The “digital” premium: Why does digitalization drive stock returns?

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Abstract

Using the MD&A section of annual firm reports we construct a text-based measure of the socio-technical phenomenon of digitalization, called digital orientation, from 1996 to 2020. Firms with a high digital orientation (digital leaders) are systematically different along several key characteristics like valuation, sales growth, and profitability. A digital orientation strategy, which is long (short) stocks with high (low) digital orientation, earns an equally weighted (value-weighted) monthly six-factor alpha of 0.92% (0.50%) per month, both statistically significant at 1%. The digital leaders’ premium is not explained by industry categories or mispricing but rather constitutes a compensation for systematic factor exposure.

Keywords: Digital orientation, asset pricing, factors, market efficiency, textual analysis, digitalization

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"There is no alternative to digital transformation. Visionary companies will carve out new strategic options for themselves – those that don't adapt, will fail." – Jeff Bezos

1 Introduction

In recent years, firms have been under pressure to transform digitally by reconsidering their business model, devising new digital business strategies, and using digital technologies to innovate (Vial 2019, Wu et al. 2019). Against this backdrop, recent studies in Information Systems indicate that increasing digitalization blurs industrial boundaries and challenges the separation of firms along traditional industrial categories. These industrial boundaries are blurring because digital innovations shift the focus from single products toward smart, connected products (physical devices connected to the internet with computing power), integrate heterogeneous areas of knowledge, and require companies to find ways to access and recombine knowledge rooted in different industries and contexts (Yoo et al. 2012, Seo 2017). Moreover, the editable and reprogrammable nature of digital technology enables the development and deployment of digital innovation across organizations and industries (Kallinikos et al. 2013). Thus, digital innovations transcend established industrial boundaries (Porter and Heppelmann 2014) and lead to a convergence of products and service offerings (Nambisan et al. 2017). Hence, firms are increasingly forced to defend their market against firms from other industries (Seo 2017, Hopp et al. 2018). For example, Microsoft has been competing with telecommunication companies, since its acquisition of Skype (Yoo et al. 2010). Digital innovation may bring together firms in product markets across traditional industry boundaries and make them competitors. At the same time, firms engaging in and driving digital innovation share similar characteristics, such as expertise in digital technology, digital devices, and digital services.

Considering these arguments, digitalization might have unexplored consequences for capital markets. For example, because digital innovation is a cross-industry phenomenon, it seems increasingly inaccurate to classify companies solely based on their industry affiliation. The heterogeneity of digital innovation and digitalization efforts among firms within one industry rather suggests the need for an additional classification to capture the digital convergence across industry boundaries leading to a peer group of digitally leading firms (Yoo et al. 2012, Seo 2017). Because digitalization affects the entire economy, one may further argue that the ability to digitally innovate is not only a useful firm characteristic to differentiate between firms, but also reflects a systematic digital factor with consequences for asset pricing. Accordingly, this study identifies systematic differences in firm characteristics and financial performance depending on firms' orientation toward digital innovation. A firm's orientation toward digital innovation (briefly digital orientation) reflects a firm's past actions as well as future intentions to adopt, use and create digital innovation.

We explore whether the rise of digital innovation across companies has indeed led to the existence of a new asset pricing factor by constructing a firm-specific measure of digital orientation (*DO*) using textual data from the MD&A section of annual firm reports. We rely on the MD&A section, since it is not audited and reflects the management's thoughts and opinions. Our methodology is similar to earlier works like Loughran and McDonald (2011), Hoberg and Philipps (2010, 2016), and Hillert et al. (2014), which, for instance, derive sentiment from text. Specifically, to obtain a *DO* measure for each firm, we follow a bag-of-words approach to parse the 10-Ks and derive vectors of words and word counts. Our digital innovation dictionary is based on validated word lists from Information Systems literature and is theoretically grounded in the notion of the layered architecture of digital technology embedded in digital innovation (Yoo et al. 2010). It measures the extent to which a firm creates and uses digital innovation using word lists of four dimensions: device, network, service, and content layer (Yoo et al. 2010). As pointed out by Loughran and McDonald (2016), the dictionary approach is easy to understand and easy to replicate. Nevertheless, despite its simplicity, our measure is well able to explain important differences between firms beyond industry affiliation.

Our analyses yields two major findings. First, we demonstrate that firms with a high digital orientation, which we refer to as digital leaders, have distinct characteristics compared to firms with a low digital orientation. Digital leaders have, among other characteristics, significantly higher valuation, considerably higher sales growth, substantially lower cost ratios, significantly higher volatility, and substantially lower profitability in the short term but significantly higher profitability in the long term. Consistent with our expectations, digital leaders are also significantly younger and have a significantly higher (market) risk.

While our digital orientation (*DO*) measure is thus able to describe firm heterogeneity across important dimensions, it is also a variable, which we cannot easily account for by other characteristics. Multivariate regressions to explain firms' digital orientation show low R^2 values ranging between 1% and 3%, even though these regressions contain explanatory variables like firm size, firm age, or Nasdaq membership, among others, which seem naturally linked to a firm's digital orientation. Even after additionally controlling for industry affiliation, the explanatory power increases only to a modest R^2 of 16%. We conclude that our text-based *DO* measure is a unique variable to describe a firm's digital orientation, which is not captured well by other characteristics. Thereby, we are able to show that firms with a high *DO* (i.e., digital leaders) are systematically different from other firms of their respective traditional industry category and form their own peer group beyond traditional industry categorizations.

Second, studying the relation between digitalization and stock returns and using our measure of digital orientation, we determine the performance of a digital orientation strategy. This strategy is long (short) in stocks of firms in the highest (lowest) digital orientation quintile as its performance is referred to as the digital leaders' premium or digital premium in the following. The equally weighted monthly return of this quintile (5) minus quintile (1) strategy is 0.69% with a t-statistic of 2.48. This effect is not driven by the smallest and most illiquid firms, because we restrict the analysis to all firms with a market capitalization above the second NYSE size decile. Doing so, we address critical assessments from earlier research (e.g., Fama and French 2008, Green et al. 2017, Hou et al. 2020) that most anomalies are concentrated in stocks with limited economic importance.[1] Furthermore, the six-factor alpha of the equally weighted portfolio, which controls for exposure to momentum and the five factors of Fama and French (2015), is higher at 0.92% per month, and it has a much higher statistical significance with a t-statistic of 6.51. Digital leaders have a high negative exposure against the profitability factor *RMW* and the *HML* value factor of Fama and French. These relations are consistent with the fact that firms with a high digital orientation have lower profitability and a higher valuation. The factor exposures explain why the alpha of the strategy is substantially above its raw return. We also observe a statistically significant six-factor alpha if we form a value-weighted long-short portfolio (0.50% per month; t-statistic: 4.22).

To verify that our results are robust we conduct several additional tests regarding modifications in the calculation of the *DO* measure, controls for industry membership, changes in

[1] Hou et al. (2020, p. 2) point out that "microcaps represent only 3.2% of the aggregate market capitalization but 60.7% of the number of stocks." Green et al. (2017) advocate the exclusion of micro-caps below the second NYSE size decile to identify return drivers with high economic importance. We follow this procedure in our main analyses. In a robustness test, we find that our conclusions continue to hold if we expand the sample to smaller firms.

the sample data set, and changes in the dictionary. First, we account for the importance of each word (such as "software" or "cloud") by adjusting for the so-called term-frequency-inverse document frequency (tf-idf) formula of Loughran and McDonald (2011). Next, we calculate the *DO* measure using alternative sections of the 10-K reports. These modifications have minimal impact on the six-factor alphas for the equally weighted and value-weighted long-short portfolios, which remain statistically significant at the 1% level.

Second, to account for industry effects, we use industry-adjusted returns that are calculated as the stock's return minus its industry return, using the 48 industries of Fama and French (1997), denoted as FF48, and the text-based network industries from Hoberg and Phillips (2010), denoted as TNIC. We find that the equally weighted and industry-adjusted six-factor alpha returns are slightly lower, but the statistical significance is slightly higher. The high statistical significance of the alpha for the *DO* strategy also remains if we use the excess return of the Nasdaq Composite Index as a market factor instead of the broad CRSP value-weighted market index.

Third, we also modify the sample data set by excluding the dot.com bubble of 1998/99 and high sentiment periods, according to the sentiment index of Baker and Wurgler (2006). These exclusions reduce the six-factor alphas slightly but do not change the level of statistical significance. The same conclusion applies if we include micro-cap stocks in the portfolio selection.

Finally, we use an alternative dictionary to measure firms' orientation toward digital innovation. This dictionary is based on the yearly published Hype Cycle by Gartner, which tracks the maturity of a new, promising digital innovation across time. The Hype Cycle displays a digital innovation's progress from the market entrance to maturity by considering both a technology's expectations and achievements. We use two versions of the dictionary, one covering the full sample list of words and one updated yearly containing all digital innovation that have appeared in the Hype Cycle so far. The results for both versions of the alternative dictionary are consistent with our baseline findings, showing a significant difference between digital leaders and laggards in the long-short portfolio returns.

Overall, the documented pattern appears very robust to reasonable changes in the methodology. If we control appropriately for the existence of the profitability factor, the return difference between digital leaders and digital laggards is economically large and statistically highly significant.

There may be several explanations why digital leaders exhibit above-average returns. Therefore, we apply additional tests. As outlined above, a high digital orientation is associated with lower current profitability and higher growth rates, implying a higher cash flow duration. One potential explanation for the digital return premium is hence the so-called discount rate channel hypothesis, which proposes that these stocks profited to a larger extent from a low-interest rate environment and loose monetary policy in recent decades (e.g., Chakraborty et al. 2020). In other words, the outperformance of digital leaders against digital laggards could stem from unexpected discount rate shocks during our sample period.

We apply two tests to investigate the discount rate channel hypothesis. First, we regress the *DO* long-short return against a dummy variable which indicates one of the four rounds of quantitative easing (QE) in our sample period (QE1 to QE4). If discount rate news is responsible for the existence of the digital premium, particularly high returns should be observed during quantitative easing periods; however, we do not find supportive evidence in this regard. Second, we compute daily long-short returns for the *DO* strategy and examine if the returns are elevated during FED meeting days and days at which the FED minutes were released. Arguably, these are the days when news about monetary policy changes hit the market. However, we do not find statistically significantly higher returns for digital leaders on these FED days in comparison to other days. Overall, we conclude that the discount rate channel hypothesis is not supported in our data.

Another explanation for the return anomaly could be that the abnormal returns of the *DO* strategy are a compensation for systematic factor exposure or a sign of market inefficiency, i.e., mispricing. Mispricing could stem from investor misperceptions about the growth or earnings potential of stocks with a high digital orientation. Our sample period from 1996 to 2020 coincides with a period of supposedly increasing market efficiency (e.g., McLean and Pontiff 2016, Green et al. 2017). Moreover, we focus on stocks of large firms for which most return anomalies are substantially less pronounced (e.g., Hou et al. 2020). This makes the market inefficiency explanation less appealing. To formally test if the digital premium is due to mispricing, we relate abnormal three-day cumulative stock returns around quarterly earnings announcements to firms' digital orientation. If investors underestimated the earnings and growth prospects of high digitalization stocks, we would expect to find particularly high returns at these earnings announcement dates. We also compute the analyst forecast bias (actual quarterly earnings per share

(EPS) minus the median analyst forecast EPS, scaled by stock price) to test if analysts consistently underestimate the earnings of stocks with a high digital orientation. Our tests do not provide evidence supporting the mispricing hypothesis, suggesting that compensation for systemic risk exposure is a likely explanation.

A systematic risk compensation may exist because new information about the potential of new digital technologies and future cash flows is first revealed in leading firms, which thereby act as early indicators for the growth prospects of other firms. Thus, digital leaders may have a risk premium because they are the first to provide a resolution of uncertainty that comes from the digital transformation of the overall economy. This uncertainty comes from the challenges of predicting which technologies and business models will succeed, as demonstrated, for instance, by neural networks. Although neural networks were first explored in the 1940s, it was not until the last 15 years, with the advent of more powerful computing, that they gained widespread popularity and commercial interest. Today, a neural network forms the basis of artificial intelligence chatbots like ChatGPT. For other digital technologies and business models the outcomes are still unclear. For example, the metaverse offers significant opportunities for early adopters, but commercial success in this emerging field is arguably still uncertain as of today. First movers must navigate substantial risks and uncertainties, pointing to a potential risk premium for digital leaders.

The idea of a risk premium for digital leaders is also broadly consistent with the reasoning in Croce et al. (2023). In their study, the authors theoretically argue and empirically show that leading industries, i.e., those that are first to resolve uncertainty about the overall economic growth, carry a risk premium. Our study differs from Croce et al. (2023) in that we do not study traditional industries but the return implications of the digital transformation which affects all industries.

In light of these arguments, we test if the digital orientation factor (denoted as *DO* factor in the following) should be considered as a priced systematic factor. We run return regressions for every stock to measure its historical exposure against the *DO* factor. We then form five stock portfolios that differ in their exposure to the *DO* factor but have, on average, the same *DO* value. It follows that the quintile (5) minus quintile (1) portfolio has a strong positive exposure against the *DO* factor but is neutral with respect to the digital orientation characteristic. Such "characteristics-vs.-covariances" tests are an established tool in the literature to separate between the systematic component of a factor (i.e., its factor loading) and the underlying firm-specific characteristic (Daniel and Titman 1997, Davis et al. 2000, Hirshleifer et al. 2012, Daniel et al.

2020). The equally weighted (value-weighted) monthly six alpha factor of the long-short *DO* factor exposure portfolio is 0.93% (0.53%). Both alphas are statistically significant at the 1% level with t-statistics of 4.14 and 2.69, respectively. As expected, this outperformance declines to 0.28% (equally weighted) and 0.20% (value-weighted) per month once we add the *DO* factor itself as a control variable in the regressions. Overall, the evidence is consistent with the *DO* factor being a new systematic factor and that exposure to this factor is priced in the cross-section of stock returns.

This research moves beyond the insights of existing literature in the following distinct ways. First, we contribute to the fast-growing field of research using textual analysis (Loughran and McDonald 2016). Earlier research has relied on textual analyses to assess the link between firms' financial performance and accounting documents' readability (e.g., Li 2008, Guay et al. 2016), the adoption of seven specific digital technologies (Chen and Srinivasan 2023), changes in the language and construction of annual reports (e.g., Cohen et al. 2020), document similarity, and the sentiment prevailing in annual reports or media (e.g., Tetlock 2007, Loughran and McDonald 2011, Hillert et al. 2014, Hillert et al. 2021). We use a bag-of-words approach, on which sentiment analysis is also based, but use the approach to assess the extent to which firms have used and created digital innovation.

The most closely related study regarding the use of textual analysis is the contemporaneous paper by Chen and Srinivasan (2023) who apply a word list encompassing seven digital technologies. Our paper differs in several significant ways. We adopt a sociotechnical perspective on digitalization by drawing on recent literature on digital innovation, which highlights its socio-technical nature. This perspective encompasses not only the technology but also, for instance, services and contents that it entails. Our measurement of digital orientation is based on validated word lists from Information Systems literature, which is theoretically grounded in the notion of the layered architecture of digital technology embedded in digital innovation (Yoo et al. 2012).

Existing research has relied on firms' R&D expenditure or patent data to study innovation (e.g., Fang et al. 2014). Due to the distinct nature of digital innovation, such traditional approaches to measuring intangible assets cannot fully account for firms' innovation activities that rely on digital technologies. The reasons are as follows: Firms' R&D expenditures are representative of innovation activities, particularly in the manufacturing sector. However, in the service sector (e.g., financial industry) R&D expenditure is frequently not reported. Similar problems exist for patents, another frequently used measure of firms' innovation activities. While patents measure product innovation, they cannot account for other types of innovation, such as business model or process innovations, which constitute significant components of firms' innovation activities. By following a bag-of-words approach, we can derive a comprehensive measure of firms' orientation towards digital innovation. The measure, which is well grounded in extant knowledge on the socio-technical phenomenon of digital innovation in the Information Systems field, allows us to draw conclusions about firms' digital orientation toward digital innovation and its connection to firms' financial performance.

Second, we contribute to the digital innovation literature, which argues that the very nature of digital technology blurs industry boundaries (Kallinikos et al. 2013, Nambisan et al. 2017, Seo 2017), by demonstrating empirically that digitalization occurs among a group of companies across traditional industry boundaries. With our study, we are among the first to test the theoretical argument of industry convergence and show that there is a convergence driven by digital orientation. Thus, we demonstrate that industry classification does not explain higher returns among digital leaders. At the same time, we shed more light on the phenomenon of convergence by showing that it is not so much about industries (according to traditional categories) that are converging, but firms across industries that form a new peer group beyond traditional industry categories. We show that firms with a high digital orientation (digital leaders) exhibit distinct characteristics compared to firms with a low digital orientation, such as considerably higher sales growth, and substantially lower cost ratios.

Third, we contribute to the literature on asset pricing for intangible assets by proposing a *DO* factor. Thus far, existing asset pricing models, such as the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model, or the Fama and French (2018) six-factor model still seem to fail to account for a firm's intangible assets, and in particular digital innovation. Yet, intangible assets account for around one-third of investment volume in the U.S. market, making them economically significant (Corrado and Hulten 2010). Accordingly, existing research has pointed to our incomplete understanding of the link between intangible assets and asset pricing in financial markets (Daniel and Titman 2006). The study by Chen and Srinivasan (2023) demonstrates that nontech firms, which are early adopters of digital technologies show similarities with tech firms in terms of economic performance, and have 0.44% higher risk-adjusted stock returns per month. Our paper differs in that we refer to asset pricing literature and demonstrate that digital orientation is an intangible asset that significantly drives the price premium of firms' respective stocks. Moreover, we empirically test competing explanations for the digital premium and report supportive evidence that it can be traced back to a risk compensation for the systematic nature of intangible assets in the digital age.

The paper is organized as follows. Section 2 outlines the theoretical foundation by reviewing the literature on digital innovation from the field of Information Systems and builds the foundation for constructing our text-based *DO* measure, described in section 3. Additionally, section 3 provides details of the data sources, descriptive statistics, and the analysis of our measure of digital orientation. Section 4 compares digital leaders, firms with a high digital orientation, to digital laggards, firms with a low digital orientation. We also present the results of portfolio tests based on the *DO* measure and historical *DO* factor exposure. Additionally, we conduct robustness tests and explore the question of why firms with a high digital orientation have above-average returns. Section 5 concludes.

2 Theoretical Foundation

Extant literature in Information Systems discusses the characteristics and effects of digital innovation and argues, among others, that the distinct properties of digital technology support the creation, diffusion, and use of digital innovation. Digital innovations are defined as "carrying out new combinations of digital and physical components to produce novel products" (Yoo et al. 2010, p. 725). These digital innovations are eventually deeply embedded in most organizational processes and market offerings, shape strategy, and unfold disruptive potential changing entire industries (Bharadwaj et al. 2013, Vial 2019). This disruptive potential stems from digital innovations' ability to enable the blurring of industrial boundaries, as we outline in the following. Since firms are under pressure to "[…] harness outside expertise and ingenuity on an unprecedented scale", organizations need to facilitate increasingly distributed ways to create digital innovation. These distributed sources of digital innovation are mainly associated with digital technologies that enable various actors to cooperate within innovation networks across organizational boundaries (Lyytinen et al. 2016), often beyond the control of the original innovator (Bogers and West 2012), and regardless of industry boundaries. In addition, digital innovations shift the focus from single products toward connected products, which transcend established industrial boundaries (Porter and Heppelmann 2014) and challenge the separation of firms along industrial areas.

Moreover, firms strive to embed digital technology in physical products ("smart products") (Yoo et al. 2012) and to provide more and more functions in the form of digital objects that can be easily changed and enhanced (Faulkner and Runde 2019). Consequently, similar digital technology is used in different products, regardless of industry boundaries. In that regard, firms across industries build up similar technological competencies and rely on the same group of suppliers. In a similar vein, digital devices process any type of digital information (Tilson et al. 2010), which leads to the similarity of devices across industries. Eventually, smart products lead to the convergence of user experiences, as demonstrated by smartphones that bring together various communication, entertainment, and computation experiences (Yoo et al. 2012). For example, as already mentioned, Microsoft competes with established telecommunication companies since the acquisition of Skype (Yoo et al. 2010). Consequently, organizations from different industries compete with each other, while relying on similar digital technologies.

At the same time, the creation of digital innovation leads to a fundamental transformation in firms' IT, structure, and strategy (Tumbas et al. 2018, Vial 2019). These transformation processes are driven by the new competitive situation that firms face, which causes them to shift their value proposition and value creation process (Vial 2019, Wessel et al. 2021). Accordingly, firms' digitalization is characterized by socio-technical changes, ranging from major technological adaptations to shifts in firms' structure and processes. These changes affect all firms and may therefore impact the valuation of their stocks systematically. On the one hand, digitalization offers firms the potential to conquer new markets and discover new revenue streams. On the other hand, wide-ranging changes to a firm's structure and processes are also associated with risks that the invested resources cannot be reaped in the long run. Accordingly, digital innovation is not only limited to product innovation. It also encompasses radical business model innovation, on the one hand, and incremental process innovation within companies, on the other hand.

The disruptive and transformational nature of digital innovation can be traced back to distinct architectural characteristics of digital technology. Yoo et al. (2010) identify that digital technology embedded in digital innovation follows a layered modular architecture consisting of the four layers of devices, networks, services, and contents. These loosely coupled layers are product-agnostic (Yoo et al. 2010) and pave the way to be applied across diverse industries and markets. Yoo et al. (2010) discuss the four layers in detail. The device layer encompasses physical machinery, such as computer hardware, and control and maintenance capabilities, such as an operating system. For example, the physical smartphone and its operating system would be assigned to the device layer. The network layer encompasses physical transport mechanisms, such as cables and transmitters, and logical network protocols, such as TCP/IP. Staying with the smartphone example, 5G connectivity and the respective communication protocols form examples of the network layer.

The content layer encompasses data, such as videos, but also directory information on where to find which data, copyright, or encoding methods. Photos on a smartphone or movies on servers are examples of this layer. The service layer provides the functionality for users to deal with content, such as storing, creating, or streaming it. The four layers are only loosely coupled, and each layer can be designed with low consideration of the other layers. This allows companies to offer products and services that concentrate on certain layers, cover several layers, or combine their offerings with other companies' offerings focusing on the same or other layers. Thus, digital innovation might be created within a certain layer or across layers. In sum, this architecture spurs an unprecedented level of generativity, where one digital innovation is used to create another one, which in turn enhances the first one, and so on (Yoo et al. 2010). This, in turn, leads to fluid product boundaries, which also enables serving different markets.

The described four layers of the modular layered architecture form the starting point for our analysis. In the next section, we create a measure of digital orientation that assesses firms' innovation activities across all four layers in order to derive an overall measure of firms' orientation toward digital innovation. We then use the derived measure of digital orientation to explore the link between firms' level of digital innovation and asset pricing (see sections 4 and 5).

3 Data and Methodology

We use firms' 10-K Management's Discussion and Analysis (MD&A) and an easy-to-use and replicable bag-of-words approach to compute firms' digital orientation (*DO*) for each firm-year. We then match this measure with data on all common stocks traded on the main stock exchanges (NYSE, AMEX, and NASDAQ) in the United States available in both CRSP and Compustat between 1996 and 2020. We outline our approach in more detail in the following.

3.1 Digital Orientation and Text Analysis of Firms' 10-Ks

We rely on computer-aided text analysis to measure the extent to which firms create and use digital innovation by deriving a quantitative measure from firms' annual reports. We web-crawl the SEC

Edgar database for all 10-K, 10K-405, and 10K-KSB filings, excluding amended documents. This results in a sample of 158,631 reports. Our sample is reduced to 91,151 reports when matching the reports with data from Compustat and CRSP (see section 3.2.). Our data collection is restricted by the availability of the annual reports in the SEC Edgar database, since electronic filing was only mandated in 1996.

Following extant research (e.g., Loughran and McDonald 2011), our baseline text analysis is constricted to the MD&A section since it is not audited and reflects the management's thoughts and opinions. We use regular expressions in Python to extract the relevant MD&A section and firm information, such as the central index key (CIK), the report type, fiscal year, and report date for each 10-K. To account for the different formats of the reports and to ensure that the right section of the report was covered for all companies in the sample, we iteratively revised our Python code until we were confident that the regular expressions we used could identify the MD&A section for all 10-Ks.

In the next step, we quantify the MD&A by using a dictionary approach to measure *DO*. Thus, we follow a bag-of-words approach to parse the 10-Ks and derive vectors of words and word counts. This approach has been used in the Finance discipline, for instance, to measure negative sentiment (Tetlock 2007, Loughran and McDonald 2011, Hillert et al. 2014, Loughran and McDonald 2016, Hillert et al. 2021). Our dictionary is based on word lists developed and validated by Kindermann et al. (2021), who originally measured firms' digitalization in general, using word lists of four dimensions: digital technology scope, digital capabilities, digital ecosystem coordination, and digital architecture configuration. We adapted this dictionary using the layered modular architecture model by Yoo et al. (2010) to achieve a categorization and explicit binding of words to the four loosely coupled layers: device, network, service, and content layer (Yoo et al. 2010). We use the characterization of each layer, as outlined in section 2, to categorize each word. We also include synonyms and alternative spellings in our dictionary. The number of words related to digital innovation in a firm's MD&A section reflects management's past actions as well as future intentions to use and develop digital innovation. Accordingly, we call the derived measure digital orientation or *DO*.

Moreover, we add terms that are related to existing elements of the wordlist and that are significant in the context of digital innovation. For instance, we include the terms "internet protocol" and "local area network" on the network layer as they build essential components of the "internet". On the content layer, we complement the list with terms related to "data", such as "data analytics" and "metadata". Occupational titles or roles, such as "or "programmer" or "chief information officer" are excluded, as they cannot be clearly assigned to a distinct layer. Moreover, words where no clear link to digital innovation exists, such as "ubiquitous" and "advanced technology" are excluded in our dictionary.

Table 1 depicts our dictionary of digital innovation with its four dimensions and the corresponding word lists. Using this dictionary, we derive a measure of firms' digital orientation and explore whether convergence processes across industries occurring due to the rise of digital innovation give rise to a new asset pricing factor that can explain similarities across firms.

Table 1: Digital innovation dictionary	
Device Layer	3-D printer, 3D printer, 3-D printers, 3D printers, computer, computers, compute, computing, control system, control systems, cybernetics, cyber physical system, cyber physical systems, desktop, desktops, digital device, digital devices, drone, drones, electronic, electronics, hardware, information system, information systems, information technology, information technologies, informatics, integrated solution, integrated solutions, IT infrastructure, IT infrastructures, IT solution, IT solutions, IT system, IT systems, operating system, operating systems, phone, phones, resource planning system, resource planning systems, robot, robots, sensor, sensors, smartphone, smartphones, software, tablet, tablets
Network Layer	bandwidth, bandwidths, bluetooth, broadband, connectivity, highspeed, high-speed, high speed, internet-based, internet, IP, internet protocol, LAN, local area network, mobile, network infrastructure, network infrastructures, network service, network services, network standard, network standards, online, on-line, peer-to-peer protocol, P2P protocol, wifi, wi-fi, wireless
Service Layer	3-D printed, 3D printed, 3D printing, 3-D printing, additive manufacturing, algorithm, algorithmic, algorithms, AI, analytics, analytical tool, analytical tools, app, apps, app-based, API, APIs, application programming interface, application programming interfaces, artificial intelligence, autonomous, automated, automating, automation, blockchain, bot, bots, cloud, cloud-based, cloudbased, cyberspace, cyber space, cybersecurity, cyber security, digital platform, digital platforms, deep learning, ecommerce, e-commerce, fintech, homepage, homepages, home page, home pages, information security, insurtech, internet of things, internet-of-things, IoT, legaltech, machine learning, open source, open-source, robotics, robotic, SaaS, self-driving, smart, software as a service, software-as-a-service, suptech, technology platform, technology platforms, telematic, telematics, telemedicine, web, web-based, webs, website, websites
Contents Layer	big data, data, data analytics, data network, data networks, data service, data services, data transmission, data-dependent, data-driven, data-enbaled, data-intensive, database, databases, digital, digitalization, digitalisation, digitally, digitization, digitisation, digitalized, digitalised, interface, GUI, graphical user interface, metadata, meta data, multichannel, multi-channel, omnichannel, omni-channel, real time, real-time, realtime, remote monitoring, social media, social technology, social technologies, streaming, user experience, UX, user interface, UI, virtual, virtualization, virtualisation, virtuality, virtualities, virtualize, virtualized

In order to derive a comparable digital orientation measure, we divide the number of words counted by the overall lengths of the MD&A section without stopwords (e.g., the, is, at, which). Thus, our measure of digital orientation (*DO* measure) is computed using the following formula:

$$DO = \frac{No.words\ digital\ innovation}{No.words\ in\ MD\&A\ section\ without\ stopwords} \qquad (1)$$

Table 2 depicts the summary statistics for the *DO* measure. Across the 91,151 10-K reports analyzed in our final sample, the average value of the *DO* measure is 0.0024 (0.24%). The device and content layer account for larger proportions of the total measure than the network and service layer. Across firm-years, we see a considerable variation, where firms with the highest *DO* value deviate significantly from the mean score across all firm-years. Further, many firm-years have a *DO* value of 0, leading to a right-skewed distribution of the measure. This is especially evident in the 25th percentile. Except for the aggregated measure of *DO* (Total), the 25th percentile only includes companies with a *DO* value of 0.

Table 2: Summary statistics of the digital orientation measure

	Mean	Standard Deviation	Minimum	25th Percentile	Median	75th Percentile	Max
Total	0.0024	0.0042	0.0000	0.0002	0.0009	0.0027	0.0909
Device Layer	0.0008	0.0015	0.0000	0.0000	0.0002	0.0008	0.0405
Network Layer	0.0005	0.0017	0.0000	0.0000	0.0000	0.0002	0.0460
Service Layer	0.0003	0.0010	0.0000	0.0000	0.0000	0.0001	0.0313
Content Layer	0.0009	0.0028	0.0000	0.0000	0.0003	0.0009	0.0909

Table 2 shows the summary statistics of the digital orientation measure in total and separately for each layer. The digital orientation measure represents the frequency of words in the digital innovation dictionary (see Table 1) relative to the overall number of words in the MD&A section of a firm's 10-K without stopwords. The analysis is based on 91,151 10-Ks covering the timespan 1996 to 2020 included in the final sample of the analysis.

Figure 1 illustrates the measure's development over time, both for the aggregated *DO* measure and the distinct layers. We observe a peak of the aggregated measure around 2000, which can be attributed to the dot-com bubble, excessive speculation with internet-related stocks that reached its peak in March 2000. After this peak, the value of the *DO* measure across firms decreases and then stabilizes at a high level. Starting around 2010, we can observe a slight increase in the *DO* measure that has been more pronounced in recent years. Figure 1 also illustrates that this evolution of the aggregated *DO* measure can be attributed to different developments across the layers. The strong peak around 2000 is driven primarily by a sharp increase in the device and network layer. Thereafter, the device and network layer measures initially drop and then continue to decrease slightly over time. In contrast, the service and content layer measures are characterized by a steady increase over the observation period.

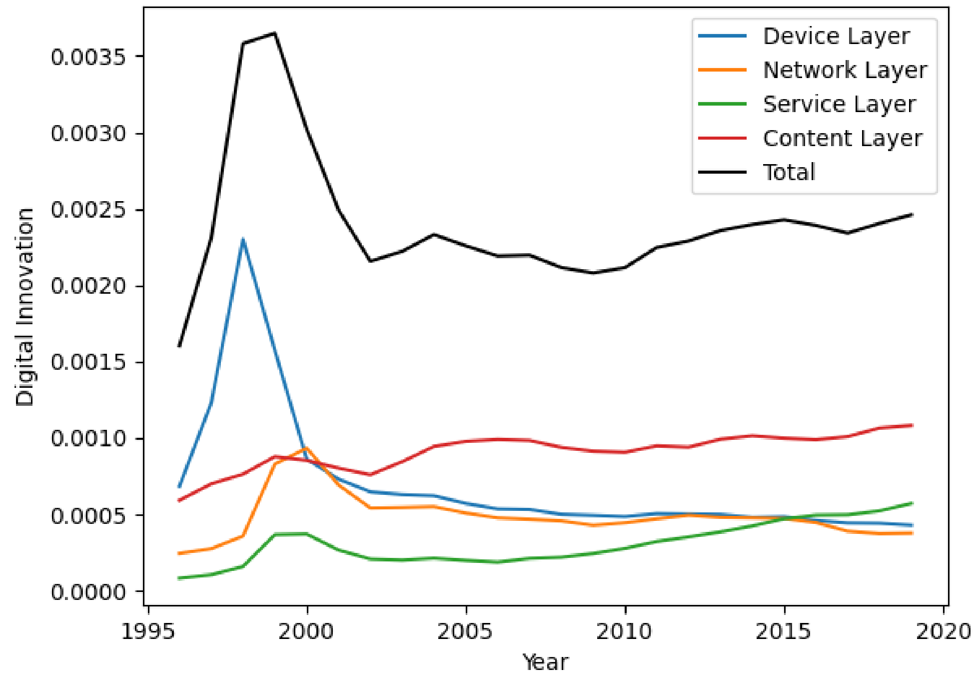

Figure 1. Digital orientation over time – Total and layers

This figure illustrates the measure of digital orientation in total and separately for each layer over time. The digital orientation measure represents the frequency of words in the digital innovation dictionary (see Table 1) relative to the overall number of words in the MD&A section of a firm's 10-K without stopwords. The analysis is based on 91,151 10-Ks covering the timespan 1996 to 2020 included in the final sample of the analysis.

Table 3 depicts the most frequent words in firms' 10-Ks across time. Unsurprisingly, very generic terms, such as software, data, internet, computer, and hardware, top the list. At the same time, we can also find more specific terms associated with *DO* in this list, such as "cloud", "analytics", and "broadband". Table 3 also illustrates the earlier observations with respect to the evolution of the *DO* measure across time. Words belonging to the device layer, such as "software", "computer", and "hardware", were most frequent between 1996 and 2010; after that, their frequency decreased but remained at a high level. For the most frequent words of the network layer (i.e., internet, online, wireless), the frequency peak primarily occurred slightly delayed between 2001 and 2010. Some words belonging to the content and service layer, however, reached their frequency peak between 2001 and 2010 (e.g., digital, web, database) and others between 2011 and 2020 (e.g., data, website, e-commerce, cloud).

Table 3: Thirty most frequent words of digital innovation dictionary in firms' 10-Ks					
Words	**Total**	**1996-2000**	**2001-2010**	**2011-2020**	**Layer**
software	353,186	78,352	172,760	102,074	Device
data	322,501	34,316	138,779	149,406	Content
internet	79,136	16,737	47,738	14,661	Network
computer	76,546	35,888	29,603	11,055	Device
hardware	67,576	16,796	30,071	20,709	Device
digital	60,526	6,044	27,286	27,196	Content
wireless	55,714	6,212	34,244	15,258	Network
online	48,932	5,066	22,337	21,529	Network
electronic	44,659	7,666	22,749	14,244	Device
information technology	42,824	6,836	18,357	17,631	Device
mobile	40,842	2,180	15,409	23,253	Network
web	28,549	5,731	17,242	5,576	Service
electronics	27,999	3,587	13,920	10,492	Device
information systems	23,364	8,846	9,629	4,889	Device
broadband	20,933	1,261	13,076	6,596	Network
website	18,197	884	7,596	9,717	Service
e-commerce	16,449	1,626	7,051	7,772	Service
computing	14,921	2,149	6,333	6,439	Device
cloud	12,327	29	240	12,058	Service
database	11,884	2,340	6,879	2,665	Content
computers	11,564	4,378	5,011	2,175	Device
IP	11,450	715	6,173	4,562	Network
automation	11,243	1,699	5,383	4,161	Service
websites	10,679	401	3,795	6,483	Service
automated	10,072	1,996	4,782	3,294	Service
connectivity	8,515	1,051	3,897	3,567	Network
phone	8,378	915	4,485	2,978	Device
analytics	8,067	78	1,517	6,472	Content
smart	8,065	609	2,941	4,515	Service
desktop	6,506	1,885	2,783	1,838	Device

Table 3 shows the 30 most frequently used words of the digital innovation dictionary in the MD&A section of firms' 10Ks in total and separately for each layer. For each word, the absolute frequency in the sample, the frequency for the three time periods 1996-2000, 2001-2010, 2011-2020, and the respective layer in the layered architecture of digitalization (see section 2) are depicted. The analysis is based on 91,151 10-Ks covering the timespan 1996 to 2020 included in the final sample of the analysis.

Since generic terms, such as software, data, internet, computer, and hardware, occur with high frequency (see Table 3), we also calculate an alternative *DO* measure. This alternative measure accounts for the importance of a word within the entire sample by adjusting for the so-called term-frequency-inverse document frequency (tf-idf) based on Loughran and McDonald (2011). The weighted measure of each word w_{ij} is calculated using the following formula:

$$w_{ij} = \left(1 + \log\left(tf_{i,j}\right)\right) * \log\left(\frac{N}{df_i}\right) \qquad (2)$$

$tf_{i,j}$ is the raw count of the ith word in the jth annual report, N measures the total number of annual reports and df_i represents the number of annual reports where the ith word occurs at least once.

3.2 Financial Data and Analysis

We match each 10-K report and the derived *DO* measure to data of the CRSP and COMPUSTAT database using the CIK and report date. We perform multiple rounds of matching by first using the exact report date and then time windows around the report and filing date for the merge to Compustat/CRSP data. Since Edgar also included 10-Ks of firms only traded over-the-counter (OTC), firms temporarily not listed on a stock exchange, and asset-backed partnerships, which are required to file with the SEC but are not included in Compustat/CRSP (CRSP 2021), our initial sample is reduced during the matching process. We also filter out firm-years that did not belong to common stocks traded on the main stock exchanges (NYSE, AMEX, and NASDAQ) in the United States. Overall, the final sample constitutes 91,151 firm-years with 24 time periods and 11,613 unique firms. In order to prevent that outliers drive our results, we use winsorization by setting all variables derived from financial statements in the bottom and top one percentiles to the value of the variables at the 1st and 99th percentile.

To study the determinants of *DO*, we run cross-sectional Fama/MacBeth regressions (Fama and MacBeth 1973) using firm age, firm size, membership in the S&P 500 and NASDAQ, and analyst coverage as explanatory variables. The construction of these variables follows earlier literature and is described in detail in Appendix A. Our baseline model uses the following regression formula:

$$\begin{aligned}\ln(\boldsymbol{DO}) = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\ln(\boldsymbol{age}) + \boldsymbol{\beta_2}\ln(\boldsymbol{size}) + \boldsymbol{\beta_3}\,\boldsymbol{S\&P}\ \mathbf{500} + \boldsymbol{\beta_4}\,\boldsymbol{NASDAQ} + \\ \boldsymbol{\beta_5}\ln(\mathbf{1} + \boldsymbol{analyst}) + \boldsymbol{\epsilon_{DO}} \qquad (3)\end{aligned}$$

Table 4 depicts the results of the cross-sectional Fama/MacBeth regressions to explain firms' (natural logarithm of) *DO*. We start with univariate regressions that contain only one of the above mentioned explanatory variables. As illustrated by specification (1), a firm's age offers explanatory power for a firm's *DO* by adding an adjusted R^2 of 1.50%. With increasing age, the *DO* of a firm decreases. Whereas a firm's size, measured as the firm's natural logarithm of market capitalization, and the membership in the S&P 500 offer low explanatory power, NASDAQ membership is another important determinant of a firm's *DO* with a R^2 of 1.50%, as the univariate specifications (2) to (4) illustrate. Analyst coverage explains *DO* to a lesser, but still statistically significant extent (see specification (5)).

Table 4: Multivariate regression to explain digital orientation

Variables	Firm Age (1)	Firm Size (2)	S&P 500 (3)	NASDAQ (4)	Analyst (5)	1 + Firm Size (6)	6 + S&P 500 (7)	7 + NASDAQ (8)	Baseline (9)	Baseline + R&D Intensity (10)	Baseline + Industry Controls (11)
Constant	0.0034*** (11.23)	0.0025*** (11.66)	0.0024*** (18.18)	0.0018*** (19.20)	0.0021*** (13.71)	0.0032*** (9.70)	0.0033*** (9.83)	0.0023*** (9.03)	0.0027*** (10.31)	0.0029*** (9.93)	0.0010*** (3.51)
Firm Age	-0.0004*** (-4.20)					-0.0004*** (-4.59)	-0.0004*** (-4.65)	-0.0004*** (-5.33)	-0.0004*** (-4.88)	-0.0005*** (-5.04)	-0.0002*** (-4.20)
Firm Size		0.0000 (-0.89)				0.0000* (1.83)	0.0000 (0.57)	0.0001*** (4.51)	-0.0001** (-2.54)	-0.0000 (-0.15)	-0.0000 (-0.76)
S&P 500			-0.0002 (-1.38)				0.0002** (2.03)	0.0003*** (3.14)	0.0003*** (2.91)	0.0003*** (3.08)	0.0001** (1.97)
NASDAQ				0.0010*** (6.03)				0.0009*** (14.01)	0.0009*** (15.20)	0.0011*** (9.64)	0.0006*** (9.49)
Analyst					0.0002*** (4.07)				0.0004*** (6.82)	0.0002*** (2.83)	0.0002*** (4.84)
R&D Intensity										0.0007** (2.02)	
No. of Obs.	91,151	90,553	91,151	91,151	91,151	90,553	90,553	90,553	90,553	45,307	90,553
R-squared	0.0154	0.0001	0.0004	0.0150	0.0005	0.0154	0.0154	0.0271	0.0300	0.0367	0.1621

Table 4 shows the results Fama-MacBeth regressions to explain digital orientation, measured as ln(1+(no. words digital innovation/no. words MD&A section without stopwords)). Regression (9) shows our baseline model, which we used to derive the residual digital orientation measure. *Firm age* is the natural log of a firm's age in years. *Firm size* is defined as the natural log of market capitalization. *S&P 500* and *NASDAQ* are dummy variables indicating the membership of the firm in the S&P 500 index or its listing on the NASDAQ. *Analyst* is defined as the natural log of (1+no. earnings estimates) and describes a firm's coverage by analysts. *R&D intensity* is a firm's R&D expenditure in relation to its assets. In regression (11) we further integrate industry controls using the Fama and French (1997) 48 industry classification system. The sample period is 1996–2020. Following Fama and Macbeth (1973), coefficients are calculated as time-series averages of yearly estimates. t-statistics (shown in parentheses) are based on time-series average coefficients and standard deviation, and adjusted for serial autocorrelation using Newy and West (1994) standard errors with a lag of two years, based on the formula $\left\lfloor [4 * (0.01 * T)^{\frac{2}{9}}] \right\rfloor$ with T=24. The significance level is indicated as follows: * significant at the 10% level; ** significant at the 5% level; and *** significant at the 1% level.

Our baseline model is depicted in the specification (9). We find that the five independent variables can explain 3.00% of *DO*'s variance, a relatively modest value. As illustrated in specification (10), the results are also robust to the inclusion of R&D intensity, which has the expected positive and statistically significant coefficient[2]. With the inclusion of industry controls of the Fama and French (1997) 48 industry classification system (FF48) in the specification (11), we observe a significant increase in the proportion of correlation explained by the explanatory variables and controls to 16.21%. The coefficients are similar in direction and slightly smaller in size and statistical significance, compared to the baseline regression without industry controls (9).

Yet, even with the inclusion of industry controls, the regression results suggest that the selected firm characteristics can explain only a small proportion of DO's variance. These findings demonstrate the benefits of inferring a firm's digital orientation directly from the MD&A section with the help of textual analysis, instead of using secondary variables, such as industry membership, that are only weak proxies for DO.

4 Results

4.1 Digital Leaders vs. Digital Laggards

We next seek to understand how digital leaders differ from digital laggards. We use two approaches to identify digital orientations' effect on key firm characteristics. First, we use the raw data of firms' aggregate *DO* measure[3] when sorting stocks into quintiles. Since a large proportion of firm-years has a digital orientation value of zero, the first quintile containing these firm-years is larger than the remaining four quintiles. Second, we derive a residual *DO* measure by following Hillert et al. (2014) and Hong et al. (2000). Thus, we use regression specification (9), where we control for the firm characteristics, firm age, firm size, S&P 500, NYSE membership, and analyst coverage, to obtain the residual *DO* measure. This second approach might be perceived as advantageous because it allows us to eliminate possible dependencies between digital orientation and firm characteristics by following a simple methodology. We note, however, that one should expect more than modest differences in the results, as the low explanatory power indicates a high correlation between the raw *DO* and residual *DO* measure. The variables used in the quintile analysis are described in detail

[2] We do not include R&D intensity in the baseline regression, since data on R&D expenditure is only available for about half of firm-years in our sample. Especially, for firms in the service sector (e.g., banks and insurances), R&D expenditure is not reported.
[3] For brevity, we focus on the aggregate *DO* measure in our analyses. We inspected the four layers of *DO* separately in unreported analyses, but in many cases, the differences were rather minor.

in Appendix A. Table 5 illustrates the distribution of firm characteristics after sorting stocks into quintiles based on the raw *DO* measure (panel A) and the residual *DO* measure (panel B).

The comparison of *DO* portfolios sorted by raw values shows notable and highly significant differences in firm characteristics. Digital leaders, i.e., firms in the high *DO* portfolio, are characterized by a lower book-to-market ratio. This finding is in line with Chen and Srinivasan (2023)'s study on nontech firms' adoption of digital technologies. Furthermore, these firms are estimated to have higher profitability in the long run, as the measure of long-term earnings forecasts shows. This finding corresponds to the notion that the value of digital innovation unfolds over time, because it depends on particular use contexts and how digital innovation can be combined with other innovation (Henfridsson et al. 2018). Developing respective capabilities to create digital innovation needs several years and may involve the creation of networks transcending the traditional organization structure (Vial 2019). In a similar vein, Svahn et al. (2017) report that building new capabilities requires breaking away from established practices and creating new capabilities, which includes rethinking existing norms. Building new capabilities requires a considerable amount of time, but also fosters firms' intangible value and long-term performance (Bharadwaj et al. 1999).

At the same time, developing capabilities bears risks as the value of digital innovation is not pre-determined but depends on, first, the design choices regarding the combination of technologies and the affordances thereof, and, second, on the use context (Henfridsson et al. 2018). In addition, "(a)s physical resources—including products—become comparatively less relevant than services, as consumers contribute to influence trends related to the use of digital technologies, and as value networks become broader and more complex, firms experience higher levels of uncertainty" (Vial 2019, p. 133). This reasoning corresponds with our finding that digital leaders are also characterized by significantly higher volatility, measured as the monthly return over the previous 60 months. Digital leaders are also characterized by lower short-term operational returns, as illustrated by lower ROA, ROE, and short-term forecasts. While developing capabilities for digital innovation and creating digital innovation impact the development of a firm's intangible value and future prospects, they are subject to uncertainty, as discussed above, and, in the short term, require considerable investment and management attention. Yet, "time lags necessary for realizing the potential of capital investments" are not accounted for by accounting measures

(Bharadwaj et al. 1999, p. 1009). Accordingly, we find lower values for digital leaders regarding short-term profitability.

In summary, the development of digital innovations, in particular radical business model or product innovations, is associated on the one hand with significant risks, as shown by the higher volatility of digital market leaders, and on the other hand with high short-term investments that lead to lower short-term returns. In the long term, however, the risks taken for the development of digital innovations may pay off, enabling digital market leaders to generate higher operational profitability in the long term.

Furthermore, firms placed in the high *DO* portfolio also have notably smaller cost ratios (COGS/assets) than digitally lagging companies. In that regard, studies show that companies increase their operational efficiency and cost positions by employing digital technologies to automate and improve business processes, by using cloud computing to provide on-demand services instead of owning data centers with high fixed costs, and by applying big data and analytics to speed up decision-making processes (Vial 2019).

Moreover, sales growth is almost double in size for firms placed in the high *DO* portfolio. Extant research shows that the growth of entrepreneurial firms is nonlinear and similar to digitally oriented firms that use digital technologies to shape entrepreneurial processes and outcomes (Vial 2019). Namely, developing digital façades – the digital coupling of firms' activities with customers and partners as a first step towards building up digital capabilities – enables growth (Tumbas et al. 2015) by attracting new customers.

Table 5: Firm characteristics for portfolios sorted by raw and residual digital orientation measure

Panel A: Quintile sorts based on the raw digital orientation measure

Variables	Book-to-market	Long-term Forecast	Stock Volatility	ROA	ROE	Short-term Forecast	COGS/ Assets	XOPR/ Assets	Sales Growth	Absorbed Slack	Potential Slack
Q1	0.71	14.45	0.12	0.03	0.02	0.04	1.99	2.57	0.16	0.31	0.82
Q2	0.75	14.51	0.14	0.01	-0.03	0.02	2.14	2.65	0.18	0.32	0.90
Q3	0.71	15.83	0.14	0.01	-0.05	0.01	1.94	2.52	0.20	0.38	0.88
Q4	0.66	17.32	0.16	0.01	-0.07	0.00	1.65	2.29	0.22	0.44	0.71
Q5	0.58	19.59	0.17	0.00	-0.11	-0.01	1.26	2.01	0.28	0.55	0.52
Q5-Q1	-0.12***	5.14***	0.05***	-0.02***	-0.13***	-0.05***	-0.73***	-0.55***	0.12***	0.24***	-0.29***
t-stat Q5-Q1	-21.02	136.27	212.81	-17.25	-21.75	-93.92	-46.04	-30.28	20.43	39.31	-9.85

Panel B: Quintile sorts based on the residual digital orientation measure

Variables	Book-to-market	Long-term Forecast	Stock Volatility	ROA	ROE	Short-term Forecast	COGS/ Assets	XOPR/ Assets	Sales Growth	Absorbed Slack	Potential Slack
Q1	0.70	17.22	0.14	0.00	-0.06	0.00	1.86	2.42	0.23	0.39	0.77
Q2	0.71	14.95	0.13	0.02	-0.02	0.02	1.97	2.53	0.16	0.35	0.88
Q3	0.72	14.84	0.14	0.02	-0.01	0.03	1.99	2.55	0.16	0.33	0.87
Q4	0.70	16.45	0.15	0.02	-0.03	0.02	1.79	2.38	0.16	0.38	0.75
Q5	0.60	19.94	0.17	0.00	-0.09	-0.01	1.33	2.08	0.23	0.51	0.52
Q5-Q1	-0.10***	2.72***	0.03***	0.00*	-0.03***	-0.01***	-0.53***	-0.35***	-0.00	0.12***	-0.25***
t-stat Q5-Q1	-16.68	17.24	31.76	1.76	-4.81	-3.83	-24.77	-14.51	-0.25	15.88	-7.99

Table 5 shows time-series averages of firm variables' yearly mean for quintile portfolios based on the raw digital orientation measure (panel A) and the residual digital orientation measure (panel B). The raw digital orientation measure is defined as ln(1+(no. words digital innovation/no. words MD&A section without stopwords)). The residual digital orientation measure is derived from Fama-MacBeth regressions with firm age, firm size, S&P500, NASDAQ, and analyst coverage as explanatory variables (see Table 4) using time-series averages of yearly estimates. *Book-to-Market* is the book value of equity divided by market value of equity following (Greenwood and Hanson 2012). *Long-term forecast* is measured as the average of analysts' forecast of the expected long-run earnings growth rate per share over the next five years following La Porta (1996). *Stock volatility* is measured using the monthly return over the previous 60 months. *Return on assets* (ROA) is calculated as the ratio between income before extraordinary items and assets. *Return on equity* (ROE) is calculated following Greenwood and Hanson (2012). *Short-term forecast* is measured as the average of analysts' earnings forecast for the fiscal year annual earnings scaled by the price per share. *Cost ratios* are defined as cost of goods sold over assets and operating expenses over assets. *Sales growth* is measured as the log change in sales over one year. *Absorbed slack* is the ratio of selling, general, and administrative expenses to sales. *Potential slack* is the ratio of debt to equity. The sample period is 1996–2020. The final rows in each panel display the difference between the fifth and first quantile as well as the t-statistic associated with this portfolio difference. The significance level is indicated as follows: * significant at the 10% level; ** significant at the 5% level; and *** significant at the 1% level.

The picture is mixed for organizational slack, considered an essential source for financing innovation in organizations. Organizational slack refers to an organization's excess resources, i.e., resources not required to maintain the existing organization but enabling the search for innovation (Pitelis 2007). Absorbed slack refers to the use of administrative resources larger than necessary for short-term operation and is defined as the ratio of selling, general and administrative expenses to sales (Greve 2003). Potential slack focuses on the financial resources acquired by lending, or which an organization would be able to lend, and is measured as the ratio of debt to equity (Greve 2003). Absorbed slack is significantly higher for digital leaders. This is in line with the stream of literature, which argues that organizations engaged in innovative activities exhibit higher levels of slack enabling slack search for innovation (Pitelis 2007). In contrast, potential slack is highest for digitally lagging firms. The tentative explanation is that digital leaders exhibit significantly higher financial resources, e.g., in the form of cash, and do not exhibit high levels of debt.

In untabulated results, we find that the differences between digitally leading firms and digitally lagging firms are equally evident when sorting stocks into quintiles based on the alternative measure tf-idf *DO*. The analysis shows, for instance, a significantly lower book-to-market ratio, higher long-term profitability, higher volatility, and lower short-term profitability for digital leaders. As expected, for portfolios sorted by residual values, Panel B mostly echoes these results. While some differences in firm characteristics between digital leaders and digitally lagging firms disappear (i.e., sales growth) or reverse (i.e., available slack), most of the described differences in firm characteristics for firms in the extreme portfolios 1 and 5 remain after controlling for firm size, age, analyst coverage, S&P 500, and NASDAQ membership. Finally, in untabulated results, we find that an analysis based on residual values of the tf-idf *DO* measure also shows similar results.

4.2 Portfolio Tests Based on the Level of Digital Orientation

The previous section highlights systematic differences between firms with high and low values for the text-based *DO* measure. In this section, we analyze if firms with high and low *DO* levels also have different stock returns. At the end of June of every year, we group stocks into quintile portfolios based on their *DO* value. The measure of *DO* is extracted from the firms' most recent fiscal year financial statements ending in the previous calendar year. For example, our sorts for

June 2009 rely on data from financial statements ending in the calendar year 2008 (in most cases December 2008).

Because a large proportion of stocks has a *DO* measure of zero, we continue to group these stocks in the first quintile. The remaining stocks are then equally spread across the other groups according to their *DO* value. Our sorts are based on the absolute *DO* value instead of the residual value from regression equation (1), because other firm variables have low explanatory power to explain *DO* (see Section 3.2). Therefore, portfolio tests based on the absolute value of *DO* and its residual value deliver similar results.

We calculate equally weighted and value-weighted quintile (5) minus quintile (1) long-short portfolio returns from July 1st until June 30th of next year, when the portfolio is rebalanced.[4] The transaction costs associated with the *DO* strategy are supposedly minimal because the annual rebalancing frequency implies a comparatively low portfolio turnover, and because we focus on non-micro-cap stocks, i.e., stocks with a market capitalization above the second NYSE size decile.

Low limits-to-arbitrage are even more emphasized for the second weighting scheme based on market values. For this scheme, we also exclude micro-cap stocks. Moreover, we use a capped value-weighting approach that winsorizes all market capitalizations at the 80th percentile of the stock universe before calculating the stock weights. The capped value weighting is advocated by Jensen et al. (2021) because it avoids a dominating influence of a few mega caps on return calculations, like the FAANG stocks (Facebook, Apple, Amazon, Netflix, Google), and hence produces more robust factors. The benefits of a capped weighting scheme seem particularly relevant in our context as many of the dominating mega-cap stocks at the end of the sample period also tend to have a high *DO*.[5]

Besides reporting raw returns, the long-short portfolio returns are also regressed on a set of commonly used factors (e.g., Fama and French 1993, Carhart 1997, Fama and French 2015) to infer the abnormal, i.e., unexplained, return of the *DO* portfolio (also referred to as the digital premium or digital leaders' premium). Results for equally weighted (value-weighted) portfolio schemes are shown in Table 6, Panel A (Panel B).

[4] Because we use financial statements for fiscal years from 1996 onwards, portfolio returns are calculated from July 1997 onwards.

[5] For example, all of the five mentioned stocks (Facebook, Apple, Amazon, Netflix, Google) belong to the highest *DO* quintile in 2020.

Column (1) in Panel A of Table 6 reports the raw return of the equally weighted long-short strategy. It amounts to 0.69% per month and is statistically significant at the 5% level (t-statistic: 2.48). We find that the Fama and French three-factor alpha, which is reported in column (3), is lower at 0.42% per month with a t-statistic of 2.40. However, as can be seen in column (6) of Panel A, the six-factor alpha of a regression that controls for the market, size, value, momentum, profitability, and investment factor, is 0.92% per month (approximately 11% annualized) with a very high t-statistic of 6.51.

The pronounced increase in the economic and statistical significance of the alpha in column (6) is largely explained by a significantly negative correlation with the profitability factor RMW. We also observe a negative correlation with the value factor HML and, to a lesser extent, with the investment factor CMA in column (6). The correlations line up with findings from Section 4.1, which shows that firms with a high *DO* tend to be growth firms with lower profitability. After accounting for these relations, the results in Panel A show that digital leaders earn much higher returns than digital laggards.

The same conclusion can be drawn from Panel B of Table 6, although the (abnormal) returns for the value-weighted long-short portfolio are lower. Column (1) shows a raw return of 0.29% per month for the strategy, which is statistically insignificant (t-statistic 1.12). The CAPM one-factor, Fama and French's (1993) three-factor, and Carhart's (1997) four-factor alpha are also statistically insignificant.

These regressions suffer from omitted variable bias because the negative correlations between the digital premium with respect to both RMW and CMA are not taken into account. In doing so, we observe a statistically significant Fama and French (2015) five-factor alpha of 0.46% per month (t-statistic of 3.88) in column (5). The alpha of a six-factor regression, which additionally controls for momentum exposure, is 0.50% per month or 6% annualized (t-statistic 4.22).

In un-tabulated tests, we find that the *DO* portfolio also changes our assessment of the performance of RMW and CMA. If we regress RMW (CMA) on the remaining five factors without the digital premium, the alpha is 0.47% (0.28%) per month with a t-statistic of 3.75 (2.88). The economic and statistical significance of the regression intercept increases to 0.55% (0.36%) per month with a t-statistic of 5.64 (3.61) after controlling for the value-weighted version of the digital premium.

Table 6: Abnormal returns of the digital orientation (DO) portfolio

Panel A: Equally weighted portfolios

	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.0069**	0.0044*	0.0042**	0.0051***	0.0087***	0.0092***
	(2.48)	(1.74)	(2.40)	(3.02)	(6.03)	(6.51)
mktrf		0.4331***	0.3216***	0.2573***	0.1194***	0.0834**
		(7.93)	(8.30)	(6.43)	(3.26)	(2.27)
smb			0.4177***	0.4429***	0.1582***	0.1849***
			(7.47)	(8.16)	(3.15)	(3.75)
hml			-0.8416***	-0.9109***	-0.4494***	-0.5241***
			(-16.02)	(-17.19)	(-7.42)	(-8.50)
umd				-0.1595***		-0.1167***
				(-4.54)		(-4.08)
rmw					-0.8252***	-0.7945***
					(-12.18)	(-11.98)
cma					-0.2717***	-0.2378***
					(-3.08)	(-2.76)
N	275	275	275	275	275	275
R-squared	0.000	0.187	0.622	0.649	0.758	0.772

Panel B: Value-weighted portfolios

	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.0029	0.0005	0.0003	0.0010	0.0046***	0.0050***
	(1.12)	(0.20)	(0.17)	(0.67)	(3.88)	(4.22)
mktrf		0.4201***	0.3195***	0.2696***	0.1260***	0.1006***
		(8.39)	(9.44)	(7.66)	(4.16)	(3.29)
smb			0.3618***	0.3813***	0.1166***	0.1355***
			(7.41)	(7.98)	(2.81)	(3.30)
hml			-0.8182***	-0.8720***	-0.4415***	-0.4941***
			(-17.84)	(-18.71)	(-8.82)	(-9.62)
umd				-0.1238***		-0.0824***
				(-4.01)		(-3.45)
rmw					-0.7819***	-0.7603***
					(-13.96)	(-13.76)
cma					-0.2706***	-0.2467***
					(-3.71)	(-3.44)
N	275	275	275	275	275	275
R-squared	0.000	0.205	0.665	0.684	0.808	0.816

Table 6 shows the results of regressions to investigate the profitability of equally weighted (Panel A) and capped value-weighted (Panel B) quintile 5-minus-1 portfolios based on digital orientation (*DO*) measure. Column (1) shows the raw returns per month of this DO portfolio. The remaining columns show the results, if the monthly long–short DO portfolio returns are regressed on the excess market return (MKTRF); on the Fama and French (1993) size and value factors (SMB, HML); on the Fama and French (2015) profitability and investment factors (RMW, CMA); and on the momentum factor from Kenneth French (UMD); t-statistics are reported in parentheses. *, ** and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

4.3 Robustness Tests

We conduct several robustness tests to demonstrate the reliability of our results when measuring digital orientation using other parts of the firms' 10-Ks, controlling for firms' industry affiliation or NASDAQ exposure, using alternative data samples, and different dictionaries. All robustness tests are summarized in Table 7, where columns (1) and (3) depict monthly equally weighted and value-weighted raw returns. Columns (2) and (4) illustrate monthly six-factor alphas, which control for exposure to the excess market return (MKTRF), the Fama and French (1993) size and value factors (SMB, HML), the Fama and French (2015) profitability and investment factors (RMW, CMA), and the momentum factor from Kenneth French (UMD). Columns (2) and (4) are essential for illustrating the unique nature of the digital premium. These demonstrate the influence of the digital premium after accounting for other established asset pricing factors. We calculate returns using equally weighted portfolios (Table 7, left) and value-weighted portfolios (Table 7, right) and outline our findings in the following.

First, we calculate equally weighted and value-weighted portfolio returns using modified *DO* measures (Table 7, Panel A). In our first robustness test, we measure firms' *DO* by accounting for the importance of each word in the dictionary using the so-called term-frequency-inverse document frequency (tf-idf) based on Loughran and McDonald (2011). The correlation between both *DO* measures is 0.59, which suggests that sorts lead to somewhat different compositions for the stock portfolios. Additionally, for robustness tests (2) and (3), we derive *DO* measures using the 10-K's section 1, which contains the business description, and the entire 10-K report.

The results in Panel A of Table 7 confirm that *DO* constitutes a distinct and statistically significant asset pricing premium, even when considering alternatively derived *DO* measures. The equally weighted six-factor alpha ranges between 0.86% and 0.95% per month. For value-weighted returns, the six-factor alpha is slightly lower and ranges between 0.50% and 0.64% depending on the *DO* measure considered. These results are comparable in economic and statistical significance to the results presented in Table 6 for the *DO* measure derived using the MD&A section. Specifically, all six-factor alphas of the portfolios are statistically significant at the 1%-level. This indicates the robustness of our results when using alternatively derived *DO* measures.

Second, we control for stocks' industry affiliation, exposure to the NASDAQ index, and style. Because digitalization is a cross-industry phenomenon, we expect that the abnormal returns associated with digital orientation are not well explained by industry affiliation. To formally test this expectation, we calculate equally weighted and value-weighted portfolio returns based on industry-adjusted stock returns for robustness analyses (4) and (5). For the industry adjustment, we use industry returns based on the Fama and French (1997) 48 industry classification system, denoted as FF48, and industry returns based on the network industry classification of Hoberg and Phillips (2010, 2016), denoted as TNIC. The results are displayed in Panel B of Table 7.

For equally weighted returns, the six-factor alpha of the industry-adjusted *DO* strategy is 0.72% (0.69%) per month using the FF48 (TNIC) industry classification. While both alphas are lower in magnitude compared to the six-factor alpha in Panel A of Table 6 (0.92% per month), the statistical significance is higher (7.13 and 6.79, respectively, versus 6.51). The reason is that the industry adjustment also reduces the strategy's volatility. For value-weighted returns, the six-factor alpha of the industry-adjusted *DO* strategy is 0.29% (0.27%) per month using the FF48 (TNIC) industry classification. The strategy alphas are lower compared to Panel B in Table 6, but remain statistically significant at the 1% level with t-statistics of 3.93 and 3.42, respectively.

In analysis (6), we further test the robustness of our results to firms' exposure to the Nasdaq. Specifically, we use the excess return of the Nasdaq Composite Index from Refinitiv instead of the broader CRSP value-weighted index as the market factor (mktrf). If the *DO* measure only serves as a proxy for technology and high cash flow duration, we expect the outperformance to disappear after using the Nasdaq as a benchmark. However, we find that the abnormal returns are not explained by a general outperformance of Nasdaq stocks. The alpha of the model remains at 0.75% per month for equally weighted portfolios and 0.34% per month for value-weighted portfolios. Both alpha estimates are statistically at the 1% level with only minor changes in the associated t-statistics. We conclude that firms' digital orientation is not satisfactorily described by being listed on the Nasdaq and that Nasdaq membership cannot explain the outperformance of digital leaders.

In robustness test (7), we follow the procedure by Daniel et al. (1997) and benchmark-adjust the stock returns before estimating the alpha of the equally weighted and value-weighted *DO* portfolio returns. The stock returns are benchmarked based on the characteristics of size, book-to-market, and prior return (denoted as *DGTW*). Our conclusions are similar based on style-adjusted DGTW-returns. Specifically, we obtain an alpha of 0.74% per month for the equally weighted portfolio and 0.33% per month for the value-weighted portfolio. Both alphas are statistically significant at the 1%-level.

Table 7: Robustness tests

	Equally weighted returns		Value weighted returns	
	Raw Return	Alpha 6F Model	Raw Return	Alpha 6F Model
	(1)	(2)	(3)	(4)
Panel A: Modification of the *DO* calculation				
1. tf-idf *DO*	0.0060**	0.0086***	0.0027	0.0050***
	(2.19)	(5.98)	(1.06)	(4.17)
2. *DO* based on section 1 (Business Description)	0.0066*	0.0095***	0.0038	0.0064***
	(1.84)	(5.18)	(1.11)	(3.94)
3. *DO* based on entire 10-K report	0.0062*	0.0090***	0.0033	0.0059***
	(1.82)	(4.87)	(1.00)	(3.54)
Panel B: Control for industry membership and Nasdaq exposure				
4. FF48 industry-adjusted returns	0.0057***	0.0072***	0.0017	0.0029***
	(3.61)	(7.13)	(1.28)	(3.93)
5. TNIC industry-adjusted returns	0.0061***	0.0069***	0.0021**	0.0027***
	(4.59)	(6.79)	(1.99)	(3.42)
6. Nasdaq as Market Index	0.0069**	0.0075***	0.0029	0.0034***
	(2.48)	(5.49)	(1.12)	(3.05)
7. DGTW-characteristic-adjusted returns	0.0063***	0.0074***	0.0023	0.0033***
	(3.80)	(6.21)	(1.54)	(3.23)
Panel C: Modification of the sample				
8. Exclusion of dot.com-bubble (98/99)	0.0036	0.0075***	0.0003	0.0041***
	(1.31)	(5.33)	(0.13)	(3.44)
9. Exclusion of high-sentiment periods	0.0098***	0.0075***	0.0071***	0.0048***
	(4.50)	(5.15)	(3.66)	(3.76)
10. Inclusion of Micro-caps with MV equity>10 Mio USD & P>1 USD	0.0039	0.0056***	0.0010	0.0031***
	(1.40)	(3.55)	(0.37)	(2.68)
Panel D: Alternative digital innovation dictionary based on the Gartner Hype Cycle				
11. Full sample dictionary	0.0034*	0.0056***	0.0015	0.0036***
	(1.65)	(4.80)	(0.80)	(3.71)
12. Rolling extended dictionary	0.0042	0.0068***	0.0019	0.0043***
	(1.63)	(4.69)	(0.83)	(3.55)

Table 7 shows the results of robustness tests. We investigate the profitability of equally weighted (Panel A) and capped value-weighted (Panel B) quintile 5-minus-1 portfolios based on the digital orientation (*DO*) measure. Three different performance measures are used: Raw returns indicate the *DO* strategy return per month without accounting for other asset pricing factors and 6F Model controls for exposure to the Fama and French (1993) three-factor alphas, the Fama and French (2015) profitability and investment factors (RMW, CMA), and the momentum factor from Kenneth French (UMD). In Panel A modified measures of *DO* are used. Here, tf-idf stands for the term-frequency-inverse document frequency based on Loughran and McDonald (2011), which accounts for the importance of each word in the dictionary to measure *DO*. Panel B controls for industry membership, Nadaq exposure and benchmark adjustments. FF48 indicates the Fama and French (1997) 48 industry classification system; TNIC refers to the network industry classification of Hoberg and Phillips (2010, 2016). The benchmark adjustments in analysis (7) rely on the set of characteristics proposed by Daniel et al. (1997), referred to as DGTW. Panel C conducts robustness tests based on modified samples. Panel D uses the alternative digital innovation dictionary derived using the Gartner Hype Cycle (see Appendix B for details). t-statistics are reported in parentheses. *, ** and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

Third, we use modified samples to ensure that our results are not driven by the dot.com bubble or high-sentiment periods (Table 7, Panel C). In analysis (8), we exclude the years 1998 and 1999 to control for the possibility that the dot.com bubble influences our results. Relying on the sentiment index suggested by Baker and Wurgler (2006), we conduct an additional robustness test to account for the possible influence of high sentiment periods in analysis (9). Thus, we exclude periods with a sentiment located in the top 20%-percentile of the index. Finally, we also run an analysis using a sample that includes micro-caps to test the robustness of our results beyond large companies. In particular, for robustness test (10), we include microcaps with market value equity of at least 10 Mio. USD and a stock price larger than 1 USD in our sample.

We find that our results are robust to excluding specific periods in the sample (dot.com bubble and high sentiment periods). The equally weighted six-factor alpha is 0.75% per month for both robustness tests. For value-weighted returns, the six-factor alpha is slightly lower and is 0.41% per month when excluding the dot.com bubble and 0.48% for a sample without high-sentiment periods. These results are again comparable in economic and statistical significance to the results presented in Table 6 for the *DO* measure over the entire sample period, further indicating our results' robustness. When calculating *DO* stock returns in a sample that includes microcaps, we find alphas that are smaller in size but remain highly statistically significant at the 1% level. The six-factor alpha of the *DO* portfolio is now 0.56% per month for equally weighted returns and 0.31% per month for value-weighted returns.

Finally, we use an alternative dictionary to measure *DO* based on digital innovation trends. This dictionary is based on the yearly published Hype Cycle by Gartner, which tracks the maturity of a new, promising digital innovation across time. We compile this alternative dictionary by considering all digital innovations (and their synonyms) mentioned in the Hype Cycle in the years 1995 to 2020 (see Appendix B for details). The results are shown in Panel D of Table 7. Robustness test (11) uses a *DO* measure that is created by applying the full sample list of words to all MD&A sections. The *DO* measure for robustness test (12) is based on a word list that contains only words that have appeared in the Hype Cycle periodicals so far and is extended every year with new words. In other words, for robustness test (12), we evaluate the digital orientation of every MD&A section only based on words that have already appeared in prior publications.

Appendix B shows the dictionary based on the Hype Cycle and the thirty most frequent words of the Hype Cycle dictionary in firms' 10-Ks. Compared to our baseline dictionary, the Hype

Cycle dictionary is substantially longer but terms are more specific in nature, which translates into fewer word counts within the MD&A section. In fact, more than 50% of the MDA sections contain zero words from the Hype Cycle. Consequently, instead of forming long-short portfolios based on quintiles, we calculate equally weighted and value-weighted returns of a portfolio, which is long in stocks with at least one word hit, and short in stocks with zero word hits.

Despite conceptional differences between the Hype Cycle dictionary and our baseline dictionary, robustness tests (11) and (12) show that the results and conclusions are remarkably similar. The equally weighted six factor alpha is 0.56% per month (t-statistic 4.80) for the full sample word list, and 0.68% (t-statistic 4.69) per month for the rolling extended dictionary. Value-weighted six factor alphas are also significant at the 1%-level, with 0.36% per month and a t-statistic of 3.71 for robustness test (11) and 0.43% per month and a t-statistic of 3.55 for robustness test (12). Moreover, we see that the differences between the first approach (full sample word list) and the second approach (continuously expanding word list) are only marginal.

4.4 Why do firms with high *DO* have above-average returns?

4.4.1 The discount rate channel hypothesis

Our sample period from 1996 to 2020 largely coincides with declining federal funds rates and other "unconventional" monetary policy practices, including four rounds of quantitative easing (QE1 to QE4). With QE, the FED purchased financial assets to stimulate economic growth (see e.g., Chakraborty et al. 2020). Arguably, the monetary stimulus helped improve corporate financing conditions and, hence, lower corporate cost of capital. As the fair price of a stock is equal to its future cash flows discounted at the cost of equity, lower discount rates imply rising stock prices. Moreover, the higher growth prospects and lower current profitability of digital leaders imply that these firms have a higher cash flow duration than other firms. This suggests that their stock price should have a higher sensitivity towards discount rate shocks, i.e., unexpected changes in firms' cost of capital. The discount rate channel hypothesis thus predicts that loose monetary policy was responsible for above-average returns of stocks with high *DO* value during our sample period.

We test this hypothesis in two ways. First, we add a dummy variable to the six-factor regression model, which equals 1 for periods of quantitative easing (QE) and is zero otherwise. The four QE programs comprise a total of 58 months in our sample (from November 2008 to June 2010, from November 2010 to June 2011, from September 2012 to October 2014, and from March

2020 to December 2020).[6] The discount rate channel hypothesis predicts particularly high returns for the DO factor in periods of the QE programs, i.e., a statistically significant positive coefficient for the QE dummy variable. We report regression results with the equally weighted and the value-weighted DO factor as the dependent variable in columns (1) and (2) of Table 8.

We find that the coefficient for the QE dummy is negative in both regressions, implying a lower return of the *DO* portfolio during QE periods. This result does not support the discount rate channel hypothesis, which predicts a statistically significant positive coefficient for the QE dummy.

Testing the discount rate channel hypothesis based on QE months might be insufficient because stock prices may react to the announcement of the QE rather than to its actual implementation. Our second test for this hypothesis, therefore, relies on daily long-short returns for the DO strategy and examines if the returns are elevated during FED meeting days and days at which the FED minutes are released. Arguably, these are the days when news about monetary policy changes enters the market. We obtain the information about relevant dates from the FED website.[7] The discount rate channel hypothesis predicts higher returns of the *DO* strategy during FED days. To test this prediction, regressions with daily returns of the *DO* strategy as the dependent variable are shown in columns (3) to (6) of Table 8. We use equally weighted (columns 3 and 4) and value-weighted (columns 5 and 6) versions of the digital premium. Columns (3) and (5) contain a dummy variable that is equal to 1 on FED meeting days, and columns (4) and (6) contain a dummy variable that is equal to 1 on FED minutes release days. Additionally, all regressions contain daily returns for the Fama and French (2015) five factors and momentum as controls.

We find that all coefficients for the FED day dummies are economically small, negative in three of four cases, and statistically insignificant in all four cases. This suggests that FED days have no particular relevance for the performance of the *DO* portfolio. Overall, we find no supportive evidence for the discount rate channel hypothesis. We next explore two alternative explanations: Mispricing and compensation for systematic factor exposure.

[6] We use the starting and ending dates from Chakraborty et al. (2020) for the first three QE programs. Beginning and ending month for QE4 are taken from https://americandeposits.com/history-quantitative-easing-united-states/.
[7] https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm.

Table 8: Tests for the discount rate channel hypothesis						
	Panel A: The effect of QE (monthly returns)		Panel B: The effect of FED announcements (daily returns)			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Return weighting *DO*	**ew**	**vw**	**ew**	**ew**	**vw**	**vw**
Alpha	0.0110***	0.0059***	0.0004***	0.0004***	0.0003***	0.0002***
	(7.11)	(4.52)	(7.53)	(7.48)	(4.66)	(4.58)
mktrf	0.0892**	0.1035***	0.0508***	0.0507***	0.0521***	0.0520***
	(2.45)	(3.39)	(10.38)	(10.37)	(10.67)	(10.65)
smb	0.1872***	0.1366***	0.1232***	0.1231***	0.1272***	0.1271***
	(3.84)	(3.33)	(13.49)	(13.49)	(13.95)	(13.94)
hml	-0.5423***	-0.5033***	-0.4681***	-0.4680***	-0.4785***	-0.4784***
	(-8.85)	(-9.77)	(-46.42)	(-46.41)	(-47.53)	(-47.52)
umd	-0.1268***	-0.0874***	-0.0578***	-0.0578***	-0.0566***	-0.0565***
	(-4.44)	(-3.64)	(-9.15)	(-9.14)	(-8.96)	(-8.96)
rmw	-0.7877***	-0.7568***	-0.6823***	-0.6824***	-0.7170***	-0.7169***
	(-12.01)	(-13.73)	(-55.47)	(-55.47)	(-58.39)	(-58.37)
cma	-0.2230***	-0.2392***	-0.2195***	-0.2194***	-0.2747***	-0.2745***
	(-2.61)	(-3.34)	(-14.28)	(-14.27)	(-17.90)	(-17.89)
QE dummy	-0.0089***	-0.0045				
	(-2.71)	(-1.63)				
FED meeting dummy			-0.0001		-0.0002	
			(-0.49)		(-0.78)	
FED minutes dummy				0.0001		-0.0001
				(0.17)		(-0.28)
N	275	275	5,766	5,766	5,766	5,766
R-squared	0.779	0.818	0.668	0.668	0.694	0.694

Table 8 shows the results of regressions to test the discount rate hypothesis and to demonstrate loose monetary policy was not responsible for above-average returns of stocks with high *DO* value during our sample period. Accordingly, the profitability of equally weighted (ew) and capped value-weighted (vw) quintile 5-minus-1 portfolios based on digital orientation (*DO*) is measured using additional controls. Panel A includes dummies for periods of quantitative easing. Panel B includes dummies to account for FED meeting days and the release dates of the FED minutes. Alpha depicts the unexplained returns per month (columns 1 and 2) or per day (columns 3 to 6) of the digital premium. MKTRF denotes the excess market return; SMB and HML denote the Fama and French (1993) size and value factors, RMW and CMA indicate the Fama and French (2015) profitability and investment, and UMD denotes the momentum factor from Kenneth French; t-statistics are reported in parentheses. *, ** and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

4.4.2 The mispricing hypothesis

The mispricing hypothesis postulates that market participants were consistently surprised by better (worse) than expected results for high (low) *DO* firms. For instance, investors, analysts, or both might have underestimated (overestimated) actual earnings or growth potential for high (low) *DO* firms.

A priori, one could arguably be skeptical that the mispricing hypothesis holds true in our case for two reasons. First, our sample period from 1996 to 2020 coincides with a period of supposedly increasing market efficiency (e.g., McLean and Pontiff 2016, Green et al. 2017). Moreover, we exclude micro-caps that typically account for most of the documented anomalous return patterns (e.g., Hou et al. 2020). Nevertheless, to empirically test the potential validity (or invalidity) of the mispricing hypothesis, we examine how earning announcement returns (EAR)[8] are related to the *DO* measure. We also test if digital leaders were more likely to beat analyst earnings forecasts by relating the analyst earnings forecast bias[9] to the *DO* measure. Regression results are shown in Table 9.

We cluster all regressions on the level of yearly quarters. While we do not include entity-fixed effects in Panel A, we account for industry-fixed effects in Panel B, and firm-fixed effects in Panel C. If the mispricing hypothesis was to hold true, we would expect positive and significant coefficients of the quantile *DO* measure. Yet, our results indicate no statistically significant bias in investors' expectations in all conducted regressions. We observe a statistically insignificant coefficient of the quantile *DO* measure for all regressions in Table 9. Accordingly, we are confident to reject the mispricing hypothesis.

[8] The variable is calculated as the cumulative stock return minus the cumulative CRSP value-weighted market return over the 3-day window around the announcement date.
[9] The variable is defined as quarterly earnings per share (EPS) from IBES minus the median analyst forecast EPS, scaled by stock price at the end of month t – 1.

Table 9: Biased expectations						
	No fixed effects		Industry-fixed effects		Firm-fixed effects	
	Analyst Bias	EAR	Analyst Bias	EAR	Analyst Bias	EAR
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	-0.0525*** (-3.0531)	0.0014 (0.1450)	-0.0594*** (-4.9231)	0.0013*** (4.6550)	0.1429** (2.2506)	-0.0012 (-0.4548)
Quantile *DO* Measure	-0.0057 (-0.4482)	0.0120 (1.2216)	-0.0084 (-0.4427)	0.0130 (1.0803)	-0.0779 (-1.0951)	-0.0964 (-1.4096)
Firm Age	-0.0019 (-0.1425)	-0.0204* (-1.9229)	-0.0097 (-0.6943)	-0.0243* (-1.7844)	-0.4511** (-2.1227)	0.1645 (0.8285)
Firm Size	0.2361*** (7.0864)	0.1339*** (6.6221)	0.2348*** (7.4369)	0.1315*** (3.9298)	-0.4268** (-2.4263)	-0.3960*** (-3.0192)
S&P 500	-0.0579*** (-4.6671)	-0.0423*** (-3.8716)	-0.0599*** (-3.9963)	-0.0397*** (-2.6105)	-0.0525 (-0.5728)	0.0266 (0.2150)
NASDAQ	0.0513*** (3.8241)	0.0078 (0.7385)	0.0263 (1.5927)	0.0054 (0.4940)	0.0260 0.0260	0.0260 (0.4042)
Analyst	-0.0170 (-0.6022)	-0.0451*** (-2.6183)	-0.0021 (-0.0814)	-0.0392** (-2.0812)	0.0120 (0.1523)	0.0378 (0.5849)
No. of Obs.	271,032	342,442	273,267	342,442	273,267	342,442
R-squared	0.0216	0.0061	0.0230	0.0063	0.0024	0.0019

Table 9 shows the results of a panel regression to explain earnings surprises. We use two measures of earning surprises. In columns (1), (3), and (5) *Analyst Bias* measures the quarterly earnings per share (EPS) from IBES minus the median analyst forecast (EPS), scaled by stock price at the end of month t – 1. In columns (2), (4), and (6) *EAR* measures earning announcement returns as the cumulative stock return minus the cumulative CRSP value-weighted market return over the 3-day window around the announcement date. All regressions are clustered at the level of annual quarters. Regressions (3) and (4) include industry-fixed effects, while regressions (5) and (6) include firm-fixed effects, using the Fama and French (1997) 48 industry classification system. *Firm age* is the natural log of a firm's age in years. *Firm size* is defined as the natural log of market capitalization lagged by two yearly quarters. *S&P 500* and *NASDAQ* are dummy variables indicating the firm's membership in the S&P 500 index or its listing on the NASDAQ. *Analyst* is defined as the natural log of (1+no. earnings estimates) and describes a firm's coverage by analysts. *Quantile DO measure* is a categorial variable depicting the five quintile portfolios formed yearly based on the raw digital orientation measure. The raw digital orientation measure is defined as ln(1+(no. words digital innovation/no. words MD&A section without stopwords)). The significance level is indicated as follows: * significant at the 10% level; ** significant at the 5% level; and *** significant at the 1% level; t-statistics are reported in parentheses.

4.4.3 The systematic factor hypothesis

A third potential explanation for the above-average returns of firms with high *DO* value is that digitalization has become a widespread and, hence, systematic market phenomenon that carries a factor exposure premium. To see if we find evidence for this possibility, we conduct "characteristics-vs.-covariances" tests in the spirit of e.g., Daniel and Titman (1997). Formally, we run rolling-window regressions for every stock to infer the stock's exposure against the high-minus-low digital orientation portfolio return. This means we treat the long-short return as a *DO* factor. To this end, we use the most recent two-year monthly stock returns and regress them on the market factor and the *DO* factor. We use two different versions of this regression, one with the equally weighted *DO* factor and one with the value-weighted *DO* factor. Based on the regression results, we form five stock portfolios that differ in their exposure to the *DO* factor but have, on average, the same characteristic *DO*.

The methodology ensures that the resulting quintile (5) minus quintile (1) portfolio is neutral with respect to the *DO* measure, i.e., according to their financial statements, stocks in quintile 5 have a similar level of *DO* as stocks in quintile 1. However, by construction, the return of the long-short portfolio should have a high positive exposure against the *DO* factor. If the abnormal returns of the *DO* factor reflect a compensation for systematic factor exposure, one would hence expect that stocks with high exposure to this factor also earn higher returns, independent of the *DO* level from financial statements.[10] To see if this is the case, we study the performance of the high minus low *DO* factor exposure portfolio. Results are shown in Table 10. Panel A (B) reports equally weighted (value-weighted) portfolio returns.

We find that the equally weighted (value-weighted) monthly six alpha factor of the long-short *DO* factor exposure portfolio, shown in column (3) of Table 10, is 0.93% (0.53%). Both alphas are statistically significant at the 1% level with t-statistics of 4.14 and 2.69, respectively.[11] In the regressions reported in column (4) of Table 10, we also add the equally weighted *DO* factor in Panel A and the value-weighted *DO* factor in Panel B as a control variable. Thus, we use the same return weighting scheme for the dependent variable based on *DO* factor exposure and the independent variable based on the *DO* measure.

We also identify that the abnormal returns decline to 0.28% (equally weighted) and 0.20% (value-weighted) per month once we add the *DO* factor as a control variable in the regressions. The equally weighted and value-weighted monthly alphas are statistically insignificant (t-statistic: 1.35 and 1.09).

[10] Kozak et al. (2018) point out that factor exposure can be priced even if the factors are the result of mispricing rather than risk. Nevertheless, characteristics vs. covariances tests can still be helpful to understand if the factor exposure is associated with above average returns.

[11] In unreported tests, we find similar results if we measure exposure to digital innovation using the tf-idf *DO* measure. In this case, the equally weighted (value-weighted) monthly six alpha factor of the long-short *DO* factor exposure portfolio is 0.96% (0.54%). Both alphas are statistically significant at the 1%-level and again comparable to our baseline results.

Table 10: Abnormal returns of long–short trading strategies based on *DO* factor exposure

Panel A: Equally weighted long-short trading strategy based on *DO* factor exposure

	(1)	**(2)**	**(3)**	**(4)**
Alpha	0.0070	0.0032	0.0093***	0.0028
	(1.63)	(1.21)	(4.14)	(1.35)
mktrf		0.2857***	0.0556	0.0000
		(4.85)	(0.96)	(0.00)
smb		0.7185***	0.3079***	0.1640**
		(8.40)	(3.90)	(2.29)
hml		-1.4047***	-0.9128***	-0.5288***
		(-17.91)	(-9.41)	(-5.47)
umd			0.0529	0.1404***
			(1.17)	(3.41)
rmw			-1.2057***	-0.6319***
			(-11.64)	(-5.58)
cma			-0.1114	0.0537
			(-0.83)	(0.44)
DO				0.7227***
				(8.58)
N	263	263	263	263
R-squared	0.000	0.641	0.766	0.818

Panel B: Value-weighted long-short trading strategy based on *DO* factor exposure

	(1)	**(2)**	**(3)**	**(4)**
Alpha	0.0035	-0.0002	0.0053***	0.0020
	(0.84)	(-0.10)	(2.69)	(1.09)
mktrf		0.2994***	0.0968*	0.0270
		(5.65)	(1.89)	(0.58)
smb		0.5921***	0.2017***	0.0982
		(7.69)	(2.90)	(1.54)
hml		-1.4263***	-0.9557***	-0.5990***
		(-20.20)	(-11.18)	(-6.72)
umd			0.0769*	0.1375***
			(1.93)	(3.76)
rmw			-1.1281***	-0.5849***
			(-12.37)	(-5.46)
cma			-0.0998	0.0717
			(-0.84)	(0.66)
DO				0.7146***
				(7.87)
N	263	263	263	263
R-squared	0.000	0.681	0.800	0.839

Table 10 shows the results of regressions to investigate the profitability of equally weighted (Panel A) and capped value-weighted (Panel B) quintile 5-minus-1 portfolios based on exposure to the digital orientation (*DO*) factor. Factor exposure is obtained from rolling-window regressions of past 24 monthly stock returns on the market factor and *DO* factor. Quintile portfolios are characteristics-neutral with regard to digital orientation. Column (1) shows the raw returns per month of this factor exposure portfolio. The remaining columns show the results, if the monthly long–short portfolio returns are regressed on the excess market return (MKTRF); on the Fama and French (1993) size and value factors (SMB, HML); on the Fama and French (2015) profitability and investment factors (RMW, CMA); on the momentum factor from Kenneth French (UMD); and on the equally weighted (Panel A) or value-weighted (Panel B) *DO* factor from Table 6; t-statistics are reported in parentheses. *, ** and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

As expected, the long-short *DO* factor exposure portfolio is indeed exposed to the *DO* factor. In column (4) of Panel A, the regression coefficient for the *DO* factor equals 0.7227 (t-statistic 8.58). In column (4) of Panel B, the regression coefficient for the *DO* factor equals 0.7146 (t-statistic 7.87). While we use historical returns to estimate stock-specific factor exposures, the strong relation between the long-short *DO* factor exposure portfolio and the actual *DO* factor suggests that stock-specific exposures are primarily persistent.

The interpretation of these findings is that the systematic *DO* factor exposure is priced in the cross-section of stock returns. This suggests that the abnormal return of the *DO* factor is a compensation for bearing exposure to a systematic factor. This result fits with the hypothesis that the digitalization is a process that affects the entire economy and is not limited to individual sectors. The resulting benefits and risks from investments in digital technology are therefore not idiosyncratic in nature, but shared across the board.

The existence of a risk premium for digital leaders is also consistent with the premium for leading industries as argued by Croce et al. (2023). In the spirit of this model, digital leaders are the first to provide resolution of uncertainty which comes from digital innovation, and investors who are exposed to this uncertainty require a compensation. Extending Croce et al. (2023), we show that such a leading premium exists not only for industries, but also for digital leaders across all industries.

5 Conclusion

Although digital innovations have led to the disruption of business models in firms and challenged the boundaries of existing industries, we know little about the impact of digital innovation in explaining asset returns. Relying on a bag-of-words approach, we analyze annual reports of US firms in the period 1996-2020 to derive a text-based, objective, and easy-to-implement measure of firms' orientation toward digital innovation (called digital orientation). We show that firms' digital orientation has significant implications for the capital market and investors' valuation of stocks. Our findings illustrate that our measure of digital innovation can explain heterogeneity in stock returns across firms that cannot be accounted for by other firm characteristics.

Based on this insight, we create a new digital orientation factor, which has significant explanatory power for expected stock returns. Against the backdrop that digitalization and the impact of digital innovation are unlikely to disappear in the next decade(s), our findings have significant implications for studying capital markets in the digital age.

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