjusted returns for portfolios formed on digital disclosure. In Panel A, we report the time-series average size, book-to-market and momentum-adjusted portfolio returns, which are computed using the methodology in Daniel et al. (1997). Each portfolio is formed at the end of June of each year, starting from 2011, and firms in the top tercile of digital disclosures are placed in the long portfolio, while firms with no digital disclosures are placed in the short portfolio. To address liquidity issues in penny stocks, we drop firms with less than $5 in share price. All portfolios are value-weighted, and if a firm delists during the holding period, the proceeds from the delisting returns are reinvested in the CRSP value-weighted portfolio. The benchmark portfolios are also allowed to change each year in June. Time-series standard errors are reported in parentheses. In Panel B, we report the fama macbeth regression of returns on size, book-to-market, operating profit, investment, momentum, SG&A, R&D, an indicator for missing R&D as well as a "Digital" long-short strategy indicator that is coded 1 for top tercile digital disclosure, -1 for no digital disclosure and 0 otherwise. We implement the fama-macbeth regressions at the portfolio year level for 1-3 year horizons in columns 1-3. To address serial correlation due to overlapping returns, we apply newey-west standard errors (reported in parentheses) with 2-3 year lags in columns 2-3 respectively. *, **, *** denote 10%, 5% and 1% significance level, respectively.

Panel A: Time-Series Average Long-Run Portfolio Returns

Portfolio	RET(1,36)	RET(1,12)	RET(13,24)	RET(25,36)
Long	0.299**	0.072*	0.096	0.187*
	(0.091)	(0.030)	(0.052)	(0.076)
Short	-0.065***	-0.017	-0.017	-0.049**
	(0.013)	(0.009)	(0.010)	(0.013)
Long - Short	0.364***	0.089**	0.111*	0.233**
	(0.082)	(0.031)	(0.055)	(0.071)

Panel B: Fama-MacBeth Returns Regressions

Dep. Var.	1-Year Ahead Buy-Hold Returns	2-Year Ahead Buy-Hold Returns	3-Year Ahead Buy-Hold Returns
$\text{Digital}_{i,t}$	0.004	0.025**	0.044**
	(0.010)	(0.009)	(0.014)
$\text{Log(Market Cap.)}_{i,t}$	-0.007	-0.021*	-0.039***
	(0.006)	(0.009)	(0.009)
$\text{Book-to-Market}_{i,t}$	-0.008	0.013	0.029
	(0.022)	(0.042)	(0.069)
$\text{Operating Profit}_{i,t}$	0.045***	0.076**	0.117**
	(0.012)	(0.029)	(0.044)
$\text{Investment}_{i,t}$	0.000*	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
$\text{Momentum}_{i,t}$	0.005	0.027	0.083**
	(0.023)	(0.026)	(0.024)
$\text{SG\&A}_{i,t}$	0.032	0.052	0.073
	(0.043)	(0.036)	(0.052)
$\text{R\&D}_{i,t}$	0.208	0.471	0.935*
	(0.213)	(0.315)	(0.437)
$\text{Missing R\&D}_{i,t}$	-0.000	-0.008	-0.020
	(0.015)	(0.030)	(0.049)
Observations	14,284	12,494	10,635
Time Periods	8	7	6
Adjusted R^2	0.027	0.029	0.025

Table 10: Calendar-Time Portfolio Returns

In this table, we report the α from regressing monthly portfolio returns from July 2011 to December 2019 on 6 risk factors—market (MKT-RF), size (SMB), value (HML), profitability (RMW), investment (CMA) and momentum (MOM). The monthly returns for the risk factors are taken from Ken French's website. The portfolios formed on digital disclosures are rebalanced monthly and are value-weighted. Portfolio allocations based on digital disclosure (top tercile digital disclosure are allocated to the long portfolio, while firms with no digital disclosures are allocated to the short portfolio) are revised at the end of June in each year. To address liquidity issues in penny stocks, we drop firms with less than $5 in share price from the portfolios. Robust standard errors are reported in parentheses. *, **, *** denote 10%, 5% and 1% significance level, respectively.

	Long-Short	Long	Short
α	0.570***	0.379**	-0.191***
	(0.190)	(0.185)	(0.068)
MKT - Rf	-0.087	0.924***	1.011***
	(0.059)	(0.053)	(0.024)
SMB	0.056	0.152	0.095***
	(0.107)	(0.101)	(0.032)
HML	-0.133	-0.031	0.102***
	(0.106)	(0.104)	(0.035)
RMW	-0.116	-0.176	-0.060
	(0.128)	(0.134)	(0.052)
CMA	-0.133	0.163	0.295***
	(0.131)	(0.130)	(0.061)
MOM	0.131*	0.120**	-0.011
	(0.068)	(0.057)	(0.023)
Observations	102	102	102
Adj. R^2	0.1236	0.7732	0.9735

Table 11: Accounting Performance

We report the coefficients of regressions of asset turnover (ATO), profit margins (MARGINS), sales growth (SALES GROWTH), and return-on-assets (ROA) on the proxy for digital activities and controls in this table for the sample of non-tech firms in fiscal years 2010-2019. We report the associations between each accounting performance measure's level, one-, two- and three-year-ahead change and digital activity in columns 1-4, respectively. Panel A reports the results for asset turnover. Panel B reports the results for profit margins. Panel C reports the results for sales growth. Panel D reports the results for return-on-assets. In all regression models, we proxy for digital by using a quantized score of the number of digital mentions in the business description of the 10-K (coded 0 for no disclosure, 1 for bottom tercile, 2 for middle tercile and 3 for top tercile disclosure). All regressions control for SIZE, AGE, LEV, MB, SALES GROWTH, SG&A, R&D, an indicator for missing R&D, market-adjusted annual returns and industry (Fama-French 48-industry) and year fixed effects. Additionally in the changes specification, we control for the industry median and the industry median-adjustment of the dependent variable. Standard errors are clustered at the firm level and are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Levels	One Year Ahead Change	Two Year Ahead Change	Three Year Ahead Change
Panel A: Asset Turnover				
Dependent Variable	ATO_t	ATO_{t+1} - ATO_t	ATO_{t+2} - ATO_t	ATO_{t+3} - ATO_t
$Digital_{i,t}$	0.020*	0.003	0.009**	0.012**
	(0.010)	(0.002)	(0.004)	(0.005)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	20,804	17,406	14,393	11,766
Adj. R^2	0.6707	0.1081	0.1664	0.2198
Panel B: Profit Margins				
Dependent Variable	$MARGINS_t$	$MARGINS_{t+1}$ - $MARGINS_t$	$MARGINS_{t+2}$ - $MARGINS_t$	$MARGINS_{t+3}$ - $MARGINS_t$
$Digital_{i,t}$	-0.010***	-0.004***	-0.005***	-0.005**
	(0.002)	(0.001)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	19,660	16,404	13,628	11,205
Adj. R^2	0.7223	0.1897	0.3008	0.3487
Panel C: Sales Growth				
Dependent Variable	SALES $GROWTH_{t,t-1}$	SALES $GROWTH_{t+1,t}$	SALES $GROWTH_{t+2,t}$	SALES $GROWTH_{t+3,t}$
$Digital_{i,t}$	-0.009***	-0.005*	-0.009	-0.018*
	(0.003)	(0.003)	(0.006)	(0.010)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	20,804	17,406	14,393	11,766
Adj. R^2	0.0990	0.1366	0.1608	0.1694
Panel D: Return-on-Assets				
Dependent Variable	ROA_t	ROA_{t+1}- ROA_t	ROA_{t+2} - ROA_t	ROA_{t+3} - ROA_t
$Digital_{i,t}$	0.001	-0.001	-0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.002)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	20,804	17,409	14,397	11,782
Adj. R^2	0.5680	0.1286	0.1983	0.2260

Table 12: Tech-Saavy Managers and Return-on-Assets

We report the coefficients of regressions of return-on-assets on the proxy for digital activities and the proxy for tech-saavy managers for the sub-sample of non-tech firms in fiscal years 2010-2019 that have made digital disclosures. We report the results for the levels, one-year-ahead change, two-year-ahead change and three-year-ahead change specifications in columns 1-4, respectively. For all regression models, we proxy for digital by using a quantized score of the number of digital mentions in the business description of the 10-K (coded 0 for no disclosure, 1 for bottom tercile, 2 for middle tercile and 3 for top tercile disclosure). All regressions control for SIZE, AGE, LEV, MB, SALES GROWTH, SG&A, R&D, an indicator for missing R&D, market-adjusted annual returns and industry (Fama-French 48-industry) and year fixed effects. Additionally, in the changes specification, we control for the industry median and the industry median-adjustment of the dependent variable. Standard errors are clustered at the firm level and are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Levels	One Year Ahead Change	Two Year Ahead Change	Three Year Ahead Change
Dependent Variable	ROA$_t$	ROA$_{t+1}$- ROA$_t$	ROA$_{t+2}$ - ROA$_t$	ROA$_{t+3}$ - ROA$_t$
Tech Manager$_{i,t}$	0.026**	0.002	0.005	0.010
	(0.012)	(0.005)	(0.008)	(0.015)
Digital$_{i,t}$	0.002	-0.000	-0.001	-0.003
	(0.004)	(0.002)	(0.003)	(0.004)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	3,204	2,472	1,867	1,400
Adj. R^2	0.5257	0.1047	0.1877	0.2579

Appendix A: Digital Terms Regex Definitions

<table>
<tr><th>Digital Term</th><th>Regex Expression</th></tr>
<tr><td>Analytics:</td><td></td></tr>
<tr><td>analytics</td><td>(\banalytics\b)</td></tr>
<tr><td>proprietary algorithm</td><td>(\bproprietary algorithm)</td></tr>
<tr><td>Automation:</td><td></td></tr>
<tr><td>automation</td><td>(\bautomation solutions\b) | (\bintelligent automation\b) | (\bmarketing automation\b) | (\bprocess automation\b) | (\brobotic process automation\b)</td></tr>
<tr><td>autonomous technology</td><td>(\bautonomous ?[-]?tech)</td></tr>
<tr><td>AI:</td><td></td></tr>
<tr><td>artificial intelligence</td><td>(artificial ?[-]?intelligence) | (\bai ?[-]?tech) | (\bai ?[-]?related) | (\bconversational ai\b) | (\bevolutionary ai\b) | (\bevolutionary computing\b)</td></tr>
<tr><td>intelligence</td><td>(\bintelligent ?[-]?system)|(\bcomputer ?[-]?vision)</td></tr>
<tr><td>neural network</td><td>(\bneural ?[-]?network)</td></tr>
<tr><td>virtual reality</td><td>(\bvirtual ?[-]?machine)|(\bvirtual realit)|(\bvirtual agent)|(\bvirtual ?[-]?assistant)</td></tr>
<tr><td>augmented reality</td><td>(\baugmented reality\b)</td></tr>
<tr><td>cognitive computing</td><td>(\bcognitive computing\b)</td></tr>
<tr><td>Big Data:</td><td></td></tr>
<tr><td>big data</td><td>(\bbig ?[-]?data)|(\bsmart ?[-]?data)</td></tr>
<tr><td>data science</td><td>(\bdata ?[-]?scien)</td></tr>
<tr><td>data mining</td><td>(\bdata ?[-]?mining)</td></tr>
<tr><td>data lake</td><td>(\bdata lake\b)</td></tr>
<tr><td>devops</td><td>(\bdevops\b)</td></tr>
<tr><td>digital twin</td><td>(\bdigital twin\b)</td></tr>
<tr><td>edge computing</td><td>(\bedge computing\b)</td></tr>
<tr><td>Cloud:</td><td></td></tr>
<tr><td>cloud platforms</td><td>(\bcloud ?[-]?platform) | (\bcloud ?[-]?based) | (\bcloud ?[-]?computing) | (\bcloud ?[-]?deployment)</td></tr>
<tr><td>cloud enablement</td><td>(\bcloud enablement\b) | (\bhybrid cloud\b)</td></tr>
<tr><td>Digitization:</td><td></td></tr>
<tr><td>digitization</td><td>(\bdigiti)|(\bdigital ?[-]?transformation)|(\bdigital ?[-]?revolution)</td></tr>
</table>

<table>
<tr><td>digital strategy</td><td>(\bdigital ?[-]?strateg)</td></tr>
<tr><td>digital marketing</td><td>(\bdigital ?[-]?marketing)</td></tr>
<tr><td>business intelligence</td><td>(\bbusiness intelligence\b) | (\bcustomer intelligence\b) | (\boperating intelligence\b)</td></tr>
<tr><td>ML:</td><td></td></tr>
<tr><td>biometric</td><td>(\bbiometric)</td></tr>
<tr><td>deep learning</td><td>(\bdeep ?[-]?learning)</td></tr>
<tr><td>machine learning</td><td>(\bmachine ?[-]?learning)</td></tr>
<tr><td>natural language processing</td><td>(\bnatural ?[-]?language ?[-]?processing)</td></tr>
<tr><td>image recognition</td><td>(\bimage ?[-]?recognition)|(\bfacial ?[-]?recognition)</td></tr>
<tr><td>speech recognition</td><td>(\bspeech ?[-]?recognition)</td></tr>
</table>

Appendix B: Tech Industry Classification Codes

Industry Codes	Industry Description
SIC Codes	
3570	Computer & Office Equipment
3571	Electronic Computers
3572	Computer Storage Devices
3575	Computer Terminals
3576	Computer Communications Equipment
3577	Computer Peripheral Equipment, NEC
3661	Telephone & Telegraph Apparatus
3663	Radio & TV Broadcasting & Communications Equipment
3669	Communications Equipment, NEC
3670	Electronic Components & Accessories
3672	Printed Circuit Boards
3674	Semiconductors & Related Devices
3677	Electronic Coils, Transformers & Other Inductors
3678	Electronic Connectors
3679	Electronic Components, NEC
4812	RadioTelephone Communications
4813	Telephone Communications (No Radiophone)
4899	Communications Services, NEC
7370	Services-Computer Programming, Data Processing, Etc.
7371	Services-Computer Programming Services
7372	Services-Prepackaged Software
7373	Services-Computer Integrated Systems Design
7374	Services-Computer Processing & Data Preparations
7377	Services-Computer Rental & Leasing
NAICS Codes	
334111	Electronic Computer Manufacturing
334112	Computer Storage Device Manufacturing
334118	Computer Terminal and Other Computer Peripheral Equipment Manufacturing
334210	Telephone Apparatus Manufacturing
334220	Radio and Television Broadcasting and Wireless Communications Equipment Manufacturing
334290	Other Communications Equipment Manufacturing
334310	Audio and Video Equipment Manufacturing
334412	Bare Printed Circuit Board Manufacturing
334413	Semiconductor and Related Device Manufacturing

334416	Capacitor, Resistor, Coil, Transformer, & Other Inductor Manufacturing
334417	Electronic Connector Manufacturing
334418	Printed Circuit Assembly (Electronic Assembly) Manufacturing
334419	Other Electronic Component Manufacturing
334613	Blank Magnetic & Optical Recording Media Manufacturing
334614	Software & Other Prerecorded Compact Disc, Tape & Record Reproducing
335921	Fiber Optic Cable Manufacturing
511210	Software Publishers
517311	Wired Telecommunications Carriers
517312	Wireless Telecommunications Carriers (except Satellite)
517410	Satellite Telecommunications
517911	Telecommunications Resellers
517919	All Other Telecommunications
518210	Data Processing, Hosting & Related Services
519130	Internet Publishing & Broadcasting & Web Search Portals
541511	Custom Computer Programming Services
541512	Computer Systems Design Services
541513	Computer Facilities Management Services
541519	Other Computer Related Services
611420	Computer Training
GICS Codes	
25502010	Catalog Retail
25502020	Internet & Direct Marketing Retail
20201020	Data Processing Services
45101010	Internet Software & Services
45102010	IT Consulting & Other Services
45102020	Data Processing & Outsourced Services
45102030	Internet Services & Infrastructure
45103010	Application Software
45103020	Systems Software
45103030	Home Entertainment Software
45201010	Networking Equipment
45201020	Communications Equipment
45202010	Computer Hardware
45202020	Computer Storage & Peripherals
45202030	Technology Hardware, Storage & Peripherals
45203010	Electronic Equipment & Instruments
45203015	Electronic Components
45203020	Electronic Manufacturing Services
45203030	Technology Distributors
45205010	Semiconductor Equipment

45205020	Semiconductors
45301010	Semiconductor Equipment
45301020	Semiconductors
50101010	Alternative Carriers
50101020	Integrated Telecommunication Services
50102010	Wireless Telecommunication Services

Appendix C: Variable Definitions

Variable Name	**Variable Description**
Fundamental Variables:	
SIZE	Logarithm of Market Capitalization at the fiscal year end ($prc \times shrout$ in CRSP).
LEV	Leverage Ratio, defined as total debt divided by stockholder's equity. ($\frac{dlc+dltt}{seq}$ in Compustat)
LOSS	Indicator for loss firms - loss defined as observations where earnings before interest and taxes < 0 (*ebit* in Compustat).
PERS	The AR(1) coefficient in seasonally adjusted quarterly earnings (defined as earnings per share before extraordinary items, *epspxq* in Compustat, minus the eps reported in the same quarter for the previous fiscal year), estimated over rolling 5-year windows.
MB	Market-to-Book Ratio, defined as the fiscal year end market cap. divided by common equity ($\frac{prccf \times csho}{ceq}$ in Compustat).
AGE	Logarithm of Firm Age. Age is determined by the number of years since the firm first appeared in Compustat.
ROA	Defined as earnings before interest and taxes scaled by average total assets from beginning to end of the fiscal period ($\frac{ebit}{(at_t+at_{t-1})/2}$ in Compustat). We also remove observations where ROA is less than -100%.
MARGINS	Profit margins defined as earnings before interest and taxes scaled by sales. ($\frac{ebit}{sale}$ in Compustat). We also remove observations where profit margins is less than -100%.
ATO	Sales scaled by average total assets from beginning to end of the fiscal period. ($\frac{sale_t}{(at_t+at_{t-1})/2}$ in Compustat)
$SALES\ GROWTH_{t+s,t}$	Sales Growth, difference in future period $t+s$ sales minus current sales in period t scaled by the current period sales. ($\frac{sale_{t+s}-sale_t}{sale_t}$ in Compustat)
CapEx	Capital expenditure intensity, defined as capital expenditures scaled by assets ($\frac{capx}{at}$ in Compustat)
SG&A	Selling, General and Administrative expenditure intensity, defined as SG&A expense minus R&D minus R&D in place scaled by assets ($\frac{xsga-xrd-rdip}{at}$ in Compustat). Following Peters and Taylor (2017) we keep the original *xsga* as SG&A expense if $xrd > xsga$ but $xrd < cogs$. If missing this variable is coded as 0.

R&D	Research and development expenditure intensity, defined as research and development expenditures scaled by assets ($\frac{xrd}{at}$ in Compustat). If missing, this variable is coded as 0.
Missing R&D	Indicator variable coded as 1 if the R&D variable is missing and 0 otherwise.
Book-to-Market	Book-to-market ratio defined as book equity divided by market equity ($prc \times shrout$ in CRSP), where book equity is defined as stockholders' equity (*seq* in Compustat) plus deferred taxes (*txdb* in Compustat) plus investment tax credit (*itcb* in Compustat) minus preferred stock (*pstkrv* in Compustat).
Operating Profit	Defined as sales (*sale* in Compustat) minus cost of goods sold (*cogs* in Compustat) minus interest expense (*xint* in Compustat) minus sales, general and administrative expense (*xsga* in Compustat), divided by book equity defined above.
Investment	Defined as the difference in current period assets (*at* in Compustat) and lagged assets scaled by lagged assets.

Returns and Liquidity Variables:

β	The beta coefficient estimated from a regression of daily returns on CRSP value-weighted market returns over the fiscal year.
β_{Tech} or β_{NTech}	The tech or non-tech beta coefficient on the technology portfolio estimated from a regression of the following factor model: $R_{i,t} = \alpha_{i,t} + \beta_{Tech}R_{Tech,t} + \beta_{NTech}R_{NTech,t}$ that is estimated over the fiscal year. $R_{Tech,t}$ is the value-weighted portfolio returns of tech firms that are defined in Appendix B, and the portfolio is re-balanced daily. $R_{NTech,t}$ is the value-weighted portfolio returns of non-tech firms, and the portfolio is re-balanced daily. The firm's own returns are removed from the value-weighted portfolio returns to remove mechanical correlations. Daily returns with stock prices of less than \$5 are dropped from the estimation, and β_{Tech} or β_{NTech} estimated with less than 200 days of returns observations are also dropped.
Market-Adj. Returns	The buy-hold raw returns in the fiscal year minus the value-weighted CRSP market return distribution.
Share Turnover	Monthly share volume divided by the shares outstanding ($\frac{vol}{shrout}$ in CRSP), averaged over the fiscal year.
Return Volatility	Standard deviation of daily returns estimated over the fiscal year.

Momentum	Defined as the past 12 month to lagged 1 month buy-and-hold returns minus the buy-and-hold value-weighted market portfolio return over the same period.
Earnings Announcement Variables:	
Days to EA	Number of business days between earnings announcement and fiscal year end.
Days to 10-K Filing	Number of business days between 10-K filing and fiscal year end.
Days Between 10-K & EA	Number of business days between 10-K filing and Earnings Announcement.
Unexpected Earnings	Unexpected earnings is actual minus median earnings per share forecasts scaled by the price at the end of the fiscal period. The median earnings forecasts is based on the most recent analyst consensus forecast, within 100 days before the earnings announcement. We remove observations where the price at the end of the fiscal period is less than $1 and where the earnings surprise is in excess of price.
Unexpected Sales	Unexpected sales is actual minus median sales (on per share basis, scaled by shares outstanding at announcement date) forecasts scaled by the price at the end of the fiscal period. The median sales forecasts is based on the most recent analyst consensus forecast, within 100 days before the sales announcement. We remove observations where the price at the end of the fiscal period is less than $1.
CAR (-1,40)	The cumulative adjusted returns from 1 day before the earnings announcement to 40 trading days after. Benchmark returns are estimated using the coefficients from the Carhart, Fama-French Four-Factor model (Carhart 1997) that are estimated based on a (-280, -60) window.
Other Variables:	
Tech Manager	An indicator that is set to 1 and 0 otherwise, if one of the firm's top 5 executive has a technology-related managerial title. We define technology-related titles as either "VP Digital", "Chief Information Officer (CIO)" or "Chief Technology Officer (CTO)". Data on the top 5 executives is sourced from CapitalIQ's People Intelligence database.
Total Words	Natural Logarithm of the total number of words in the business description section. Data taken from 10-K filings obtained through SEC Edgar.

Appendix D: Examples of Digital Disclosure

Mistras Group Inc, Fiscal Year: 2011
Historically, NDT solutions predominantly used qualitative testing methods aimed primarily at detecting defects in the tested materials. This methodology, which we categorize as traditional NDT, is typically labor intensive and, as a result, considerably dependent upon the availability and skill level of the certified technicians, engineers and scientists performing the inspection services. The traditional NDT market is highly fragmented, with a significant number of small vendors providing inspection services to divisions of companies or local governments situated in close proximity to the vendor s field inspection engineers and scientists. Today, we believe that customers are increasingly looking for a single vendor capable of providing a wider spectrum of asset protection solutions for their global infrastructure that we call one source . This shift in underlying demand, which began in the early 1990s, has contributed to a transition from traditional NDT solutions to more advanced solutions that employ automated digital sensor technologies and accompanying enterprise software, allowing for the effective capture, storage, analysis and reporting of inspection and engineering results electronically and in digital formats. These advanced techniques, taken together with advances in wired and wireless communication and information technologies, have further enabled the development of remote monitoring systems, asset-management and predictive maintenance capabilities and other data analytics and management. We believe that as advanced asset protection solutions continue to gain acceptance among asset-intensive organizations, only those vendors offering broad, complete and integrated solutions, scalable operations and a global footprint will have a distinct competitive advantage. Moreover, we believe that vendors that are able to effectively deliver both advanced solutions and data analytics, by virtue of their access to customers data, develop a significant barrier to entry for competitors, and so develop the capability to create significant recurring revenues.

Korn Ferry International, Fiscal Year: 2014
Talent Analytics
Companies are increasingly leveraging big data and analytics to measure the influence of activities across all aspects of their business, including HR. They expect their service providers to deliver superior metrics and measures and better ways of communicating results. Korn Ferry's go-to-market approach is increasingly focused on talent analytics we are injecting research-based intellectual property into all areas of our business, cascading innovation and new offerings up to our clients.

Insperity Inc., Fiscal Year: 2015
Our long-term strategy is to provide the best small and medium-sized businesses in the United States with our specialized human resources service offering and to leverage our buying power and expertise to provide additional valuable services to clients. Our most comprehensive HR services offerings are provided through our Workforce Optimization and Workforce Synchronization solutions (together, our PEO HR Outsourcing solutions), which encompass a broad range of human resources functions, including payroll and employment administration, employee benefits, workers compensation, government compliance, performance management and training and development services, along with our cloud-based human capital management platform, the Employee Service Center (ESC). Our Workforce Optimization solution is our most comprehensive HR outsourcing solution and is our primary offering. Our Workforce Synchronization solution, which is generally offered only to our mid-market client segment, is a lower cost offering with a longer commitment that includes the same compliance and administrative services as our Workforce Optimization solution and makes available, for an additional fee, the strategic HR products and organizational development services that are included with our Workforce Optimization solution.

TransUnion, Fiscal Year: 2015
Our addressable market includes the big data and analytics market, which continues to grow as companies around the world recognize the benefits of building an analytical enterprise where decisions are made based on data and insights, and as consumers recognize the importance that data and analytics play in their ability to procure goods and services and protect their identities. International Data Corporation ("IDC") estimates worldwide spending on big data and analytics services to be approximately $52 billion in 2014, growing at a projected compounded annual growth rate (CAGR) of approximately 15% from 2014 through 2018. There are several underlying trends supporting this market growth, including the creation of large amounts of data, advances in technology and analytics that enable data to be processed more quickly and efficiently to provide business insights, and growing demand for these business insights across industries and geographies. Leveraging our 48-year operating history and our established position as a leading provider of risk and information solutions, we have evolved our business by investing in a number of strategic initiatives, such as transitioning to the latest big data and analytics technologies, expanding the breadth and depth of our data, strengthening our analytics capabilities and enhancing our business processes. As a result, we believe we are well positioned to expand our share within the markets we currently serve and capitalize on the larger big data and analytics opportunity.

Camping World Holdings, Inc., Fiscal Year: 2017
Customer Database. We have over 15.1 million unique RV contacts in our database of which approximately 3.6 million are Active Customers related to our RV products. We use a customized CRM system and database analytics to track customers and selectively market and cross-sell our offerings. We believe our customer database is a competitive advantage and significant barrier to entry.