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Going Digital: Implications for Firm Value and Performance*

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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 10-Ks and conference calls. Digital adoption is associated with a market-to-book ratio 7-23% higher than industry peers. Portfolios formed on digital disclosure earn a DGTW-adjusted return of 21% over a 3-year horizon and a monthly alpha of 49-basis-points. While there is no improvement in overall performance as measured by return-on-assets conditional on digital activities, there is a significant increase in asset turnover but also a significant decline 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 terms¹, and obtain word counts of digital terms in firms' 10-K reports and earnings conference call transcripts 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

1. We define the digital terms in Appendix A.

recent years. Our sample consists of all US-listed non-tech firms, which are identified by their industry classification², for the years 2010-2017. Based on our measurement from the business description of the 10-K and presentation portion of the conference calls, we find that companies are indeed disclosing more about digital activities. For instance, the proportion of firms in our sample using at least one digital label in the earnings conference call increased from 4% in 2010 to 20% in 2017.

We find that our proxy for digital activities³ 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 43-130%. In addition, relative to industry peers, firms that engage in digital activities exhibit less co-movement with the non-tech portfolio by 5-15%. 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 have evolved 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 38-115% and decreases in co-movement with the non-tech portfolio by 2-7% over a 3-year span. Combined, our analysis on co-movement suggests that our measure of digital activities identifies firms that have gradually differentiated 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, less CapEx intensive, hold more cash and are in industries with higher digital activity. Past digital activities significantly predict current digital activity. We also find that poor return performance predicts

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 earnings calls and 10-Ks, see Section 3 on the text extraction and quantization procedure.

digital activity, which suggests that market pressures create incentives for firms to go digital. Moreover, we report negative, albeit not statistically significant, associations between digital activity and sales growth, which is consistent with the performance pressure channel. We also find that firms that exhibit greater co-movement with the tech portfolio and business-to-business oriented firms are more likely to go digital.

Building on the technology adoption literature, we hypothesize that 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. Consistent with this hypothesis, we find that the market-to-book ratio of non-tech firms that engage in digital activities is higher than their industry peers in an economically significant way. Notably, we estimate that a firm that adopts digital activities has a 7-23% higher market-to-book than its peers. The difference widens over subsequent years, as we find significant increases in market-to-book over a 2-year period. In particular, firms that go digital increase market-to-book by 4-14%, relative to industry peers, over the following 2 years.

Additionally, we examine the valuation benefits of going digital in the cross-section of firms. We find that firms with higher CapEx, greater sales growth and firms in industries that have significant digital activity tend to experience higher valuations for going digital. The latter two findings suggest that digital firms that show early signs of success and firms that are already in industries that are going digital tend to receive higher valuations from investors. We also find that firms that cater to business customers benefit more from going digital, as these firms experience incrementally higher valuations from going digital.

We corroborate our market-to-book results with an analysis of the Earnings Response Coefficient (ERC), conditional on digital activity. If firms that go digital are

more highly valued by investors, we expect that their ERCs would increase as investors would increase their pricing multiples on earnings. 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 43-127% higher annual ERC and a 5-15% higher quarterly ERC than its industry peers.

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 asset pricing tests to investigate this conjecture, and in general, we find that digital disclosure predicts future returns. In particular, we find that for long-short portfolios formed on digital disclosure, these portfolios earn, on average, a 21% DGTW-adjusted return⁴ over a three-year horizon⁵. 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 49 basis points, or 6% 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 return-on-assets (ROA), net margins, asset turnover and sales growth. Based on the existing literature, we expect that improvements to firm performance will only realize in the long term due to the challenges involved in integrating new technologies (Bresnahan and Greenstein 1996). Consis-

4. 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)

5. 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.

tent with this expectation, we find that ROA weakly declines over the first year after the firm engages in digital activity. However, net margins and sales growth decline significantly after the firm engages in digital activity, as net margins fall by approximately 10-30%, and sales growth falls by 11-34% in the year when the firm engages in digital activity. 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) these results could also reflect the fact that 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 managers exhibit 43% higher ROA relative to industry peers.

On the other hand, we find that there are immediate improvements in asset turnover following the disclosure of digital activities, consistent with prior literature that documents productivity gains from the adoption of data-driven technologies (Tambe 2014). Starting from the first year after digital activity, we document that asset turnover continues to increase over the following 3 years. Specifically, in the 3rd year, firms that engage in digital activity increase asset turnover by 2-7% compared to industry peers, which is consistent with digital adoption improving productivity in firms.

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 show that digital activity is determined by poor performance. We argue that the second effect is

unlikely as ROA does not improve even 3 years after the disclosure of digital activities. We evaluate the third concern by examining our results after dropping potentially misclassified firms and we find that our main inferences are unchanged without these firms.

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 through improving workflow efficiencies. 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 potential consequences of adopting digital technologies, such as data analytics and AI suggest that these technologies will also improve firm productivity (e.g., Tambe 2014). For example, studies on FinTech have also found that adopting these technologies leads to

significant 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 explore 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.

Combined, these two features of digital technologies suggest that adopting them should substantially increase firm value. Consistent with this hypothesis, we find that non-tech firms experience large increases in valuation, as measured by the market-to-book ratio and earnings response coefficient, from digital technology adoption.

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 explain 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 explain the US-Europe productivity gap in IT adoption. Specifically, the authors find that US firms have better “people-management” practices⁶ 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

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

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 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. Consistent with these frictions, we document a strong and immediate valuation impact of digital activity but find little evidence of firm performance changes. Moreover, 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 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 capturing 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 espe-

cially 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 in our study speak to the value implications of non-financial information. Specifically, we show that disclosure of digital activities provides non-financial information that is value-relevant to markets. Additionally, we also find that markets tend to be sluggish at incorporating the value implications of digital activities into prices, as we find that disclosure of digital activities can predict returns.

III DATA

We construct our sample from several sources. We begin with all firms from the intersection of COMPUSTAT and CRSP from 2010 to 2017 with share codes 10 and 11 in CRSP. We also include earnings forecasts from IBES, conference call transcripts from Thomson Reuters Streetevents 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 draw from prior literature (e.g., Collins et al. 1997; Francis and Schipper 1999; Kile and Phillips 2009) to create a parsimonious filter for tech firms based on a combination of SIC, NAICS and GICS codes. 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)⁷—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. For the “analytics” topic, we develop the word list by searching through the 10-Ks for word bigrams with the term “analytics”, and including the main bigrams for the dictionary.

We use two disclosure mediums to count mentions of digital terms. The first is the presentation portion of earnings calls. We identify the beginning and end of this portion of the earnings call by searching for the “presentation” and “question and answers” line⁸. The second source is the business description section of the 10-K. We

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

8. If the “Q&A” line is missing, we assume that the entire transcript is the presentation portion.

identify the beginning and end of this section by searching for the line with either “Item1” or “Business.” and the lines with either “Item1A” or “Risk Factors”.

To address concerns that the raw count of words is a noisy measure of digital activity, we first combine raw counts from both disclosure sources and quantize the raw counts into terciles that are coded as follows: 0 if there are no mentions of digital activity, 1 if digital mentions fall in the bottom tercile of digital mentions in the year, 2 if digital mentions fall in the middle tercile of digital mentions in the year and 3 if digital mentions fall in the top tercile of digital mentions in the year. In the subsequent tests, we use this score as our main proxy for digital activity.⁹

Sample Statistics

We report the sample statistics for the main variables in our study in Table 1¹⁰ 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 2.4 (1.6), compared to 4.7 (2.9) for tech firms. Additionally, the sample firms are older, with a mean (median) age of 24 (19) years compared to 16 (15) years for tech firms.

The non-tech firms in the sample do not significantly co-move with the tech portfolio, as the average beta on this portfolio is 0.06. By contrast, the sample of digital firms co-move strongly with the non-tech portfolio, as the average beta on this portfolio is close to 1. In addition, the average returns performance of the sample is also worth noting. The average market-adjusted return is 3%. However, the median returns of -1% suggests a significant right skew in the returns distribution and that the representative non-tech firm in the sample is performing poorly relative to the market.

9. In untabulated analysis, we examine the same analysis based on quantized scores of the digital terms in the business description section of the 10-K and in the presentation portion of the earnings call and find similar results.

10. The construction of these variables are detailed in Appendix C

IV NON-TECH FIRMS AND DIGITAL ACTIVITY

Our first key finding is that non-tech firms are increasingly adopting digital technologies over time. To illustrate this, we aggregate the number of digital terms in earnings conference calls and the 10-K and plot the distribution over time. Figure 1, plots the number of digital terms mentioned in the two disclosure mediums and shows that the disclosure of digital activity is steadily increasing over time¹¹. This trend speaks to the increasing relevance of the phenomenon and motivates our study.

Next, we break down the aggregate digital terms by topic group in Table 2 and find that the increasing trend exists across all topics. Notably, digital terms are most concentrated in “analytics”, which has 968 mentions in conference calls and 10-Ks across 234 firms in 2017. The disclosure of “digitization” is also quite frequent, with 757 mentions across 207 firms in 2017. In addition, we report the digital word counts across industries in Table 3 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 β s in the following regression:

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

where daily returns, $R_{i,t}$, is regressed on the value-weighted returns of the tech portfolio ($R_{Tech,t}$) and the value-weighted returns of the non-tech portfolio ($R_{NTech,t}$) over the

11. Our assumption is that the number of digital words measures digital activity and so in Appendix D, we provide some examples of how these digital terms are used in the firms’ disclosures

fiscal period for each firm-year¹². 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 β s due to digital activities, we regress the non-tech and tech β s on the quantized score for digital activity and a set of control variables: market capitalization, firm age, leverage ratio, market-to-book, return-on-assets, share turnover and past year’s market-adjusted return.

Specifically, we implement the following regression model:

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

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 ($\sum_j X_{j,i,t}$) 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 4 presents our results on the association between β_{Tech} and digital activity using the levels specification and 1-3-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 43-130% higher co-movement with this portfolio (i.e., a firm in the top tercile of digital disclosure has a β_{Tech} that is 0.08 higher than the sample average of 0.06, or 130%).

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 0.8, 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. Columns

12. The tech portfolio consists of all firms that are classified as tech firms under the industry classification scheme in Appendix B. The portfolio is rebalanced monthly, and returns within the portfolio are value-weighted. The non-tech portfolio is defined similarly but consists of firms that are classified as non-tech. Return windows with less than 200 observations are dropped from the analysis.

2-4 report the changes from 1-3 years-prior to current β_{Tech} , respectively, regressed on the digital activity proxy and the lagged controls. Our results suggests that our proxy for digital activity identifies firms that have become more tech-like over time. Column 4 shows that digital firms have increased co-movement by approximately 38-115% over 3 years (that is, a firm in the top tercile of digital disclosure increases β_{Tech} by 0.07 relative to the sample average of 0.06, or 115%), which is approximately 88% of the contemporaneous difference between the β_{Tech} of digital firms and industry peers. Combined, 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 columns 2-4. Our results indicate that digital activity is associated with less co-movement with the non-tech portfolio, as digital firms exhibit 5-15% 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. Columns 2-4 report the changes from 1-3 years-prior to current β_{NTech} , respectively, regressed on on the digital activity proxy and the lagged controls. Our results in these columns mostly indicate that current digital activity is associated with decreasing co-movement with the non-tech portfolio. Column 4 reports that digital firms have decreased co-movement by 2-7% over 3 years, which is approximately 50% of the contemporaneous difference between the β_{NTech} of digital firms and industry peers. Combined, 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, our co-movement results indicate that firms that engage in digital activities have become more similar to tech firms and less similar to non-tech firms over time. Notably, the statistical and economic significance of these results suggests that digital

activities are making substantive changes to firm characteristics. Thus, these results can also be viewed as a validation of our text-based digital activities proxy.

Determinants of Digital Activity

To better understand the growing trend of digital activities within non-tech firms, we examine various determinants of firm-level digital activity in the following regression model, which regresses our proxies for digital activity on lagged determinant variables:

$$\begin{aligned}
 Digital_t = & \beta_1 Digital_{t-1} + \beta_2 SIZE_{t-1} + \beta_3 MB_{t-1} + \beta_4 LEV_{t-1} + \beta_5 ROA_{t-1} \quad (3) \\
 & + \beta_6 AGE_{t-1} + \beta_7 Herfindahl_{t-1} + \beta_8 SALES_{t-1,t-2} + \beta_9 CASH_{t-1} + \beta_{10} R\&D_{t-1} \\
 & + \beta_{11} CapEx_{t-1} + \beta_{12} Returns_{t-1} + \beta_{13} \beta_{Tech,t-1} + \beta_{14} \beta_{Non-Tech,t-1} + \beta_{15} B2B_{t-1} \\
 & + \beta_{16} TechManager_{t-1} + \xi_j + \eta_t + \epsilon_{i,t}
 \end{aligned}$$

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

Table 5 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 without observations where the firm makes subsequent 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 (industry aggregate minus firm’s digital score) 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, cash, CapEx and the lagged industry-level of digital activity. R&D is also a significant determinant of the quantized score, but not for the first disclosure model. Notably, lagged digital activity explains a significant amount of variation in the determinants model as including lagged digital activity increases the adjusted R^2 from 0.21 to 0.59. Furthermore, a firm that has disclosed at least 1 digital term has a 78% probability of disclosing at least 1 term in the next year, which suggests that digital activity is a fairly persistent process.

For initial digital disclosures, three other variables also exhibit statistically significant associations with these disclosures. The first and second are β_{Tech} and β_{NTech} , which measures the firm’s co-movement with the tech and non-tech portfolio respectively. We compare the differences between the coefficients on β_{Tech} and β_{NTech} , and find that the coefficient on β_{Tech} is significantly greater (at the 5% level) than β_{NTech} , which suggests that more “tech-like” firms are more likely to go digital. The third variable is B2B, which proxies for business-to-business firms by indicating whether the firm reports a major corporate customer. Thus, these results show that more “tech-like” and business-to-business firms tend to initiate adoption of digital technologies.

Finally, we note that our determinant regressions generally indicate a negative relationship between returns/sales growth and digital activities. This negative relationship is interesting as it suggests that weak performance spurs firms to undertake digital technology adoption.

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, 1-2-year-ahead changes in market-

to-book on our digital activity proxy and controls, in the following regression model:

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

where $MB_{i,t}$ is either the level, current changes, 1-year-ahead changes or 2-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.

We use the quantized scores for digital activities, described in Section 3. Control variables are the log of market capitalization, firm age, leverage ratio, return-on-assets, sales growth, R&D expenditures, an indicator for missing R&D, capital expenditures and market-adjusted annual returns. For regressions with dependent variables in changes, we control for mean reversion by controlling for the industry median and industry-adjusted market-to-book.

Panel A, Table 6 presents our market-to-book results. Columns 1 to 4 of Table 6 report the results using the current changes, levels, 1-2-year-ahead changes specifications respectively. 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 results show that firms with digital activity are associated with a market-to-book that is 7-23% higher than their industry peers (i.e., a firm in the top tercile of digital disclosure has a market-to-book ratio that is 0.55 higher than the sample average of 2.38, or 23%). Columns 3 and 4 report the 1-2-year-ahead changes in market-to-book, and show that digital activity is significantly associated with positive changes in market-to-book in the following 2 years. In particular, by the 2nd year, firms that go digital exhibit a 4-14% 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 0.33 relative to the sample average of 2.39, or by 14%).¹³

13. In untabulated analysis, we also examine the market-to-book effects using a firm fixed effects model. We find qualitatively similar results for 1-2-year-ahead market-to-book.

To examine which digital firms exhibit greater valuation in the cross-section, we perform a regression of market-to-book on our digital proxy, interacted with various cross-sectional variables, in Panel B of Table 6. The cross-sectional variables are: size, age, R&D, CapEx, market-adjusted returns, indicator for business-to-business firms, Herfindahl index, sales growth, cash balances, co-movement with the tech portfolio, co-movement with the non-tech portfolio and the industry-level of digital adoption.

Results in Panel B of Table 6 show that firms that service business customers, have greater CapEx expenditure and higher sales growth tend to receive higher valuations when they go digital. In particular, the positive relationship between sales growth and digital activity suggests that markets value firms more for their digital investment when there are early indications of success in the form of current sales growth. Additionally, the positive relationship between higher capital expenditures and digital activity suggests that digital technologies are general purpose technologies (Cockburn et al. 2017), which complement other investments. On the other hand, we find that the firm-level interactions with size, R&D, cash do not incrementally explain the higher valuations from digital activities.

For the cross-industry interaction variables, regression results in Panel B of Table 6 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. We measure the changes in investors' valuation of earnings using the following ERC regression:

$$CAR_{i,t} = \beta_1 UE + \beta_2 Digital_{i,t} + \beta_3 UE_{i,t} \times Digital_{i,t} + \sum_s \gamma_j X_{i,s,t} + \sum_s \delta_s UE \times X_{i,s,t} + \xi_j + \eta_t + \epsilon_{i,t} \quad (5)$$

where $CAR_{i,t}$ represents the cumulative abnormal returns around the earnings announcement and is regressed on the unexpected earnings (UE), which are estimated by the actual EPS minus the most recent median IBES consensus¹⁴, 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 and earnings announcement lag. To ensure that industry- or time-based trends do not influence our findings, we also add industry and time fixed effects, and cluster standard errors at the firm level.

We first investigate the incremental impact of digital activities¹⁵ on ERCs at the quarterly frequency using the 3-day cumulative abnormal return¹⁶ as our dependent variable. Table 7, Columns 1 and 2 reports the results of ERC tests at the quarterly frequency. Column 1 presents the baseline ERC coefficient and we report an ERC coefficient of 4.887. Column 2 explores the interactive effect of digital activity, proxied

14. We remove consensus forecasts that are more than 100 days and less than 3 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.

15. To convert the quantized score for digital activity to the quarterly frequency, we estimate the raw digital word counts using the counts obtained from the most recent quarterly earnings conference call and the most recently available 10-K.

16. Abnormal daily returns are calculated by taking the raw return minus the Carhart four-factor expected returns, where the expected returns are estimated with the β s of the four-factor model that are estimated in a (-280,-60) window.

by the quantized score of digital terms, on the ERC model. Consistent with our expectations, we find that the coefficient $UE \times Digital$ is statistically significant, and suggests that a firm that engages in digital activities exhibits ERCs that are 5-15% higher than industry peers (i.e., a firm in the top tercile of digital disclosure has an ERC that is 0.81 higher than the sample average of 5.314, or 15%).

Finally, we examine ERCs at the annual frequency. The specifications of the tests remain similar except for the returns window. As we measure digital activities using information in 10-Ks, our return window needs to be sufficiently long to cover the 10-K filing date. Sample statistics in Table 1 indicate that the median lag between 10-K filing and earnings announcement is 6 business days, and the 75th-percentile lag is 19 business days. Thus, we use a (-1,30) CAR window in our annual ERC tests because this return window covers the 10-K filing date of 90% of firms in the sample¹⁷.

Columns 3 and 4 of Table 7 report the results for the ERC regressions at the annual frequency. As before, we report the baseline ERC model in Column 3, which is 2.920. In Column 4, we explore the interactive effects of digital activities by using the quantized score for digital activities. Broadly, our results in Column 4 mirror the results obtained in the quarterly ERC tests and suggest that firms that engage in digital activities exhibit an ERC that is 43-127% higher than industry peers.¹⁸

In summary, our ERC 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 market-to-book results also indicates that the effects of digital activity are fairly persistent and increase for up to 2 years after the initial disclosure of digital activities.

17. We also remove observations that have a filing date outside of the return window

18. In untabulated analysis, we run the ERC model with firm fixed effects, and find similar results.

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 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 or earnings calls¹⁹, 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 the methodology in Daniel et al. (1997). These risk-adjusted returns are first calculated at the firm level by deducting the corresponding 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.

As illustrated in Figure 2, we find that 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 21% risk-adjusted return. We tabulate the average return performance at the 1-, 2- and 3-year horizons in columns 1 to 3 of Table 8 and find that the long-short portfolio formed on digital disclosure exhibits statistically significant returns at the 1 and 3 year horizons. In particular, in the 1st year of the strategy, an investor can earn a 3.7% risk-adjusted return with a long-only strategy and a 5% risk-adjusted return on a long-short strategy formed on digital disclosures. One caveat to our return results is that a portion of the long-short returns comes from the

19. We assume 10-K information and the earnings call information for the quarters within the fiscal year to be publicly available by three months after the fiscal year end.

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, as a whole, our results suggest that non-tech firms have performed poorly relative to size, book-to-market and momentum matched portfolios in our sample period.²⁰

To further address concerns that other forms of risk may be driving our results, we turn to calendar portfolio regressions. We implement this by evaluating the alpha from a regression of the long-short portfolio returns on the Fama-French five-factor model (Fama and French 2015) and the momentum factor as described below:

$$R_{pt} = \alpha_p + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \beta_6 MOM_t + \epsilon_{pt} \quad (6)$$

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. The monthly portfolio return is estimated by value-weighting the firm-level raw returns, and the weights/positions are re-balanced monthly. MKT_t is the monthly market return in excess of the risk-free rate, SMB_t represents the monthly returns to a portfolio that trades on small stocks, HML_t denotes the monthly returns to a portfolio that trades on value firms, RMW_t represents the monthly returns to a portfolio that trades on the profitability of firms, and CMA_t denotes the monthly returns to a portfolio that trades on the levels of investment of firms. 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.

Panel B of Table 8 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 49-basis-point alpha on average, which on an annualized basis, is approximately 6%. We examine the long-side and short-side returns in column 2 and find that the

20. Further note that in our sample, the median market-adjusted returns for the fiscal year of firms is -1%, which suggests that non-tech firms in our sample typically performed poorly during the period of study.

portfolios return a positive 36-basis-point alpha and a negative 12-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 report the changes to fundamental performance due to digital activity. The previous sections have revealed a link between digital activity and higher valuations and returns. We 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 control variables ($\sum_j X_{i,j,t}$): size, age, leverage ratio, return-on-assets, R&D expenditures, an indicator for missing R&D, capital expenditures and annual market-adjusted returns, 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:

$$VAR_{i,t} = \beta_1 Digital_{i,t} + \sum_j \gamma_j X_{j,i,t} + \phi_s + \delta_t + \epsilon_{i,t} \quad (7)$$

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

The first fundamental performance measure that we examine is return-on-assets (ROA). Panel A of Table 9 presents the results of regressing levels, 1-3-year-ahead changes in ROA in columns 1 to 4. We do not find statistically significant evidence of changes in ROA, and the coefficients on ROA are generally negative. Thus, our results indicate that digital activities have a negligible effect on performance.²¹

21. An alternative interpretation of this result is that firms that go digital are firms that are expected

Next, we investigate how digital activity affects the components of ROA, namely, net margins, asset turnover, and sales growth in panels B, C and D. In panel B, we find that firms that go digital are associated with 10-30% lower net margins relative to their industry peers (i.e., a firm in the top tercile of digital disclosure has net margins that is 0.015 lower than the sample average of 0.05, or 30%). Following the digital disclosure, net margins continue to fall for the next year by 12-36% relative to industry peers (that is, a firm in the top tercile of digital disclosure decreases net margins by 0.018 relative to the sample average of 0.05, or 36%). The net margins results could be a consequence of the accounting system that expenses the investments in digital activities through R&D, SG&A, and other expense items as they are not allowed to be capitalized as an asset. To confirm this conjecture, we check and find that digital activities are associated with higher levels of R&D and SG&A in untabulated analysis.

We also find lower sales growth in Panel D of Table 9. In the year of the digital disclosure, we find a 11-34% lower sales growth relative to industry peers. Columns 2 and 3 show that sales growth is also lower in the years following the digital disclosure, as we find a 9-27% lower sales growth relative to industry peers by the 2nd year of the disclosure (i.e., a firm in the top tercile of digital disclosure has 2-year sales growth that is 0.039 lower relative to the bi-annualized sample average of $1 - (1 + 0.07)^2 = 0.14$, or 27%). However, by the 3rd year, the differences in sales growth dissipates.

In contrast to our net margins and sales growth results, we find that asset turnover improves following digital activity, which is consistent with prior work that find productivity benefits of digital investments (Tambe 2014). In Panel C of Table 9, we find that the level of asset turnover is 6-18% higher for firms that go digital relative to their industry peers. Asset turnover continues to increase for the next 3 years and by

to face weaker performance in future years, and going digital reduces the impact of expected weak performance. We investigate this possibility by running the ROA regression on a industry-year fixed effect model that benchmarks the firm's performance against the industry-year average performance, and include controls for abnormal ROA, Asset turnover, margins and sales growth to proxy for potential current indicators of future weak performance. Our inferences under this specification remain unchanged.

the 3rd year, firms that go digital increase asset turnover by 2-7%, relative to industry peers, consistent with digital technologies improving long-term productivity.

Finally, motivated by the idea that management plays a key role in technology adoption (Bloom et al. 2012), we investigate how firms with tech managers can improve performance through digital adoption. In Table 10, we re-run the ROA regressions in Panel A of Table 9 for the sub-sample of non-tech digital firms, and include a proxy for tech managers, based on executive titles in Capital IQ's People Intelligence database (a variable that is coded as 1 if the firm has a top-5 executive with a tech-related title). In our analysis with this proxy, we find that the presence of a tech manager improves performance through digital activities. In column 1 of Table 10, we find that non-tech digital firms with tech managers exhibit higher ROA performance as these firms exhibit a 43% higher ROA relative to industry peers (i.e., a digital firm with tech managers has ROA that is 1.3% higher than the sample average of 3%, or 43% higher). Furthermore, the difference in ROA widens over 1-3 years and by the 3rd year, these firms increase ROA by another 36% relative to industry peers. Thus, our results in this table suggest that managerial expertise within the firm is important for integrating and generating value from new digital technologies.

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 net 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 perfor-

mance. 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 net margins suggest that digital technologies are costly in the short run, as we report negative changes to net 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 net margins and sales growth, there may be little improvement in these performance measures if competitors are also making similar investments in digital technologies²². 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.

22. In particular, we find some evidence for this conjecture in untabulated analysis, as we also document declines in gross margins (defined as revenues minus cost of goods sold, scaled by sales) that persists for up to 2 years after digital disclosure. This suggests that even without factoring in the high investment in digital, market competition also erodes margins.

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 managers consistently perform better than firms without such management teams. In fact, these firms experience an immediate positive increase in ROA relative to their industry peers when going digital of 43%, which suggests that the presence of such managers are critical for successful implementation of new technologies.

Potential Selection Bias

A key 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 relationship between valuation and digital activity would thus be an artifact of the higher market valuation of better performing firms. We argue that this form of selection bias is unlikely, as our determinant results show that lagged market-to-book is unrelated to digital disclosure. In fact, the negative coefficient on annual return performance and sales growth in the determinants table (Table 5) suggests that firms with weaker performance firms are more likely to adopt digital technologies.

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 misclassified tech firms. We address this concern in two ways. First, we drop firms that exhibit a median β_{Tech} that is 2 standard deviations away from the cross-sectional average median β_{Tech} . With this sample, we find that our main inferences are unchanged. Second, we address the concern by dropping firms that disclosed more than 1 digital term in the years before 2010, which is the year when most non-tech firms started to go digital. Similarly, we find that our main inferences are unchanged with this sample.

VI CONCLUSION

In recent years, a growing number of non-tech firms have made investments in the new wave of digital technologies that have the potential to transform businesses and create greater firm value (Brynjolfsson et al. 2017). Motivated by this growing phenomenon, our objective in this study is to characterize the firms that adopt these technologies and to evaluate the valuation and performance benefits of adopting these technologies.

To that end, 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, hold larger cash balances, invest more in R&D, invest less in capital expenditures, co-move more with the tech portfolio, are business-to-business oriented 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 7-23% higher than their industry peers. The valuation benefits of going digital accrue slowly as 2-year-ahead market-to-book of firms that go digital increases by a further 4-14% over time. Moreover, portfolios formed on digital disclosure significantly predict returns and deliver a 49 basis point alpha in a Fama-French 5 factor plus momentum model²³.

23. Note, we do not factor in transaction costs in our estimation, so real-time abnormal profits will

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, financial performance measures ROA, net 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 a profit from conducting research on digital activities in 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. 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.

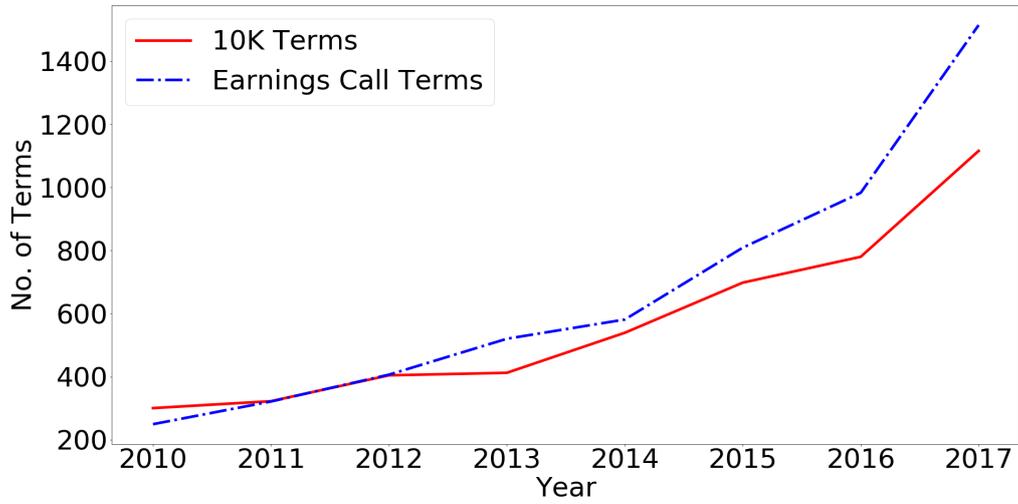
be lower when factoring in these costs.

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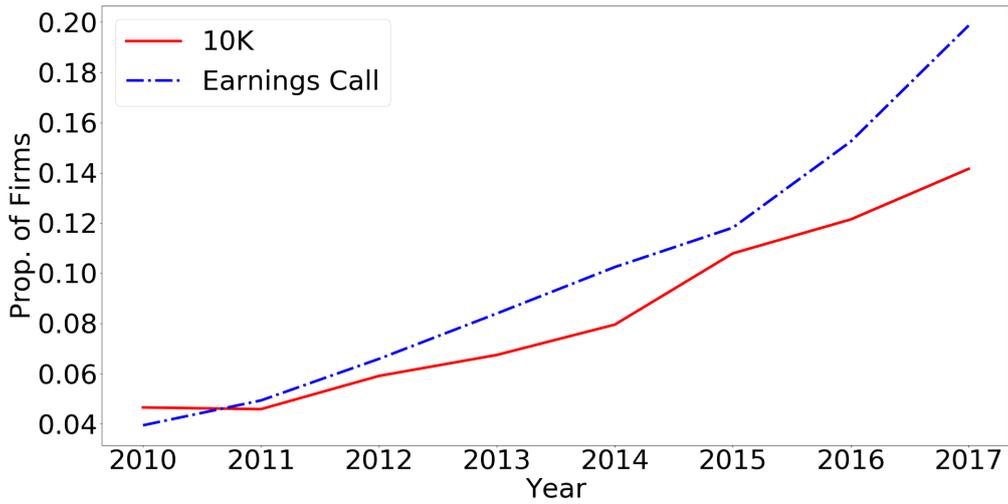
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(a) Number of Digital Terms



(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 and Presentation Portion of Earnings Calls

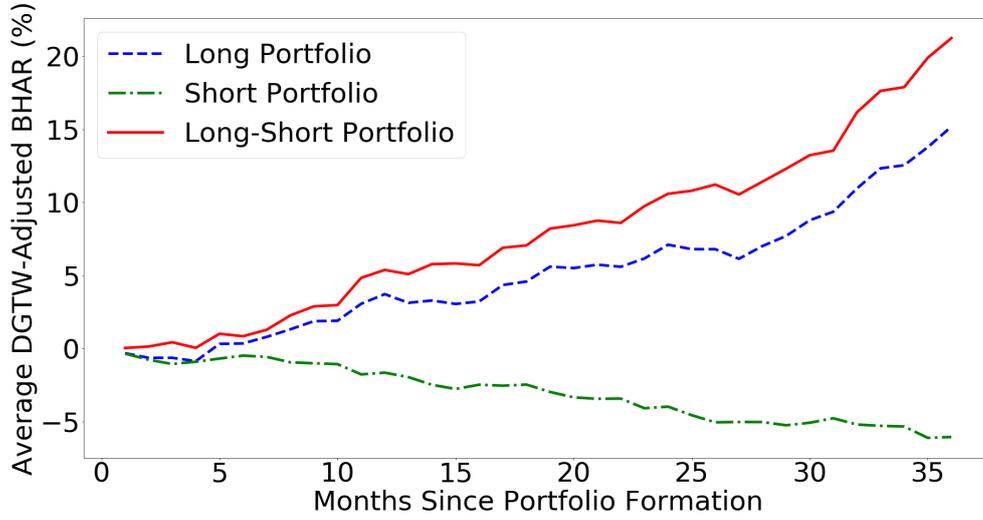


Figure 2: Average Size, Book-to-Market and Momentum (DGTW) Adjusted Returns to Portfolios Formed on “Digital” Disclosure

Table 1: Summary Statistics

We report the summary statistics of the main control variables in this table. Descriptions of the variables are described in detail in the Appendix C.

	Mean	Std Dev	Median	25%	75%	N
Market Cap. (Millions)	3956	8823	709	156	2956	13903
Market-to-Book	2.38	2.36	1.6	1.06	2.67	13903
Firm Age	24	17	19	10	33	13903
Leverage Ratio	1.08	1.49	0.63	0.23	1.24	13844
β	1.01	0.56	1.03	0.67	1.37	13367
β_{Tech}	0.06	0.48	0.06	-0.18	0.33	13285
β_{NTech}	0.93	0.72	0.86	0.46	1.31	13285
Business-to-Business	0.39	0.49	0	0	1	13903
Earnings Persistence	0.22	0.38	0.14	-0.06	0.46	12190
Return Volatility	0.03	0.02	0.02	0.02	0.03	13466
Days to EA	35	16	34	23	43	13891
Days to 10-K Filing	46	13	43	40	52	13903
Days Between 10-K & EA	10	13	6	0	19	13891
EA CAR(-1,30)	0.01	0.11	0.01	-0.05	0.07	10801
Unexpected Earnings	-0	0.01	0	-0	0	9707
Market-Adj. Annual Returns	0.03	0.51	-0.01	-0.2	0.19	13334
Return-on-Assets	0.03	0.07	0.03	0.01	0.06	13392
Net Margins	0.05	0.21	0.07	0.02	0.14	13899
Asset Turnover	0.75	0.76	0.54	0.08	1.14	13392
Sales Growth $_{t,t-1}$	0.07	0.2	0.05	-0.03	0.14	13255
Loss (Indicator)	0.17	0.37	0	0	0	13903
Tech Manager	0.04	0.19	0	0	0	13903

Table 2: Distribution of Digital Words by Year

We report the distribution of individual digital words in 10-Ks and earnings call transcripts by year in panels A and B, respectively. The regex expressions used to identify these words are described in the Appendix A.

	Analytics	Automation	AI	Big Data	Cloud	Digitization	ML
Panel A: 10-K Reports							
2010	139	22	14	10	10	84	21
2011	141	27	14	12	8	99	21
2012	168	32	16	17	32	113	26
2013	171	19	8	13	48	113	40
2014	264	21	8	21	65	119	41
2015	331	26	7	47	72	172	43
2016	363	21	25	55	78	189	49
2017	457	35	88	82	116	252	86
Panel B: Earnings Conference Calls							
2010	122	6	15	4	12	86	4
2011	130	1	10	5	39	129	7
2012	168	2	7	23	42	150	14
2013	204	12	5	38	56	192	13
2014	235	22	9	37	51	215	12
2015	303	15	29	81	66	287	28
2016	326	15	81	71	78	364	48
2017	511	29	155	125	89	505	101

Table 3: Digital Activity Across Industry-Years

We report the distribution of digital words in 10-Ks and earnings call transcripts by SIC divisions-years in panel A and B. 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: Digital Words in Business Description of 10K											
	0100-0999	1000-1499	1500-1799	2000-3999	4000-4999	5000-5199	5200-5999	6000-6799	7000-8999	Total Firms	Prop. Firms
2010	1	4	0	56	5	10	3	110	111	110	0.047
2011	0	3	0	61	11	10	7	115	115	105	0.046
2012	0	3	1	70	11	12	10	138	159	131	0.059
2013	0	0	1	70	17	16	12	123	173	148	0.067
2014	1	1	1	74	30	12	8	203	209	175	0.08
2015	0	2	3	100	50	13	33	220	277	226	0.108
2016	1	4	8	111	56	19	38	219	324	246	0.121
2017	1	11	11	209	57	20	38	354	415	283	0.142
Panel B: Digital Words in Earnings Call Transcripts											
	0100-0999	1000-1499	1500-1799	2000-3999	4000-4999	5000-5199	5200-5999	6000-6799	7000-8999	Total Firms	Prop. Firms
2010	0	0	0	44	20	4	28	95	58	99	0.039
2011	0	0	2	69	27	7	59	90	67	120	0.049
2012	0	0	3	117	23	7	56	106	94	155	0.066
2013	2	4	3	134	47	20	76	127	107	193	0.084
2014	5	2	1	113	58	15	99	163	125	235	0.102
2015	14	3	1	174	38	19	130	239	191	266	0.118
2016	4	15	10	261	65	32	140	252	204	327	0.152
2017	2	70	18	344	109	50	252	381	289	420	0.199

Table 4: 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. 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 columns 2-4, we perform regressions on the past 1-year, 2-year and 3-year changes, respectively. 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 both the business description of the 10-K and the presentation portion of the earnings conference call (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, Market-Adjusted Annual Returns and Share Turnover, as well as industry (Fama-French 48-industry) and year fixed effects. 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 1 Year Change	Past 2 Year Change	Past 3 Year Change
Panel A: Tech Portfolio Co-Movement (β_{Tech})				
Dependent Variable	$\beta_{Tech,t}$	$\beta_{Tech,t} - \beta_{Tech,t-1}$	$\beta_{Tech,t} - \beta_{Tech,t-2}$	$\beta_{Tech,t} - \beta_{Tech,t-3}$
Digital _t	0.026*** (0.006)	0.004 (0.005)	0.018*** (0.007)	0.023*** (0.008)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	12,673	11,684	11,681	11,214
Adj. R^2	0.1836	0.0291	0.0425	0.0491
Panel B: Non-Tech Portfolio Co-Movement (β_{NTech})				
Dependent Variable	$\beta_{NTech,t}$	$\beta_{NTech,t} - \beta_{NTech,t-1}$	$\beta_{NTech,t} - \beta_{NTech,t-2}$	$\beta_{NTech,t} - \beta_{NTech,t-3}$
Digital _t	-0.048*** (0.010)	-0.003 (0.006)	-0.022*** (0.008)	-0.024** (0.010)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	12,673	11,684	11,681	11,214
Adj. R^2	0.3296	0.0548	0.0784	0.0694

Table 5: Determinants of Digital Activity

We report the determinants of digital activity in this table. In Columns 1 and 2, we use the quantized score of digital mentions in the business description of 10-Ks and presentation portion of the earnings call (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 or the presentation portion of the earnings call 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
Digital _{t-1}	0.747*** (0.016)	0.781*** (0.015)		
SIZE _{t-1}	0.030*** (0.003)	0.030*** (0.003)	0.012*** (0.001)	0.014*** (0.001)
Market-to-Book _{t-1}	0.003 (0.003)	0.006* (0.003)	-0.000 (0.001)	0.001 (0.001)
Leverage _{t-1}	0.003 (0.004)	0.001 (0.004)	0.000 (0.002)	-0.001 (0.002)
Return-on-Assets _{t-1}	-0.040 (0.091)	-0.112 (0.085)	0.030 (0.040)	-0.024 (0.039)
AGE _{t-1}	-0.026*** (0.007)	-0.023*** (0.006)	-0.010*** (0.003)	-0.012*** (0.003)
Herfindahl _{t-1}	0.237 (0.145)	-0.049 (0.038)	0.116 (0.071)	-0.026 (0.023)
Sales Growth _{t-1,t-2}	-0.025 (0.019)	-0.027 (0.019)	-0.008 (0.010)	-0.007 (0.010)
CASH _{t-1}	0.112** (0.053)	0.172*** (0.047)	0.027 (0.018)	0.058*** (0.018)
R&D _{t-1}	2.626*** (0.834)	1.165* (0.671)	0.378 (0.273)	-0.614** (0.247)
CAPEX _{t-1}	-0.415*** (0.106)	-0.239*** (0.071)	-0.112** (0.050)	-0.066 (0.040)
Stock Returns _{t-1}	-0.010** (0.005)	-0.011** (0.005)	-0.006 (0.004)	-0.009* (0.005)
$\beta_{Tech,t-1}$	0.004 (0.013)	0.024** (0.012)	0.019*** (0.006)	0.031*** (0.007)
$\beta_{NTech,t-1}$	-0.013 (0.010)	-0.009 (0.009)	0.010** (0.005)	0.008* (0.004)
B2B _{t-1}	0.019 (0.012)	0.031*** (0.011)	0.008* (0.005)	0.007 (0.005)
Tech Manager _{t-1}	-0.011 (0.025)	-0.007 (0.024)	0.004 (0.010)	0.005 (0.010)
Industry Digital _{t-1}		0.003*** (0.001)		0.000* (0.000)
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Observations	11,497	11,497	11,130	11,201
Adj./Pseudo. R^2	0.5977	0.5899	0.1380	0.0852

Table 6: Market-to-Book

We report the coefficients of the regressions of market-to-book on the proxy for digital activities. We report the associations between market-to-book current changes, levels, one-, two-year-ahead changes and digital activity in columns 1-4, respectively, in Panel A. In Panel B, 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 and the presentation portion of the earnings conference call. All regressions control for SIZE, AGE, LEV, ROA, SALES GROWTH, R&D, an indicator for missing R&D, CapEx, 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.

	Current Changes	Levels	One Year Ahead Changes	Two Year Ahead Changes
Panel A: Average Effects				
Dependent Variable	$MB_t - MB_{t-1}$	MB_t	$MB_{t+1} - MB_t$	$MB_{t+2} - MB_t$
Digital _t	0.080*** (0.021)	0.183*** (0.049)	0.055*** (0.021)	0.109*** (0.037)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	12,582	13,093	11,699	9,590
Adj. R ²	0.0924	0.4118	0.1178	0.1527
Panel B: Cross-Sectional Effects				
Dependent Variable	MB_t	MB_t		
Digital _t	-0.015 (0.070)	-0.084 (0.098)		
Digital _t × SIZE _t	0.034 (0.027)	0.017 (0.026)		
Digital _t × AGE _t	0.101 (0.062)	0.120* (0.063)		
Digital _t × R&D _t	-4.725 (3.665)	-2.750 (3.699)		
Digital _t × CAPEX _t	5.045*** (1.393)	5.799*** (1.446)		
Digital _t × Market Adjusted Returns _t	0.372*** (0.100)	0.386*** (0.102)		
Digital _t × B2B _t	0.194** (0.096)	0.204** (0.094)		
Digital _t × Herfindahl _t	0.674 (0.495)	0.573 (0.555)		
Digital _t × Sales Growth _t	0.395** (0.166)	0.385** (0.163)		
Digital _t × CASH _t	0.100 (0.383)	-0.173 (0.389)		
Digital _t × β _{Tech} _t	0.152 (0.128)	0.147 (0.131)		
Digital _t × β _{NTech} _t	-0.146 (0.095)	-0.176* (0.095)		
Digital _t × Industry Digital _t				0.007** (0.003)
Controls	Yes	Yes		Yes
Time FE	Yes	Yes		Yes
Industry FE	Yes	Yes		No
Observations		12,527		12,527
Adj. R ²		0.4532		0.4329

Table 7: Market Response to Earnings

We report the coefficients to the ERC regression with the proxy for digital activities in this table. In Columns 1 and 2, we report the ERC regression at the quarterly frequency, where $CAR(-1,1)$ is regressed on unexpected earnings, controls and interactions. In Columns 3 and 4, we report the ERC regression at the annual frequency, where $CAR(-1,30)$ is regressed on unexpected earnings, controls and interactions. Columns 1 and 3 report the estimates of the baseline ERC regression models. 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 presentation portion of the earnings conference call and 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 and the no. of days to EA. For the ease of interpretation of the UE coefficient, we mean-center all continuous control variables. In addition, we control for the interaction of these variables with the UE. We also add industry and time fixed effects (calendar quarter for columns 1 and 2, year for columns 3 and 4). 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	Quarterly ERCs		Annual ERCs	
	Baseline	With Digital	Baseline	With Digital
	$CAR(-1,1)$	$CAR(-1,1)$	$CAR(-1,30)$	$CAR(-1,30)$
UE_t	4.887*** (0.153)	5.314*** (0.178)	2.920*** (0.286)	2.664*** (0.316)
$Digital_t$		0.000 (0.000)		0.002 (0.002)
$Digital_t \times UE_t$		0.271* (0.140)		1.136*** (0.277)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	41,642	33,783	8,756	7,938
Adj. R^2	0.1247	0.1270	0.0506	0.0551

Table 8: Portfolio Returns

We report the risk-adjusted returns for portfolios formed on digital disclosure. In Panel A, we report the average returns net of their corresponding size, book-to-market and momentum quintile returns, which are constructed using the methodology in Daniel et al. (1997). Each portfolio is formed in June of each year, 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. 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. Standard errors are reported in parentheses. In Panel B, we report the α from regressing monthly portfolio returns 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. Robust standard errors are reported in parentheses. *, **, *** denote 10%, 5% and 1% significance level, respectively.

Panel A: Long-Run Portfolio Returns				
Portfolio	RET(1,12)	RET(13,24)	RET(25,36)	RET(1,36)
Long	0.037** (0.015)	0.033 (0.026)	0.116* (0.052)	0.152** (0.053)
Short	-0.017* (0.008)	-0.024*** (0.005)	-0.037** (0.014)	-0.061*** (0.015)
Long - Short	0.054*** (0.015)	0.050 (0.029)	0.150** (0.052)	0.212*** (0.057)
Panel B: Calendar Long-Short Portfolio Returns				
	Long-Short	Long	Short	
α	0.491** (0.191)	0.366** (0.177)	-0.125** (0.056)	
MKT - Rf	-0.147** (0.066)	0.846*** (0.063)	0.993*** (0.021)	
SMB	0.085 (0.076)	0.147** (0.072)	0.062** (0.028)	
HML	-0.283** (0.112)	-0.094 (0.103)	0.188*** (0.028)	
RMW	-0.064 (0.096)	0.021 (0.092)	0.084** (0.040)	
CMA	0.408** (0.173)	0.559*** (0.154)	0.151*** (0.049)	
MOM	0.093 (0.063)	0.077 (0.057)	-0.017 (0.021)	
Observations	104	104	104	
Adj. R^2	0.1458	0.8053	0.9800	

Table 9: Accounting Performance

We report the coefficients of regressions of return-on-assets (ROA), net margins (MARGINS), asset turnover (ATO), and sales growth (SALES GROWTH) on the proxy for digital activities and controls in this table. 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 ROA. Panel B reports the results for net margins. Panel C reports the results for asset turnover. Panel D reports the results for sales growth. 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 and the presentation portion of the earnings conference call. All regressions control for SIZE, AGE, LEV, MB, SALES GROWTH, R&D, an indicator for missing R&D, CapEx, 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: ROA				
Dependent Variable	ROA _t	ROA _{t+1} - ROA _t	ROA _{t+2} - ROA _t	ROA _{t+3} - ROA _t
Digital _t	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	13,093	11,699	9,590	7,644
Adj. R ²	0.3310	0.2089	0.3305	0.3414
Panel B: Net Margins				
Dependent Variable	MARGINS _t	MARGINS _{t+1} - MARGINS _t	MARGINS _{t+2} - MARGINS _t	MARGINS _{t+3} - MARGINS _t
Digital _t	-0.005** (0.003)	-0.006*** (0.002)	-0.010*** (0.002)	-0.008*** (0.003)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	13,093	11,698	9,589	7,643
Adj. R ²	0.5703	0.2655	0.3990	0.3613
Panel C: Asset Turnover				
Dependent Variable	ATO _t	ATO _{t+1} - ATO _t	ATO _{t+2} - ATO _t	ATO _{t+3} - ATO _t
Digital _t	0.047*** (0.015)	0.006*** (0.002)	0.010** (0.004)	0.018*** (0.007)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	13,093	11,698	9,589	7,643
Adj. R ²	0.5759	0.0929	0.1666	0.2269
Panel D: 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 _t	-0.008*** (0.003)	-0.007*** (0.002)	-0.013** (0.006)	-0.012 (0.010)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	13,093	11,692	9,582	7,638
Adj. R ²	0.1302	0.1715	0.1504	0.1429

Table 10: Tech 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 managers for the sub-sample of firms 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 and the presentation portion of the earnings conference call. All regressions control for SIZE, AGE, LEV, MB, SALES GROWTH, R&D, an indicator for missing R&D, CapEx, 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 _t	0.013*** (0.005)	0.002 (0.003)	0.008* (0.004)	0.011* (0.006)
Digital _t	-0.002 (0.002)	-0.001 (0.001)	-0.003 (0.002)	-0.002 (0.003)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,966	1,694	1,243	879
Adj. R ²	0.3410	0.1486	0.2352	0.2717

Appendix A: Digital Terms Regex Definitions

Digital Term	Regex Expression
Analytics:	
analytics	(\btalent analytics\b) (\bmarketing analytics\b) (\bdata analytics\b) (\bpredictive analytics\b) (\butility analytics\b) (\benterprise analytics\b) (\benterprise-wide analytics\b) (\binformation analytics\b) (\binteractive analytics\b) (\bcredit analytics\b) (\banalytics feature) (\badvanced analytics\b) (\bvisual analytics\b) (\banalytics technolog) (\banalytics product) (\banalytics service) (\brisk analytics\b) (\bperformance analytics\b) (\bsophisticated analytics\b) (\breal ?[-]?time analytics\b) (\banalytics engine\b) (\banalytics team) (\bbusiness analytics\b) (\bvideo analytics\b) (\bproprietary analytics\b) (\bpowerful analytics\b) (\bweb analytics\b) (\bpend analytics\b) (\bportfolio analytics\b) (\bcall analytics\b) (\bmarket analytics\b) (\btrading analytics\b) (\bmobile analytics\b) (\benhanced analytics\b) (\bsoftware analytics\b) (\bmedia analytics\b) (\bcustomer analytics\b) (\bdecision analytics\b) (\bmanagement analytics\b) (\bbehavioral analytics\b) (\bhealthcare analytics\b) (\bspeech analytics\b) (\bprocess analytics\b) (\bintegrated analytics\b) (\btraffic analytics\b) (\bwebsite analytics\b) (\bdetailed analytics\b) (\bsoftware analytics\b) (\bcustom analytics\b) (\bprescriptive analytics\b) (\bcomprehensive analytics\b) (\bnew analytics\b) (\brobust analytics\b) (\bapplication analytics\b) (\bcommercial analytics\b) (\bembedded analytics\b) (\bhealth analytics\b) (\beconomic analytics\b) (\bsecurity analytics\b) (\bintelligence analytics\b) (\binformation analytics\b) (\btext analytics\b) (\breporting analytics\b) (\bdeep analytics\b) (\bdesktop analytics\b) (\bpricing analytics\b) (\bin-memory analytics\b) (\bindustry-specific analytics\b) (\bin-depth analytics\b) (\bdatabase analytics\b) (\brich analytics\b) (\bbehavior analytics\b) (\badvertising analytics\b) (\bclinical analytics\b) (\bnetwork analytics\b) (\bprofitability analytics\b) (\bdigital analytics\b) (\bbuilt-in analytics\b) (\bretail (\btrading analytics\b) (\bfraud analytics\b) (\boperational analytics\b) (\bvaluation analytics\b) (\bsearch analytics\b) (\bspecialized analytics\b) (\bintelligent analytics\b) (\bin-database analytics\b) (\bchain analytics\b) (\btime analytics\b)

| (\bstrong analytics\b) | (\bgraph analytics\b) | (\binteraction analytics\b) | (\bcritical analytics\b) | (\binternal analytics\b) | (\bcloud-based analytics\b) | (\bcustomized analytics\b) | (\badaptive analytics\b) | (\blearning analytics\b) | (\bdetection analytics\b) | (\bpersonalized analytics\b) | (\bservice analytics\b) | (\bexpert analytics\b) | (\buser analytics\b) | (\bpost-campaign analytics\b) | (\bfinancial analytics\b) | (\boptimization analytics\b) | (\bcomplex analytics\b) | (\bimage analytics\b) | (\bindustry-leading analytics\b) | (\bonline analytics\b) | (\bstate-of-the-art analytics\b) | (\busage analytics\b) | (\bdata-driven analytics\b) | (\bsupport analytics\b) | (\bpre-trade analytics\b) | (\bassessment analytics\b) | (\boption analytics\b) | (\binnovative analytics\b) | (\bworkforce analytics\b) | (\bcapital analytics\b) | (\blocation analytics\b) | (\binvestment analytics\b) | (\binvestment-related analytics\b) | (\bfeedback analytics\b) | (\bcloud analytics\b) | (\bsales analytics\b) | (\bmortgage analytics\b) | (\bsite analytics\b) | (\bcyber analytics\b) | (\bcutting-edge analytics\b) | (\bpre-collection analytics\b) | (\blarge-scale analytics\b) | (\bsmart analytics\b) | (\bidentity analytics\b) | (\btechnology analytics\b) | (\bautomated analytics\b) | (\banalytics capabilities\b) | (\banalytics solution) | (\banalytics service) | (\banalytics platform) | (\banalytics platform) | (\banalytics software) | (\banalytics product) | (\banalytics application) | (\banalytics engine) | (\banalytics tech) | (\banalytics expertise) | (\banalytics infrastructure) | (\banalytics database)

proprietary
algorithm

(\bproprietary algorithm)

Automation:

automation

(\bautomation solutions\b) | (\bintelligent automation\b) | (\bmarketing automation\b) | (\bprocess automation\b) | (\brobotic process automation\b)

autonomous
technology

(\bautonomous ?[-]?tech)

AI:

artificial
intelligence

(artificial ?[-]?intelligence) | (\bai ?[-]?tech) | (\bai ?[-]?related) | (\bconversational ai\b) | (\bevolutionary ai\b) | (\bevolutionary computing\b)

intelligence
neural net-
work

(\bintelligent ?[-]?system)|(\bcomputer ?[-]?vision)
(\bneural ?[-]?network)

virtual reality

(\bvirtual ?[-]?machine)|(\bvirtual reality)|(\bvirtual agent)|(\bvirtual ?[-]?assistant)

augmented reality	(\baugmented reality\b)
cognitive computing	(\bcognitive computing\b)

Big Data:

big data	(\bbig ?[-]?data) (\bsmart ?[-]?data)
data science	(\bdata ?[-]?scien)
data mining	(\bdata ?[-]?mining)
data lake	(\bdata lake\b)
devops	(\bdevops\b)
digital twin	(\bdigital twin\b)
edge computing	(\bedge computing\b)

Cloud:

cloud platforms	(\bcloud ?[-]?platform) (\bcloud ?[-]?based) (\bcloud ?[-]?computing) (\bcloud ?[-]?deployment)
cloud enablement	(\bcloud enablement\b) (\bhybrid cloud\b)

Digitization:

digitization	(\bdigiti) (\bdigital ?[-]?transformation) (\bdigital ?[-]?revolution)
digital strategy	(\bdigital ?[-]?strateg)
digital marketing	(\bdigital ?[-]?marketing)
business intelligence	(\bbusiness intelligence\b) (\bcustomer intelligence\b) (\boperating intelligence\b)

ML:

biometric	(\bbiometric)
deep learning	(\bdeep ?[-]?learning)
ML	(\bmachine ?[-]?learning)
NLP	(\bnatural ?[-]?language ?[-]?processing)
image recognition	(\bimage ?[-]?recognition) (\bfacial ?[-]?recognition)
speech recognition	(\bspeech ?[-]?recognition)
sentiment analysis	(\bsentiment ?[-]?analysis)

Appendix B: Tech Industry Classification Codes

Industry Codes	Industry Description
Panel A: 3 Digit SIC Codes	
283	Drugs
357	Computer and Office Equipment
366	Communications Equipment
382	Laboratory Apparatus and Analytical, Optical, Measuring, and Controlling
384	Surgical, Medical, and Dental Instruments and Supplies
481	Telephone Communications
482	Telegraph and other Message Communications
489	Communication Services, not elsewhere classified
737	Computer Programming, Data Processing, and other Computer Related
873	Research, Development, and Testing Services
Panel B: 3 Digit NAICS Codes	
334	Computer and Electronic Product Manufacturing
517	Telecommunications
518	Data Processing, Hosting, and Related Services
Panel C: 4 Digit NAICS Codes	
3254	Pharmaceutical and Medicine Manufacturing
3353	Electrical Equipment Manufacturing
3391	Medical Equipment and Supplies Manufacturing
5112	Software Publishers
5133	Telecommunications
5141	Information Services
5415	Computer Systems Design and Related Services
5417	Scientific Research and Development Services
Panel D: 6 Digit GICS Codes	
201040	Electrical Equipment
255020	Internet and Catalog Retail
351010	Health Care Equipment and Supplies
351030	Health Care Technology
352010	Biotechnology
352020	Pharmaceuticals
352030	Life Sciences Tools and Services
451010	Internet & Software Services
451020	Information Technology Services
451030	Software

452010	Communications Equipment
452020	Computers and Peripherals
452030	Electronic Equipment and Instruments
452050	Semiconductor Equipment
453010	Semiconductors
501010	Diversified Telecommunications Services
501020	Wireless Telecommunications Services

Panel E: 8 Digit GICS Codes

20201020	Data Processing Services
20201040	Human Resource Services
25502020	Internet Portal

Appendix C: Variable Definitions

Variable Name	Variable Description
SIZE	Logarithm of Market Capitalization at the fiscal year end ($prccf \times csho$ in Compustat).
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 negative income before extraordinary and special items ($ib - spi$ in Compustat).
β	The beta coefficient estimated from a regression of daily returns on CRSP value-weighted market returns over the window between earnings announcements.
β_{Tech}	The 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 monthly. $R_{NTech,t}$ is the value-weighted portfolio returns of non-tech firms, and the portfolio is re-balanced monthly.
β_{NTech}	The beta coefficient on the non-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 monthly. $R_{NTech,t}$ is the value-weighted portfolio returns of non-tech firms, and the portfolio is re-balanced monthly.
PERS	The AR(1) coefficient in seasonally adjusted quarterly earnings (defined as earnings per share before extraordinary items, $epspxq$ in Compustat), estimated over rolling 5-year windows.
RetVol	Standard deviation of daily returns estimated over the window between earnings announcements.
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.
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.

B2B	Indicator variable that captures if the firm has a major corporate customer recorded (entries not classified as “not reported” or “customers” in the company-type field) in the customer segment data in Compustat.
CAR (-1,1)	The cumulative adjusted returns over a 3-day window. Benchmark returns are estimated using the coefficients from the Carhart, Fama-French Four-Factor model that are estimated based on a (-280, -60) window.
UE	Unexpected earnings is actual minus median earnings 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 100-3 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.
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.
CAR (-1,30)	The cumulative adjusted returns from 1 day before the earnings announcement to 30 days after. Benchmark returns are estimated using the coefficients from the Carhart, Fama-French Four-Factor model that are estimated based on a (-280, -60) window.
ROA	Defined as income before extraordinary items and special items scaled by average total assets from beginning to end of the fiscal period. ($\frac{ib_t - spi_t}{(at_t + at_{t-1})/2}$ in Compustat)
MARGINS	Net margins defined as income before extraordinary and special items scaled by sales. ($\frac{ib - spi}{sale}$ in Compustat)
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 current t and future period $t + s$ sales 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)
R&D	Research and development expenditure intensity, defined as research and development expenditures scaled by assets ($\frac{rdd}{at}$ in Compustat)
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.

Appendix D: Examples of Digital Disclosure

Part 1: Business Description of 10-Ks

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.

Insperty 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.

Part 2: Presentation Portion of Earnings Conference Calls

Visteon Corp., Fiscal Period: 2016Q4

In 2016, we also ramped up our autonomous driving technology platform development, which will focus on the development of fault-tolerant hardware and software to enable centralized processing or sensor information using algorithms based on deep **machine learning** capability. This extends our product portfolio from cockpit HMI and into the very heart of the vehicle driving experience of the future.

Harte Hanks Inc., Fiscal Period: 2015Q1

The revenue challenge is related to a more fundamental weakness in the sales pipeline. We're actively recruiting sales professionals to bolster the existing team. and this new talent will enable us to regain our share of the market growth. The new service offerings from Trillium that I mentioned in last quarter's call, relating to cloud or software as a service and **big data** will take some time to impact revenue performance. But again, i believe that we have invested wisely in the future of our solution. Our pipeline at Trillion is building, but we have some distance still to go, but i don't anticipate catching up to 2014 revenues until much later in the year.

Deckers Outdoor Corp., Fiscal Period:: 2016Q1

Beginning first with our focus on driving profitable growth in our DTC channel. Despite the flat comp in Q1, we feel confident in achieving our low single-digit positive comp target for the year. as a reminder, Q1 is our smallest DTC quarter, in which we do less than 10% of our DTC sales for the year, and it's also when we faced big year-over-year pressure from the stronger dollar. Looking forward, I expect DTC comps to improve due to the following. We have retail-driven product launches in our concept stores and targeted inventory investments for our outlet stores, that I believe will drive traffic and conversion. Our international DTC comps continue to be strong, and have momentum for us to build on in both e-commerce and brick and mortar. we have adjusted our assortments to drive increases in AUR, and we are enhancing our **digital marketing** strategy to be more effective and targeted at driving store and site traffic, by leveraging our CRM and consumer insights data.

Equifax Inc., Fiscal Period: 2015Q3

We believe this opportunity is a nice strategic fit for Equifax. it expands our geographic footprint in a core segment that we know very well. Veda has a strong market position, great products and data assets, they are very profitable, and give us a strong management team in Asia. we believe Equifax's strength in **advanced analytics**, enterprise growth initiative, new product innovation, and others can act to make Veda even stronger.

UnitedHealth Group Inc., Fiscal Period: 2010Q4

We are cultivating distinctive capabilities in connectivity, integrated care and clinical services, **data analytics** and information sharing, revenue cycle management, and compliance. We provide clinical services with more than 10,000 physicians and nurses on staff and an integrated pharmacy management capability. We deliver clinical services to patients directly through our clinics and collaboratively through services offered with care providers.