Essays on corporate disclosures, innovation, and investments

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Essays on Corporate Disclosures, Innovation, and Investments

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TILBURG UNIVERSITY

Essays on Corporate Disclosures, Innovation, and Investments

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Contents

CHAPTER 1

General Introduction

In this dissertation, I present three essays on corporate disclosures and investment in intangible capital. Innovation or, in broader terms, intangible capital is argued to be the main driver of economic growth and today's business success—while at the same time being at the center of a critical accounting debate on the value-relevance of accounting disclosures. In this regard, my dissertation attempts to answer important questions about whether and how corporations disclose innovation-related qualities and how these disclosures benefit firms, capital markets, and even rivals to understand the underlying firm fundamentals and future potential.

In Chapter 2 of the dissertation, *"Text-based innovation measure and firm performance"* (co-authored with Philip Joos), we examine whether firms disclose their innovative qualities through their textual filings and, if so, whether these disclosures may help understand the intangible capital of a firm that is generally not recognized in financial statements. Despite its critical role in economic growth and firm success, measuring innovation poses challenges. Conventional proxies (such as R&D investments and patents) are either unavailable or only capture technological advancements, thereby overlooking the broader array of innovative activities (e.g., innovation in organizational methods or business model) that can give a competitive edge to corporations. In order to address this gap, we develop a novel text-based innovation measure based on financial statement text by capturing the novel product, services, or organizational methods firms introduce to their business descriptions. We show that our innovation measure help understand firms' strategic assets and explain future sales growth, market performance, and future net income beyond historical accounting numbers.

Our study contributes to the accounting literature by showing the usefulness of textual disclosures in assessing a firm's degree of innovation (intangible capital) and might benefit not only researchers but also investors who, in general, fail to differentiate the outcomes of innovative activities. Our study also has implications for the critiques around boilerplate financial statements. We demonstrate that firms disclose valuable information regarding their strategic assets that can be extracted from financial statement texts using text mining tools, even if the disclosures are argued to be boilerplate.

Chapter 3 of the dissertation explores the implications of innovation-related disclosures. While firms inform capital markets through such disclosures; investors may inform back managers by trading on firms' stocks, reflecting market participants' overall opinion regarding the future potential of a particular investment. Using this market feedback as input, managers may update their information set and change their subsequent investment behavior. Firms bundle or separate information releases for strategic reasons, such as burying bad news with good news. However, the effect of separating or bundling information releases may also have consequences regarding what they can learn from stock price movements.

In the paper, titled "*Simultaneous information releases and capital market feedback: Evidence from patent Tuesdays"* (co-authored with Tim Martens and Christoph J. Sextroh), we investigate whether separating versus bundling the release of multiple pieces of information affects managers' ability to gather information from stock prices. Using the plausibly exogenous timing of patent grant disclosures by the United States Patent and Trademark Office, we show that the market's response to patent grants is more informative for managerial decisions if the firm receives fewer patent grants on the same day. We further show that this effect is more pronounced for patents that relate to relatively more exploratory (risky) innovative strategies for which feedback is arguably more important. We also find that firms having, on average, more distinct information releases, thus having more informative feedback, produce more valuable and higher-quality innovations in the future. Taken together, the evidence in this paper suggests that bundling the release of multiple pieces of information at once impedes managers' ability to benefit from the market's feedback and may have consequences for the future value of their innovation-related investments.

Firms may not always find it optimal to disclose their innovation-related investments due to proprietary costs when disclosed information can be particularly useful for rival firms and used against them. In Chapter 4, I examine a very interesting setting in which the Securities and Exchange Commission allows U.S. public firms to omit some information from mandatory disclosures i.e., material contracts (e.g., R&D agreements or supply contracts). In case of a potential competitive harm, firms are allowed to redact, i.e., (self-)censor some parts of these contracts. While censoring proprietary information, firms also reveal to rivals that information hidden in these contracts might be useful for them, such as information regarding profitable markets. This may, in turn, increase rivals' attention and motivation to extract more information from these contracts. In the final chapter of this dissertation (Chapter 4), *"Less is more: Peer learning from non-disclosures"*, I examine whether firms can extract valuable information from rivals' non-disclosures or, in other words, (self-)censored documents.

Using EDGAR downloads on company filings, I find that censored/redacted contracts receive significantly more attention compared to their non-redacted counterparts disclosed by the firm. Moreover, I find that competitors change their investment behavior in response to censoring behavior: Product market peers increase their R&D investments and seem to become closer to redacting peers in the product space, consistent with the learning from peers' non-disclosures. Using exogenous CEO departures as a shock to rivals' attention, I find that increased firm attention to these filings might be one potential mechanism to explain how firms can learn from these disclosures. Overall, my research extends the literature by showing the specific channels and mechanisms regarding peer learning and adds to our knowledge of firm response to peer censoring behavior. My research also has implications for the SEC's decision to allow such non-disclosures that has already been shown to have negative capital market consequences.

Overall, my dissertation attempts to answer important research questions surrounding corporate disclosures, their effect on capital markets and firms' future investment decisions, along with proprietary costs of such disclosures and their usefulness for rival firms.

CHAPTER 2

Text-Based Innovation Measure and Firm Performance

with Philip Joos

Abstract

In this study, we examine whether firms disclose their innovative qualities through their textual filings and, if so, whether these disclosures may help understand the intangible capital of a firm that is generally not recognized in financial statements. Using the introduction of *novelties* to firms' business descriptions in their 10-K filings, we develop a novel text-based innovation measure, which is particularly appealing for firms operating in non-R&D industries that offer innovative products and services. Our innovation measure captures not only firms' product and service innovations, but also innovations in business models or organizational methods, which is not captured by conventional innovation proxies. We find that novelties introduced in firms' textual filings help explain future sales growth, operating profitability, and capital market performance beyond historical accounting numbers. We find that not only R&D investments but also SGA expenses related to intangible capital explain the variation in our text-based innovation measure. Our study extends the earlier work showing the usefulness of textual disclosures in terms of assessing a firm's degree of innovation (intangible capital) and contributes to the long-standing debate regarding the recognition of intangibles in financial statements.

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2.1. Introduction

In this paper, we introduce a novel text-based innovation measure derived from firms' content-rich textual filings, which can offer valuable insights into firms' strategic assets and innovative capabilities. Innovation is widely recognized as a primary driver of economic growth in 'new economy' (e.g., Corrado and Hulten, 2010) and a crucial determinant of firm success (Damanpour et al., 1989). However, measuring innovation and intangible capital poses significant challenges. Financial statements provide little information regarding such investments: Accounting numbers are aggregate and sometimes even incomplete (Koh and Reeb, 2015), and may not communicate such investments well due to uncertainty (Merkley, 2014).[1]

Patents, as an outcome measure, may give more granular information about firms' innovation-related investments (e.g., Hegde, Lev and Zhu, 2018; Ahci, Martens and Sextroh, 2022), however, even R&D intensive firms may prefer not to file patents and choose for trade secrecy (Glaeser, 2018).[2] Our proposed text-based innovation measure is widely applicable to all public firms and might be particularly appealing for firms having little to no information regarding conventional proxies.

It is not an easy task to predict the implications of innovative activities since outcomes of such activities are inherently uncertain. Indeed, existing literature provides evidence that investors frequently misvalue innovation. For instance, studies have shown that investors fail

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[1] Critics argue that conventional financial statements fail to capture the growing significance of intangible capital in modern business operations, resulting in a decline in the value-relevance of accounting numbers (e.g., Lev and Zarowin, 1999; Dichev and Tang, 2008; Srivastava, 2014; Lev and Gu, 2016).

[2] Firms with innovative products and services may not engage in any R&D or patenting activity. Data from the 2020 Annual Business Survey by National Center for Science and Engineering Statistics and Census Bureau reveal that 76% of firms that exhibit some level of product or business process innovation (25% of all firms surveyed) do not report any R&D activity. Our own analysis supports this, with nearly half of the sample firms (45% firm-years) displaying no R&D investments (see Figure 1), and over half (63% firm-years) lacking patents despite some of them demonstrating high R&D intensity.

to differentiate the outcomes of innovative activities between firms with similar levels of R&D investments (Cohen et al., 2013) or patent (citation) numbers (Hirshleifer et al, 2013). Although these results suggest limited investor attention or difficulties in processing innovation-related news as underlying reasons for misvaluation, it might also be that these conventional proxies capture only technological advancements, thereby overlooking the broader array of innovative activities that have the potential to influence future firm performance.[3] We argue that leveraging a novel innovation measure derived from content-rich textual information can provide additional insights into the broader range of firms' innovative activities, which might benefit investors. The information provided in the text of financial statements may unravel the expectations of firms regarding the future potential of such activities, thereby resolving some of the uncertainty surrounding these investments.

Firms provide information about their main products and services and how they conduct their businesses under Item 1 (Description of Business) of 10-K filings. Therefore, we contend that the content found under this item can give insights into firms' innovative products, services, and novel methods of conducting business, including organizational methods. Our methodology to identify innovative firms using the text is as follows. While acknowledging that innovation encompasses various dimensions such as product innovation, process innovation, and business model innovation, we define innovation as any *change* or *novelty* in firm routines that generates future value.[4] Relying on this definition, we first identify *novel* terms introduced in firms' business descriptions within a given year that were absent in the previous year's 10-K filings. To ensure that we identify genuinely novel cases and eliminate terms that are still new to the 10-K text but unrelated to innovation (for instance a change in

[3] Innovation encompasses broad array of activities including technological advancements. Based on the Oslo Manual (2005), innovation is defined as "the implementation of a *new* or significantly improved *product (good or service), or process*, a *new marketing method*, or a *new organizational method* in business practices, workplace organization or external relations.*"* (*Italics* are my own)
[4] Merriam-Webster defines innovation as *"a new idea, method, or device"* or *"introduction of something new"*. (*Italics* are my own)

regulation or economic-wide event that may suddenly appear in 10-Ks), we require that these innovative terms be used by no more than 5% of all firms in a given year.[5] We then switch to the firm-level and identify innovative firms based on the usage of these novel terms as the stock of intangible capital.[6]

Our text-based innovation measure can successfully identify not only product and service innovations but also business model innovations or culture of innovation disclosed in firms' 10-K filings.[7] For instance, Whole Foods Market Inc has been frequently listed as one of the most innovative companies in Forbes rankings and one of "100 Best Companies to Work for in America" in the FORTUNE list. The company operates in grocery retail sector focusing on a sustainable and healthy diet by also providing innovative shopping experience to its customers. Amazon's acquisition deal of Whole Foods in 2017 also alludes to these capabilities, in which around 70% of the total deal (13,6 billion dollars) was for its intangible assets.[8] The company has neither R&D investments nor patents granted during our sample period. However, our innovation measure successfully captures the firm as one of the most innovative companies in the top quintile of the distribution of our innovation score. Our innovation measure successfully captures the company's innovative products and services with terms *Eco-Scale* and *Healthy Eating (Education)*, its engaging marketing strategies with *word-of-mouth*

[5] Although the choice of the 5% threshold may appear arbitrary, it is based on the assumption that innovative products or services may be introduced by only a subset of firms within a given year. Supporting this assumption, the 2020 Annual Business Survey reveals that only 4.1% of firms report a new-to-market product innovation during the period of 2017-2019. See https://ncses.nsf.gov/pubs/nsf22344 for more information.

[6] While we use intangible capital and innovation interchangeably throughout the paper, we acknowledge that they are not always referring to the same concept. Innovation refers to the process of creating and implementing new ideas, products, processes, or methods. While a firm may develop a tangible asset, such as a novel product, this physical asset is ultimately an outcome of the firm's intangible assets, such as intellectual capital and organizational capabilities. On the other hand, intangible assets may not necessarily be an innovation, such as brands or knowledge. We are particularly interested in capturing novel ideas and methods that might also relate to assets of physical substance.

[7] Managers believe that corporate culture is one of the driving factors for creating future firm value (Graham, Grennan, Harvey and Rajgopal, 2022).

[8] See an 8-K filing by Amazon to give proforma financial information on the transaction (Ex-99.3) https://www.sec.gov/Archives/edgar/data/1018724/000101872417000143/amzn-201711138ka.htm

recommendations, and its innovative team culture with *self-managed teams* and *Gainsharing program*.[9,10]

Another example is Adobe Inc, again one of the most innovative companies in Forbes list and one of the R&D-intensive companies in our sample. Our innovation measure timely captures how the company transformed itself by changing its business model by introducing *Creative Cloud* in 2011 and gradually switched to subscription-based business model in 2013.[11] This change in business model allowed the company to increase revenue by targeting mobile devices, having recurring revenue, increasing customer retention with subscriptions, and reducing malicious usage (see Appendix B for examples of innovative word combinations).[12]

First, we examine the determinants of the innovation measure to validate our measure. Not surprisingly, we find that both R&D investments and acquisitions explain the variation in our innovation measure. It seems that our innovation measure captures both internally generated and acquired innovation (Philips and Zhdanov, 2013).[13] We also find that innovative firms are, on average, smaller and less profitable but show higher market-to-book values and spend more on capital expenditures and advertising expenses. We see that our innovation measure is positively associated with the growth/investment component of SG&A as in Enache and Srivastava (2018), suggesting that our text-based measure can also capture intangible

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[9] See https://www.forbes.com/sites/davidburkus/2016/06/08/why-whole-foods-build-their-entire-business-on-teams/

[10] See "in-store *healthy-eating* centers" or "store tours focused on making *healthy eating* choices", "*Eco-Scale*™ rating system that allows shoppers to easily identify a product's environmental impact and safety", "*self-managed teams*", and how company "strive to create a company-wide consciousness of *"shared fate"* with *Gainsharing* program", in the company's 10-K filing for fiscal year 2013 (Item 1. Business) at https://www.sec.gov/Archives/edgar/data/865436/000086543613000134/wfm10k2013.htm#sF9D03E1AF7156A4E9241A7B16ABCBA4F

[11] Besides *creative cloud*, it is no coincidence that Adobe introduces in its 2011 annual report (disclosed on January 26th 2012) novel word combinations such as *cloud-based capabilities*, *cloud-based model, browser-based applications, digital age, digital business, digital delivery, e-learning market, online presence, on-premise software, software-as-a-service (SaaS),* etc. See, for instance, an interview how Adobe transformed itself to compete in digital age: https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/reborn-in-the-cloud

[12] Between 2013 and 2018, the company enjoyed an average yearly sales growth of 17.4%, which is more than the double of the 2-digit industry average of 7.72%.

[13] For instance, 41% of Google's intangible capital reported in 2013 was due to acquisitions (Peters and Taylor, 2017)

capital embedded under SG&A expenses. Interestingly, the growth component of SG&A explains the variation for both R&D and non-R&D firms, which indicates that even R&D intensive firms use SG&A (excluding R&D) as an investment for intangible capital. We also find that innovative firms are followed by more analysts and have more institutional ownership. The latter is consistent with Aghion et al. (2013), providing evidence that long-term focused investors incentivize managers to innovate more by reducing managers' career concerns due to their higher tolerance for interim failures.

Next, we test whether our innovation measure is linked with future firm performance. We find that innovation measure is positively associated with future sales growth, operating profitability, and capital market performance. Particularly, we show that moving from the first to the last quartile of innovation is associated with a 2,2% increase in sales growth that is also persistent over the years (0.8% increase in annualized 3-year sales growth). This increase corresponds to 17% (9% for 3-year annualized growth) of the sample mean. The results are also robust to including past sales growth due to the possible momentum effect of the past performance. We further show that more innovative firms enjoy higher operating profitability in the future after controlling for R&D, which is shown to be effective on future income in previous studies (Ciftci and Cready, 2011; Curtis et al., 2020). A move in innovation score from the bottom to the top quartile leads to a 2,8% to 5,5% increase of the sample mean for 5-year future operating profitability.

Finally, we show that our innovation score is positively associated with 1- to 3-year future capital market returns while it is not associated with current year returns, which alleviates concerns that our measure simply picks up the current performance that is persistent over the years. To confirm our regression results, we also conduct a time-series portfolio analysis since we believe that innovation shows its effect in longer-term. To this end, we sort firms based on innovation score and assign stocks to innovation quintiles each year and track the mean stock returns for each quintile over the subsequent five years. We also adjust returns based on similar size- and book-to-market portfolio returns each year to fix the effects of time-varying risk factors that can explain the future returns. We find that a hedge portfolio that takes a long position in firms with high innovation and a short position in firms with low innovation show significant abnormal returns in the long-term but not in the immediate term.

The association with future returns suggests that investors fail to recognize the novelties in business descriptions, which materializes with future returns. This is in line with Cohen et al. (2020) showing that investors overlook the implications of changes in 10-Ks and stock prices only gradually reflect this information, consistent with investor inattention to financial statements. In contrast to their findings, however, we find a positive abnormal return for 'changers', suggesting that the changes in different parts of 10-K might have different implications and the information captured by our innovation measure is fundamentally different from the *change* in Cohen et al. (2020).

Next, we partition our sample into R&D and non-R&D firms and replicate our main tests for future firm performance to check whether the link between our innovation measure and future performance changes for firms that differ in the availability of investments in intangible capital in financial statements, particularly investments in R&D. We see that our innovation measure can also explain future performance for firms with no R&D investments. Although the coefficients on our innovation measure are lower for the non-R&D sample, they are positive and significant. This is particularly important because it shows how our innovation measure is able to capture firms' investments in intangible capital when financial statements provide little or no information.

Finally, we check whether the ability of our innovation measure to link intangible capital with future performance is sensitive to firms' disclosure policies since our measure depends on corporate disclosures. One may argue that firms may be reluctant to disclose their innovative activities due to proprietary costs. Although business descriptions are mandatory for all public firms, which alleviates some of our concerns regarding the selection issue, firms have sufficient room for what to include under this item. This may create some bias in our results if, for instance, firms with higher performance disclose more, which mechanically increases the ability of our measure to capture future performance.

Our results regarding the negative association with current profitability and insignificant relation with current market return do not support this view. Furthermore, we show that innovation shows its effect in the longer term but not in the immediate term. Nevertheless, we also attempt to test whether proprietary costs or information demand plays a role in explaining the documented relation since both information demand and information supply (managers' willingness to provide disclosure) may affect the ability of our measure to capture intangible capital. Using several proxies for information demand and proprietary cost, we find no evidence that disclosure incentives play a significant role in explaining the observed association.

Our study contributes to the literature in several ways. First, our study extends the earlier work showing that textual disclosures may bridge the gap between firm fundamentals and financial statements (Merkley, 2014). We distinguish our study from prior literature by identifying novel terms in business descriptions related to firms' long-term prospects rather than focusing on short-term performance-related narrative disclosures. Our study mostly relates to the growing literature on textual filings that are used to identify different firm and industry-related characteristics (e.g., Hoberg and Philips, 2016; Li et al., 2013) and show that corporate disclosures can also be used to identify firms' innovative qualities. Our study might also be informative to investors who are shown to consistently misprice innovative firms (Cohen et al., 2013; Hirshleifer et al., 2013) and has implications on the critiques of boilerplate disclosures (e.g., Dyer et al., 2017; Kravet and Muslu, 2013). We demonstrate that firms disclose valuable information regarding their strategic assets that can be extracted from the 10-K filings using text mining tools even if the disclosures are argued to be boilerplate.

Second, we contribute to the long-standing debate on whether to recognize or expense intangibles by proposing an alternative way to rank firms on intangible capital. Even though some of these investments are observable in the income statement (Penman, 2009), aggregate accounting numbers may not communicate firms' intangible capital well (Merkley, 2014). We show that textual disclosures in annual reports may provide valuable information about firms' long-term prospects beyond accounting numbers.

Third, our study is related but not limited to earlier work on the benefits of intangible capital and innovation (Lev and Sougiannis, 1996; Ciftci and Cready, 2011; Curtis et al., 2020). We introduce an alternative measure for the degree of corporate innovation that is widely available for public firms in contrast to other measures (R&D or patent measures) used in the literature. Consistent with prior work, we show that our innovation measure can successfully capture firm fundamentals that create future value and is not susceptible to managers' disclosure incentives.

Finally, our study is distinct from Bellstam et al. (2021), which introduces an innovation measure based on analyst reports for S&P 500 firms in terms of contribution, the sample of firms, and methodology. Our study is applicable to all public firms and shows that innovation mainly comes from smaller firms, whereas Bellstam et al. (2021) show innovative characteristics of mature firms in the S&P 500. Second, rather than information produced by analysts, we use public disclosures and examine whether these disclosure help explain innovative characteristics of firms that is usually not captured by financial statements. Finally, we use rather a simple approach and let the text speak for itself to identify innovative products and services rather than a topic modeling approach using analyst reports, which are not widely available for all firms, and which are shown to have biases (e.g., Lourie, 2019).

2.2. Background and Literature Review

Intangibles or innovation are argued to be the main engine for economic growth (e.g., Corrado and Hulten, 2010; Aghion, 2013) and firm expansion (Hoberg and Philips, 2021). The literature also demonstrates its strong link with future firm value; however, accounting numbers convey little information about firms' degree of innovation.[14] This also led to long-standing debate among accounting scholars regarding the value relevance of financial statements and accounting numbers (e.g. Lev, 2001; Lev and Zarowin, 1999; Lev and Gu, 2016; Dichev and Tang, 2008; Srivastava, 2014).[15]

Even though some information is already embedded in income statement such as R&D investments (e.g., Skinner, 2008; Penman, 2009), most firms in the economy do not disclose any R&D (or not even engage in R&D activities) while some of them still offer innovative products and services or show innovative characteristics (Roh and Keeb, 2015).[16] For instance, almost half of the Compustat firms do not disclose any R&D, although these firms have innovative products, services, or organizational designs. Moreover, aggregate R&D disclosures do not give precise information regarding intangible investments. As a result, firms with similar levels of R&D investments can have different future performance (Cohen et al., 2013; Joos and Zhdanov, 2008). In contrast with aggregate R&D investment figures, patents can give more granular information to capital markets regarding firms' innovative investments (e.g., Hegde,

[14] See the relevant studies for the link between firm value and brands (Barth et al., 1998), customer satisfaction (Ittner and Larcker, 1998), and advertising (Lev and Sougiannis, 1996).
[15] See Barth et al (2022) for a review. They do not find supportive evidence for a decrease in value relevance of overall accounting information but find a shift of importance to some items other than earnings.
[16] Roh and Keeb (2015) show that firms with missing R&D in their financial statements exhibit innovative characteristics (such as issuing patents) similar to those with non-zero R&D investments.

Lev and Zhu, 2018). However, even some R&D intensive firms do not file patents and may prefer trade secrecy to protect their proprietary assets (Glaeser, 2018).

Innovation is a multidimensional concept and R&D investments, which more relates to science and technology development, may not capture its other dimensions, such as business model innovation or innovations in organizational methods (Corrado and Hulten, 2010). Relatedly, the recent literature shows that intangible capital extends beyond research and development (R&D) expenditures. SG&A expenses, which account for 26 to 37 percent of a company's total assets compared to only 4 percent attributed to R&D, can create intangibles, and include investments in human capital, brand development, and other areas (Banker et al., 2019; Enache and Srivastava, 2018). However, SG&A expenses are commingled with expenses with different characteristics and yet again, firms do not generally give detailed information regarding its components, other than R&D or advertising expenses, making it challenging to distinguish the investments relating to intangible capital.[17]

Outcome of innovative activities are inherently uncertain since innovation relates to experimentation of new ideas and novel methods. This might be one of the reasons why investors consistently fail to correctly price firms with high degree of innovation (Cohen et al., 2013; Hilshleifer et al, 2013; Fitzgerald et al., 2021). We argue that information extracted from corporate narrative disclosures can offer a solution to this measurement problem and alleviate some of the uncertainty surrounding these investments. These disclosures can give more granular information regarding the outcome of firms' innovative activities or investments in intangible capital that standard accounting numbers may not convey well. Our innovation measure is particularly appealing for firms with little or no information in their financial

[17] SG&A expenses may include investments to improve organizational knowledge and capabilities that may affect firms' long-term performance, such as market research, customer and social networks, IT and software development, and human capital.

statements regarding their intangible investments, such as firms operating in non-R&D industries while still showing innovative characteristics (e.g., telecommunication industry).

However, we are not the first to show that narrative disclosures are informative beyond accounting numbers. Merkley (2014), one of the first studies examining narrative R&D disclosures in 10-Ks, show that firms modify their disclosures to assist market participants in better understanding their earnings performance. Our study, however, attempts to identify intangible capital that can create future value and explain long-term performance of a firm, diverging from the focus on explaining short-term performance. Our work mostly relates to prior work using textual disclosures to measure firm and industry characteristics (e.g., Hoberg and Philips, 2016; Li et al., 2013) and differs from other studies regarding linguistic characteristics of disclosures that change based on other time-varying firm characteristics (e.g., Li, 2008; Feldman et al., 2010). [18,19] We are the first to show that public disclosures can also be utilized to extract firms' innovative qualities which might be useful for capital market participants. We also extend Cohen et al. (2020) and show that changes in different sections of 10-K documents may have different implications on future performance of firms. We show that our innovation measure captures *unique* 'positive' changes in contrast to positive sentiment changes that do not predict significant positive returns in Cohen et al. (2020).

2.3. Measuring innovation from 10-K filings

In this section, we define the text-based measure extracted from 10-K filings of U.S. public firms and give the intuition behind the methodology. Throughout the study, we use *10K*

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[18] Corporate text is used to measure firms' financial constraints (Bodnaruk, Loughran, and McDonald, 2015); industry peers (Hoberg and Philips, 2016); product market competition (Hoberg et al., 2014); perception of competitive threats (Li et al., 2013), or to gather information regarding firms' investment opportunity set (Basu, Ma, and Briscoe-Tran, 2022).

[19] For example, Merkley (2014) is one of the first to show that managers adjust their narrative disclosures based on their performance and provide relevant information to investors about their innovative activities that ultimately affect their earnings numbers. Other studies show that the linguistic characteristics of textual disclosures, such as tone, varies with manager's disclosure choices (Li, 2008; Feldman et al., 2010; Li, 2010; Muslu et al., 2014). For a recent review see Bochkay et al., 2022.

reports/filings and *annual reports* interchangeably, although they may sometimes refer to different types of reporting.[20]

We identify innovative firms by capturing the introduction of 'novel terms' into their business descriptions (Item 1) of their annual 10-K filings. Regulation S-K[21] mandates public firms to disclose their products and services, describe business development, and mention 'any material changes in the mode of conducting the business'. We use the same text as in Hoberg and Philips (2016) and Hoberg, Philips and Prabhala (2014); however, we differ from these studies by identifying only *novel* products and services in firms' disclosures using the following methodology.

We start constructing our innovation measure by building a vocabulary that reflects the *change* and *novelty* in the whole 10-K universe in a given year. Rather than introducing our own vocabulary, we let the data (text) speak for itself. We first download all 10-K text and parse Item-1 Business Descriptions using Python scripts. We keep only nouns, proper nouns, and adjectives and remove numbers and tables in the text. We identify novel terms consisting of every unique monogram (one-element words such as '*eCommerce'*) or bigrams in terms of adjective phrases (such as '*online grocery*') introduced to business descriptions within a year that does not appear in the 10-K universe of the previous year. We use adjective phrases because some novelties can only be captured when words are used in combination rather than used separately. For instance, it was the first time when Walmart used *'online grocery'* in its annual report for 2016 when neither '*online'* nor '*grocery'* was novel to the retail industry. However, at the time, '*online grocery'* was a novel service used by many retail stores now, enabling customers to order foods online and have them delivered. So, our innovation measure

[20] Although some firms only report 10-K format required by SEC, other prefer to issue additional reports for investors with more visual and non-technical information.
[21] The SEC amended regulation S-K rules after our sample period on 26th August 2020 to modernize public firm disclosures and our sample covers the period before this change.

successfully captures similar novel word combinations, such as *'augmented reality', 'cloud computing', 'e-learning',* etc. which are all innovative products/services mentioned by different firms (see Appendix B for more examples).

For a term to be in the innovation vocabulary, we require two conditions: (1) for a given year *t*, a term must be novel, i.e., not used in the previous year (*t-1)* business sections of any firm, and (2) these terms can only occur in 5% of the 10-K documents in a given year[22]. While the first condition is basically to capture novel terms, the second condition is to eliminate, as much as possible, incidental use of any word combination which suddenly appeared in the text but is irrelevant to innovation.[23] In addition, to avoid that arbitrary word combinations (such as clerical errors perceived as a novelty) are included in the vocabulary, we also require that the same term be consistently appear in 10-K universe in the subsequent two years, *t+1* and *t+2*. The terms which do not have consistency throughout the years are highly likely to be irrelevant terms that would only add noise to our innovation measure.[24]

After constructing the innovation vocabulary, we identify which firms use these novel terms in which year. For each firm-year, we construct the innovation score by simply counting the number of novel terms used in a given year's business sections as a stock measure for intangible capital.

One question still remains as to what extent our bags-of-words approach is still valid, especially with the introduction of more advanced NLP techniques, including GPT language models. A potential suggestion would be to use more advanced techniques, such as word embeddings instead of bags-of-words. Although we acknowledge more sophisticated

[22] The results are robust to different thresholds.
[23] For instance, an accounting rule change, such as FIN 48, may occur in many documents at the same time in its introduction year of 2007 but it is unrelated to innovation. Similarly, Covid19 can be used by many firms starting from 2019.
[24] We see that our main results are robust to removing this restriction (untabulated).

approaches can provide additional insights, we believe our approach has several advantages, and using more sophisticated models has some limitations in the given context. First, word embeddings should be trained on large corpora to capture the semantic relationships between words. Our dataset, however, spans a relatively limited number of documents. It is also possible to use pre-trained language models; however, these versions may also not fit financial statements since their structure and language may differ from regular texts. Moreover, we attempt to capture novel products and services that are unique to the text, therefore, infrequent and specific to the firm. A trained language model may treat them as out-of-vocabulary (OOV) words or assign them low weights due to their limited occurrence in the training data. This may result in unexpected and incorrect weightings for our innovative words and bias our results.

An alternative approach might be to introduce our own innovation vocabulary. However, it is quite challenging to anticipate any word combinations that refer to innovative products and services. Therefore, we believe our novel approach, together with its simplicity, gives our methodology an edge and can be more effective in identifying novel terms that are relevant to our research question. We also acknowledge that our approach exploits unweighted representation of text data and, therefore, disregards word order and context, potentially overlooking important nuances and relationships within the text. While we can identify the presence of innovative terms, our approach does not provide an assessment of their relative significance or impact on firm performance. Additionally, it is important to note that although we can rank firms based on their usage of innovative terms, our measure is not designed to differentiate the value or cost associated with the novel products and services introduced in the text. These limitations should be taken into consideration when interpreting our results and understanding the potential implications of our findings.

2.4. Data, sample, and descriptive statistics

2.4.1. Data and sample

Our sample period covers the period from 1996 to 2018. We start constructing the sample based on the availability of annual reports electronically at the SEC's EDGAR system by all public firms. We download 10-K files of all U.S. public firms from U.S. Securities and Exchange Commission (SEC) EDGAR filings. We also use CRSP & Compustat data for firms' yearly accounting data. We merge SEC filings and Compustat data using the central key index CIK. We only use ordinary shares and remove public firms that are not traded in NYSE, NASDAQ, or NYSE America (former AMEX) since reporting characteristics and pricing of these stocks may significantly differ from firms traded in stock exchanges. The sample selection criteria leave us with 51,727 firm-year observations comprising 5,362 unique firms.

2.4.2. Descriptive Analyses

Table 1 shows the overall descriptive statistics of our sample. The description of variables is given in Appendix A, and all variables are winsorized at 1% level.

Our innovative measure ranges from a minimum of 1 to a maximum of 7, with a mean (median) value of 5.16 (5.28). This indicates that firms, on average, use 190 innovative words or word combinations in their business descriptions. On average, firms exhibit an R&D intensity of 6%. Notably, 55% of the firm-years in our sample have non-zero R&D investments, while 37% have non-zero patent grants. This means that almost half of the sample firms do not disclose any R&D, while almost two-thirds do not have any patent grants. Furthermore, we observe considerable diversity in firm performance metrics. The average 1-year sales growth stands at 13%, with a standard deviation of 37%. This wide dispersion underscores the heterogeneity in firms' sales growth rates and further emphasizes the significance of examining their innovative activities.

In Panel B, we partition our sample into quintiles of the innovation score and report statistics for each of these quintiles. Innovative firms seem to exhibit a U-shape relationship with size: as we move from quintile 1 to 5, the size of a firm (market cap) first decreases and then increases. Innovative firms show consistently higher future sales growth, lower current operating profitability, and higher growth opportunities, as indicated by the book-to-market ratio. Additionally, a high Tobin's Q measure for innovative firms also indicates that the capital market highly values these firms. There is a clear pattern and positive association between our innovation measure and conventional proxies of innovation, namely R&D investments and patents. Innovative firms, on average, show high R&D investments (intensity) and patenting behavior (number of patents). This is the first confirmation that our innovation measure captures the innovative characteristics of firms. While there are no substantial differences across quintiles regarding CAPEX (capital expenditures) and advertising expenses, there is some evidence suggesting that innovative firms are more active in acquisitions.

In Panel C, we show the distribution of our innovation score across industries and report average values of the innovation score (measured in terms of the number of innovative terms) along with common investment items for the top and bottom industries based on their average innovation score. Not surprisingly, industries such as Pharmaceuticals, Medical Equipment, Computers, and Electronic Equipment, known for their intensive research and development (R&D) activities, exhibit the highest innovative characteristics according to our innovation score. However, our innovation score also successfully identifies some non-R&D industries, such as Entertainment and Communication, as highly innovative. This is not surprising since these industries have leveraged digitalization and technological tools to create innovative revenue streams and business models, such as online platforms, on-demand content, and virtual reality technologies. On the other hand, our innovation score identifies some industries, such as steel works, business supplies, and textiles, as having lower innovative characteristics, despite some of these industries demonstrating innovative activities based on traditional proxies, such as consumer goods and business supplies. These results suggest that our innovation score captures a unique underlying innovation characteristic that extends beyond the scope of R&D and patenting.

2.5. Main Analyses

In this section, we test whether our innovation score is associated with future performance since we expect that these firms show a better operating performance as a result of introducing successful products, services, or business models. In order to test whether our innovation measure is associated with future firm performance, we estimate the following model using pooled cross-sectional regressions with fixed effects:

$$
\begin{aligned}
&Performance_{i,t+T} \\
&\quad = \beta_0 + \beta_1 * Innovation_{it} + \sum_j \beta_j * Firm\ characteristics_{it} \\
&\quad + \sum_k \beta_k * Industry\ Dummy_k + \sum_t \beta_t * Year\ Dummy_t + \varepsilon_{it}
\end{aligned}
$$

where β_1 captures the association between our innovation measure and future firm performance.

We use several dependent variables for firm performance. First, we use future sales growth, in terms of 'compound annual growth rate (CAGR)' for 1-year, 2-year, and 3-year periods to make sales growth in different time horizons comparable. We argue that new products and services introduced in product descriptions should manifest first in higher future sales growth. Second, firms with higher innovation are expected to show higher future profitability (e.g., Curtis et al., 2020; Lev and Sougiannis, 1996; Ciftci et al., 2011). For this, we follow the literature and use operating income before depreciation, advertising, and R&D

expenses. We sum *adjusted* operating income over the years t+1 through t+5 and scale it by total assets in year t. The adjustment should overcome the systematic decrease in profitability due to higher investments by innovative firms. Our third measure focuses on the stock market performance of firms, which we capture using current and future stock returns as a proxy. Stock market performance provides valuable insights into investors' perceptions and expectations regarding a firm's innovative capabilities and its potential for future growth.

We use a battery of time-varying firm characteristics to control for factors that explain future performance, and that could be correlated with our innovation measure. We include R&D, CAPEX, and advertising expense (ADV) to control for investments that can explain future performance (Lev and Sougiannis, 1996; Curtis et al., 2020). We also include SGA expenses to control for any other investments related to intangible capital (Enache and Srivastava, 2018). We include acquisitions into our model to control for the effect of acquisitions on firm performance and innovation (e.g., Phillips and Zhdanov, 2013). In order to control for the growth opportunities, which may be correlated with innovation and future performance, we include the book-to-market ratio (BM) in our regressions. We also include market capitalization as a proxy for the size of a firm that can affect innovation and future performance (Ciftci et al., 2011).

Finally, for future income regressions, we follow the literature and add the level of operating income (OpINC) and the change in operating income (ΔOpINC) to control for persistency and mean reversion characteristics of income. In addition, we use industry fixed effects to control for differences across industries in terms of innovation. We include year fixed effects to control for timing effects and cluster the standard errors by firm to adjust for the correlation of residuals across years (Peterson, 2009).

In Tables 2-4, we present our main findings. Table 2 reports the results for future sales growth with different time horizons and controls across columns. Our innovation measure consistently shows a positive and statistically significant coefficient across all columns (at the 1% level). The effect is persistent over three years for sales growth, with the highest impact observed in the first year. Importantly, the results are economically meaningful, as an increase in the innovation score from the 25th to the 75th percentile corresponds to a 2.2% (Column 1) and 0.8% (Column 6) increase in 1- and 3-year annualized sales growth, respectively. These correspond to 17% and 9% increases of the sample means, respectively. Furthermore, the results are robust to controlling for industry variations, timing effects, and the inclusion of past sales growth that may have persistent impacts over the years.

Table 3 shows the regression results for future operating income. Similarly, firms with higher innovation score seem to enjoy higher operating profitability in the future as the coefficient on innovation is positive and statistically significant across different models with and without fixed effects. The coefficient varies between 0.065 and 0.034 across columns. Although controlling for R&D decreases the coefficient up to 48% due to its correlation with our innovation measure, the innovation coefficient remains positive and significant at the 1% level. A move in innovation score from the bottom to the top quartile leads to a 5,5% (Column 1: 0.065*0.99/1.18) to 2,8% (Column 6) increase of the sample mean for 5-year future operating income. Overall, the results in Table 3 confirm our inferences that firms with higher innovation score show superior future operating performance.

Finally, Table 4 reports the results for capital market performance.[25] We calculate the yearly returns starting from the fourth month after the fiscal year-end when the innovation measure and accounting variables are observable to the third month of the next year. The findings indicate that innovative firms achieve higher future returns, although there is no

[25] We also use Tobin's Q as a market-based performance and find similar results (untabulated).

significant impact on returns in the current year. This finding alleviates concerns that our innovation measure essentially captures unobserved firm characteristics that relate to performance, which might be persistent over time. To further mitigate concerns about whether the observed relation is affected by some outliers or non-linearity between innovation and future capital market performance, we employ a rank measure instead. Each year, we rank firms within a given industry based on their innovation score and normalize this rank by the number of firms in each industry-year so that our alternative *innovation rank* measure varies between zero and one. We confirm our previous findings: firms with a higher innovation rank compared to their industry peers show superior performance in the future but not in the current year.

The findings on stock returns provide intriguing insights into capital market behavior. The observed disparity between current and future market performance suggests that investors initially fail to fully recognize the value of the disclosed innovative activities. It seems that it is only when these innovations materialize into tangible outcomes, such as increased sales growth, that stock prices begin to reflect this information. This aligns with the findings of Cohen et al. (2020), which show that investors do not appreciate the value of forward-looking disclosures upon their release until its realization in the future. However, we also acknowledge that we might not be able to control risk factors adequately, and higher returns may simply represent compensation for higher risk for innovative firms. In Section 5, we will delve into more detail and examine the long-term impact of innovation through time-series portfolio analyses, which gives deeper insights into the sustained effects of innovation on capital market outcomes.

2.5.1. Robustness Checks

In this section, we show that our results are not attributable to our research design choices, namely the distributional characteristics of our innovation measure, the attrition effect, and the time horizon for future profitability. The results are tabulated in Table 5.

First, similar to regressions for future capital market returns, we instead use *innovation rank* measure and ensure that our future profitability results are not driven by the distributional characteristics of our innovation measure. We continue to confirm our main results: The coefficient on *innovation rank* is again significantly positive at the 1% level. Second, our results may be driven by sample attrition since the availability of future operating income is not exogenously determined: Firms may leave the sample for various reasons, and observations with missing future profitability could relate to the firm's innovation characteristics. We address this concern by replacing missing values either by zeros (Column 2) or by the most recent available operating profitability (Column 3). We again confirm our main inferences after taking measures to mitigate attrition bias. Although the coefficients become smaller (0.034 to 0.016 and 0.024), they are still positive and significant, which is in line with our main results that firms with a higher innovation score exhibit higher future operating profitability.

Last, we use different time horizons to see whether the benefit of innovation also materializes in the more recent and distant future. To this end, we construct 3- and 8-year future operating profitability similar to our main variable for profitability and repeat our tests. The results in columns 4-5 show that innovation is still associated with higher profitability in the near and long term, although the coefficients become smaller. It seems that the effect of innovation on future profitability rises gradually and then attenuates over the years. Overall, the results in this section reassure us that our main inferences are valid.

2.5.2. Determinants of Innovation and Additional Analyses

In previous sections, we show that our text-based innovation measure is associated with future firm performance. In this section, we analyze the determinants of our innovation measure and validate our measure as a proxy for innovation. To this end, we regress our innovation measure on time-varying firm characteristics by also controlling year and industry effects.

The results in Table 6 show that the innovation measure is associated with a set of investment variables: Innovative firms are not only R&D-intensive firms but also show higher capital expenditures and advertising expenses. This supports the idea that firms increase their CAPEX and advertising after introducing new products and services. However, we also see that the positive association with CAPEX and advertising expenses is generated by non-R&D firms (Column 3 versus 4). Innovative firms are smaller in size and less profitable, which is also in line with the results in Philips and Zhdanov (2013), showing that smaller firms invest more in innovation when they can sell out to larger firms. We also find that there is a negative relation between SGA and the innovation measure. However, when we decompose SGA into its maintenance and growth components, as in Enache and Srivastava (2018), the association between our innovation measure and the investment component of SGA becomes positive. Interestingly, the positive association is persistent for both R&D and non-R&D firms. This suggests that our innovation measure successfully captures investments under aggregate SG&A expenses (other than R&D and advertising expenses).

The innovation measure is positively associated with analyst following and institutional ownership. The result for institutional ownership is consistent with Aghion et al. (2013) since long-term-focused investors tolerate interim failures, thereby reducing managers' career concerns and incentivizing them to innovate more. The relation between analyst following and innovation is mixed. On the one hand, analyst following may put pressure on managers and may lead them to focus on short-term goals, thereby reducing innovation performance that requires long-term focus (He and Tian, 2013). On the other hand, analysts may also play an informational role in reducing information asymmetry between firms and investors. This role allows firms to make more efficient innovation investments, thereby increasing innovation output (Guo et al., 2019). The positive association between analyst following and innovation in Table 6 confirms the informational role of analysts. However, since our innovation measure is based on textual disclosures, in Section 7, we will revisit the role of analysts and institutional investors on firm disclosures to understand to what extent firms' disclosure incentives play a role in the ability of our innovation measure to capture future performance.

We also test whether income persistence plays a role in explaining how innovative firms show higher future profitability since firms can maintain their competitive advantage through innovation (Kung and Schmid, 2015). If introducing new products and services enhances firms' market power, we expect the persistence of income to be higher for innovative firms. To test this, we interact the innovation measure with current income (persistence component) and change in income (reversal component) and report the results in Table 7. We find some evidence that the persistency of income increases with innovation (positive and significant interaction term with current operating income), but find no evidence that innovation has an effect on income reversal (no significant interaction term with the change in operating income).

Finally, we test whether our measure is able to capture the performance effect of innovation in non-R&D-intense firms as well as R&D-intense firms. To this end, we repeat our tests for future performance by partitioning our sample into R&D and non-RD firms and report the results in Table 8. The results show that our innovation measure can explain the future sales growth and profitability for both R&D and non-R&D firms. Although the coefficients on the innovation score are smaller for the non-R&D sample, they are positive and all significant at the 1% level.

In addition, we conduct industry analyses by interacting the innovation score with industry dummies and report the coefficients to demonstrate the differential effect of innovation on future performance. We report the coefficients and confidence intervals for each of the 12 Fama & French industries (excluding financials and utility) in Figure 2. The figure shows that the association between our innovation measure and future performance is highest for R&D intense industries such as healthcare & drugs (including pharmaceuticals), computer, software & electronics, and manufacturing. However, the relation is also positive and significant for non-R&D industries such as wholesale & retail, and consumer nondurables. These results reassure us that our innovation measure can capture innovative qualities or intangible capital, particularly for non-R&D firms or industries where extracting information regarding firms' innovative qualities is challenging.

2.6. Long-term Market Performance

In this section, we analyze whether investors value innovation disclosures and anticipate the documented future performance of innovative firms. Since we expect innovation to show its effect in the future, we conduct a time-series analysis to investigate whether innovative firms exhibit abnormal market performance in the long term. We expect the valuation effect of innovation to accumulate over time and not be immediately observed in the cross-sectional returns. We form a hedge portfolio that takes a long position in a portfolio of firms with high innovation scores and a short position in a portfolio of firms with low innovation scores. We assign stocks to innovation quintiles each year in April (based on the disclosure of 10-Ks) and track the mean stock returns for each quintile over the subsequent five years.[26]

[26] We argue that accounting numbers and 10-Ks on which our innovation measure is based are available by three months after fiscal year-end. Since the majority of firms have December fiscal year-end, we sorted portfolios three months later, i.e., in April of the following year.

We calculate the hedge portfolio return by subtracting the mean return of the lowest quintile from the mean returns of the highest quintile innovation portfolio. We also adjust stock returns with returns of equivalent size and book-to-market portfolios (5x5) where we readjust the size and book-to-market portfolio membership of a stock at the beginning of each year. By yearly adjusting size and book-to-market effects, we aim to fix these time-varying factors that are shown to explain future stock returns.[27]

The raw returns, together with size-, book-to-market, and double-sorted size & book-to-market adjusted returns of the hedge portfolio, are depicted in Figure 3. We report both equal-weighted (Figure 3.a) and value-weighted portfolio returns (Figure 3.b). In line with our expectation, the valuation effect of innovation is not immediate (even slightly negative) and the hedge portfolio starts accumulating returns only six months after portfolio formation. The hedge portfolio reaches its highest cumulative return around three years at 15% (BM matched returns) after which the cumulative return starts to decline. Interestingly, while raw returns turn negative, book-to-market matched returns remain positive and stable around 15% three years after portfolio formation. This difference is in line with the results shown in Skinner and Sloan (2002) where high growth stock (more likely to be innovative) shows asymmetric negative price responses to earnings surprises due to over-optimistic expectations about earnings. Returns for value-weighted portfolios follow a similar pattern but are smaller in magnitude. Size and book-to-market matched returns still earn positive abnormal returns over the years. Collectively, the results reported in the figure suggest that investors do not seem to fully understand the underlying innovative characteristics of firms that are disclosed in the annual 10-K filings.

[27] Skinner and Sloan (2002), for instance, shows that higher market-to-book firms show systematic negative abnormal returns over time due to investors' overoptimistic expectations.

2.7. Firms' disclosure incentives

We further check whether disclosure incentives, i.e., proprietary costs and information demand play a role in the ability of our innovation measure to capture intangible capital since our measure relies on firm disclosures. Firms may not disclose their innovative qualities due to proprietary costs (Wagenhofer, 1990; Breuer et al., 2019). We use number of analysts and percentage of institutional ownership at the beginning of the year as proxies for information demand. Following Merkley (2014), we use an indicator variable for the years after the passage of Regulation Fair Disclosure (Reg FD) since the regulation limited private communication channels, thereby increasing the information demand by capital markets.[28]

Prior literature shows a negative relation between industry competition and disclosures.[29] However, even holding the proprietary cost of disclosures constant, competition may still interact with the observed association because innovative firms may have a competitive advantage relative to their peers. For example, if increased competition gives a competitive advantage to innovative firms, the relation between our innovation measure and future performance may increase, i.e., innovative firms perform even better when competition is high (the interaction is positive). If, however, due to heightened competition, firms are less likely to disclose their innovative qualities, then this may negatively impact the ability of our innovation measure to explain future performance (the interaction is negative) because the measure now fails to capture the underlying innovative capabilities.

Following the literature, we use several proxies for proprietary costs. We use the inverse concentration ratio (HHI) in a given 2-digit SIC industry as our first proxy for proprietary cost.

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[28] We restrict our analyses 5 years surrounding the regulation passage.

[29] Managers mention proprietary cost as an important barrier for more voluntary disclosures (Graham et al, 2005). Verrecchia and Weber (2006) shows that firms are more likely to redact information in highly concentrated industries. Moreover, Li (2010) documents that firms are less likely disclose management forecasts due to competitive threats from existing rivals. Ellis, Fee, and Thomas (2012) show that firms are less likely to disclose information about their customers when the competition is high.

The second proxy is the ease of entry by Karuna (2007) measured by the natural logarithm of the sales-weighted average PP&E of the 2-digit SIC industry multiplied by -1. Third, we use industry-level leverage because higher leverage limits firms' ability to invest, thereby reducing the intensity of competition from existing rivals (Philips, 1995; Ali et al., 2014). The fourth measure is the firm-level and disclosure-based competition measure developed by Li et al. (2013).[30] The measure captures managers' perceived competition that may also affect their disclosure choices, and hence the ability of our innovation measure. Finally, we use a firm-level proxy for proprietary costs based on whether a firm files a confidential exhibit (redacted contract) in a given year (Verrecchia and Weber, 2006)[31]. We adjust each measure so that a higher value represents a higher proprietary cost.

We interact our innovation measure with these proxies (disclosure incentives) to test whether the relation between innovation and future sales growth becomes weaker or stronger. For brevity, we only report the results when we use 3-year future sales growth as our proxy for future performance.[32] Table 9, columns 1-3, reports the results for information demand. The sign of the coefficients on the interaction term are mixed, but the coefficients are consistently insignificant, suggesting that information demand does not seem to explain the association between our innovation measure and future performance. When we look at proprietary cost proxies (Columns 4-8), we see that the interaction terms are consistently positive, although in some cases insignificant. This means that firms do not seem to decrease their disclosures on

[30] Li, Lundholm, and Minnis (2013) develop a firm-level competition measure by counting competition-related words in 10-K text. They show that the measure is correlated with existing competition measures and diminishing marginal returns. This measure is particularly appealing for two reasons. First, it provides within industry variation compared to other measures that vary across industries. Second, the source of the document in which the measure is derived is the same (10-K disclosures). The data is only available until 2009.

[31] The measure takes the value 1 if a firm files a redacted contract in a given year. Our data for confidential contracts is only available between 2005 and 2018. %8 of firm-years include at least one redacted filing.

[32] The results are qualitatively similar to those reported for all future firm performance except that the interactions for information demand turns negative and significant when we use future returns as the dependent variable. This is understandable since information demand proxies also correlate with the information available in capital markets that can affect the future returns.

business descriptions, which could negatively affect our ability to link our measure with future performance. On the contrary, the link seems to become even stronger, suggesting that innovation gives a competitive advantage to firms, especially in highly competitive environments. Overall, the result in this section suggests that disclosure incentives, on average, do not seem to play a role and our measure continues to successfully capture intangible capital that creates future firm value.

2.8. Conclusion

We develop a novel text-based innovation measure based on public firms' business descriptions disclosed in yearly 10-K filings and show that our innovation measure can explain future firm performance. Our innovation measure is particularly appealing for firms that do not disclose any R&D or show any patenting behavior. We contribute to the long-standing discussion regarding the value relevance of accounting numbers by showing that narrative disclosures might be informative about firms' intangible capital or strategic assets, which are usually not recognized in financial statements. We also add to the debate on boilerplate public disclosures by showing that firms disclose their information on their innovation, and it is possible to extract these from public disclosures by eliminating redundant information even if the disclosures appear to be boilerplate.

2.9. Appendix

Appendix A. Description of Variables

Variable	Description of Variable
Innovation Score	The innovation score calculated using the methodology under Section 3
SG_{t+T}	Annualized sales growth calculated by $\left(\frac{Sale_{t+k}}{Sale_t}\right)^{1/k} - 1$
$OpINC_t$	Operating income before depreciation, R&D, advertising scaled by total assets: *(oiadp+dp+xrd+xad)/at*
$OpINC_{t+5}$	The sum of operating income before depreciation, R&D, advertising for *t+1* to *t+5* scaled by the total assets at time *t*
Size	Market value of equity: *prcc_f x csho* (logarithm in regressions)
BM	Book-to-Market value calculated as *(ceq + txdb) / MVE*
ACQ	Acquisitions from cash flow statement scaled by total assets: *aqc/at*
ADV	Advertising expenses scaled by total assets: *xad/at*
CAPEX	Capital expenditures scaled by total assets: *capx/at*
SGA	SG&A before R&D and advertising expenses: *(xsga – xrd – xad)/at*
R&D	Research and Development expense scaled by total assets: *xrd/at*
R&D firm	Dummy variable for firm-years having a non-zero R&D investments
TobinsQ	*(at+MVE-ceq) / at*
Log(Patents)	The natural logarithm of one plus number of granted patents in a year
Patenting firm	Dummy variable for firm-years having a non-zero patent number

Appendix B: Examples of Innovation Vocabulary

Firm	Year	Industry	Selection of Innovation Vocabulary
Whole Foods	2013	Retail	sustainable agriculture, healthy education, micronutrient, personal wellness, fresh fields, eco-scale, organic grocer, commissary kitchens, biometric screenings, healthier lifestyle, green innovations, phytochemical, green standards, red-orange-yellow-green scale, artificial additives, entire ecosystem, long-term health, healthy animals, dense fats, recycling, nutritionist transparent methods, full ingredients, healthy eating, healthy centers, healthy choices, global responsibility, organic foods, homemade, biometric criteria, companywide consciousness, bakehouse, ecosystem, social media, high standards, organic product, open kitchens, biofuel, innovative practices, regional kitchens, proprietary system, healthy fats, instore activities, reusable bag, traceability, medical doctors, self-managed teams, farm-to-fork, personal shopping, available guide, authentic retailer, whole planet, lively atmosphere, online resource, fresh air, gainsharing, sustainable aspects, wise practices, budget-conscious recipes, educated choices, sustainable fisheries, artificial ingredients, natural balance, green globes, organic rule, mindful approach, inspirational atmosphere, healthy program, word-of-mouth recommendations, caloric content
Adobe	2013	Business Services	digital marketing, interactive experiences, rich interface, macromedia, efficient workflow, cyberattack, software-as-a-service, creative version, digital area, annual subscriptions, online delivery, collaborative workflows, social networking, central dashboard, powerful platform, digital advertising, e-business applications, media-digital trends, webinar, digital company, educational content, creative applications, digital environments, creative cloud, saas products, perpetual subscription, best-in-class security disruptive software, website, social channels, android, online commerce mobile devices, cloud-based model, online marketing, smartphone, digital offerings, iphone, rapid technology, modular platform, digital channel, social web, rapid innovation, perpetual subscription, personalized experience, social advertising, sophisticated editing, robust capabilities, mobile app, real-time dashboards

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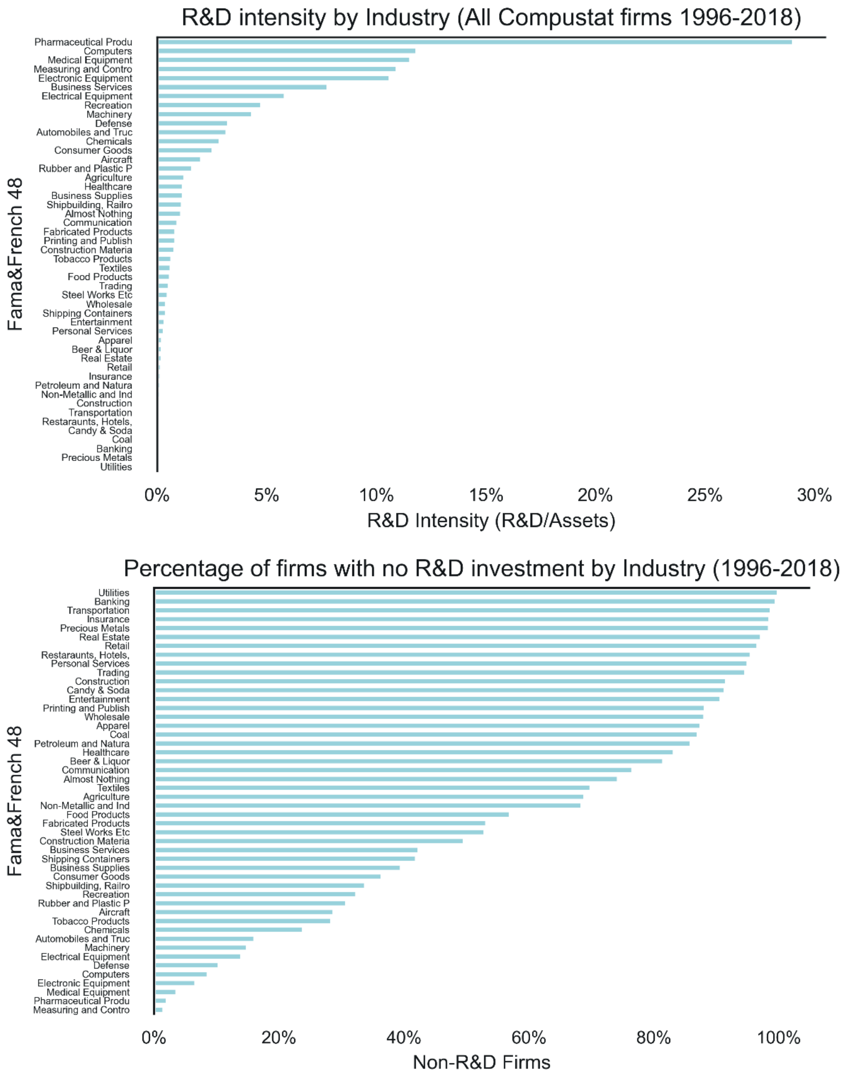


Figure 1. R&D Investments across industries, all Compustat firms, 1996-2018

The Figures demonstrate the R&D investments for all Compustat firms from 1996 to 2018 across Fama & French 48 industries. Figure 1.A. shows the average R&D intensity in an industry (R&D scaled by total assets), while Figure 1.B shows the percentage of firms with no R&D investments. Missing values are replaced with zero.

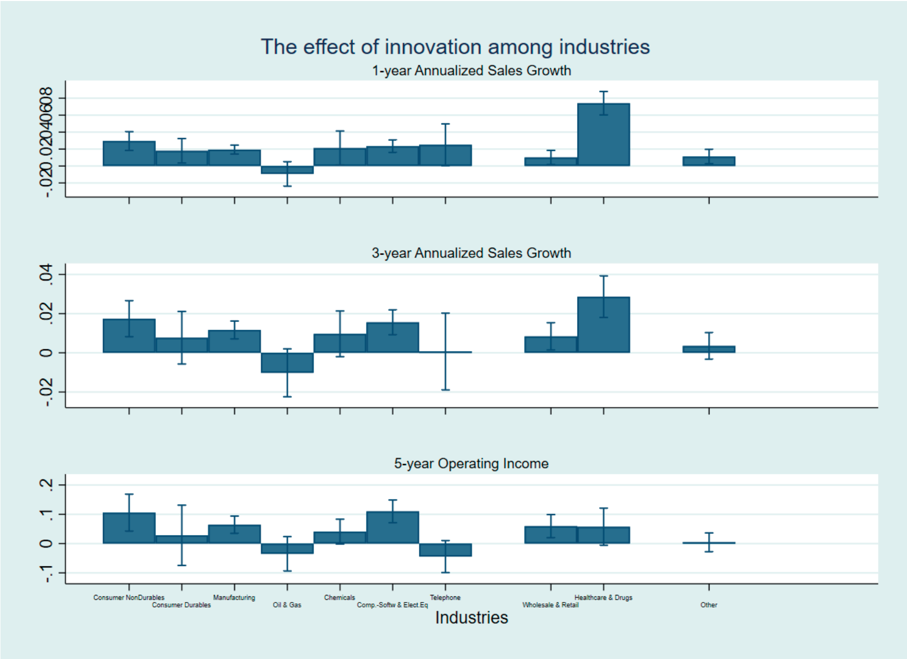
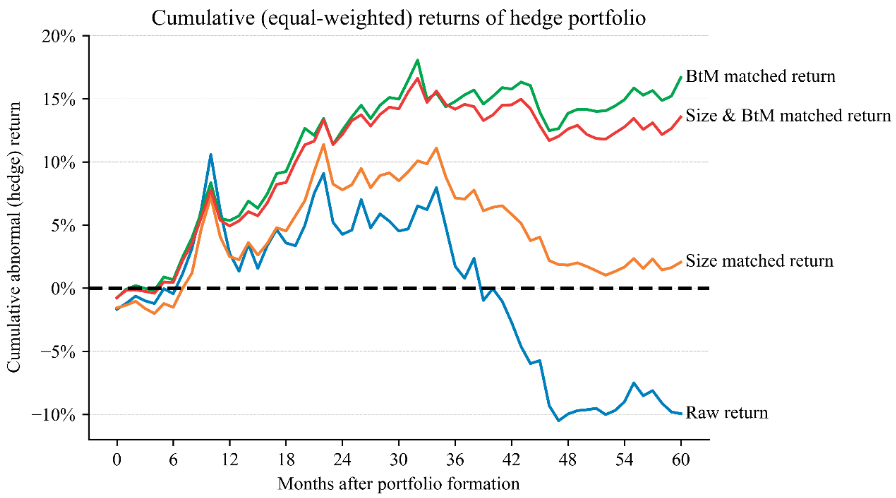


Figure 2. Cross-industry analysis

The Figure plots the coefficients on the interaction term for Fama-French 12 industries (excluding financials and utilities). We repeat our analyses of future firm performance (1- and 3-year sales growth and future operating net income) including an interaction of the innovation score with industry dummies and report the coefficients of interaction with confidence intervals at 10% level.



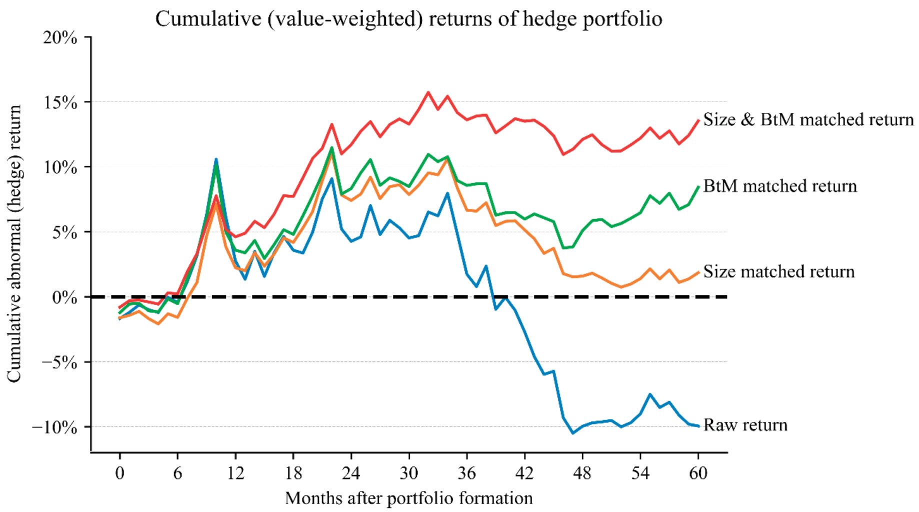


Figure 3. Long-term capital market performance of innovative firms

The Figure shows the time-series abnormal return of a hedge portfolio based on the difference between a long position on the top quintile and a short position on the bottom quintile innovation firms. The figure is plotted as follows: each year in March (when the innovation score is available), we sorted firms on innovation score (five quintiles) and follow each quintile firms' abnormal stock performance over five years. Size and BM adjusted returns are calculated by subtracting value-weighted returns of Size and/or BM matched portfolios. Membership of Size and BM portfolios are reformed yearly at the beginning of the year to control the time-varying factors within innovation portfolios.

Table 1. Descriptive Statistics

Panel A: Descriptive Statistics

	N	Mean	Sd	p25	p50	p75
log(Innovation)	51,727	5.16	0.88	4.74	5.28	5.73
SG_{t+3}	39,092	0.09	0.19	-0.00	0.07	0.16
SG_{t+1}	48,234	0.13	0.37	-0.02	0.07	0.19
$OpINC_t$	51,727	0.15	0.15	0.09	0.15	0.22
$OpINC_{t+5}$	31,913	1.18	1.05	0.57	0.98	1.56
SIZE	51,727	6.29	2.01	4.84	6.24	7.61
MVE	51,727	4,054	13,181	125.95	513.35	2026.27
BM	51,727	0.59	0.60	0.25	0.46	0.76
ACQ	51,727	0.03	0.06	0.00	0.00	0.02
ADV	51,727	0.01	0.03	0.00	0.00	0.01
CAPEX	51,727	0.05	0.06	0.02	0.03	0.06
SGA	51,727	0.21	0.23	0.08	0.17	0.32
R&D	51,727	0.06	0.10	0.00	0.01	0.07
R&D firm	51,727	0.55	0.50	0.00	1.00	1.00
log(patents)	51,727	0.83	1.38	0.00	0.00	1.39
Patenting firm	51,727	0.37	0.48	0.00	0.00	1.00
TobinsQ	51,727	2.13	1.65	1.18	1.59	2.41

Panel B: Innovation Quintiles

	Innovation Quintiles					
	Q1	Q2	Q3	Q4	Q5	Diff. (Q5-Q1)
log(Innovation)	3.85	4.88	5.28	5.63	6.15	**2.30***
SG_{t+1}	0.08	0.09	0.11	0.14	0.22	**0.14***
$OpINC_t$	0.16	0.16	0.16	0.15	0.12	**-0.04***
SIZE	6.32	6.19	6.28	6.29	6.38	**0.06***
BM	0.67	0.64	0.60	0.56	0.47	**-0.20***
ACQ	0.02	0.03	0.03	0.03	0.03	**0.00***
ADV	0.01	0.01	0.01	0.01	0.01	**0.00***
CAPEX	0.05	0.05	0.05	0.05	0.05	**-0.01***
SGA	0.24	0.24	0.23	0.21	0.15	**-0.09***
R&D	0.02	0.03	0.04	0.06	0.12	**0.10***
log(patents)	0.69	0.71	0.79	0.90	1.08	**0.39***
TobinsQ	1.81	1.82	2.03	2.25	2.73	**0.92***

Panel C: Industry Distribution of #Innovative Words

	N	#Innovative Words	#Patents	R&D	CAPEX	SG&A	ACQ	ADV
		Mean						
Top 10 Innovation Industries								
Pharmaceutical Products	3,844	464.059	14.087	0.241	0.029	0.007	0.013	0.007
Coal	83	360.072	0.012	0.000	0.080	0.026	0.030	0.000
Medical Equipment	2,134	351.261	11.831	0.095	0.037	0.318	0.025	0.006
Communication	1,666	335.940	19.696	0.008	0.067	0.138	0.030	0.011
Healthcare	1,179	302.111	0.440	0.012	0.047	0.228	0.052	0.002
Personal Services	746	284.920	0.088	0.000	0.066	0.197	0.034	0.031
Entertainment	854	257.193	2.252	0.003	0.075	0.110	0.022	0.015
Computers	2,296	250.560	46.314	0.103	0.035	0.250	0.026	0.006
Electronic Equipment	3,823	244.046	55.255	0.104	0.045	0.170	0.023	0.003
Business Services	7,792	232.773	26.961	0.071	0.039	0.292	0.035	0.011
Bottom 10 Innovation Industries								
Steel Works Etc	811	155.131	2.350	0.004	0.049	0.106	0.028	0.001
Rubber & Plastic Prodcts	443	156.736	3.404	0.016	0.052	0.220	0.032	0.004
Consumer Goods	881	153.465	33.586	0.025	0.044	0.310	0.021	0.057
Construction Materials	1,103	149.269	6.753	0.008	0.045	0.198	0.032	0.009
Agriculture	161	148.876	24.565	0.013	0.048	0.105	0.022	0.002
Business Supplies	774	144.944	27.868	0.014	0.049	0.189	0.028	0.008
Textiles	220	143.623	2.741	0.007	0.042	0.204	0.023	0.004
Food Products	1,061	142.599	1.766	0.004	0.055	0.238	0.029	0.028
Shipping Containers	193	141.093	6.720	0.005	0.058	0.087	0.043	0.000
Fabricated Products	132	130.212	0.689	0.009	0.040	0.149	0.026	0.002
TOTAL Avg		**232.100**	**18.802**	**0.0552**	**0.051**	**0.213**	**0.026**	**0.012**

Table 1 reports the descriptive statistics. Panel A presents overall descriptives of our sample, while Panel B displays the distribution of variables among innovation quintiles. Panel C provides the distribution of innovation words usage (before logarithm) and common investment proxies across the top 10 and bottom 10 innovation industries that are defined based on the rank of innovation word usage (or innovation score) across industries, excluding financials and utilities. We calculate log(Innovation) by taking the natural logarithm of the number of innovation words in business descriptions. SIZE represents the natural logarithm of the market value of equity (MVE). OpINC denotes the operating income scaled by total assets, while OpINC5 represents the sum of subsequent five-year operating income scaled by current total assets. BM denotes the book-to-market ratio. R&D represents research and development expenses scaled by total assets. log(patents) is the natural logarithm of the number of patents granted to a firm in a given year. The variable *Patenting firm* is a dummy variable that equals one when the number of patents in a year is above zero. Similarly, *R&D firm* refers to firm-years that have non-zero R&D investment. CAPEX denotes capital expenditures, ADV represents advertising expenses, ACQ refers to acquisitions from the cash flow statement, and SGA denotes the SG&A expenses before R&D, advertising, and depreciation, all scaled by total assets. The definitions of variables are also detailed in the Appendix A.

Table 2. Future Sales Growth

	(1) SG_{t+1}	(2) SG_{t+1}	(3) SG_{t+2}	(4) SG_{t+2}	(5) SG_{t+3}	(6) SG_{t+3}
log(Innovation)	0.022***	0.015***	0.014***	0.010***	0.011***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SG_{t-1}		0.100***		0.053***		0.039***
		(0.012)		(0.008)		(0.007)
SIZE		-0.010***		-0.006***		-0.006***
		(0.001)		(0.001)		(0.001)
BM		-0.071***		-0.053***		-0.046***
		(0.004)		(0.003)		(0.003)
ACQ		0.513***		0.260***		0.167***
		(0.033)		(0.022)		(0.019)
ADV		-0.177***		-0.173***		-0.172***
		(0.062)		(0.057)		(0.055)
CAPEX		0.068		0.098***		0.094***
		(0.043)		(0.034)		(0.032)
SGA		-0.153***		-0.084***		-0.059***
		(0.013)		(0.011)		(0.010)
Constant	0.002	0.151***	0.025**	0.119***	0.029***	0.109***
	(0.012)	(0.014)	(0.010)	(0.012)	(0.009)	(0.012)
Observations	45,655	45,655	41,147	41,147	37,191	37,191
Adjusted R^2	0.063	0.105	0.075	0.108	0.078	0.109
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

$$Sales\ Growth_{i,t+T} = \beta_0 + \beta_1 * Innovation_{it} + \sum_j \beta_j * Controls_{it} + \sum_k \beta_k * \theta_k + \sum_t \beta_t * \tau_t + \varepsilon_{it}$$

The Table presents findings regarding the association between innovation score and future sales growth. The model effectively controls for time-varying firm characteristics that might explain future sales growth other than innovation. We include industry and year fixed effects to control differences across industries and timing effects. While Columns 1,3,and 5 report the results without any controls, columns 2,4, and 6 report the results with firm-level controls. The descriptions of variables are given in Table 1 and in Appendix A. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denotes significance levels.

Table 3. Future Operating Income

	(1) $OPINC_{t+5}$	(2) $OPINC_{t+5}$	(3) $OPINC_{t+5}$	(4) $OPINC_{t+5}$	(5) $OPINC_{t+5}$	(6) $OPINC_{t+5}$
log(Innovation)	0.065***	0.078***	0.044***	0.035***	0.048***	0.034***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
R&D				1.279***	1.193***	0.957***
				(0.177)	(0.175)	(0.196)
$OpINC_t$	3.959***	3.957***	3.979***	4.020***	4.018***	4.032***
	(0.110)	(0.109)	(0.108)	(0.109)	(0.108)	(0.107)
$\Delta OpINC_t$	-0.388***	-0.376***	-0.389***	-0.418***	-0.409***	-0.426***
	(0.103)	(0.102)	(0.101)	(0.100)	(0.099)	(0.098)
BM	-0.230***	-0.240***	-0.212***	-0.191***	-0.201***	-0.195***
	(0.014)	(0.015)	(0.014)	(0.013)	(0.013)	(0.013)
ACQ	0.066	0.123	0.226**	0.266***	0.321***	0.322***
	(0.095)	(0.096)	(0.092)	(0.094)	(0.095)	(0.093)
ADV	1.281***	1.442***	1.885***	1.438***	1.575***	1.820***
	(0.435)	(0.438)	(0.472)	(0.430)	(0.433)	(0.468)
CAPEX	1.212***	1.099***	1.113***	1.483***	1.385***	1.139***
	(0.152)	(0.153)	(0.172)	(0.152)	(0.153)	(0.172)
SGA	0.524***	0.494***	0.589***	0.600***	0.568***	0.626***
	(0.062)	(0.062)	(0.067)	(0.061)	(0.060)	(0.067)
Constant	0.145***	0.096*	0.216***	0.167***	0.120**	0.196***
	(0.055)	(0.055)	(0.055)	(0.054)	(0.054)	(0.055)
Observations	30,460	30,460	30,460	30,460	30,460	30,460
Adjusted R^2	0.365	0.382	0.394	0.376	0.391	0.398
Industry FE	NO	NO	YES	NO	NO	YES
Year FE	NO	YES	YES	NO	YES	YES

$$Operating\ Income_{i,t+5} = \beta_0 + \beta_1 * Innovation_{it} + \sum_j \beta_j * Controls_{it} + \sum_k \beta_k * \theta_k + \sum_t \beta_t * \tau_t + \varepsilon_{it}$$

The Table presents findings regarding the association between innovation score and future operating income. The model effectively controls for time-varying firm characteristics that might explain future income. To control for persistency and reversal of income, we include the level and change in operating income in the model. Across columns we report results with and without industry and year fixed effects. While Columns 1-3 report the results without R&D as a firm-level control, columns 4-6 report the results with R&D included. The descriptions of variables are given in Table 1 and in Appendix A. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denotes significance levels.

Table 4. Future Returns

	(1) Return(t)	(2) Return(t+1)	(3) Return(t+2)	(4) Return(t)	(5) Return(t+1)	(6) Return(t+2)
Log(Innovation)	0.002	0.014***	0.016***			
	(0.003)	(0.004)	(0.004)			
InnovRank				0.002	0.045***	0.056***
				(0.009)	(0.010)	(0.010)
SIZE	0.009***	-0.013***	-0.012***	0.009***	-0.013***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
BM	-0.186***	0.107***	0.042***	-0.186***	0.108***	0.043***
	(0.007)	(0.011)	(0.007)	(0.007)	(0.011)	(0.007)
ACQ	-0.301***	-0.145***	-0.106**	-0.300***	-0.146***	-0.107**
	(0.043)	(0.047)	(0.053)	(0.043)	(0.047)	(0.053)
ADV	-0.127	0.454***	0.360***	-0.126	0.446***	0.346***
	(0.109)	(0.123)	(0.118)	(0.109)	(0.122)	(0.118)
CAPEX	-0.707***	-0.094	0.121*	-0.706***	-0.089	0.127*
	(0.065)	(0.069)	(0.073)	(0.065)	(0.069)	(0.073)
SGA	-0.002	0.087***	0.030	-0.002	0.089***	0.034*
	(0.017)	(0.020)	(0.019)	(0.017)	(0.020)	(0.019)
Constant	0.268***	0.098***	0.124***	0.277***	0.147***	0.175***
	(0.023)	(0.027)	(0.026)	(0.016)	(0.020)	(0.016)
Observations	51,446	47,985	43,132	51,446	47,985	43,132
Adjusted R^2	0.196	0.196	0.191	0.196	0.196	0.191
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

$$Return_{i,t+T} = \beta_0 + \beta_1 * Innovation_{it} + \sum_j \beta_j * Controls_{it} + \sum_k \beta_k * \theta_k + \sum_t \beta_t * \tau_t + \varepsilon_{it}$$

The Table presents findings regarding the association between innovation score and (future) stock returns. The model effectively controls for time-varying firm characteristics that might explain returns, including size, book-to-market. Across columns, we report results with industry and year fixed effects. While Columns 1-3 report the results with the natural logarithm of innovation score, Columns 4-6 report the results with a rank variable for innovation. The descriptions of variables are given in Table 1 and in Appendix A. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denotes significance levels.

Table 5. Robustness Checks

	(1) $OPINC_{t+5}$ (innovscaled)	(2) $OPINC_{t+5}$ (filledwithzero)	(3) $OPINC_{t+5}$ (filledpast)	(4) $OPINC_{t+3}$	(5) $OPINC_{t+8}$
InnovRank	0.158***				
	(0.029)				
log(Innovation)		0.016**	0.024***	0.012***	0.157***
		(0.007)	(0.007)	(0.003)	(0.030)
$OpINC_t$	3.991***	2.948***	4.230***	2.410***	6.207***
	(0.108)	(0.075)	(0.078)	(0.045)	(0.313)
$\Delta OpINC_t$	-0.394***	-0.438***	-0.502***	-0.335***	0.052
	(0.101)	(0.065)	(0.073)	(0.045)	(0.284)
BM	-0.209***	-0.196***	-0.176***	-0.101***	-0.454***
	(0.014)	(0.010)	(0.010)	(0.006)	(0.040)
ACQ	0.220**	0.119*	0.207***	0.134***	0.039
	(0.092)	(0.068)	(0.061)	(0.035)	(0.276)
ADV	1.818***	1.774***	1.466***	1.028***	4.498***
	(0.471)	(0.358)	(0.330)	(0.179)	(1.545)
CAPEX	1.131***	0.943***	0.900***	0.527***	3.023***
	(0.172)	(0.137)	(0.126)	(0.066)	(0.542)
SGA	0.600***	0.294***	0.374***	0.238***	1.511***
	(0.067)	(0.045)	(0.047)	(0.024)	(0.214)
Constant	0.356***	0.307***	0.221***	0.136***	0.252
	(0.030)	(0.043)	(0.040)	(0.020)	(0.171)
Observations	30,460	48,835	48,835	37,190	22,190
Adjusted R^2	0.395	0.334	0.459	0.508	0.274
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

$$Operating\ Income_{i,t+5} = \beta_0 + \beta_1 * Innovation_{it} + \sum_j \beta_j * Controls_{it} + \sum_k \beta_k * \theta_k + \sum_t \beta_t * \tau_t + \varepsilon_{it}$$

The Table reports the results of robustness checks regarding the association between innovation score and future operating income. Column 1 uses an alternative innovation measure (Innovation rank) as the independent variable. Columns 2 and 3 report the results with alternative dependent variables to alleviate concerns regarding attrition bias. In Column 2, we replace missing future operating income with zeros, while in Column 3, we replace missing values with the latest available figure for the given firm. In columns 4 and 5, we test our model using future operating income with alternative time horizons, namely 3-year and 8-year future operating income. We include industry and year fixed effects in our models for all columns. The descriptions of variables are given in Table 1 and in Appendix A. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denotes significance levels.

Table 6. Determinants of Innovation

VARIABLES	(1) All	(2) InvestmentSGA	(3) nonRD_firms	(4) RD_firms
R&D	1.198***	1.279***		1.019***
	(0.091)	(0.093)		(0.098)
SIZE	-0.050***	-0.045***	-0.040***	-0.050***
	(0.009)	(0.009)	(0.013)	(0.011)
BM	-0.036***	-0.025*	-0.038**	0.009
	(0.014)	(0.014)	(0.017)	(0.022)
ACQ	0.355***	0.361***	0.561***	0.195**
	(0.073)	(0.074)	(0.116)	(0.092)
ADV	1.505***	1.350***	1.958***	0.564
	(0.316)	(0.327)	(0.485)	(0.421)
CAPEX	0.414**	0.362**	0.597***	0.106
	(0.165)	(0.177)	(0.217)	(0.244)
OpINC	-0.385***	-0.365***	-0.530***	-0.319***
	(0.050)	(0.054)	(0.101)	(0.062)
SGA	-0.149***			
	(0.043)			
Investment-SGA		0.425***	0.382***	0.391***
		(0.075)	(0.128)	(0.093)
ANALYST	0.167***	0.150***	0.144***	0.155***
	(0.015)	(0.015)	(0.023)	(0.020)
INSTOWN	0.104***	0.216***	0.222***	0.214***
	(0.027)	(0.032)	(0.047)	(0.043)
Constant	5.141***	5.001***	4.846***	5.169***
	(0.052)	(0.047)	(0.072)	(0.060)
Observations	51,727	48,549	22,230	26,319
Adjusted R^2	0.219	0.220	0.150	0.244
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

$$Innovation_{i,t} = \beta_0 + \sum_j \beta_j * Firm\ Characteristics_{it} + \sum_k \beta_k * \theta_k + \sum_t \beta_t * \tau_t + \varepsilon_{it}$$

The Table reports the determinants of the innovation score based on time-varying firm characteristics while controlling for industry and year fixed effects. We include industry and year fixed effects in our models for all columns. Investment-SGA is the growth component of SG&A, as in Enache & Srivastava (2018). The descriptions of variables are given in Table 1 and in Appendix A. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denotes significance levels.

Table 7. Persistence and Reversal Effect of Innovation

	(1) $OPINC_{t+5}$	(2) $OPINC_{t+5}$	(3) $OPINC_{t+5}$
log(Innovation)	0.007	0.013	0.003
	(0.017)	(0.017)	(0.017)
OpINC	3.102***	2.846***	2.999***
	(0.521)	(0.520)	(0.516)
log(Innovation)xOpINC	***0.171****	***0.218*****	***0.192*****
	(0.099)	***(0.098)***	***(0.098)***
ΔOpINC	-0.347	-0.082	-0.183
	(0.483)	(0.480)	(0.472)
log(Innovation)xΔOpINC	***-0.013***	***-0.061***	***-0.046***
	(0.092)	***(0.091)***	***(0.089)***
Observations	30,460	30,460	30,460
Adjusted R^2	0.376	0.392	0.398
Controls	YES	YES	YES
Industry FE	NO	NO	YES
Year FE	NO	YES	YES

$$OpINC_{i,t+5} = \beta_0 + \beta_1 * Innovation_{it} + \beta_2 * Innovation_{it} * OpINC + \beta_3 * Innovation_{it} * \Delta OpINC + \sum_j \beta_j * Controls_{it} + \sum_k \beta_k * \theta_k + \sum_t \beta_t * \tau_t + \varepsilon_{it}$$

The Table reports the results for the persistence and reversal of operating income and their interaction with innovation. We use firm-level controls across all columns, as in Table 3. Columns 1-3 report the interaction effects with and without using industry and year fixed effects. The coefficients on controls are not reported for brevity. The descriptions of variables are given in Table 1 and in Appendix A. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denotes significance levels.

Table 8. R&D compared to non-R&D Firms

	(1) SG_{t+1} (No R&D)	(2) SG_{t+1} (R&D)	(3) SG_{t+3} (No R&D)	(4) SG_{t+3} (R&D)	(5) $OPINC_{t+5}$ (No R&D)	(6) $OPINC_{t+5}$ (R&D)
log(Innovation)	0.007***	0.022***	0.004*	0.011***	0.029**	0.051***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.012)	(0.014)
1-year SGt-1	0.172***	0.061***	0.069***	0.022***		
	(0.017)	(0.015)	(0.010)	(0.008)		
SIZE	-0.006***	-0.013***	-0.005***	-0.006***		
	(0.001)	(0.002)	(0.001)	(0.001)		
BM	-0.048***	-0.104***	-0.038***	-0.058***	-0.176***	-0.272***
	(0.004)	(0.007)	(0.003)	(0.005)	(0.016)	(0.025)
ACQ	0.604***	0.409***	0.184***	0.136***	0.256*	0.207*
	(0.051)	(0.041)	(0.030)	(0.023)	(0.142)	(0.118)
ADV	-0.181***	-0.174	-0.176***	-0.190**	1.829***	1.721**
	(0.061)	(0.113)	(0.067)	(0.091)	(0.641)	(0.685)
CAPEX	0.114**	-0.058	0.087**	0.085	0.646***	2.129***
	(0.049)	(0.081)	(0.038)	(0.058)	(0.185)	(0.370)
SGA	-0.071***	-0.203***	-0.033***	-0.073***	0.349***	0.784***
	(0.011)	(0.020)	(0.011)	(0.015)	(0.075)	(0.099)
OpINC(t-1)					4.102***	3.865***
					(0.166)	(0.138)
ΔOpINC					-0.687***	-0.284**
					(0.121)	(0.132)
Constant	0.112***	0.007	0.108***	0.020	0.276***	0.205**
	(0.020)	(0.021)	(0.017)	(0.016)	(0.074)	(0.082)
Observations	20,938	24,717	17,241	19,950	14,261	16,199
Adjusted R^2	0.140	0.097	0.130	0.107	0.425	0.380
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

The Table reports the effect of innovation on future performance, namely sales growth and future operating income, by partitioning the sample into R&D and non-RD firms. *R&D firm* refers to firm-years that have non-zero R&D investment. While columns 1-4 report the results for 1-year and 3-year annualized sales growth, columns 5-6 report the results for future 5-year operating income. The models include industry and year fixed effects. The descriptions of variables are given in Table 1 and in Appendix A. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denotes significance levels.

Table 9. Disclosure Incentives and Innovation Performance Relation

	Information Demand			Proprietary Cost				
VARIABLES	(1) $ANALYST_{t-1}$	(2) $INSTOWN_{t-1}$	(3) PostRegFD	(4) Comp. (HHI)	(5) Perceived Comp.	(6) EaseEntry	(7) Redaction	(8) Leverage Industry
log(Innovation)	0.006*	0.009***	0.011***	0.012***	0.004	0.018*	0.006**	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.010)	(0.002)	(0.002)
log(Innovation)xDiscIncentive	0.001	-0.002	-0.002	0.045**	0.004	0.001	0.012	0.027**
	(0.002)	(0.004)	(0.004)	(0.021)	(0.004)	(0.001)	(0.008)	(0.012)
DiscIncentive	-0.004	0.013		-0.205*	-0.021	-0.003	-0.058	-0.133**
	(0.008)	(0.021)		(0.107)	(0.022)	(0.006)	(0.045)	(0.062)
Observations	37,191	37,191	20,216	37,191	16,786	37,191	20,582	37,191
Adjusted R^2	0.109	0.109	0.119	0.109	0.126	0.109	0.094	0.109
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

$$Sales\ Growth_{i,t+3} = \beta_0 + \beta_1 * Innovation_{it} + \boldsymbol{\beta_2 * Innovation_{it}xDisclosure\ Incentives} + \sum_j \beta_j * Controls_{it} + \sum_k \beta_k * \theta_k + \sum_t \beta_t * \tau_t + \varepsilon_{it}$$

The Table reports the results to what extent disclosure incentives play a role in explaining the association between the innovation measure and future firm performance, namely 3-year sales growth. We report the interactions with the common proxies for information demand in columns 1-3. We report the interactions with the common proxies for proprietary costs in columns 4-8. $ANALYST_{t-1}$ refers to the number of analysts following the firm in the previous year before 10-Ks are disclosed. Similarly, $INSTOWN_{t-1}$ is the percentage of institutional investors holding the firm stocks in the previous year. PostRegFD is a dummy variable taking the value of one for the years after the regulation fair disclosure. Competition - HHI is the Herfindahl–Hirschman index for the 2-digit SIC industry multiplied by -1. Perceived competition is a firm-level text-based competition measure introduced by Li et al. (2013). EaseEnrty is the ease of entry by Karuna (2007) measured by the natural logarithm of the sales-weighted average PP&E of the 2-digit SIC industry multiplied by -1. Leverage Industry is 2-digit SIC level industry leverage is calculated by average net debt weighted by total assets and multiplied by -1. Redaction is a firm-level proxy for proprietary costs based on whether a firm files a confidential exhibit (redacted contract) each year. We adjust each measure so that a higher value represents a higher proprietary cost.

CHAPTER 3

Simultaneous Information Releases and Capital Market Feedback: Evidence from Patent Tuesdays

with Tim Martens and Christoph J. Sextroh

Abstract

We examine whether the simultaneous release of information affects managers' ability to gather decision-relevant information from market prices. Using the plausibly exogenous timing of patent grant disclosures by the United States Patent and Trademark Office as a source of variation in the simultaneous release of value-relevant information, we show that the market's response to patent grants is more informative for managerial decisions if the firm receives fewer patent grants on the same day. This effect is more pronounced for patents that relate to relatively more exploratory innovative strategies for which feedback is arguably more important. Firms with more distinct information releases also produce more valuable and higher-quality innovations in the future. Taken together, our results suggest that bundling the release of multiple pieces of information at once potentially impedes managers' ability to benefit from the market's feedback.

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3.1. Introduction

We study the impact of simultaneous information releases on managers' ability to gather decision-relevant information from market prices. While it is well known that market prices can affect real firm decisions by providing valuable feedback to managers (see, e.g., Bond et al., 2012; Goldstein, 2022, for a review), the interaction between market feedback and disclosure remains a subject of debate. For instance, the recent theoretical and empirical literature suggests that disclosure may both solicit or impede market feedback (e.g., Arya et al., 2017; Bae et al., 2022; Goldstein and Yang, 2019; Jayaraman and Wu, 2019, 2020; Luo, 2005; McClure et al., 2022; Pinto, 2022). However, whether disclosures allow managers to extract valuable feedback from market prices may not only depend on its effect on the information contained in prices, but also on managers' ability to attribute price signals to specific pieces of information. We extend the prior literature by highlighting that it is not only the presence or quantity of disclosures that matters, but also the way how information is disclosed can influence managerial learning from stock prices.

The direction of the relation of how simultaneous information releases affect managerial learning is not straightforward. On one hand, when multiple pieces of information are released at the same time, market prices reflect the market's assessment of the combined disclosure, making it difficult for managers to distinguish feedback specific to each piece of information (Ramanan, 2015). Additionally, managers may perceive short-term market signals to be less informative when information is bundled due to associated processing costs (e.g., Blankespoor et al., 2020; Wertz, 2021). In both cases, managers may be able to obtain clearer signals from the market by separately releasing information, which is then also more useful for subsequent decision making. On the other hand, however, releasing those pieces all at once could also facilitate price formation and thus provide more informative feedback signals to managers (e.g., Hirshleifer and Sheng, 2022; Kaplan, 2014). In such cases, bundling information may facilitate managerial learning from prices. Hence, it becomes an empirical question whether simultaneous information releases enhance or hinder managerial learning from prices.

Despite theoretical predictions, there is little empirical evidence on whether and how the bundling of information affects managers' ability to gather feedback from market prices. We believe that three challenges explain this gap in the literature. First, in equilibrium, firms optimize their disclosure policies to derive maximum benefit from market feedback vis-à-vis other disclosure incentives. For example, the extant literature documents that managers often coordinate the timing of information releases to achieve certain reporting objectives (e.g., Chapman et al., 2019; deHaan et al., 2015; Kothari et al., 2009; Lansford, 2006; Miller, 2002; Segal and Segal, 2016).[33] Recent studies have also documented that managers may strategically issue or withhold voluntary disclosures to facilitate learning from stock prices (Bae et al., 2022; Chen et al., 2021; Fox et al., 2021). Identifying the effect of simultaneous versus separate information releases thus requires an exogenous source of variation in disclosures across firms over time.

Second, disentangling the effect of feedback from other concurrent information sources that simultaneously affect corporate decision-making requires the identification of distinct pieces of information and, more importantly, the ability to trace managers' subsequent decision making back to the specific feedback obtained for each piece of information. Finally, it is unclear what the market's feedback and corresponding managerial reactions would have been, if such a distinct piece of information would have been released separately versus together with other pieces of information. In particular, market signals themselves may be affected by how

[33] Rogers and Van Buskirk (2013), for example, also discuss s similar problem in the context of measuring bundles forecast news, i.e., news in management forecasts issued concurrently with earnings announcements.

much information is released at the same time (e.g., Blankespoor et al., 2020; Kaplan, 2014; Wertz, 2021).

To overcome these challenges, we focus on corporate investments in innovation and take advantage of several features of the United States Patent and Trademark Office's (USPTO's) disclosure mechanism for firm-specific patent information. Investments in innovation are inherently uncertain and their success often critically depends on factors outside the control of the firm (e.g., Kumar and Li, 2018; Manso, 2011). Market participants' collective assessment of past and ongoing investments is thus likely a valuable source of information concerning the viability of ongoing innovative activities and potential future investment opportunities. Patent grant announcements create an opportunity for firms to extract such feedback as they represent the release of value-relevant information about firm's investment activities to the market (e.g., Austin, 1993; Kogan et al., 2017; Martens, 2021; Pakes, 1985).

The patent setting has several benefits for identification. First, patent grant announcements provide an exogenous source of variation of information bundling that is not affected by firm-specific disclosure incentives. When the USPTO grants a new patent to a firm, information about this patent is first published in the Official Gazette, the official journal of the USPTO published weekly on Tuesdays. The exact timing of the release of this information is determined by the USPTO's patent application and examination process and not by the firm itself. Even if a firm receives multiple patents within a short period of time, in which week specifically each patent is published largely depends on the administrative processes of the USPTO. These "Patent Tuesdays" thus allow us to use the timing of patent grant disclosures by the USPTO as a plausibly exogenous source of variation in the extent to which firm-specific value-relevant information are released simultaneously or not.

Second, the patent setting allows us to establish a direct link between managers' subsequent decision making and market feedback obtained for distinct pieces of information. Specifically, we use firms' references to their own prior technological advances in subsequent patent applications (i.e., self-citations) to capture the relation between firm-specific investments over time (e.g., Hall et al., 2005). This unique feature allows us to track how firm-specific future investments in innovation relate to specific past investments and the feedback received regarding these investments upon publication of the patent. Third, patent events are relatively frequent for innovation-active firms. This allows us to abstract from structural differences in firms' patenting behavior over time or markets' processing of bundled information by using an extensive set of fixed effects. Specifically, our research design only exploits variation within firms and release days with similar or even the same number of patent grants released at once.

To illustrate the concept of managerial learning in a patent setting, suppose a firm obtains a patent for a novel technology that is relatively new to the company. This patent grant is news to the market that reveals the firm's investments in this particular technology, therefore triggering a market response. Now suppose that the market does not seem very excited, indicating a negative sentiment. This aggregate price movement conveys shareholders' overall opinion on the investment, suggesting that the market does not view it favorably. Although the initial investment in the granted patent has already been made, managers can gain valuable insights from this feedback and may decide to adjust their future investment strategy by refraining from further investments in the same technology. Consequently, we expect to observe a decrease in follow-up patent applications in that technology, resulting in lower self-citations for the initial patent. Importantly, our study suggests that this association between market feedback and managerial decision-making becomes even more pronounced when fewer patents are granted simultaneously. Because, in such cases, managers can more easily attribute the market's response to the specific patent and technology, enabling them to make more informed choices regarding future investments.

We first test whether market reactions around patent grants exhibit stronger association with firms' subsequent investments when there are one or multiple patent releases at the same time (separate vs. simultaneous release). If the simultaneous release of information impairs managers' ability to link feedback to a specific patent among others, the market response to patent grants should be less (more) predictive for subsequent patent filings related to the same technology when there are many (fewer) grants disclosed at the same time.

Consistent with the notion of learning, we find that patents that receive favorable market response upon their disclosures are more likely to be followed-up and cited by the firm's future patent applications. But more important to our research question, the market's signal for a patent's economic value is more likely to indicate that the patent will be cited in the future if fewer patents are issued at once or if these patents relate to similar technology classes. These results indicate that managers can establish a better connection between market feedback and specific investments, particularly when there is less simultaneous information released or when the information released is more complementary in nature. The results are robust to alternative definitions of the treatment variable, alternative measures of patent value, the presence of other simultaneous information releases, and structural differences in patenting behavior.

The relevance of market feedback for managerial learning likely depends on the nature of the patent and the underlying innovation. Not all patents represent the fundamental search for new technologies that have the potential to transform businesses and markets. In fact, firms often file patents to utilize, refine, and protect existing technologies against potential workarounds from competitors (e.g., Almeida et al., 2018; Benner and Tushman, 2003; Manso, 2011; March, 1991). We test whether the effect of separate information releases is more pronounced for patents that relate to more exploratory technologies, which are new to the firm. In particular, since investments in new technologies are typically riskier than investments that refine existing technologies, managers are more likely to incorporate a broader set of information into their decision process (e.g., Bai et al., 2016; Ferracuti and Stubben, 2019; Fleming, 2001). We find that a firm's ability to extract clearer signals from the market's response seems to be more relevant for patents that relate to more exploratory innovative activities. This suggests that the clarity of market feedback is more important for managerial decision making if it concerns relatively riskier innovative strategies that are new to firm. This result also further supports the idea that managerial learning from market prices depends on the ability to attribute price signals to specific pieces of information.

Next, we investigate whether the bundling of information releases also affects other firms' ability to extract timely information from stock price reactions to competitors' actions and disclosures (Arya and Ramanan, 2022; Foucault and Fresard, 2014; Xiong and Yang, 2021). Consistent with the notion of competitor learning, we find that the market's response to patent grants has higher predictive ability for future patent citations by other firms if fewer pieces of information (i.e., other patent grants for the same firm) are released simultaneously. This suggest that the structure of information releases not only affects firms' own ability to extract information from the market but also affects other firms and competitors.

In our last set of tests, we abstract from market reactions to specific patents and examine the relation between simultaneous vs. separate information releases and subsequent innovative activities at the firm level. We explore whether those firms that are able to gather more precise feedback because their patent information is released separately rather than simultaneously also produce more valuable and higher quality innovation in the future. Based on all weekly patent release dates on which a firm received at least one patent, we construct a yearly measure of firm exposure to simultaneous vs. separate information releases. We find that firms with more separate information releases subsequently invest in innovation that receives higher market valuations and more citations and is thus more important. These findings are robust to controlling for the number of patents received in a year, firm fixed effects and industry-specific time trends.

Taken together, the results indicate that managers find it easier to infer feedback from the market's response to information releases if the response can be more easily tracked back to specific pieces of firm-specific information. At the same time, market reactions that can be attributed to specific pieces of information may also convey more valuable information to competitors and other market participants.

These findings are important given the recent efforts to better understand the mechanisms that facilitate or reduce managers' ability to gather decision-relevant information from capital markets. While several studies have examined the effect of capital market feedback on firm behavior (e.g., Bai et al., 2016; Chen et al., 2007; Dessaint et al., 2019; Martens and Sextroh, 2021), less is known about how disclosures affect the availability and relevance of feedback. While some studies have documented that managers may use voluntary disclosures to solicit market feedback (e.g., Bae et al., 2022; Fox et al., 2023; Jayaraman and Wu, 2020), others have suggested that additional disclosures may in fact reduce managerial learning from market prices if it discourages informed trading (e.g., Chen et al., 2021; Gao and Liang, 2013; Goldstein and Yang, 2019; Goldstein et al., 2022; Jayaraman and Wu, 2019; McClure et al., 2022; Pinto, 2022). We complement this literature by documenting that the effect of disclosures on the usefulness of prices for managerial decisions also depends on managers' ability to infer a clear feedback signal from the market's response to a disclosure. In fact, disclosure regulations that mandate the release of multiple pieces of information all at once may potentially impede managers' ability to benefit from the market's feedback.

Our results also provide yet another perspective on managerial preferences for "bundling" information, for example, when releasing information about new strategic initiatives or managerial forecasts concurrently with earnings announcements. Prior research has provided evidence that such information bundling often occurs for strategic reasons, e.g., to bury bad news with other corporate news, to manage investor perceptions by releasing optimistic guidance, or to reduce potential detrimental effects of information overload (e.g., Billings and Cedergren, 2015; Bliss et al., 2018; Chapman et al., 2019; deHaan et al., 2015; Kothari et al., 2009; Rawson et al., 2020). Taking into account potential feedback effects, however, managers may also prefer to unbundle information if the objective is to maximize the feedback that can be extracted from the market's response to a particular disclosure (Ramanan, 2015). In addition, more precise market feedback may also convey valuable and timely information to competitors. The trade-off between bundling and unbundling specific pieces of information may thus be more nuanced than previously thought of.

We also contribute to the ongoing debate about the benefits and costs the disclosure of firms' innovative activities (see Glaeser and Lang, 2023, for a review of the literature). While recent literature in economics and management has generally documented that patent disclosures increase informational efficiency (e.g., Graham and Hegde, 2015; Hegde et al., 2018), recent studies have also suggested that the potential benefits and costs of innovationrelated disclosures warrant a more nuanced investigation (e.g., Breuer et al., 2022; Dyer et al., 2023; Glaeser, 2018; Glaeser and Landsman, 2021; Kim and Valentine, 2021; Saidi and Zaldokas, 2021). Our results suggest that disclosures about firms' innovative activities, such as the publication of patents, may also affect corporate decision making by shaping the information flowing from capital markets back to firms.

Finally, our study should also be of interest for academics and practitioners interested in the determinants of corporate innovation (e.g., Acharya et al., 2014; Atanassov, 2013;

Balsmeier et al., 2017; Chemmanur et al., 2014; Fang et al., 2014; Reeb and Zhao, 2021; Sunder et al., 2017). In this context, it extends the debate on organizational learning processes that foster technological change (e.g., March, 1991; Tseng, 2022). In particular, our findings suggest that firms are likely to use feedback on realized innovations as an input when determining ongoing and future investments in innovation.

3.2. Related literature

A considerable debate on disclosure regulation centers on the question of how informational efficiency ultimately affects real efficiency. We study a potentially important factor to consider when debating how disclosure regulations ultimately affects real efficiency: feedback effects from financial markets.

The general idea behind feedback effects is that market participants produce information that is reflected in prices. Decision makers in the real economy observe these prices, extract critical information, and act accordingly. While feedback effects originate in the informational role of market prices, there are various reasons why managers may find this information useful (see, e.g., Edmans et al., 2012, for a more comprehensive discussion). Feedback effects can emerge when market participants collectively form a better assessment of the implications of an investment opportunity for firm value than managers (e.g., Edmans et al., 2015; Grossman, 1976; Hayek, 1945). The price-formation process observed in capital markets may then reveal new information to the manager, which in turn could facilitate managerial learning and affect subsequent decision making (Bond et al., 2012; Dye and Sridhar, 2002).[34]

[34] Even if market prices do not contain any new information for decision makers, they may still act correspondingly. On the one hand, managers whose compensation is tied to market prices, for example, have an incentive to take actions that are also reflected in the firms' stock price. On the other hand, decision makers may irrationally use market prices as an anchor when making real decisions.

Empirical evidence generally supports the feedback role of financial markets. Luo (2005), for example, studies acquisition announcements and finds that if the market responds negatively, managers may decide to cancel the deal. Chen et al. (2007), Kau et al. (2008), and Bakke and Whited (2010) present evidence consistent with managers incorporating information from stock prices into their investment decisions. Goldstein et al. (2021) survey Chinese public companies and provide direct evidence that firms pay attention to the stock market to gather feedback that guides investment decisions. Feedback effects have also been documented to be relevant in the context of corporate innovation, as they may help to resolve constraints emerging from secondary markets, such as economic upswings or downturns (e.g., Mace, 2020), by providing information about the firms' relative economic condition and innovative positioning. Kumar and Li (2018), for example, examine the generation of information by stock markets and the corresponding feedback effects on firm-level innovation-related investment. They document a positive association between the idiosyncratic volatility of stock returns and the response rate of subsequent innovation-related investment. Taken together, prior literature has documented that financial markets do not only *reflect* what firms are doing, but also have the potential to *affect* what firms are doing.

Despite evidence about the relevance of capital market feedback to various corporate decisions, it is ambiguous whether and how corporate disclosures affect the ability of managers to learn from these signals. On the one hand, theoretical and empirical studies suggest that increased levels of disclosure trigger feedback effects if the disclosure facilitates discovery of previously unknown information that is impounded in market prices (Bae et al., 2022; Jayaraman and Wu, 2020). On the other hand, corporate disclosures could also potentially crowd out informed trading, which would reduce the amount of private information in market prices and, hence, managers' ability to extract previously unknown information (Gao and Liang, 2013; Goldstein and Yang, 2019; Jayaraman and Wu, 2019).

In this study, we investigate whether managers' ability to extract information from market prices depends on the amount of information disclosed at the same time. Theoretical work by Ramanan (2015) suggests that information bundling may impair managerial learning from prices. The idea is that when multiple pieces of information are released at the same time, prices will reflect an aggregate response to the entire bundle of information. As a consequence, managers will find it more difficult to extract feedback for specific pieces of value-relevant information. By releasing information separately, however, managers may be able to obtain a clearer signal of market feedback, which is also more useful for subsequent decision making. At the same time, there are also good reasons to believe that information bundling may enhance managerial learning from market prices. For example, if different pieces of information are complements, releasing these pieces at once could facilitate price formation and, hence, provide better feedback to managers (e.g., Hirshleifer and Sheng, 2022).[35] Whether the bundled release of information affects managers' ability to gather decision-relevant information from market prices is thus ultimately an empirical question.

3.3. Identifying simultaneous information releases: "Patent Tuesdays"

We use the timing of patent grant disclosures by the USPTO as a plausibly exogenous source of variation in the simultaneous release of value-relevant information. Firms frequently bundle the release of information, e.g., when combining the announcement of a new product or strategy with information about recent financial performance. However, firms typically have the choice whether to release these separate pieces of information all at once or to delay the

[35] Information bundling may also affect price formation due to differences in investor attention and processing costs when multiple pieces of information are released at once (see, e.g., Blankespoor et al., 2020, for a review). That being said, the direction is not necessarily clear. On the one hand, releasing multiple pieces of information at once could impair investor decision making (and thus also the quality of market feedback) due to information overload (Casey Jr, 1980; Einhorn, 1971; Iselin, 1988; Malhotra, 1982). On the other hand, releasing multiple pieces of information during a pre-scheduled event could positively affect investor attention and thus improve signals available from market prices. Our research design seeks to abstract from such structural differences in market valuations related to the amount of information released primarily to ensure that our findings are not affected by systematic measurement error or correlated omitted variables.

dissemination of one piece of information until a later date. In equilibrium, firms optimize their disclosure policies to derive the maximum benefit from market feedback vis-à-vis other disclosure incentives. Prior literature, for example, suggests that managers adapt their corporate disclosure practices, such as voluntary management guidance, to the signals observed in the market (e.g., Cao et al., 2022; Chapman and Green, 2018; Langberg and Sivaramakrishnan, 2010; Zuo, 2016). Additionally, managers strategically bundle information releases to achieve specific reporting objectives (e.g., Kothari et al., 2009; Lansford, 2006; Miller, 2002; Segal and Segal, 2016). Identification thus requires a source of exogenous variation in information releases that is free from firm-specific disclosure incentives or even considerations related to the elicitation of market feedback, especially as these may be correlated with firm-specific drivers of future investment.

A patent grant represents a firm-specific piece of value-relevant information that is not published by the firm itself but by the USPTO as the relevant regulatory authority. At the same time, patents still constitute a firm-specific disclosure since it is the firm's choice to apply for a patent and to accept any corresponding publications by the USPTO. Patent grants are announced via the Official Gazette, the official journal of the USPTO. The journal is published weekly on Tuesdays, unless there is a federal holiday, and includes information on each patent granted during the previous week. These "Patent Tuesdays" come with several institutional features that allow us to exploit plausibly exogenous variation in the simultaneous vs. separate release of individual pieces of firm-specific information that are news to the market but already known by the firm.[36]

[36] One may argue that patent-related information is already known to the market prior to the actual patent grant. In particular, since the enactment of the American Inventor's Protection Act (AIPA) in 2000, firms have been required to disclose their patent applications 18 months after filing, regardless of whether the application is eventually granted. However, patent grants still constitute considerable news to the market, as the uncertainty about patent rights and the associated economic benefits is resolved. In addition, the majority of our patent grant sample is from the pre-AIPA period.

While firms decide whether and when to apply for a patent, the grant itself is subject to the USPTO's patent application and examination process. This process involves a number of formal steps and rounds of communication between the applicant and the examiner. The average total pendency, i.e., the time from the filing of an application until either the patent is granted or the application is abandoned, is approximately 24 months but can take considerably longer (United States Patent and Trademark Office, 2020). Due to the length of the process, any strategic considerations regarding the timing of application filings hardly affect the timing of patent grant announcements. Within our sample, approximately 73.3 percent of all patent applications are filed concurrently with other applications from the same firm, but only 4.4 percent of these applications are also granted at the same time (See Figure 2.A). Additionally, patent grants are fairly evenly distributed across weeks (See Figure 2.B).

Even though firm actions may influence the length of the application process, if and when a patent is granted is ultimately determined by the examiners at the USPTO. Similarly, the specific date when the patent will be issued and announced in the Official Gazette largely depends on the administrative processes within the USPTO.[37] As such, the timing of firm-specific patent grant disclosures by the USPTO and, more importantly, the degree to which information are released separately or all at once, is plausibly exogenous to firms' own disclosure strategies.

[37] Prior to issuing a patent, the applicant receives a *Notice of Allowance* (NOA) from the USPTO with the request to pay the corresponding issuance fees within 90 days. As a consequence, it is possible that firms strategically time the payment of fees to affect the timing of patent grants. Descriptive statistics on the timing of NOAs, fee payments and patent grants, however, suggest that this is hardly the case (see Online Appendix OA.1). For one, there is considerable variation in the time between fee payment and issue date. For another, even if fees are paid simultaneously, there is a high change these patents will be issued in different weeks. This suggests that the ultimate timing of patent grants still largely depends on administrative processes within the USPTO, which is hardly influenced by firm-specific actions. A related concern may be that, since firms receive the NOA before the actual patent issuance, they voluntarily disclose the successful application already earlier. Again, this seems rarely to be the case. Lansford (2006), for example, reviews more than 10,000 patent-related articles issued by companies between January 1990 and November 2000 to identify different types of patent-related disclosures. He finds only 203 instances of companies voluntarily disclosing an NOA, although more than 400,000 patents were issued during the same time period. Similarly, Carter et al. (2016) search 176,232 8-K filings between 1996 and 2006 and find that only 92 of them mention the term "Notice of Allowance".

Besides benefits for identification, the context of corporate innovation also provides a setting in which feedback effects are likely to affect corporate decision making. The success of research and development activities is inherently uncertain and depends critically on factors outside the control of the firm, such as technological advances and key market developments (see, e.g., Kumar and Li, 2018; Manso, 2011). Prior research has documented that when making such decisions under uncertainty, disclosures can enhance opportunities to learn from other sources of information, such as stock prices (e.g., Ferracuti and Stubben, 2019, for a more detailed discussion). Extracting market participants' collective assessment of past and ongoing investments may thus be a valuable source of information concerning the viability of ongoing innovative activities and potential future investment opportunities. In fact, Bai et al. (2016) document that the real effects of prices are salient in R&D-type investments.

3.4. Simultaneous information releases and the informativeness of market prices for corporate decision making

3.4.1. Empirical specification

To examine whether the simultaneous release of value-relevant information affects managers' ability to learn from market prices, we exploit variation in USPTO patent grant releases within firms over time by conducting tests on the level of individual patents:

$$log(1 + Self - citations_{PATENT,\,10y})$$

$$= \beta_1 Market\ feedback_{PATENT} + \beta_2 Separate\ info\ release_{PATENT/TECH,\,i,\,t}$$

$$+\beta_3 Market\ feedback_{PATENT} \times Separate\ info\ release_{PATENT/TECH,\,i,\,t}$$

$$\sum Controls_{i,t} + \sum Firm_i\ X\ Tech\ class_j\ \sum Date_t\ X\ Tech\ class_j\ +$$

$$\sum Industry_s\ X\ Year_t + \sum Release\ cluster\ /\ \#patents_{i,t} + \varepsilon \qquad (1)$$

Focusing on the individual patent allows us to trace managers' subsequent decision making back to feedback obtained for the past investments revealed by patent grants. Specifically, we use firms' references to their own prior technological advances in *subsequent* patent applications (i.e., self-citations) to capture the relation between firm-specific investments over time. These self-citations show how a firm builds upon its past innovations and are, according to Hall et al. (2005), more valuable to the firm than external citations. The dependent variable, $\textit{Self-citations}_{PATENT,10y}$, is the number of citations that a patent receives in future patent applications by the same firm within 10 years after the patent grant.[38]

The specification relies on two core constructs: (1) the patent-specific market signal observed by managers ($\textit{Market feedback}_{PATENT}$) and (2) the impact of simultaneous information releases on the usefulness of this signal for managerial decision-making ($\textit{Separate information release}_{PATENT/TECH}$). If managers take the market's response around the publication of patent grants into account when making subsequent investment decisions, future patent applications should include more (fewer) references to patents that received a more (less) favorable market reaction (β_1). More importantly, if the separate release of information results in more informative market reactions for managerial decision making, those reactions should then also be more predictive of future self-citation behavior (β_3).

To measure the signal that managers receive from the market about their past investment activities ($\textit{Market feedback}_{PATENT}$), we rely on Kogan et al. (2017)'s estimates of patents' economic value. The patent value is calculated as follows:

$$\xi_i = (1-\bar{\pi})^{-1}\frac{1}{N_j}E\left[v_j|R_j\right]M_j$$

38 Results are robust to using shorter horizons of 3- or 5-years to determine future self-citations (see Appendix Table OA.7).

Where $\bar{\pi}$ is the probability of a successful patent application, N_j is the number of patents granted on the same date with patent j, and M_j is the market capitalization of the firm on the date before the disclosure of patent grant. $E\left[v_j|R_j\right]$ is the estimate of three-day idiosyncratic stock return due to the value of patent grant.[39]

There are two compelling reasons why this measure is preferred over raw returns. Firstly, the patent value is a filtered cumulative abnormal return abstract from stock price movements contaminated by news other than patent grants, providing a clearer and less noisy measure compared to raw returns. This filtering process effectively eliminates confounding factors, ensuring a more reliable signal. Secondly, the patent value reflects not just raw returns but also how much investment (trade) has been made in the firm's stocks to drive the prices. This feature makes it arguably a better measure compared to CARs, as it captures the market's evaluation of the patent grant's impact on the firm's value in terms of actual dollars invested. Thus, we consider the patent value as a superior measure of market feedback compared to raw abnormal returns for our analysis.

Although these estimates primarily intend to capture the economic importance of an innovation, market-based proxies have certain properties that make them useful for the feedback that managers are likely to extract from aggregate market reactions about individual patents. For one, since the success of research and development activities is inherently uncertain and depends critically on factors outside the control of the firm (see, e.g., Kumar and Li, 2018; Manso, 2011), market reactions to patent grants are likely to include incremental information not already known by management. For another, testing for the effect of bundled information releases on managers' ability to extract feedback from market reactions requires

[39] More specifically, the measure is based on a firm's idiosyncratic return defined as the firm's stock return minus the return on the market portfolio after the patent grant controlled for stock returns unrelated to patent grant, adjusted by the unconditional probability of a successful patent application. Please refer to Kogan et al. (2017) for a more detailed explanation of their measurement approach.

an assumption about how managers allocate the market's (aggregate) response to the different pieces of information that are released at the same time. Kogan et al. (2017) assume that for cases where multiple patents are released on the same day, the value of each individual patent is an equal fraction of the total value as indicated by the market's aggregate response on that day.

Following the principle of indifference this is also plausible assumption of how managers would allocate market responses to individual patents in the absence of informative priors. That is, for decisions made under uncertainty a manager should assign equal probabilities to all events or choices if she has no additional information that gives reason to favor any specific allocation over another. Under the assumption that the manager has no other logical or empirical reason to use a different allocation, using an equal fraction of the total market response is thus the best estimate of the information that managers can extract about the value of each patent released at the same time.[40] As such, Kogan et al. (2017)'s estimates of patent values also provide for plausible and useful proxies for the signal that managers can obtain for these patents from aggregate market responses.

We use two alternative measures to capture firm-specific variation in the degree to which individual pieces of information are released separately or simultaneously: (1) the inverse of the number of patents granted to firm i on release day t (*Separate information release$_{PATENT}$*) and (2) the inverse of the number of unique technology classes these patents relate to (*Separate information release$_{TECH}$*), respectively:

$$Seperate\ info\ release_{PATENT\ i,t} = \frac{1}{\#Patents_{i,t}}$$

[40] We conduct several robustness tests to ensure that our inferences are not affected by assumptions about how managers allocate an aggregate market signal to individual patents. See Appendix C for details.

$$Seperate\ info\ release_{TECH\ i,t} = \frac{1}{\#USPTO\ Technology\ Classes_{i,t}}$$

Both measures follow a similar logic. If a firm has multiple patents pending and these patents are granted close together in time, it is possible for these patents to be published in the same issue of the Official Gazette. In that case, multiple separate pieces of value-relevant information would be released at once, and the market price would reflect only an aggregate response to the combined information release. Managers should then also find it more difficult to attribute an aggregate market's response to a specific piece of patent information. Instead, if firms receive only one patent grant on a release day, the market price reflects the reaction to a specific piece of information, i.e., managers can obtain a clearer signal of the market's assessment of the investment activity associated with the particular patent granted. *Separate information release$_{PATENT}$* assumes that each patent constitutes a distinct piece of information and captures the effect of multiple patents released at the same time (see Figure 1A).

Irrespective of the number of patents a firm receives on a given day, managers may also extract feedback on more aggregated information levels. For example, a firm that receives multiple patents for innovations in the same technology class on the same day may still be able to extract relatively clear feedback about its activities in that particular technology class or scientific area even though specific feedback for individual patents may be limited. *Separate information release$_{TECH}$* thus captures an alternative definition of what constitutes a distinct piece of information (see Figure 1B).

For *Separate info release$_{PATENT}$*, a value close to one indicates that the firm received only a few patents on a particular release day, while a measure closer to zero marks release days with multiple firm-specific patent grants. Similarly, for *Separate info release$_{TECH}$*, a value close to one indicates that the patents the firm received on a particular release day relate to the same USPTO technology class, while a measure closer to zero indicates the degree to which patents released on the same day relate to different technology classes. The fewer the number of patents granted on the same day or the fewer the corresponding number of unique technology classes, the higher the firms' ability to learn from the market's response to a specific piece of information. Both measures are non-linear, which corresponds to the notion that the marginal effect of releasing an additional piece of information should be larger the fewer pieces are released at once. The more information is released at once, the lower the marginal effect of releasing an additional piece of information on managerial learning. [41]

Together, both measures also help to overcome important remaining concerns for identification. For one, the model assumes that the treatment (*Separate information release*) is exogenous with respect to patent values and market's processing of information. However, structural differences in firms' innovation cycles, strategic patenting behavior, or markets' processing of bundled information could manifest empirically as a correlation between $\textit{Separate information release}_{PATENT}$ and $\textit{Market feedback}_{PATENT}$. To alleviate this concern, we include fixed effects for any two adjacent release clusters in terms of the number of patents released at the same time (i.e., 1-2 patents, 2-3 patents, 3-4 patents, etc.) when estimating specifications using $\textit{Separate information release}_{PATENT}$. Our specification thus only exploits marginal differences in the treatment variable. General differences in innovation activities or strategic patenting behavior that would result in higher (lower) valued patents being more likely released separately (simultaneously) are subsumed by these release cluster fixed effects. The same holds for structural differences in market reactions for different types of information releases. Identification only requires the assumption that patent values and market's processing

[41] Additional robustness tests show that our results are robust to using a linear measure to capture the extent of separate information releases.

of information will be similar for patents released in adjacent clusters in terms of the number of patents released at the same time.[42]

For another, *Separate information release*$_{TECH}$ helps to address concerns related to systematic measurement error of *Market feedback*$_{PATENT}$. Specifically, the number of firm-specific patent grants (*Separate information release*$_{PATENT}$) directly relates to managers' assumed allocation of the aggregate market response to individual patents (i.e., both measures are based on the number of patents released on the same day). As a consequence, if *Market feedback*$_{PATENT}$ contains measurement error that increases with the number of patents released at the same time, the coefficient for the interaction term of *Market feedback*$_{PATENT}$ x *Separate information release*$_{PATENT/TECH}$ may in fact indicate this measurement error and not the effect of separate information releases on managers' ability to extract useful feedback. Measuring separate information releases based on technology classes allows us to include fixed effects for the number of patents a firm receives on a given day and thus to explicitly separate the measurement of information releases from the number of patents released at once. Tests based on *Separate information release*$_{TECH}$ thus exploit only the residual variation in the degree of patent complementary based on technology classes while abstracting from the number of patents and, hence, the potential effect of measurement error.[43]

We further include various fixed effects to abstract from general firm-, technology-, or industry-specific developments. Specifically, we include firm × technology class fixed effects

[42] We validate this assumption empirically. More specifically, we compare the average patent value (*Marketfeedback*$_{PATENT}$) for all adjacent number of patent releases (i.e., 1 vs 2 patents, 2 vs. 3 patents, 3 vs. 4 patents, etc.). We do not find a systematic and monotonically decreasing relation between *Marketfeedback*$_{PATENT}$ and *Separate information release*$_{PATENT}$ within adjacent clusters. Including fixed effects for adjacent clusters thus alleviates concerns that results are driven by correlated omitted variables such as differences in market's processing of information or structural differences in firms' innovation activities over time.

[43] One may argue that a remaining concern for identification is that as a result of the variation in firm innovation cycles over time, high-value patents are more likely to be released separately compared to follow-up innovations of potentially lower economic value. However, the mean patent valuation on grant day shows no clear relationship with the number of patents granted simultaneously. See Online Appendix Figure OA.3.

control for structural differences in citation behavior within a firm across technology classes (e.g., core technology classes and peripheral technology classes). Technology class × grant day fixed effects avoid truncation bias since patents that are granted earlier have more time to accumulate forward self-citations. We also include industry × year fixed effects to control for changes within an industry that affect innovation quality and subsequent investment (e.g., shifts in industry-wide innovative strategies). Finally, we include a vector of standard control variables that have been shown to affect corporate investment in innovation (see Reeb and Zhao, 2021, for a discussion). Thus, our patent-level analyses effectively exploit only the patent-specific residual variation in market valuations and the amount of information released at the same time irrespective of firm-, technology-, or industry-specific developments.

To control for potential correlations among the residuals, we calculate two-way clustered standard errors by firm and year (Petersen, 2009).

The analyses are based on a sample of all granted patents of public US firms between 1926 and 2020, which we obtain from the Kogan et al. (2017) patent database. We merge this sample with data about patent citations from Patentsview.org. In addition, we obtain firm-specific data from CRSP, Compustat, and the Capital IQ Key Developments database. The final sample includes 1,964,350 patents granted between 1976 and 2020.

3.4.2. Results

Table 1 presents basic descriptive statistics. Please refer to Appendix A for a full description of all variables. The patents in our sample receive on average 1.13 self-citations within 10 years after the patent has been granted. The mean (median) of *Separate info release*$_{PATENT}$ is 0.24 (0.083), which implies that each patent release is accompanied by the contemporaneous release of 4 (12) other patents on the same day for the same firm. However, there is considerable variation in the number of patent grants published for a given firm on a given grant day, ranging from patents that are released by themselves (Max(*Separate info release$_{PATENT}$*) = 1) to the simultaneous release of 436 patents (Min(*Separate info release$_{PATENT}$*) = 0.002).

Table 2 presents the regression estimates for equation [1]. We find that the market's response to a patent grant positively predicts references to that patent in the firms' future patent applications ($p \leq 0.01$). Consistent with prior literature that documents a general "learning from market feedback" effect (e.g., Bakke and Whited, 2010; Chen et al., 2007; Luo, 2005), firms seem to incorporate the market's response to successful investments when making decisions about future investments in innovation.[44]

However, whether firms can extract useful feedback from the market's response to a patent grant also seems to depend on whether the information is released separately or together with other pieces of information all at once. The coefficient on *Separate info release$_{PATENT}$* (Column 1) and on the interaction of *Market feedback$_{PATENT}$* and *Separate info release$_{PATENT}$* (Column 2) is significantly positive ($p \leq 0.05$). This suggests that firms put more weight on patent valuations when fewer patents are released on the same day, i.e., when the market's aggregate response can be more clearly attributed to a specific piece of information.

The coefficient estimates suggest that if a patent is released itself (*Separate info release$_{PATENT}$* = 1) instead of together with another patent (*Separate info release$_{PATENT}$* = 0.5), it will receive 1.64% more self-citations within the next 10 years.[45] Similarly, the coefficient on the interaction term in column [2] indicates that for a patent with *Market feedback$_{PATENT}$* equal

[44] The positive coefficient for *Market Feedback* also somewhat alleviates concerns of systematic measurement error in patent valuation as this argument does not apply to results involving only the base effect of *Separate info release$_{PATENT}$* or *Separate info release$_{TECH}$*.
[45] $(e^{0.0324} - 1) * 100 * 0.5 = 1.64$

to one (i.e., patent value equals 2.7 million) a change in market feedback is associated with a 0.8% larger change in self-citations within the next 10 years if the patent is released separately.

While this effect seems economically small, it nevertheless indicates a change in firm behavior, especially considering that the average patent receives only 1.13 self-citations in total over a period of 10 years. Additionally, due to the idiosyncratic nature of feedback effects, it is inherently difficult to identify the channels by which these feedback effects occur. While self-citations allow us to link past signals to future decisions, they are not the only dimension along which feedback materializes. Similar to firms that adjust various features of their strategies to cater to the financial market, firms can also adjust their patents to incorporate feedback (e.g., citations, technological focus, wording). As such, the identified effect likely captures only a fraction of the true feedback effect.

We find similar results for specifications including *Separate info release$_{TECH}$* alleviating concerns that results are due to systematic measurement error in patent valuations that increases with the number of patents released at the same time (Columns 3 and 4). Taken together, these patent-specific estimates suggest that firms not only utilize market feedback for subsequent decision making but that the ability to extract critical feedback also depends on whether the market's response can be tied to a specific piece of information.[46]

3.4.3. Patent characteristics and capital market feedback

Corporate innovation strategies include both uncovering new possibilities through the generation of previously unknown knowledge (i.e., exploration) and exploiting existing possibilities through the use of already existing knowledge (i.e., exploitation) (e.g., Almeida et

[46] To ensure the robustness of our results, we also consider two alternative regression specifications. First, we estimate equation [1] without singletons (see, e.g., deHaan and Breuer, 2021, for a discussion). Coefficient estimates remain significant and quantitatively similar to those reported in Table 2. Second, we repeat the analysis using a Poisson regression (see, e.g., Cohn et al., 2022, for a discussion). We continue to find a significant positive relation between separate information releases and future patent citations.

al., 2018; Benner and Tushman, 2003; Manso, 2011; March, 1991). As a result, not all patents represent a fundamental search for new technologies that have the potential to transform businesses and markets. In fact, firms often file patents to utilize, refine, and protect existing technologies against potential workarounds from competitors, e.g., to prevent more firms from entering the market or to ensure continuing licensing revenue (e.g., Cohen et al., 2000). While such exploitative patents still have economic value, e.g., because they protect the continuance of future cash flows, market feedback may be more important for patents that relate to more risky investments in exploratory innovative activities. For such activities, management must critically assess whether future investments to further develop and exploit the newly developed and patented technology are worthwhile.

Since investments in new technologies are typically riskier than investments that refine existing technologies, managers are more likely to incorporate a broader set of information into their decision-making process (e.g., Bai et al., 2016; Ferracuti and Stubben, 2019; Fleming, 2001). Thus, to the extent that managers incorporate market feedback into their decision making, they should also rely more on the market's response if it concerns patents that relate to relatively more risky and exploratory investments. As a result, if the concurrent release of information affects managers' ability to extract useful information from market prices, the effect of separate information releases should be more pronounced for patents that relate to more exploratory technologies.

We test this idea by estimating equation [1] separately for patents that are more/less exploratory. Similar to several innovation-related studies (e.g., Benner and Tushman, 2003; Custódio et al., 2019; Fitzgerald et al., 2021; Gao et al., 2018), we measure patent explorativeness as the total number of citations made that represent new knowledge for the firm divided by the total number of citations in the patent, where the firm's existing knowledge includes all patents that were either filed by the firm itself or cited in one of its existing patents between year t-5 and year t-1. The more new knowledge cited in a patent, the more exploratory the corresponding innovation.

On average, more and less exploratory patents are relatively similar with respect to their likelihood of a separate release and their economic value. In fact, the average value appears to be slightly higher for less exploratory patents, alleviating concerns that exploratory patents are, on average, both of higher value and originating from specific innovation cycles that also makes them more likely to be released separately from other patents. Table 3 reports the regression results separately for information releases based on the number of patents (columns 1 and 2) and the number of unique technology classes (columns 3 and 4). As expected, it appears that the firm's ability to extract clearer signals from the market seems to be particularly important for patents that relate to more exploratory innovative activities. The coefficient estimates for β_3 are significantly positive and significantly larger for patents with above-median explorativeness compared to those with below-median explorativeness ($p \leq 0.05$). These results further confirm the notion that firms' ability to extract clear feedback from market prices depends on the amount of concurrent information released at the same time and that the clarity of such feedback may be more important for managerial decision making if it concerns relatively riskier innovative strategies.[47]

3.4.4. Robustness tests

We run several robustness tests to ensure that our results are not driven by the definition of the treatment variable, by other simultaneous information releases, or by structural differences in patenting behavior. First, we repeat the analysis using the number of patents and technology classes issued on the same date as an alternative treatment variable (see Appendix

[47] Besides that, the results also alleviate remaining concerns that the observed relation between market responses and future investments is merely due to market responses being correlated with managers' private information. Since managers have by definition less information about more exploratory endeavors, observing relatively stronger effects for exploratory patents suggests that it is not managers' private information, but the market's feedback they are reacting to.

Table OA.2 Panel A and B column 1). Second, to control for the potential effect of other simultaneous information releases, we limit the sample to observations without concurrent events (see Appendix Table OA.2 Panel A and B column 2). Finally, we exclude the bottom 5% (column 3) and top 5% (column 4) of observations in terms of the total number of patents granted per year. Overall, the results remain similar across all alternative specifications (see Appendix Table OA.2 Panel A and B columns 3 and 4).[48]

In extensive additional analyses, we also consider alternative measures to capture signals of patent value observed by management to further alleviate any remaining concerns related to potential systematic measurement error in patent valuations (see Appendix Table OA.4 and OA.5). For one, we re-estimate equation [1] including the market valuation of all the patents granted on a single day as our measure of market feedback observable by managers. For another, we abstract from the assumption that management would equally attribute aggregate market reactions to individual patents and construct an alternative allocation of total value that takes into account the characteristics of patents released and their association with patent value. Finally, we construct a test that fully abstracts from multiple patent release days and instead relies on alternative simultaneous events for identification. All three tests suggest that our results are unlikely to simply reflect measurement error in patent valuations.

3.5. Capital market feedback and competitor learning

If managers can extract useful information from the market's response to their firm's actions or disclosures, this response may also convey timely information to other firms and competitors (e.g., Arya and Ramanan, 2022; Foucault and Fresard, 2014; Giuri et al., 2007; Xiong and Yang, 2021). We examine whether the separate vs. simultaneous release of information is associated with competitor learning and decision-making by re-estimating

[48] Our results are also robust to clustering standard errors by firm or firm and grant date (see Online Appendix Table OA.6).

equation [1] but using non-self-citations (i.e., citations from other firms) as the dependent variable. If the number of unique pieces of information released at a time affects competitors' ability to learn from stock market reactions to other firms' disclosures, other firms should be more likely to cite a firm's patent or technology class if a favorable market response on the release day can be more clearly attributed to that particular patent or technology class.

Table 4 presents the results. Consistent with the notion of competitor learning from other firms' stock prices, the market response around patent grant announcements predicts future citations by other firms, and more importantly, this effect becomes stronger when fewer pieces of information (i.e., other patent grants for the same firm that may even relate to other technology classes) are released simultaneously. This suggests that the structure of information releases not only affects firms' ability to extract information from stock price reactions to their own actions and disclosures but also extends to their ability to extract such information from reactions to other firms' and competitors' actions and disclosures.

3.6. Capital market feedback and firms' future patent portfolios

3.6.1. Main specification

In our final set of tests, we investigate whether firms that receive more market feedback also exhibit different levels of corporate innovation. Even if the interaction between disclosures and market feedback affects firm investment choices, this does not necessarily imply that firms also become more innovative or invest in activities with economic benefits. To test this conjecture, we abstract away from market reactions to specific patents and examine the relation between firm exposure to simultaneous vs. separate information releases and the value of their future investment portfolios at the firm level. If the simultaneous release of information about past investments in innovation impairs firms' ability to learn information critical to future investment decisions from the market's response, firms that are exposed to more (fewer) simultaneous information releases should exhibit relatively less (more) valuable investment portfolios in the future.

We explore this idea by aggregating the firm-specific measure of weekly "Patent Tuesday" information releases by year and testing for its predictive ability regarding the valuation of future patent portfolios:

$$
\begin{aligned}
&log\left(Patent\ portfolio\ valuation_{i,t+T}\right) \\
&\qquad = \beta_1 Separate\ info\ release\ exposure_{PATENT\ or\ TECH\ i,t} \\
&\qquad + \beta_2 \log\left(\#Patents_{i,t}\right) + \sum Controls_{i,t} + \sum Firm_i \\
&\qquad + \sum Industry_s\ X\ Year_t + \varepsilon \qquad (2)
\end{aligned}
$$

The dependent variable, *Patent portfolio valuations*$_{i,t+T}$, is the average patent valuation across all applications that were filed by firm *i* in year *t+T* that are eventually granted. We construct a measure of firm-specific exposure to simultaneous vs. separate information releases, *Separate info release exposure*$_{PATENT,i,t}$, as the sum of the patent-specific *Separate info release* measure for firm *i* aggregated over year *t* and scaled by the firm-specific number of Patent Tuesdays with patent grants in year *t*:

$$Separate\ info\ release\ exposure_{PATENT\ i,t} = \frac{\sum Separate\ info\ release_{PATENT\ i,t}}{\#Patent\ release\ days_{i,t}}$$

$$Separate\ info\ release\ exposure_{TECH\ i,t} = \frac{\sum Separate\ info\ release_{TECH\ i,t}}{\#Patent\ release\ days_{i,t}}$$

Higher values indicate that the firm is exposed to relatively more separate information releases. Since *Separate info release exposure*$_{PATENT,i,t}$ and *Patent portfolio valuation*$_{i,t+T}$ are naturally affected by the number of patents a firm receives during the year, we also include the number of patents granted to firm *i* in year *t* (*#Patents*$_{i,t}$). Conceptually, this variable captures the total number of individual pieces of information released during the year. As such, the coefficient on *Separate info release exposure*$_{PATENT,i,t}$ should reflect the effect of the relation between the distribution of these pieces of information (i.e., more simultaneous or more separate releases) and the average valuation of future patent portfolios. We again include standard controls from the prior literature as well as firm fixed effects and industry-specific time trends. The fixed effects control for the possibility that specific firms generate more or less valuable patents as well as potential trends across industries over time. (See Appendix A for a full description of all variables.)

The pool of patents included in the firm-level analyses is slightly larger than in the patent-level analyses due to fewer data requirements. The final sample includes 26,101 firm-year observations from 1962 to 2017. Table 5 presents the descriptive statistics. Sample firms receive an average of 59.4 patents per year and generate future patents with an average value of \$10.45 m (\$10.81 m) [\$11.34 m] in year t+1 (t+2) [t+3]. The average value of the firm-specific exposure to separate information releases is 0.831, with considerable variation across firms and years (min = 0.006; max = 1).

Table 6 presents the regression results for equation [2]. We estimate a regression for the valuation of the patents applied for in years t+1, t+2, and t+3. *Separate info release exposure*$_{PATENT}$ exhibits a significant positive association with *Patent portfolio valuations* across all specifications ($p \leq 0.01$). These results are consistent with the notion that those firms that can obtain more specific market feedback also invest in innovative activities that lead to more valuable patents, on average.

To ensure that our results are not driven by the construction of *Separate info release exposure*$_{PATENT/TECH}$, we re-estimate equation [2] using a binary variable that differentiates only between separate and simultaneous information releases but ignores the number of concurrent pieces of information disclosed at the same time. The coefficient estimate for *Separate info release exposure*$_{PATENT/TECH,BIN}$ remains statistically significant (see Appendix Table OA.8 columns 1 and 4).

The descriptive statistics in Table 5 further suggest that the total number of patents a firm receives per year varies considerably across firm–years. To ensure that the results are not driven by observations with a very low or high number of patents, we re-estimate the specification excluding the bottom and top 5% of firms in terms of the number of patents. The coefficient estimate for *Separate info release exposure*$_{PATENT/TECH}$ remains statistically significant and similar in size, alleviating concerns regarding the total number of patents received (see Appendix Table OA.8, columns 2-3 and 5-6).[49]

Finally, we also examine whether market feedback is associated with the scientific quality of subsequent innovation investments. We use two proxies for the scientific quality of subsequent patent grants: For one, we use the number of citations. For another, we use the patent importance measure developed by Kelly et al. (2021). Overall, we find that not only patent valuations, but also scientific quality increases with firms being able to extract more specific information from market prices (see Online Appendix Table OA.9). These results further support the notion that the structure of information releases will affect whether management will be able to extract feedback from market prices.

[49] In unreported tests, we further repeat the analysis by dropping one year at a time, one industry at a time, and one firm at a time to ensure that the results are not driven by any specific year, industry or firm. The coefficient estimate for *Separate info release exposure*$_{PATENT}$ remains statistically significant at the $p \leq 0.05$ level across all estimations.

3.7. Conclusion

We investigate whether the simultaneous release of value-relevant information affects managers' ability to gather decision-relevant information from market prices. Theory predicts that when multiple pieces of information are released at once, management may find it more difficult to infer useful feedback since the observed market response aggregates all individual pieces of information into a single signal. Instead, if pieces of information are released separately, management can obtain a clearer signal of the market's assessment of a particular piece of information.

We take advantage of the USPTO's disclosure mechanism for firm-specific patent information and use the timing of patent grant disclosures as a source of plausibly exogenous variation in the simultaneous release of value-relevant information. We find that the market valuation of individual patents is more predictive of future firm behavior when less information on other patents is released simultaneously on the grant date. The firm's ability to extract clearer signals from the market's response also seems to be more relevant for patents that relate to relatively riskier innovative strategies. Firms' ability to extract clear feedback signals around information releases positively predicts the value and quality of future investments in innovation. The effect of separate information releases on firm ability to extract information from market prices also extends to peer firm disclosures. Taken together, our results are consistent with the notion that the structure and timing of information releases affect managerial learning from market prices.

These findings are important in light of efforts to better understand the effect of informational efficiency on real efficiency. While the effect of market prices on real decision making has been well documented, there is still considerable debate about whether and how corporate disclosures facilitate or impede managers' ability to gather decision-relevant information from secondary markets. Our results suggest that the interplay of disclosures, capital market feedback, and managerial decision making may be more nuanced.

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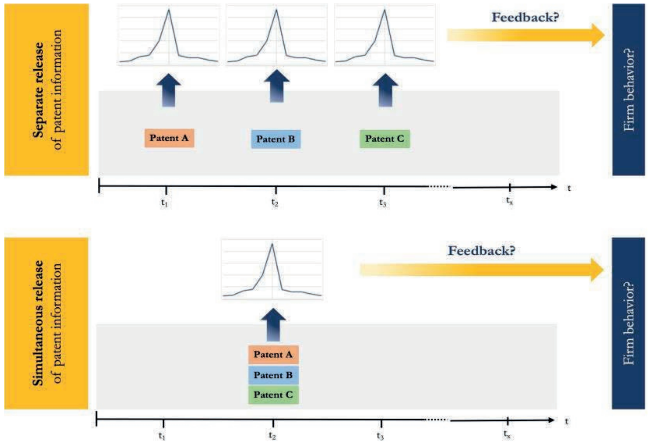
3.9. Appendix

Appendix A. Description of Variables	
Outcome variables	
Patent portfolio valuation$_{t+1/2/3}$	The average patent valuations of firm i's patents filed in year t + 1/2/3 and eventually granted. Source: Kogan et al. (2017) updated data as of 2020.
*Self-citationsPATENT,*10*y*	The number of forward self-citations that firm i makes to patent p within 3/5/10 years after patent grant. Source: Patentsview citation data.
*Non-self-citationsPATENT,*10*y*	The number of forward citations that are no self-citations of firm i's patent p within 10 years after patent grant. Source: Patentsview citation data.
Treatment variables	
Separate info release$_{PATENT}$	A continuous separateness measure defined as: $$Seperate\ info\ release_{PATENT\ i,t} = \frac{1}{\#Patents_{i,t}}$$ where $\#Patents_{i,t}$ is the number of firm i's patents granted at Patent Tuesday t. Source: Kogan et al. (2017) updated data as of 2020.
Separate info release exposure$_{PATENT}$	The *Separate info release* measure aggregated to the firm-year level and divided by the number of firm i's Patent Tuesdays in year t. Source: Kogan et al. (2017) updated data as of 2020.
Separate info release$_{TECH}$	A continuous separatedness measure defined as: $$Seperate\ info\ release_{TECH\ i,t} = \frac{1}{\#Unique\ Tech\ Classes_{i,t}}$$ where $\#Unique\ Tech\ Classes_{i,t}$ is the number of unique technology classes of firm *i*'s patents granted at Patent Tuesday *t*. Source: Patentsview application data.
Separate info release exposure$_{TECH}$	The *Separate tech info release* measure aggregated to the firmyear level and divided by the number of firm i's Patent Tuesdays in year t. Source: Patentsview application data.
Control Variables	
#Patents	Firm i's number of patents granted in year t. Source: Kogan et al. (2017) updated data as of 2020.
Total assets	Firm i's book value of total assets in year t. Source: CRSP Compustat Merged data.
R&D assets	Firm i's research and development (R&D) expenditure divided by book value of total assets in year t, set to zero if missing. Source: CRSP Compustat Merged data.
Age	Firm i's age approximated by the number of years listed on Compustat. Source: CRSP Compustat Merged data.

ROA	Firm i's operating income before depreciation divided by book value of total assets in year t. Source: CRSP Compustat Merged data.
Leverage	Firm i's book value of debt divided by book value of total assets in year t. Source: CRSP Compustat Merged data.
CAPEX assets	Firm i's capital expenditure scaled by book value of total assets in year t. Source: CRSP Compustat Merged data.
TobinsQ	Firm i's market-to-book in year t, calculated as market value of equity plus book value of assets minus book value of equity minus balance sheet deferred taxes, set to zero if missing, divided by book value of assets. Source: CRSP Compustat Merged data.
Innovative specificity	The measure is calculated as: $$Innovative\ Specificity_p = \sum_j^n m_{p,j}^2$$ where $m_{p,j}$ denotes the percentage of citations made by patent *p* that belong to patent class *j*, out of *n* technology classes assigned by the USPTO. The measure is the inverse of the Trajtenberg et al. (1997) patent originality measure. Source: Patentsview citation data.
Explorativeness	An explorativeness measure that is calculated as the total number of citations made to new knowledge divided by the total number of citations made by the patent. We define firm i's existing knowledge in year t as all patents either produced by firm i or that were cited by firm i's patents within 5 years up to year t-1. Source: Patentsview citation data and Kogan et al. (2017) updated data as of 2020.
PPE assets	Firm i's property, plant & equipment divided by book value of total assets measured at the end of fiscal year t. Source: CRSP Compustat Merged data.
Turnover	Firm i's average turnover in year t. Source: CRSP Daily Stock data.

A. Variation in the number of patent grants



B. Variation in the number of unique USPTO technology classes

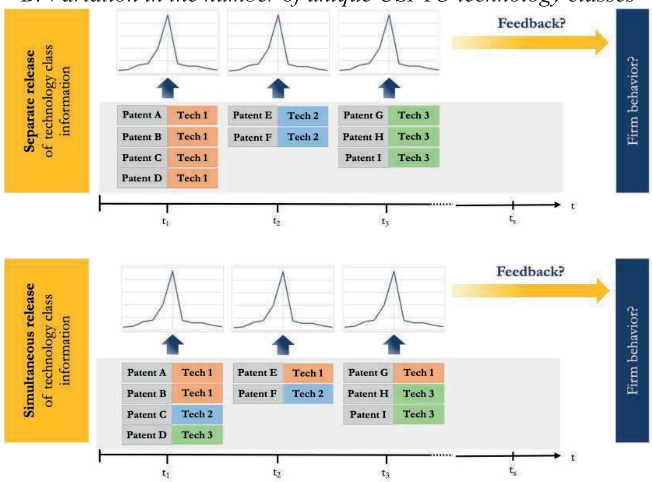
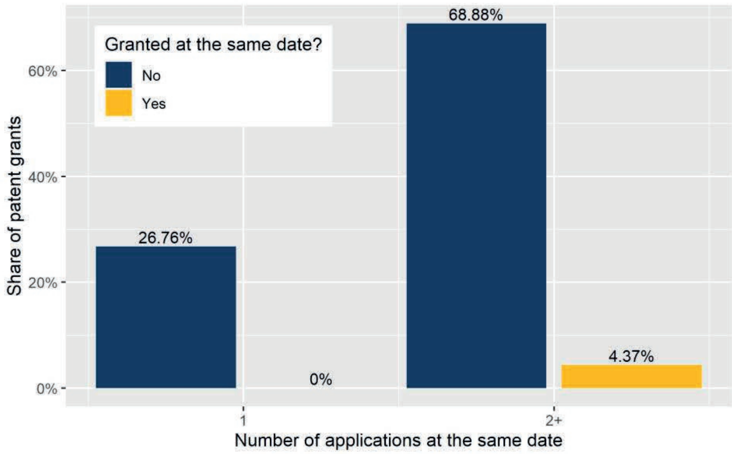


Figure 1. Simultaneous vs. Separate Release of Patent Information on "Patent Tuesdays"

The figure demonstrates the mechanism how simultaneous vs. separate information releases may affect capital market feedback and firm subsequent investment behavior. While Figure 1.A shows the effect in individual patent level, Figure 1.B shows the 'complementarity effect' using technology classes.

A Clustering of Patents Filed and Granted on the Same Day



B Distribution of Patent Grant Disclosures Across "Patent Tuesdays"

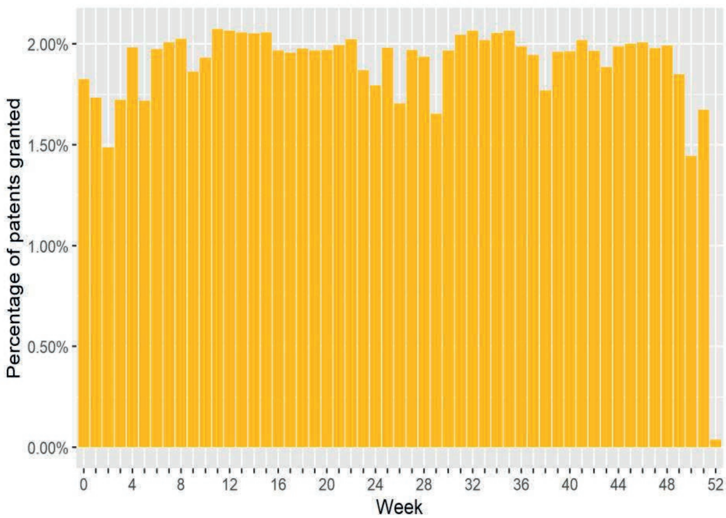


Figure 2. Distribution of Patent Grant Disclosures

Figure 2.A presents the percentage of concurrent patent applications that are also granted at the same time. For those applications filed at the same day, the majority is granted on different days. Figure 2.B demonstrates the distribution of patent grant disclosures in our sample across weeks.

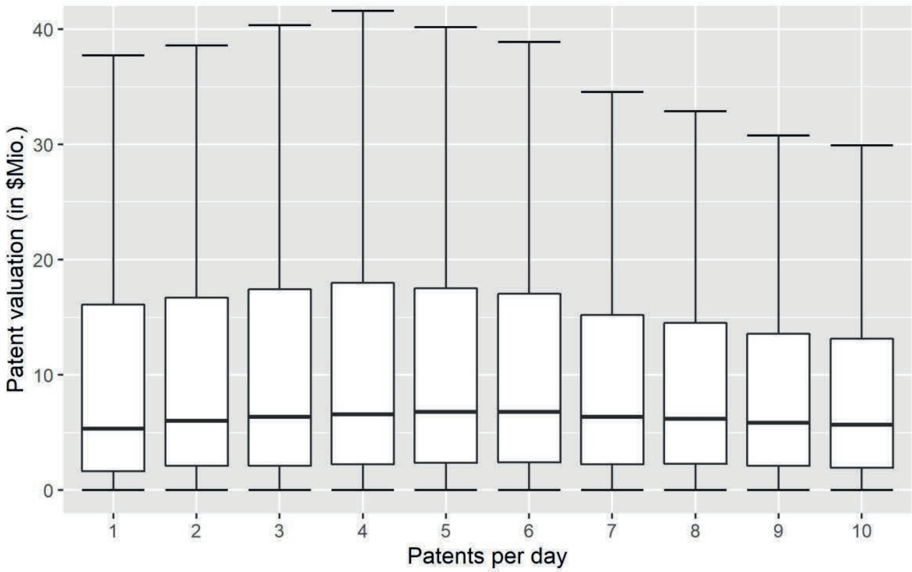


Figure 3. Distribution of Patent Valuations across Simultaneous Information Releases

Figure 3 presents the distribution of patent valuations across firms and "Patent Tuesdays" grouped by the firm-specific number of patents issued on a given day. We limit the analysis to a maximum of 10 patent issued per day.

Table 1. Descriptive Statistics: Patent-Level Analyses

	N	Mean	SD	Min	P25	P50	P75	Max
Outcome variables								
Self-citations$_{PATENT,10y}$	1,964,350	1.130	3.098	0	0	0	1	19
Citations$_{PATENT,10y}$	1,964,350	3.063	6.956	0	0	0	3	41
Treatment variables								
Separate info release$_{PATENT}$	1,964,350	0.235	0.315	0.002	0.031	0.083	0.333	1.000
#Patents	1,964,350	25.263	38.424	1	3	12	32	436
Separate info release$_{TECH}$	1,964,350	0.282	0.326	0.015	0.056	0.125	0.333	1.000
#Technology classes	1,964,350	11.884	11.573	1	3	8	18	67
Patent valuation	1,964,350	10.524	19.088	0.009	0.734	3.887	10.878	116.495
Market feedback$_{PATENT}$	1,964,350	0.854	2.204	-4.751	-0.309	1.358	2.387	4.758
Control variables								
Total assets	1,964,350	65,057	92,892	28	7,555	28,744	89,409	495,023
Age	1,964,350	31.129	18.065	0.000	17.000	30.000	44.000	69.000
ROA	1,964,350	0.132	0.089	-0.238	0.086	0.129	0.181	0.357
TobinsQ	1,964,350	1.965	1.171	0.746	1.167	1.585	2.358	7.137
Turnover	1,964,350	0.009	0.008	0.000	0.004	0.006	0.011	0.046
PPE assets	1,964,350	0.227	0.156	0.021	0.100	0.199	0.309	0.775
CAPEX assets	1,964,350	0.054	0.042	0.004	0.024	0.043	0.073	0.226
R&D assets	1,964,350	0.065	0.055	0.000	0.030	0.051	0.084	0.302
Leverage	1,964,350	0.224	0.149	0.000	0.111	0.213	0.315	0.632
Innovative specificity	1,964,350	0.560	0.286	0.123	0.333	0.500	0.802	1.000
Explorativeness	1,964,350	0.575	0.380	0.000	0.200	0.667	1.000	1.000

The table reports the descriptive statistics for patent-level analyses. Please refer to Appendix A for a full description of all variables.

Table 2. Simultaneous Information Releases and Capital Market Feedback

	log(1+ Self-citations$_{PATENT,}$10y)			
	PATENT		*TECH*	
	(1)	(2)	(3)	(4)
Separate info release$_{PATENT}$	0.0324***	-0.0069		
	(0.0153)	(0.0174)		
Market feedback$_{PATENT}$ × Separate info release$_{PATENT}$		0.0158***		
		(0.0062)		
Separate info release$_{TECH}$			0.0291*	0.0027
			(0.0170)	(0.0194)
Market feedback$_{PATENT}$ × Separate info release$_{TECH}$				0.0156**
				(0.0060)
Market feedback$_{PATENT}$	0.0144*	0.0110	0.0142*	0.0100
	(0.0080)	(0.0085)	(0.0081)	(0.0087)
Control variables				
log(Total assets)	-0.0941***	-0.0948***	-0.0935***	-0.0943***
	(0.0188)	(0.0188)	(0.0188)	(0.0188)
log(1+Age)	-0.0838***	-0.0851***	-0.0832***	-0.0844***
	(0.0261)	(0.0260)	(0.0261)	(0.0261)
ROA	-0.0623	-0.0621	-0.0613	-0.0608
	(0.0848)	(0.0847)	(0.0850)	(0.0849)
TobinsQ	0.0221***	0.0217***	0.0222***	0.0218***
	(0.0060)	(0.0059)	(0.0060)	(0.0059)
log(Turnover)	0.0025	0.0011	0.0024	0.0009
	(0.0084)	(0.0084)	(0.0084)	(0.0084)
PPE assets	-0.1451*	-0.1460*	-0.1443*	-0.1451*
	(0.0762)	(0.0761)	(0.0762)	(0.0762)
CAPEX assets	0.2106	0.2130	0.2118	0.2147
	(0.2313)	(0.2309)	(0.2312)	(0.2309)
R&D assets	-0.3715**	-0.3668**	-0.3693**	-0.3654**
	(0.1809)	(0.1802)	(0.1807)	(0.1801)
Leverage	-0.1642***	-0.1617***	-0.1636***	-0.1609***
	(0.0568)	(0.0565)	(0.0567)	(0.0565)
Innovative specificity	-0.0504***	-0.0504***	-0.0504***	-0.0505***
	(0.0073)	(0.0073)	(0.0073)	(0.0073)
Explorativeness	-0.0677***	-0.0678***	-0.0677***	-0.0678***
	(0.0121)	(0.0121)	(0.0121)	(0.0121)
Firm × Tech class FE	Yes	Yes	Yes	Yes
Tech class × Date FE	Yes	Yes	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes	Yes	Yes
Group of patents FE	Yes	Yes	No	No
Number of patents FE	No	No	Yes	Yes
Observations	1,964,350	1,964,350	1,964,350	1,964,350
Adjusted R^2	0.29	0.29	0.29	0.29

The table reports the results for patent-level tests given in equation [1] whether simultaneous information releases affect managerial ability to get market feedback from observed stock prices. Two-way clustered standard errors by firm and year in parentheses. $*$, $**$, and $***$ represent significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table 3. Explorative Patents, Simultaneous Information Releases, and Capital Market Feedback

	log(1+ Self-citations$_{PATENT,}$10y)			
	PATENT		*TECH*	
	Explorativeness			
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Separate info release$_{PATENT}$	-0.0385**	0.0371		
	(0.0163)	(0.0234)		
Market feedback$_{PATENT}$ × Separate info release$_{PATENT}$	0.0261***	0.0053		
	(0.0056)	(0.0082)		
Test for difference in coefficients [p-value]	*[0.0354]***			
Separate info release$_{TECH}$			-0.0203	0.0329
			(0.0174)	(0.0258)
Market feedback$_{PATENT}$ × Separate info release$_{TECH}$			0.0274***	0.0034
			(0.0057)	(0.0078)
Test for difference in coefficients [p-value]			*[0.0131]***	
Market feedback$_{PATENT}$	0.0040	0.0181*	0.0019	0.0181
	(0.0063)	(0.0107)	(0.0065)	(0.0108)
Control variables				
log(Total assets)	-0.0836***	-0.1102***	-0.0828***	-0.1096***
	(0.0134)	(0.0239)	(0.0135)	(0.0238)
log(1+Age)	-0.0679***	-0.1558***	-0.0674***	-0.1545***
	(0.0170)	(0.0500)	(0.0170)	(0.0499)
ROA	-0.0089	-0.0926	-0.0078	-0.0914
	(0.0690)	(0.1007)	(0.0693)	(0.1009)
TobinsQ	0.0173***	0.0195**	0.0174***	0.0195**
	(0.0050)	(0.0074)	(0.0050)	(0.0074)
log(Turnover)	0.0038	-0.0012	0.0033	-0.0011
	(0.0064)	(0.0117)	(0.0064)	(0.0117)
PPE assets	-0.1375**	-0.0887	-0.1359**	-0.0887
	(0.0544)	(0.1174)	(0.0543)	(0.1172)
CAPEX assets	0.1792	0.2511	0.1823	0.2534
	(0.1663)	(0.2854)	(0.1665)	(0.2851)
R&D assets	-0.4179***	-0.3805	-0.4150***	-0.3782
	(0.1394)	(0.2518)	(0.1390)	(0.2516)
Leverage	-0.1462***	-0.1968***	-0.1451***	-0.1962***
	(0.0441)	(0.0725)	(0.0440)	(0.0724)
Innovative specificity	-0.0158***	-0.0681***	-0.0159***	-0.0681***
	(0.0048)	(0.0114)	(0.0048)	(0.0114)
Explorativeness	-0.2540***	-0.0287**	-0.2539***	-0.0288**
	(0.0231)	(0.0129)	(0.0232)	(0.0129)
Firm × Tech class FE	Yes	Yes	Yes	Yes
Tech class × Date FE	Yes	Yes	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes	Yes	Yes
Group of patents FE	Yes	Yes	No	No
Number of patents FE	No	No	Yes	Yes
Observations	912,219	1,052,131	912,219	1,052,131
Adjusted R^2	0.24	0.32	0.24	0.32

The table reports the results for patent-level tests and compare and contrast the effect of simultaneous information releases on managerial learning for explorative patents. Please refer to Appendix A for a full description of all variables. Two-way clustered standard errors by firm and year in parentheses. *, **, and *** represent significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table 4. Capital Market Feedback and Competitor Learning

	log(1+ Non-self-citations$_{PATENT,}$ $10y$)	
	PATENT	*TECH*
	(1)	(2)
Separate info release$_{PATENT}$	-0.0158	
	(0.0144)	
Market feedback$_{PATENT}$ × Separate info release$_{PATENT}$	0.0143***	
	(0.0050)	
Separate info release$_{TECH}$		-0.0108
		(0.0129)
Market feedback$_{PATENT}$ × Separate info release$_{TECH}$		0.0116**
		(0.0049)
Market feedback$_{PATENT}$	0.0120	0.0120
	(0.0076)	(0.0077)
Control variables		
log(Total assets)	-0.0436***	-0.0431***
	(0.0116)	(0.0115)
log(1+Age)	-0.0427*	-0.0409*
	(0.0233)	(0.0229)
ROA	-0.1483**	-0.1480**
	(0.0678)	(0.0677)
TobinsQ	-0.0075	-0.0069
	(0.0055)	(0.0054)
log(Turnover)	0.0451***	0.0450***
	(0.0081)	(0.0081)
PPE assets	-0.1084	-0.1046
	(0.0699)	(0.0698)
CAPEX assets	0.3137**	0.3115**
	(0.1174)	(0.1176)
R&D assets	-0.0094	-0.0128
	(0.1957)	(0.1952)
Leverage	-0.0974**	-0.0964**
	(0.0405)	(0.0403)
Innovative specificity	-0.1022***	-0.1022***
	(0.0149)	(0.0149)
Explorativeness	0.0290***	0.0291***
	(0.0080)	(0.0080)
Firm × Tech class FE	Yes	Yes
Tech class × Date FE	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes
Group of patents FE	Yes	No
Number of patents FE	No	Yes
Observations	1,964,350	1,964,350
Adjusted R^2	0.39	0.39

The table reports the effect of simultaneous information releases on competitor learning and investment behavior. Please refer to Appendix A for a full description of all variables. Two-way clustered standard errors by firm and year in parentheses. *, **, and *** represent significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table 5. Descriptive Statistics: Firm-Level Analyses

	N	Mean	SD	Min	P25	P50	P75	Max
Outcome variables								
Patent portfolio valuation$_{t+3}$	26,101	11.340	21.492	0.043	1.350	3.898	10.397	128.869
Patent portfolio valuation$_{t+2}$	26,101	10.811	20.354	0.044	1.339	3.788	9.933	122.192
Patent portfolio valuation$_{t+1}$	26,101	10.456	19.783	0.045	1.324	3.668	9.605	119.944
Treatment variables								
Separate info release exposure$_{PATENT}$	26,101	0.831	0.239	0.006	0.768	0.928	1.000	1.000
Separate info release exposure$_{TECH}$	26,101	0.813	0.281	0.011	0.757	0.944	1.000	1.000
Control variables								
#Patents	26,101	59.414	144.607	1.000	3.000	10.000	40.000	882.920
Total assets	26,101	9,195	26,105	7	200	944	4,511	166,374
Age	26,101	18.815	14.323	0.000	7.000	16.000	28.000	58.000
ROA	26,101	0.092	0.177	-0.673	0.069	0.131	0.182	0.383
TobinsQ	26,101	2.169	1.718	0.656	1.140	1.573	2.475	10.338
Turnover	26,101	0.007	0.008	0.000	0.002	0.005	0.009	0.039
PPE assets	26,101	0.252	0.174	0.009	0.114	0.222	0.352	0.756
CAPEX assets	26,101	0.057	0.044	0.002	0.025	0.046	0.077	0.236
R&D assets	26,101	0.079	0.106	0.000	0.014	0.042	0.099	0.567
Leverage	26,101	0.196	0.161	0.000	0.051	0.183	0.296	0.681

The table reports the descriptive statistics for firm-level analyses. Please refer to Appendix A for a full description of all variables.

Table 6. Simultaneous Information Releases and Value of Future Patents

	log(Patent portfolio valuation$_{t+T}$)					
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
Separate info release exposure$_{PATENT}$	0.9109***	0.8062***	0.6299***			
	(0.1107)	(0.1114)	(0.1132)			
Separate info release exposure$_{TECH}$				0.8471***	0.7639***	0.6560***
				(0.1172)	(0.1089)	(0.1033)
Control variables						
log(#Patents)	-0.0327***	-0.0269**	-0.0295**	-0.0502***	-0.0413***	-0.0363***
	(0.0117)	(0.0124)	(0.0128)	(0.0131)	(0.0129)	(0.0126)
log(Total assets)	0.2624***	0.1904***	0.1368***	0.2579***	0.1866***	0.1347***
	(0.0290)	(0.0296)	(0.0293)	(0.0283)	(0.0290)	(0.0288)
log(1+Age)	0.0298	0.0092	-0.0006	0.0326	0.0112	-0.0013
	(0.0295)	(0.0309)	(0.0315)	(0.0291)	(0.0307)	(0.0312)
ROA	0.5845***	0.5488***	0.4514***	0.5829***	0.5470***	0.4487***
	(0.0969)	(0.1075)	(0.0998)	(0.0969)	(0.1072)	(0.0993)
TobinsQ	0.1033***	0.0768***	0.0552***	0.1027***	0.0763***	0.0548***
	(0.0096)	(0.0100)	(0.0100)	(0.0095)	(0.0099)	(0.0099)
log(Turnover)	-0.0602**	-0.0642***	-0.0590***	-0.0573**	-0.0617***	-0.0573***
	(0.0238)	(0.0221)	(0.0209)	(0.0236)	(0.0220)	(0.0207)
PPE assets	-0.3080*	-0.2325	-0.1388	-0.3329**	-0.2551*	-0.1589
	(0.1541)	(0.1519)	(0.1567)	(0.1532)	(0.1509)	(0.1557)
CAPEX assets	0.5089**	0.2406	0.0559	0.4727**	0.2076	0.0259
	(0.2341)	(0.2195)	(0.2575)	(0.2317)	(0.2183)	(0.2571)
RD assets	0.8768***	0.7887***	0.6556***	0.8592***	0.7731***	0.6432***
	(0.1959)	(0.2039)	(0.2154)	(0.1965)	(0.2037)	(0.2150)
Leverage	-0.2124**	-0.1097	-0.0424	-0.2045**	-0.1026	-0.0363
	(0.0799)	(0.0762)	(0.0790)	(0.0795)	(0.0756)	(0.0783)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,101	26,101	26,101	26,101	26,101	26,101
Adjusted R^2	0.89	0.88	0.88	0.89	0.89	0.88

The table reports the effect of simultaneous information releases (exposure) on the quality or value of firm's future patent portfolios. Two-way clustered standard errors by firm and year in parentheses. *, **, and * * * represent significance at the 10 percent, 5 percent, and 1 percent level, respectively. Please refer to Appendix A for a full description of all variables.

Simultaneous Information Releases and Capital Market Feedback: Evidence from Patent Tuesdays

ONLINE APPENDIX

Appendix OA.A Plausibly exogeneous timing of patent grants

Prior to issuing a patent, the applicant receives a *Notice of Allowance* (NOA) from the USPTO with the request to pay the corresponding issuance fees within 90 days. As a consequence, it is possible that firms strategically time the payment of fees to affect the timing of patent grants. To ensure that the timing of patent grants is plausibly exogeneous to corporate incentives, we analyse the timing of NOAs, fee payments and patent grants. Results in Table OA.1 suggest that there is considerable variation in the time between fee payment and issue date. Also, even if fees are paid simultaneously, there is a high change these patents will be issued in different weeks (see Panel B). This suggests that the ultimate timing of patent grants largely depends on administrative processes within the USPTO and is hardly influenced by firm-specific actions.

Table OA.1
Notification of Allowance, Fee Payments, and the Timing of Patent Grants

Panel A: Additional sample restrictions

	#	#
Patent sample		1,964,350
less: Missing data in PatEx database	-978	1,963,372
less: Patent applications with duplicate events	-124,243	1,839,129
less: Missing event information	-564,036	1,275,093
less: Different patent issue date	-13	1,275,080
less: Extreme date differences (top/bottom 1%)	-59,362	1,215,718

Panel B: Descriptive statistics for timing differences

	N	Mean	SD	Min	P25	P50	P75	Max
Days between NOA and issue date	1,215,718	122.9	33.3	47	109		125	133
Days between NOA and fee payment	1,215,718	72.6	23.6	5	62		84	90
Days between fee payment and issue date	1,215,718	50.7	27.02	28	36		42	50
Patents issued on the same day for which also the fee was paid on the same day:								
Days with 2 patents issued	73,246	1.18	0.38	1	1	1	1	2
Days with 4 patents issued	45,475	1.47	0.76	1	1	1	2	4
Days with 6 patents issued	35,644	1.69	1.02	1	1	1	2	6
Days with 8 patents issued	29,972	1.97	1.33	1	1	1	2	8
Days with 10 patents issued	27,165	2.23	1.64	1	1	2	3	10
Difference in days between fee payments for patents issued on the same day:								
Days with 2 patents issued	73,246	13.87	27.71	0	0	3	12	199
Days with 4 patents issued	45,475	26.63	37.19	0	4	9	34	201
Days with 6 patents issued	35,644	34.56	41.73	0	7	15	48	204
Days with 8 patents issued	29,972	41.47	46.07	0	8	19	63	205
Days with 10 patents issued	27,165	46.56	48.44	0	9	24	74	208
Patents paid on the same day which are also issued on the same day:								
Days with 2 patents issued	73,246	13.87	27.71	1	1	1	2	2
Days with 4 patent fees paid	91,048	2.48	1.16	1	1	3	4	4
Days with 6 patent fees paid	63,360	3.46	1.80	1	2	4	5	6
Days with 8 patent fees paid	49,072	4.40	2.42	1	2	5	7	8
Days with 10 patent fees paid	37,270	5.31	3.00	1	2	6	8	10

Table OA.1 present additional sample restrictions (Panel A) as well as descriptive statistics for timing differences in patents' Notification of Allowance (NOA), applicants' fee payment, and the final issuance of the patent by the USPTO (Panel B). The initial sample includes all 1,964,350 patents from the regression sample. Information on events during the examination process is from the USPTO's Patent Examination Research Dataset (PatEx). The database includes all information that can be obtained from the "*Transaction History*" tab on USPTO's Public PAIR website.

Appendix OA.B Additional Robustness Tests for Patent-level Analyses

Table OA.2
Robustness Tests

Panel A: Simultaneous information release *PATENT*

	log(1+ Self-citations$_{PATENT,10y}$)			
	PATENT			
	Count	No Other Event	#Patents > 5%	#Patents < 95%
	(1)	(2)	(3)	(4)
Separate info release$_{PATENT,COUNT}$	-0.0031			
	(0.0020)			
Market feedback$_{PATENT}$ × Separate info release$_{PATENT,COUNT}$	-0.0005***			
	(0.0001)			
Separate info release$_{TECH}$		-0.0132	-0.0108	-0.0080
		(0.0178)	(0.0192)	(0.0175)
Market feedback$_{PATENT}$ × Separate info release$_{PATENT}$		0.0149**	0.0145**	0.0155**
		(0.0063)	(0.0061)	(0.0062)
Market feedback$_{PATENT}$	0.0228***	0.0150*	0.0113	0.0121
	(0.0071)	(0.0087)	(0.0087)	(0.0085)
Control Variables	Yes	Yes	Yes	Yes
Firm × Tech class FE	Yes	Yes	Yes	Yes
Tech class × Date FE	Yes	Yes	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes	Yes	Yes
Group of patents FE	Yes	Yes	No	No
Number of patents FE	No	No	Yes	Yes
Observations	1,964,350	1,396,918	1,861,457	1,864,044
Adjusted R^2	0.29	0.28	0.29	0.29

(Continued on next page)

Panel B: Simultaneous information release *TECH*

	log(1+ Self-citations$_{PATENT,10y}$)			
	TECH			
	Count	No Other Event	#Patents > 5%	#Patents < 95%
	(1)	(2)	(3)	(4)
Separate info release$_{TECH,COUNT}$	-0.0010			
	(0.0012)			
Market feedback$_{PATENT}$ × Separate info release$_{TECH,COUNT}$	-0.0009***			
	(0.0003)			
Separate info release$_{TECH}$		-0.0074	0.0149	-0.0014
		(0.0188)	(0.0198)	(0.0186)
Market feedback$_{PATENT}$ × Separate info release$_{TECH}$		0.0149**	0.0130**	0.0155**
		(0.0060)	(0.0060)	(0.0060)
Market feedback$_{PATENT}$	0.0221***	0.0140	0.0106	0.0111
	(0.0076)	(0.0088)	(0.0088)	(0.0086)
Control Variables	Yes	Yes	Yes	Yes
Firm × Tech class FE	Yes	Yes	Yes	Yes
Tech class × Date FE	Yes	Yes	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes	Yes	Yes
Group of patents FE	Yes	Yes	No	No
Number of patents FE	No	No	Yes	Yes
Observations	1,964,350	1,396,918	1,861,457	1,864,044
Adjusted R^2	0.29	0.28	0.29	0.29

The table presents the results for estimating the main specification using different treatment variables or different samples for robustness. Two-way clustered standard errors by firm and year in parentheses. ∗, ∗∗, and ∗∗∗ represent significance at the 10 percent, 5 percent, and 1 percent level, respectively. The variable Separate info release$_{PATENT,COUNT}$ is a continuous separatedness measure defined as the number of firm i's patents granted at Patent Tuesday t. The variable Separate info release$_{TECH,COUNT}$ is a continuous separatedness measure defined as the number of firm i's unique technology classes granted at Patent Tuesday t. Please refer to Appendix A for a full description of all other variables.

Table OA.3
Controlling for the Number of Simultaneous applications

	log(1+ Self-citations$_{PATENT,10y}$)					
	PATENT			*TECH*		
	(1)	(2)	(3)	(4)	(5)	(6)
Separate info release$_{PATENT}$	-0.0063	-0.0130	-0.0185			
	(0.0174)	(0.0174)	(0.0173)			
Market feedback$_{PATENT}$	0.0161**	0.0153**	0.0152**			
× Separate info release$_{PATENT}$	(0.0061)	(0.0061)	(0.0061)			
Separate info release$_{TECH}$				0.0020	0.0024	0.0010
				(0.0194)	(0.0193)	(0.0193)
Market feedback$_{PATENT}$				0.0159**	0.0151**	0.0150**
× Separate info release$_{TECH}$				(0.0060)	(0.0059)	(0.0059)
Market feedback$_{PATENT}$	0.0109	0.0113	0.0113	0.0099	0.0104	0.0105
	(0.0085)	(0.0085)	(0.0085)	(0.0086)	(0.0086)	(0.0087)
Controls for the number of simultaneous applications:						
log(#Filed patents weekly)	0.0089***			0.0089***		
	(0.0029)			(0.0029)		
log(#Filed patents quarterly)		-0.0243***			-0.0242***	
		(0.0052)			(0.0052)	
log(#Filed patents yearly)			-0.0408***			-0.0408***
			(0.0066)			(0.0066)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Tech class FE	Yes	Yes	Yes	Yes	Yes	Yes
Tech class × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Group of patents FE	Yes	Yes	Yes	No	No	No
Number of patents FE	No	No	No	Yes	Yes	Yes
Observations	1,964,350	1,964,350	1,964,350	1,964,350	1,964,350	1,964,350
Adjusted R^2	0.29	0.29	0.29	0.29	0.29	0.29

Two-way clustered standard errors by firm and year in parentheses. ∗, ∗∗, and ∗∗∗ represent significance at the 10 percent, 5 percent, and 1 percent level, respectively. The variables log(#Filed patents weekly), log(#Filed patents quarterly), and log(#Filed patents yearly) are defined as the natural logarithm of the firm i's number of patent applications in the same week/quarter/year that are eventually granted. Please refer to Appendix A for a full description of all other variables.

Appendix OA.C Alternative measures of market feedback

While the main tests using *Separate info release*$_{TECH}$ already explicitly address concerns related to potential systematic measurement error in patent valuations, we nevertheless perform a number of additional tests that use alternative measures to capture signals of patent value observed by management to further alleviate any remaining concerns.

First, we re-estimate equation [1] including the market valuation of all the patents granted on a single day as our measure of market feedback observable by managers (*Market feedback*$_{AGG}$). This specification abstracts from any specific assumptions regarding true patent value or managements' allocation of aggregate patent valuations to individual patents. Instead, it focuses on the aggregate signal observable by management. According to our hypothesis, management should find it more difficult to allocate this aggregate signal to individual patents the more patents are released at the same time. The same holds for the number of unique technology classes theses patents relate to. Table OA.4 columns [1] and [2] present the results. The aggregate patent valuations do not show any significant association with patent-specific future self-citations. However, we again find a significantly positive coefficient for the interaction of *Market feedback*$_{AGG}$ and *Separate info release*$_{PATENT}$/*Separate info release*$_{TECH}$.

Second, we test whether our results continue to hold if we abstract from the assumption that management would equally attribute aggregate market reactions to individual patents. To do so, we construct an alternative allocation of total value that takes into account the characteristics of patents released and their association with patent value (*Market feedback*$_{REW}$). For each firm-year, we first estimate the relation of patent value and various patent characteristics for all single patent release observations in the previous year. More specifically, we use the sample of single patent releases and estimate the following regression model on a yearly basis:

$$\begin{aligned} \textit{Patent valuation} = \beta_1 \textit{Innovative specificity} + \beta_2 \textit{Explorativeness} \qquad (3) \\ +\beta_3 log(\textit{Backward citations}) + \beta_4 log(\textit{Grant lag}) \\ +\beta_5 log(1 + \textit{Scientific backward citations}) + \beta_6 log(\textit{Independent claims}) \\ +\sum Tech\ classj + \epsilon \end{aligned}$$

The choice of explanatory variables follows prior literature that identifies patent characteristics likely associated with patent valuations (e.g., Higham et al., 2021). We then use the coefficient estimates to calculate the expected value of individual patents for all simultaneous patent release days based on their characteristics. To avoid hindsight bias and stale information, we use the coefficients estimates in year t-1 to measure the expected patent valuations in year t. To ensure positive fitted values, we add the minimum fitted patent valuation for firm i at date t plus $1 to all patent valuations for firm i at date t. This ensures strictly positive valuations while not affecting the relative rank within each release day. We then use these adjusted fitted values to calculate the share of the aggregate market reaction that is attributable to the individual patent. Overall, this approach yields unique patent valuations for simultaneous release days. The resulting valuations correspond to a plausible alternative allocation of aggregate market reactions based on patents' observable characteristics.

We then use these coefficient estimates to compute expected patent values for all individual patents released on simultaneous release days based on observable characteristics. These expected patent values are then used to compute alternative weights for allocating aggregate market reactions to individual patents released on simultaneous release days. Conceptually, the resulting individual patent values capture a hypothetical allocation of aggregate market reactions to individual patents based on information also observable by management. Results are similar to the main specification (see Table OA.4 columns [3] and [4]). *Market feedback*$_{REW}$ remains to be significantly positively associated with future self-citations. We again find significantly positive effects for *Separate info release*$_{PATENT}$ as well as the interaction on *Market feedback*$_{REW}$ and *Separate info release*$_{PATENT}$ (column [3]). Similarly, the coefficient on the interaction of *Market feedback*$_{REW}$ and *Separate info release*$_{TECH}$ remains positive and statistically significant (column [4]).

Finally, we construct a test that fully abstracts from multiple patent release days and instead relies on alternative simultaneous events for identification. Specifically, we limit the sample to single patent release days only and study the effect of simultaneous major events (e.g., earnings announcements, guidance, product-related announcements, M&A-related announcements, etc.) that are likely to affect the stock price and, hence, impair the informativeness of market prices to learn about patent value. We find that market signals are less predictive of future self-citations, if a patent is released on days with alternative major news announcements (see Table OA.5). The results are again consistent with the notion that simultaneous events impair managers' ability to extract specific information from market prices.

Taken together, these additional robustness tests all suggest that our results are unlikely to simply reflect measurement error in patent valuations associated with the number of patents released at once.

Table OA.4
Alternative Measures of Market Feedback

	log(1+ Self-citations$_{PATENT,}$10y)			
	Aggregate daily patent valuation (Market feedback$_{AGGREGATE}$)		*Patent-characteristics-re-weighted patent valuation* (Market feedback$_{REW}$)	
	PATENT	*TECH*	*PATENT*	*TECH*
	(1)	(2)	(3)	(4)
Separate info release$_{PATENT}$	0.0199		0.0018	
	(0.0158)		(0.0162)	
Market feedback$_{AGGR/REW}$ × Separate info release$_{PATENT}$	0.0147**		0.0143**	
	(0.0061)		(0.0055)	
Separate info release$_{TECH}$		-0.0127		0.0012
		(0.0222)		(0.0187)
Market feedback$_{AGGR/REW}$ × Separate info release$_{TECH}$		0.0147**		0.0137**
		(0.0060)		(0.0053)
Market feedback$_{AGGR/REW}$	0.0117	0.0111	0.0056	0.0048
	(0.0089)	(0.0090)	(0.0043)	(0.0044)
Control variables	Yes	Yes	Yes	Yes
Firm × Tech class FE	Yes	Yes	Yes	Yes
Tech class × Date FE	Yes	Yes	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes	Yes	Yes
Group of patents FE	Yes	No	Yes	No
Number of patents FE	No	Yes	No	Yes
Observations	1,964,350	1,964,350	1,730,797	1,730,797
Adjusted R^2	0.28551	0.28552	0.28460	0.28461

Two-way clustered standard errors by firm and year in parentheses. ∗, ∗∗, and ∗∗∗ represent significance at the 10 percent, 5 percent, and 1 percent level, respectively. The variable Market feedback$_{AGG}$ is defined as the natural logarithm of the Kogan et al. (2017) patent valuation measure aggregated at the firm-date level. The variable Market feedback$_{REW}$ is defined as the natural logarithm of the reweighted Kogan et al. (2017) patent valuation measure using the estimations based on the regression model in (3). The variable Backward citations is defined as the number of citations of firm i's patent p to other patents. The variable Grant lag is defined as the number of years between patent filing date and patent grant date of firm i's patent p. The variable Scientific backward citations is defined as the number of citations of firm i's patent p to scientific publications as documented in the reference section on the front-page of the patent. The variable Independent claims is defined as the number of independent claims of firm i's patent p. Please refer to Appendix A for a full description of all other variables.

Table OA.5
Simultaneous Major Events

	$\log(1+\text{Self-citations}_{PATENT,}10y)$
	MAJOR EVENT
	(1)
Market feedback$_{PATENT}$	0.0377***
	(0.0087)
Selected major event	0.0274*
	(0.0162)
Market feedback$_{PATENT}$ × Selected major event	-0.0113**
	(0.0055)
Control variables	Yes
Firm FE	Yes
Tech class × Date FE	Yes
Industry SIC2 × Year FE	Yes
Observations	236,575
Adjusted R^2	0.24

The table presents the results for estimating the main specification using the sample of single patent release days and simultaneous major events. We use the Capital IQ Key Developments database and include the following events to construct our alternative treatment variable *Selected major event*: Announcements of Earnings (28), Earnings Calls (48), Delayed Earnings Announcements (61), Corporate Guidance - Lowered (26), Corporate Guidance - Raised (27), Guidance/Update Calls (49), Corporate Guidance - New/Confirmed (29), Product-Related Announcements (41), Labor-related Announcements (44), M&A Calls (52), M&A Transaction Announcements (80), M&A Transaction Closings (81), M&A Transaction Cancellations (82), Regulatory Authority - Regulations (205), Regulatory Authority - Compliance (206), Regulatory Authority - Enforcement Actions (207), Lawsuits & Legal Issues (25), Executive Changes - CEO (101), Executive Changes - CFO (102), Special Dividend Announced (94), Dividend Affirmations (45), Dividend Increases (46), Dividend Decreases (47), Dividend Cancellation (213), Dividend Initiation (214), Preferred Dividend (215), Operating Results Release Date (219), Operating Results Calls (221), Announcement of Operating Results (226), Seeking to Sell/Divest (1), Seeking Acquisitions/Investments (3), Seeking Financing/Partners (5), Strategic Alliances (22). The variable *Selected major event* takes the value of one if at least one of these events occurred on the grant date, and zero otherwise. We use a sample of patents that are granted alone to rule out that our results are driven by simultaneous patent grants. In addition, we cut the sample at 2019-12-07 due to data availability. The table presents two-way clustered standard errors by firm and year in parentheses. *, **, and *** represent significance at the 10 percent, 5 percent, and 1 percent level, respectively. Please refer to Appendix A for a full description of all variables.

Appendix OA.D Alternative clustering of standard errors

Table OA.6
Alternative Clustering

	log(1+ Self-citations$_{PATENT,}$10y)			
	PATENT		*TECH*	
	Firm	*Firm & Date*	*Firm*	*Firm & Date*
	(1)	(2)	(3)	(4)
Separate info release$_{PATENT}$	-0.0069	-0.0069		
	(0.0167)	(0.0184)		
Market feedback$_{PATENT}$ × Separate info release$_{PATENT}$	0.0158***	0.0158**		
	(0.0058)	(0.0064)		
Separate info release$_{TECH}$			0.0027	0.0027
			(0.0159)	(0.0169)
Market feedback$_{PATENT}$ × Separate info release$_{TECH}$			0.0156***	0.0156**
			(0.0059)	(0.0065)
Market feedback$_{PATENT}$	0.0110	0.0110	0.0100	0.0100
	(0.0074)	(0.0082)	(0.0076)	(0.0083)
Control variables	Yes	Yes	Yes	Yes
Firm × Tech class FE	Yes	Yes	Yes	Yes
Tech class × Date FE	Yes	Yes	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes	Yes	Yes
Group of patents FE	Yes	Yes	No	No
Number of patents FE	No	No	Yes	Yes
Observations	1,964,350	1,964,350	1,964,350	1,964,350
Adjusted R	0.29	0.29	0.29	0.29

The table presents the results for our main test based on standard errors clustered by firm as well as firm and grant date. $*$, $**$, and $***$ represent significance at the 10 percent, 5 percent, and 1 percent level, respectively. Please refer to Appendix A for a full description of all variables.

Appendix OA.E Alternative citation horizons for patent-level analyses

Table OA.7
Alternative Citation Horizons

	log(1+ Self-citations$_{PATENT,}$T)					
	PATENT			*TECH*		
	3y	*5y*	*All*	*3y*	*5y*	All
	(1)	(2)	(3)	(4)		
Separate info release$_{PATENT}$	-0.0222*	-0.0191	-0.0271			
	(0.0128)	(0.0153)	(0.0185)			
Market feedback$_{PATENT}$ × Separate info release$_{PATENT}$	0.0090**	0.0136**	0.0196***			
	(0.0042)	(0.0051)	(0.0066)			
Separate info release$_{TECH}$				-0.0068	-0.0044	0.0022
				(0.0127)	(0.0156)	(0.0208)
Market feedback$_{PATENT}$ × Separate info release$_{TECH}$				0.0106**	0.0137***	0.0193***
				(0.0041)	(0.0050)	(0.0063)
Market feedback$_{PATENT}$	0.0134**	0.0133*	0.0166*	0.0128**	0.0125*	0.0155
	(0.0060)	(0.0072)	(0.0092)	(0.0062)	(0.0074)	(0.0093)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Tech class FE	Yes	Yes	Yes	Yes	Yes	Yes
Tech class × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Group of patents FE	Yes	Yes	Yes	No	No	No
Number of patents FE	No	No	No	Yes	Yes	Yes
Observations	1,964,350	1,964,350	1,964,350	1,964,350	1,964,350	1,964,350
Adjusted R^2	0.18	0.23	0.31	0.18	0.23	0.31

The table presents results for our main specification using shorter and longer horizons to measure future self-citations. Two-way clustered standard errors by firm and year in parentheses. ∗, ∗∗, and ∗∗∗ represent significance at the 10 percent, 5 percent, and 1 percent level, respectively. The variables Selfcitations$_{\mathrm{PATENT,3y/5y/all}}$ are defined as the number of forward self-citations that firm *i* makes to patent p within 3/5/all years after patent grant. Please refer to Appendix A for a full description of all other variables.

Appendix OA.F Future Patent Portfolios

Table OA.8
Robustness Tests for Firm-level Analyses

	log(Patent portfolio valuation$_{t+3}$)					
	PATENT			*TECH*		
	Binary	#Patents > 5%	#Patents < 95%	Binary	#Patents > 5%	#Patents < 95%
	(1)	(2)	(3)	(4)	(5)	(6)
Separate info release exposure$_{PATENT,BIN}$	0.1732*** (0.0521)					
Separate info release exposure$_{PATENT}$		0.3405** (0.0921)	0.5717*** (0.1146)			
Separate info release exposure$_{TECH,BIN}$				0.2879*** (0.0607)		
Separate info release exposure$_{TECH}$					0.3467*** (0.0881)	0.5717*** (0.1031)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,101	24,793	23,320	26,101	24,793	23,320
Adjusted R^2	0.88131	0.88217	0.88228	0.88164	0.88221	0.88260

Notes: Two-way clustered standard errors by firm and year in parentheses. $*$, $**$, and $***$ represent significance at the 10 percent, 5 percent, and 1 percent level, respectively. The variable Separate info release exposure$_{PATENT,BIN}$ is defined as a binary separatedness measure that is based on an indicator variable that takes the value of one if only one patent is granted for firm i at day t, and zero otherwise. This binary separate info release is measure aggregated to the firm-year level and divided by the number of firm i's Patent Tuesdays in year t. The variable Separate info release exposure$_{TECH,BIN}$ is defined as a binary separatedness measure that is based on an indicator variable that takes the value of one if only one unique technology class is granted for firm i at day t, and zero otherwise. This binary separate info release is measure aggregated to the firm-year level and divided by the number of firm i's Patent Tuesdays in year t. Please refer to Appendix A for a full description of all other variables.

Appendix OA.G Quality of Future Patent Portfolios

Table OA.9
Quality of Future Patent Portfolios – Future Citations

	log(Patent portfolio non-self-citations$_{t+T}$)					
	PATENT			*TECH*		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
Separate info release exposure$_{PATENT}$	0.0765	0.1630***	0.1461**			
	(0.0600)	(0.0508)	(0.0616)			
Separate info release exposure$_{TECH}$				0.0800	0.1347***	0.1008*
				(0.0538)	(0.0539)	(0.0522)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,101	26,101	26,101	26,101	26,101	26,101
Adjusted R^2	0.80	0.82	0.82	0.80	0.82	0.82

Notes: Two-way clustered standard errors by firm and year in parentheses. $*$, $**$, and $***$ represent significance at the 10 percent, 5 percent, and 1 percent level, respectively. The variables Patent portfolio non-self-citations$_{t+1/2/3}$ are defined as the average number of forward citations that are no self-citations of firm i's patents filed in year t + 1/2/3 and eventually granted. Please refer to Appendix A for a full description of all other variables.

Table OA.10
Quality of Future Patent Portfolios – Patent Importance

	Patent portfolio importance$_{t+T}$					
	PATENT			*TECH*		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
Separate info release exposure$_{PATENT}$	0.0177***	0.0234***	0.0147**			
	(0.0078)	(0.0073)	(0.0072)			
Separate info release exposure$_{TECH}$				0.0096	0.0148***	0.0096
				(0.0068)	(0.0068)	(0.0072)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry SIC2 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,117	20,117	20,117	20,117	20,117	20,117
Adjusted R^2	0.86	0.87	0.88	0.86	0.87	0.88

Notes: Two-way clustered standard errors by firm and year in parentheses. $*$, $**$, and $***$ represent significance at the 10 percent, 5 percent, and 1 percent level, respectively. The variables Patent portfolio importance$_{t+1/2/3}$ are defined as the average of Kelly et al. (2021) patent importance measure calculated on a 1-year forward window of firm i's patents filed in year t + 1/2/3 and eventually granted. Please refer to Appendix A for a full description of all other variables.

CHAPTER 4

Less Is More: Peer Learning From Non-Disclosures

(Single authored)

Abstract

The US Securities and Exchange Commission requires US public firms to disclose their material agreements while allowing them to redact/censor parts of these contracts due to proprietary cost concerns. While firms censor contracts to hinder competitor learning, they also reveal to rivals that something valuable is hidden in these contracts. This may result in a stronger motive for rivals to unravel the information concealed in these contracts. In this paper, I investigate whether competitors can extract valuable information from peers' redacted disclosures that might be useful for their future investment decisions. Using the EDGAR log files, I find that redacted material agreements receive up to 53% more downloads than their unredacted counterparts, indicating greater attention and information demand for censored documents. Consistent with peer learning from redacted disclosures, I also find that firms increase their R&D spending and become more similar to redacting peers. Using two plausibly exogenous shocks, I show that the learning effect attenuates when rival attention is disrupted, suggesting that increased *attention* to redacted disclosures might be a potential mechanism that explains peer learning. My study contributes to the literature on corporate investment under uncertainty and provides insight into the underlying mechanisms of peer learning documented in the literature.

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4.1. Introduction

Can firms learn from the relative silence or the censorship behavior of their peers? The US Securities and Exchange Commission requires US public firms to disclose their material agreements (e.g. licensing contracts, research collaboration agreements etc.) while allowing them to redact/omit proprietary information from these contracts due to competitive harm if disclosed. In this study, I investigate whether firms can extract valuable information from rivals' redacted disclosures useful for their subsequent investment or market entry decisions.

Investments are fundamental for creating shareholder value, however, even absent information asymmetry, managers are less responsive to investment opportunities due to uncertainty (Dixit, 1990; Bloom et al., 2007). A considerable amount of research examines the sources managers incorporate into their investment decisions to reduce this uncertainty (e.g., Badertscher et al., 2013; Ahçı, Martens, and Sextroh, 2022). The literature documents that firms adjust their investments by learning from peers' stock prices (e.g., Foucault and Fresard, 2014) or corporate disclosures (Badertscher et al., 2013; Chen et al., 2012; Bustamante and Frésard, 2021), however, it is yet unclear whether firms can learn from the *non-disclosures* of their rivals.

Starting from Bushman and Smith (2001), peer disclosures are seen as one source of information for corporate investment decisions. However, which specific peer information firms incorporate into their decision-making process is not extensively studied (Ferracutti and Stubben, 2019). I posit that redacted material agreements (contracts) might be one specific source of information that can provide valuable information to competitors. Redacted contracts may convey an imperfect signal to peers about promising new opportunities or increase the precision of known growth options. Upon observing this signal, managers can update their information set and make better-informed investment decisions since firms face similar supply and demand conditions with their product-market peers.

However, whether and how firms can learn from their rivals' redacted disclosures is ex-ante, not clear. On the one hand, conventional wisdom suggests that firms redact proprietary information to hinder competitor learning. Therefore, the contract in redacted form may provide no useful information to peers. But on the other hand, the redaction choice itself is an additional disclosure that signals that something valuable is hidden, creating a stronger motive for rivals to unravel the information concealed in the contracts. This is referred to as the *"Streisand effect"*, which is used to describe the unintended consequences of censorship, resulting in higher motivation to search for the information and a higher chance of revelation than without censorship (e.g., Hagenbach and Koessler, 2017).

Suppose a firm redacts information concerning its novel invention or strategic partnership from its contract. While omitting the proprietary information, the firm also reveals that the contract is censored, which is clearly visible to outsiders and may draw competitors' attention.[50] Since only a part of the contract has been redacted (such as royalty rates, payment terms, etc.), peers can still extract valuable information from the contract, such as the parties of the agreement, the underlying technology, and the broad context of the deal (see Appendix C). While the redaction increases the cost of information acquisition by competitors, at the same time, it may send an imperfect signal to competitors regarding a profitable market, reducing competitors' search and awareness costs. Observing such an agreement might lead competitors to develop expectations about a specific investment (e.g., profitable markets),

[50] During our sample period, competitors can observe the redactions in two ways. First, the redacting firm "*mark the exhibit index to indicate that portions of the exhibit or exhibits have been omitted"*(see https://www.sec.gov/rules/final/2019/33-10618.pdf). Therefore, as soon as the confidential contract is attached to a filing (e.g., 10-K) firms put a mark for the exhibit containing the contract under the list of exhibits (Item 14 for 10-K or Item 6 for 10-Q). Second, after the the publication of redacted contract, the SEC publishes another document called Confidential Treatment Orders, which indicates the location of such contracts. See also Section 2.1 for details.

provoking them to extract additional information from the contracts, including utilizing alternative information sources of their own.

Before documenting the learning effect, I first check whether there is higher information demand for redacted contracts. Using EDGAR log files, I collect download information for all material exhibits only in human-readable forms to mimic competitor downloads as a proxy for competitor attention. I find that the Streisand effect is in play: As shown in Figure 1, redacted material agreements are downloaded around 50% more than their unredacted counterparts starting from the first date they appear in the EDGAR system. This indicates greater attention to redacted agreements. Using contract-level data and regression analysis, I show that the greater attention is robust to the timing of a filing, along with time-varying firm characteristics that may determine the downloads of these filings. Greater attention seems to be persistent even within the same filing, i.e., a redacted material exhibit is downloaded significantly more than an unredacted exhibit attached to the very same filing (e.g., 10-Q), reassuring that other confounding factors do not drive the greater information demand.

Next, I examine whether peers' subsequent investment behavior or market entry decisions change after observing redactions by their competitors, consistent with the notion of peer learning from redacted contracts. To this end, I construct a panel using product market peers that I obtained from Text-based Industry Classification (TNIC) developed by Hoberg and Philips (2016). I test whether redacted material agreements filed by a peer predict its rivals' future R&D investments and product similarity for a given firm-peer pair, while controlling for the differences across firm-peer pairs, timing-specific effects along with time-varying firm- and peer-specific characteristics. The sign of the relation, however, is not obvious. On the one hand, if redactions help firms to prevent competitor learning of their new inventions, then the distance between redacting firm and its rivals in product space should increase due to successful product differentiation from rivals, leading to less product similarity. Conversely, if rivals can still learn from redacted contracts and chose to enter a similar market with redacting peers, product similarity may increase in the future. The research design allows me to capture a firm's future response to a particular peer having a redacted filing in the given quarter compared to when there is no redacted filing by the same peer or alternatively a firm's movement toward a particular redacting peer while not to the others with no redactions.

The results show that firms increase their R&D spending after observing redacted filings from peers, abstract from any common shock to firm-peer pair in a given year.[51] More interestingly, I find that firms become more similar to redacting peers in product markets in the future despite the peer efforts to keep competitors at bay using redactions. Redacted peer disclosures lead to an increase up to 2.7% product similarity between firm-peers. The results suggest that firms are encouraged rather than deterred from joining a similar market with redacting peers. The effect is persistent over 1- to 3-year ahead similarity change between firm-peers and robust to various fixed effects. Moreover, peer redactions do not seem to explain the lagged product similarity change (untabulated), mitigating any reverse causality concerns. I further find that innovation-related redacted contracts are mainly responsible for the observed increase in product similarity between firm-peer pairs.

I conduct a battery of robustness checks to ensure that the results are not susceptible to my design choices. The results are robust to an alternative treatment variable for peer redaction choice (i.e., the number of confidential filings) and the exclusion of firm-peer pairs having customer-supplier relationships that may affect firm product decisions without learning from peer disclosures. I also removed any confidential filings regarding *joint* projects that may

[51] Quarterly data on R&D investments allows me to use firm-peer-year fixed effects to control any common shock to a particular firm-peer pair competing in a similar product space. This can mitigate the reflection problem as discussed in Leuz and Wysocki (2016) and Roychowdhury et al., (2019).

explain the similarity of products of firm-peers independent from firm learning. My inferences are again robust to this exclusion.

In additional analyses, I check whether firms always find it feasible to become closer to redacting peers. Particularly, I test whether the decision to join a similar market depends on firm-peer-specific relations or redacting peers' existing market structure. As opposed to the main results, I find that firms do not seem to find it optimal to join a similar product market if redactions come from strong rivals or rivals having already highly similar competitors, suggesting a deterrence effect instead.

Next, I focus on the redacting firms to check whether firms redact to protect proprietary information that is useful for peers. In contrast, Bao et al. (2021) find that firms may exploit confidential treatments to conceal unfavorable contracting terms, consistent with managers withholding bad news (Verrechia, 1983; Kothari et al., 2009).[52] In this case, the observed increase in peer investments might simply be an overreaction to misleading disclosures, as in Beatty et al. (2013). Particularly, I test whether redacting firms show superior operating performance after redactions. In my additional tests, I find that redacting firms show higher operating profitability before R&D and become more innovative in the near future.[53] I also show that the performance effect is attenuated for firms with higher product market fluidity, a measure for increasing product market rivalry. This suggests a wealth transfer between redacting firms and their rivals. In addition, my findings reveal that redacting firms experience

[52] While my hypothesis does not rule out the potential for firms to conceal bad news through redactions, I posit that, on average, redacted information is likely to be relevant to rivals, irrespective of its positive or negative nature. It is important to recognize that bad news for the subject firm does not necessarily imply bad news for rivals. For example, firms may strategically hide unfavorable contracting terms to prevent predatory behavior from rivals (Bernard, 2016).

[53] Using within industry analyses, Bao et al. (2021) show that redacting firms show weaker performance measured by bottom-line profitability. However, redacting firms, on average, tend to be smaller, R&D-intense, and less profitable due to high R&D investments that may suppress the bottom-line profitability even more (e.g., Joos and Zhdanov, 2008; Gu, Lev and Zhu, 2021). Therefore, cross-sectional differences between redacting and non-redacting firms may explain the weak future performance results in Bao et al. (2021). I conduct within-firm analyses to control for any cross-sectional differences and find that redacting firms exhibit higher future operating profitability before R&D.

a notable increase in product market fluidity in the future. This reinforces the main results documenting an overall increase in similarity between firms and redacting peers and address concerns that increasing similarity may be attributed to redacting peers instead of rivals observing redactions.

Next, I explore whether increased attention may explain how redactions facilitate peer learning. The strategy literature argues that limited attention due to cognitive capacity significantly influences decision-making in organizations (Eggers and Kaplan, 2009; Lavie 1995; Ocasio, 1997; 2011). Although the download analyses provide some evidence that increased competitor attention may play a role, it is still challenging to attribute the observed learning effect to rivals' increased attention. To this end, I exploit a quasi-natural experiment that provide reasonably exogenous variation in firm attention that is unrelated to peer's redaction choice. I use exogenous CEO departures from a rival firm as a firm-specific shock to its attention.[54] Using the data provided by Gentry et al. (2021), I find that the learning effect attenuates when peer redactions coincide with exogenous CEO departures from rival firms. This is consistent with the idea that increased rival attention in response to redactions might be one potential mechanism of peer learning.

My study adds to the existing literature in several ways. First, my study contributes to the literature on corporate investment under uncertainty. Uncertainty surrounding investment outcomes that is particularly relevant for research and development investments might lead to investment inefficiencies. However, firms' actions to reduce this uncertainty are not extensively studied (Ferracuti and Stubben, 2019; Bernard et al., 2020). My study might

[54] Exogenous CEO departures are arguably a temporary shock to rivals' attention unrelated to peers' redaction choice, for instance, due to industry competition that might also be correlated with the board's decision to replace the CEO. The literature suggests that exogenous CEO departures (e.g. death or departures due to health reasons) do not lead to a significant change in corporate policies, such as investment policy, in contrast to the departures due to performance reasons (Fee et al., 2013).

improve our understanding of the role of information flow between firm-peers in facilitating capital allocation decisions.

Second, my study adds to our understanding of peer effects documented in the literature by showing a potential channel and mechanism of how firms learn from their peers' disclosures. Although information flows through public filings is shown to affect peer investments (Bernard et al., 2020), I show that redacted agreements might be a particular channel that facilitates peer learning. This answers the question of which specific peer information firms incorporate into their decision-making (Ferracuti & Stubben, 2019). Moreover, I also argue that competitor attention might be a potential mechanism that enables peer learning from redacted disclosures. Increasing disclosure overload (Chapman et al., 2019) and boilerplate public disclosures (e.g., Dyer et al., 2017; Kravet and Muslu, 2013) may urge peers to direct their limited attention to what is *worthwhile.* Despite the role of attention in decision-making in organizations (e.g., Eggers and Kaplan, 2009), the accounting literature examines the role of attention or information overload mostly from a capital market perspective, e.g., investor attention (see Blankespoor et al., 2021). To the best of my knowledge, the moderating role of attention in firm learning is not yet explored.

Third, my study extends the disclosure literature on proprietary costs. The theory and empirical literature on voluntary disclosures suggest that managers have incentives to withhold bad news (e.g., Verrechia, 1983; Kothari et al., 2009). However, in the presence of competitors, firms may still find it optimal to withhold favorable information when the proprietary cost of disclosure exceeds its benefits (e.g., Wagenhofer, 1990; Darrough, 1993; Guo, Lev and Zhou, 2003). The literature, however, does not generally distinguish the effects of proprietary versus non-proprietary disclosures on peers (Roychowdhury et al., 2019), possibly due to the challenges of identifying the true nature of observed firm disclosures. In the extreme, firms only disclose (withhold) stale (valuable) information, making it challenging to observe truly proprietary disclosures unless mandated by regulation. Redacted material agreements provide a unique setting in a large sample of firms to study the effect of proprietary disclosures on peer behavior. I show that firms can benefit from peers' proprietary disclosures that may lead to wealth transfer from redacting firms to their rivals.[55]

Finally, my study also contributes to the growing body of literature on confidential filings. Although the determinants (Glaeser, 2018; Tian and Yu, 2018), the capital market effects (Verrecchia and Weber 2006; Heinle et al., 2022; Boone et al. 2016; Kankanhalli et al., 2021) of redacted filings or whether redacted information is material to investors (Thompson et al., 2022) are studied, to the best of my knowledge, my study would be one of the first to examine the effects of confidential filings on peers. On the other hand, Chen (2021) documents an association between redactions and an increase in investments by industry firms. This association, however, might be spurious due to the reflection problem. For instance, using a more rigorous methodology to mitigate the reflection problem, I do not find evidence that peers increase their capital expenditures, although I can confirm the results of an increase in R&D investments by peers, as shown in in Chen (2021). Differently and more interestingly, however, I show that peers actively respond to redacting peers and become more similar in product space. Moreover, my study also differs from the subject paper by showing that redacted filings counter intuitively increase information demand and attention, documenting an important yet unexplored underlying mechanism in peer-learning.

4.2. Institutional Setting and Literature Review

4.2.1. Confidential Filings

The SEC mandates US public firms to publicly disclose their material contracts while allowing them to redact/omit certain information from these contracts due to competitive harm.

[55] Although peer firms seem to enjoy higher profitability, they also seem to suffer from expropriation from rivals as shown in redacting firm analyses.

When a firm opts to redact a material contract due to proprietary concerns, it first publishes the contract in the *redacted form* as an exhibit (typically exhibits 10.XX) to its regular filings (e.g., 10-K, 10-Q, 8-K, etc.) through the EDGAR system. At the same time, it also requests *confidential treatment* by providing a complete (unredacted) version of the contract to the SEC for approval. [56] The SEC may approve, ask for an amendment, or deny the request. If approved (or denied), the SEC issues a confidential treatment order (Form CT Order), which is made public through the EDGAR by the SEC after May 1, 2008. A typical CT Order includes information regarding the exhibit (e.g., Ex-10.15), the type of the form (e.g., 10-K), the filing date of the redacted filing, and the date when the CT Order expires (usually several years). Firms can also ask for an extension to a redaction made before, also approved and published by the SEC. A single CT Order may contain information about several redacted filings and/or exhibits and whether the request is about an extension to a prior filing.

Firms may censor pricing terms, milestone payments, technical specifications of products, patent information, and/or the research undertaken. While doing so, firms also reveal that the contract is redacted by making it visible which exhibits are subject to confidential treatment under the list of exhibits of the corresponding filing.[57] Therefore, competitors already know that the contract is redacted even before accessing the document.

Appendix C provides an excerpt from a redacted agreement between Arcturus Therapeutics, Ltd. and Millennium Pharmaceuticals, Inc filed as Exhibit 10.15 of 10-K on 18 March 2019 by Arcturus Therapeutics, Ltd. (CIK: 1566049). Although the redactions are

[56] The SEC has changed the application and approval process starting from March 2019. Before the change, firms were required to seek approval and subject to ex-ante monitoring by the SEC. With this change, the SEC now allows firm to redact information without approval but with an ex-post monitoring. See https://www.sec.gov/corpfin/confidential-treatment-applications for more information.
[57] There are mainly two ways that redactions are observable to competitors. First, the SEC requires registrants to "*mark the exhibit index to indicate that portions of the exhibit or exhibits have been omitted*". Therefore, as soon as the confidential contract is attached to a filing, firms mark the corresponding exhibit under the list of exhibits (Item 14 for 10-K or Item 6 for 10-Q), usually with a star or cross sign, indicating that contract is redacted. Second, competitors can also observe confidential treatment order (CTO) published by the SEC after the original filing under the subject firm's filings. Figure 1, for instance, clearly shows increasing demand after a CTO is published even though the redactions are observable before.

marked up by […***…] that makes them nonvisible, the contracting parties, the underlying technology (e.g., *"lipid nanoparticle technology", "mRNA designs and processes"*), and the overall purpose of the agreement *("conduct the research .... for the purpose of generating, producing and/or optimizing therapeutic mRNA molecules"*) are identifiable from non-redacted portions of the agreement.

4.2.2. The Background and Literature

4.2.2.1. Investment under uncertainty and peer disclosures

In a frictionless world (such as Modigliani and Miller framework), investments are primary sources through which firms create value for investors. However, uncertainty can reduce managers' appetite to undertake positive NPV projects even absent information asymmetry (e.g., Dixit and Pindyck, 1994; Bloom et al., 2007). In this case, firms may pursue a *'wait and see'* strategy since delaying an investment would allow managers to observe the outcome of an investment before irreversibly committing resources (Bernanke, 1983).

A considerable amount of research examines the sources managers incorporate into their investment decisions (e.g., Badertscher et al., 2013; Bustamante and Frésard, 2021; Ahci, Martens, and Sextroh, 2022). Peer disclosures may aid firms in resolving the uncertainty surrounding their investment outcomes since peers are affected by similar economic factors (e.g., demand shocks or growth opportunities). Competitors may use peer financial reporting to identify *promising new opportunities* (Bushman and Smith, 2001). Badertchser et al. (2013), for instance, show that private firms are more responsive to investment opportunities when there is a greater public firm presence in their industry, suggesting that mandated peer disclosures reduce the overall uncertainty in an industry.

The growing body of literature on the effects of peer disclosures on firm investment misses several important aspects. First, although the literature shows an association between firm disclosures (e.g., financial reporting quality, R&D spending, etc.) and peer investments (e.g., Bustamente and Fresard, 2021), which *specific characteristics* of disclosures may help peers' decision-making are not extensively studied (Ferracuti and Stubben, 2019; Roychowdhury et al., 2019).[58] Therefore, exploring underlying learning channels that help firms reduce the uncertainty surrounding their investments would add to our existing knowledge of peer effects. For instance, using downloads of EDGAR filings (e.g., 10-K filings) by peers, Bernard et al. (2020) show that information flows can explain peer investment decisions. However, which specific parts of these filings are useful for peer decision-making remains unanswered (Roychowdhury et al., 2019). I argue that detailed textual disclosures regarding material contracts might be a particular channel that facilitates peer learning.[59] Observing such a contract regarding a specific investment (even redacted) may provide more precise information to peers than simply observing an increase in aggregate R&D spending.

Second, the literature does not generally distinguish the effects of proprietary versus non-proprietary disclosures on peer investment behavior.[60] I believe this is partly because of the difficulty of finding suitable settings where the nature of a given disclosure (proprietary or not) is clearly identifiable. For instance, the theories on voluntary disclosure suggest that firms withhold favorable information when the proprietary cost of disclosure exceeds its benefits (e.g., Wagenhofer, 1990; Darrough, 1993).[61] In the extreme, firms only disclose (withhold) stale (valuable) information. Put differently; observed firm disclosures are not truly proprietary unless mandated by regulation, making it challenging to identify settings with proprietary disclosures. Redacted material agreements, in which the disclosures are mandated by

[58] For example, do peer firms look at profitability, cost, and/or segment disclosures? Are textual disclosures more informative than financial statement items? If so, which specific part is more informative for competitors?
[59] Basu et al. (2022), for instance, show that investment opportunity measure created using textual disclosures (10-Ks) outperform Tobin's q in predicting future investments.
[60] Two exceptions are the studies by Krieger (2021) and Zhang (2020). These studies, however, examine the effects of proprietary disclosures on peer investments either in a voluntary setting and/or in a specific industry using disclosures regarding clinical trials in pharmaceutical industry.
[61] On the one hand, disclosure of favorable information may reduce cost of capital and increase prices. On the other hand, opponents (e.g. competitors, regulators, etc.) can use this information to harm the disclosing firm.

regulation, provide a unique setting to study the effect of proprietary disclosures for a large sample of firms since the redaction of information is due to proprietary concerns.[62]

4.2.2.2. The mechanism behind learning from disclosures

We have a limited understanding of how firms react to peers' relative *non-disclosure* behavior, especially when this behavior is *observable*. Whether firms can learn from their rivals' redacted disclosures is ex-ante, not clear. On the one hand, redactions may render the remaining portions of such contracts redundant, which would hinder competitor learning as intended. On the other hand, the redaction choice itself is an additional disclosure that signals something valuable is hidden, creating a stronger motive for rivals to unravel the information concealed in the contracts.[63] While the redaction increases the cost of information acquisition by competitors, it may also send an imperfect signal regarding a profitable market, potentially reducing competitors' search costs.

For instance, assume that a firm enters new contractual agreements or strategic partnerships to develop a new technology that might disrupt the market. In order to protect its intellectual property or strategic plans, the firm chooses to redact a part of the contract but cannot hide it entirely since the disclosure is mandatory.[64] This concealment behavior is instantly observable by outsiders and may leak information to competitors regarding the firm's investment outlays or strategic plans. This may, in turn, induce rivals to extract more information from these contracts, increasing rivals' own information production and learning.

Moreover, despite growing evidence in peer learning, the underlying *mechanisms* through how disclosures show its effects on peer investment behavior received little attention.

[62] Firms can still exploit the regulation to conceal bad news. Bao et al (2021), for instance, argue that firms may use confidential filings to conceal bad contracting terms. However, the redactions are only allowed for proprietary reasons and also audited by the SEC. I revisit the effect of redactions on disclosing firm performance in Section 6.

[63] Since withholding information is punished by capital markets (e.g. Verrechia and Weber, 2006), I expect that firms only redact to protect their valuable assets due to competitive harm.

[64] The literature, for instance, finds that firms withhold information internally developed innovations especially when they are at development stage (e.g., Guo, Lev and Zhou, 2004)

I argue that *firm attention* to redacted disclosures might be a particular mechanism that can explain how redacted disclosures enable peer learning. The strategy literature argues that limited attention due to cognitive capacity significantly influences decision-making in organizations (Eggers and Kaplan, 2009; Lavie 1995; Ocasio 1997; 2011).[65] The effect of firm attention on learning might be particularly relevant in the disclosure setting considering the critiques of increasing disclosure overload (Chapman et al., 2019) and boilerplate public disclosures (e.g. Dyer et al., 2017; Kravet and Muslu, 2013).

Upon observing redacted disclosures, firms may direct their limited attention to what is *worthwhile* in peer disclosures. This is analogous to the *'Streisand effect'*, a phenomenon that is used to explain the counterproductive consequences of censorship.[66] Despite its fit into the disclosure setting, the Streisand effect has received limited attention in the literature except for a few studies in non-accounting fields.[67] Contrary to firms' desire to keep rivals at bay, censoring behavior may increase competitor awareness and induce them to snoop more on these disclosures, increasing peer learning if firms can unravel the hidden information. To the best of my knowledge, the moderating role of competitor attention on peer learning is yet to be explored.

4.2.2.3. The literature on confidential filings

Prior studies show that firms redact to protect their own proprietary information (Glaeser, 2018; Boone et al., 2016; Kankanhalli et al., 2021), especially in dynamic product

[65] Accounting literature, however, approaches attention or information overload mostly in a capital market setting (see Blankespoor et al., 2021). One exception might be a recent study on the effect of attention in analyst setting by Du (2021), who show that distracted female analysts strategically allocate their limited attention to forecasts of firms with high institutional ownership.

[66] Attributed to American singer Barbra Streisand, the 'Streisand effect' is a phenomenon to describe unintended consequences of withholding information. An attempt to suppress photos of her private property unintentionally increased the awareness of public of the existence of these photos. The concealment behavior attracted more attention and resulted in greater awareness by the public.

[67] Hagenbach and Koessler (2017) model the Streisand effect in a signaling game. They find that censorship sends a signal to receivers that motivates them to unravel what is hidden, resulting in higher chance to be found. Several studies in political economy (e.g., Hobbs and Roberts, 2018; Glàßel and Paula, 2020) also examine the consequences of government censorhip. They find that the censorship in general backfires and induces citizens to unravel information using alternative resources, especially when they are able to detect misinformation.

markets (Tian and Yu, 2018), or to protect their customers' proprietary information (Chen et al., 2022).[68] Others examine the capital market consequences of the redaction choice. While Verrechia and Weber (2006) show that redactions lead to an increase in adverse selection and lower market turnover, others find a favorable market response to redactions (Kankanhalli et al., 2021; Lee, 2019). In addition, several studies show that firms increase their voluntary disclosures (Heinle et al., 2022; Barth et al., 2020) to mitigate the negative consequences of withholding information. While Bao et al. (2021) find that firms exploit the regulation to conceal the bad contracting terms, which is consistent with the notion of managers withholding bad news (e.g., Kothari et al., 2009), Thompson et al. (2022) show that firms hide information material to investors.

In this study, I focus on the effect of redactions on peers and explore the underlying mechanisms of peer learning.

4.3. Research Design and Empirical Analyses

I conduct two sets of empirical analyses. I first test whether peers change their subsequent investment behavior or market entry decisions after observing redactions by peers. In the following sections, to explore the underlying mechanism of peer learning from redacted disclosures, I further test whether redacted material exhibits receive more attention than their non-redacted counterparts and how shocks to firm attention impair the ability to learn from these disclosures.

[68] Firms may exploit this rule to conceal bad news (see Bao et al., 2021), however, the SEC allows redactions only when there is a potential competitive harm. The rule indicates that firms may omit information when "redacted information would be competitively harmful if publicly disclosed" (see e.g., section 2 of Release No. 33-10618; 34-85381) and redactions are subject to monitoring by the SEC, thereby limiting firms' behavior for unintended use. Footnote 45 of the document particularly reads: "Of the list of available FOIA disclosure exemptions provided in Section 552(b), *most applicants for confidential treatment* rely on paragraph (b)(4), which exempts certain *trade secrets* or *privileged* or *confidential commercial* or *financial information*." (*italics* are my own).

4.3.1. Data and Sample Construction

I begin by identifying 12,664 confidential treatment orders published on the SEC EDGAR website between May 1, 2008 and December 31, 2018. Then, I parse the text of these confidential treatment orders using Python scripts to locate the filings, including the exhibits redacted. Particularly, I collect the data regarding the Central Identification Key (CIK) of the filing company, the filing date, and the form type of the relevant filing and exhibit. I also determine the nature of the CT Order, whether it is about granting, denial, or an extension to a prior filing. Following the literature on confidential filings, I exclude denial and the extensions to prior filings. I further exclude confidential exhibits filed with form types other than 10-K, 10-Q, or 8-K. This leaves me with 9,625 confidential treatment orders with a total of 16,397 exhibits filed under 9,729 distinct filings (See Table 1 - Sample construction).

4.3.2. Sample and Descriptive Statistics

The sample covers the years between 2008 and 2018. The sample begins in 2008 because the SEC made CT Orders available in 2008. The sample ends in 2019 because the rule to seek approval from the SEC for redacted disclosures has changed in 2019, which reduces the observability of redacted filings using CT Orders. In addition, for download analyses, I restrict the sample to the filings between 2008 and 2016 since EDGAR log files are available until June 2017 during my sample period.

Since my aim is to investigate whether the information disclosed in redacted filings is used as input by rivals for their investment decisions, identifying firm-peers competing in similar product markets is essential. To this end, I use Hoberg and Phillips (2016) text-based network industry classification data (TNIC3 industry). The data provides information regarding firm-peers and their corresponding product similarity extracted using the product descriptions in yearly 10-K filings. The advantage of this industry classification system compared to static Standard Industrial Classification (SIC) is that the TNIC industries can capture even minor competitors and provide dynamic (time-varying) information regarding firm-peer similarity in product space. Moreover, it allows me to identify whether the same firm moves toward a particular peer in a product space but not to the others based on their disclosure policy.

Moreover, I use CRSP-Compustat merged data from quarterly files for quarterly company financials. Using quarterly data allows me to identify the timing of redacted filings and the change in R&D investments more precisely and use a more granular fixed effects structure. Finally, I merge quarterly financial data with firm-peer pairs that I obtained from TNIC3 industry data by aligning the similarity data from $q+1$ to the following year's $q+1$. This is because 10-Ks that is used to construct the similarity measure are mostly available in the first quarter following the calendar year-end. I also remove financial and utility firms from my sample. The final sample consists of around 9.7 million firm-peer-quarters over the sample period, with confidential treatment requests of 6,319 filings and 10,757 exhibits filed by peer firms.

The data reveals that, on average, sample firms redact approximately 13% of the time, with a relatively stable ratio of redacting firms over time. Notably, 35% of firms engage in redaction at least once during the sample period, and this percentage rises to 78% among pharmaceutical companies. Redacting firms, on average, redact 1.46 filings and 2.49 exhibits per year (Table 1).

While Table 2 Panel A reports overall statistics for sample firms, Panel B presents the differences between redacting vs non-redacting firms. It seems that redacting firms tend to be smaller, exhibit significantly higher R&D intensity (13% vs. 4% of total assets), with higher market-to-book ratios, and hold greater cash reserves. Additionally, they also exhibit more innovative behavior by introducing more innovative products and services in their business descriptions (Ahci and Joos, 2019).

Panel C shows the distribution of redactions across industries. The pharmaceutical industry stands out with the highest number of redacted filings, with 39% of redactions observed among companies within this sector. Remarkably, 78% of firms in this industry engage in redaction at least once. Interestingly, however, while high redacting industries generally display high R&D intensity, redactions are also relatively common in non-R&D intense sectors such as Transportation, Retail, Wholesale, and Petroleum and Natural Gas. Overall, the findings strongly suggest that firms tend to redact filings when proprietary costs are higher, supporting the notion that strategic motives underlie the decision to redact certain information.

4.3.3. Regression Model

To document the learning effect, I test whether firms change their investment behavior after observing redacted filings by peers. For this section, I use two different dependent variables to proxy firm investment behavior. First, I focus on R&D spending because prior literature shows that firm expansion and growth, and differentiation in product market decisions are realized mostly through R&D investments (e.g., Hoberg and Philips, 2021). Particularly, I first test whether firms increase their R&D spending after observing a redacted disclosure, which may signal that firms actively respond to peer redacted disclosures. Second, I use product similarity between firm-peers as a proxy for firms' investment outcomes. Particularly, I test whether the distance between firm-peers in product space changes after redactions by peers. For instance, if a peer successfully protects its valuable innovation using redactions and, as a result, diversifies from its rivals in the future, the distance between the peer and its rival firms is expected to increase. On the other hand, if rival firms are encouraged to join a profitable market signaled by redactions of peers, the distance between firm-peers may even decrease.[69]

The model to test for subsequent firm investment behavior is given as follows:

$$Investment_{i(j),t+T} = \beta_0 + \beta_1.confidential\ dummy_{ijt} + \sum Firm\ Controls_{i,k} + \sum Peer\ Controls_{j,l} + \sum FEs + \varepsilon_{ijt}$$

$Investment_{ij,t+T}$ takes two different versions for R&D investments. First, I use R&D investments as measured by immediate one-quarter R&D intensity and the sum of four subsequent quarter R&D spending scaled with the total assets in the current quarter to mitigate seasonal effects in R&D spending, e.g., due to earnings manipulation (Graham et al., 2005; Roychowdhury, 2006). In addition, as an outcome measure for investment activities, I use future product similarity $Similarity_{ji,t+T}$ by Hoberg and Philips (2016), which measures the product similarity between firm i and peer j in a given year. This variable measures to what extent a firm's product portfolio becomes similar to those of its peers in the future after redactions.

The variable of interest is $confidential\ dummy_{j,t}$, which takes a value of one if the firm observes at least one confidential exhibit by its peers in a given quarter.[70] The positive (negative) coefficient β_1 implies that firms increase (decrease) their R&D spending or alternatively become more similar (distant) to redacting peers in product space following redacted filing. I further include a battery of time-varying firm and peer characteristics such as Size, R&D intensity, a dummy for missing R&D, MB, Leverage, ROA, and LOSS dummy that

[69] Alternatively, firms may also be deterred by rival disclosures thinking that they lost the competition race. In this case, firms can still learn from rivals' redactions but instead are deterred to join a similar market that shows its effect in higher distance (lower similarity) between firm-peers. In additional analyses section, I explore the cases where competitors may not find it optimal to compete in similar markets even though they can learn from redacted disclosures.

[70] In robustness checks, I use the number of confidential filings in a given quarter as an alternative treatment variable.

may correlate with firm investment and peer disclosure behavior. I also add the current similarity between firms and peers in the regressions to control any effects arising from the current proximity between firms and peers. All variables are winsorized at 1% level.

In addition, quarterly accounting data allows me to use a highly granular fixed effects structure. Specifically, I include firm-peer fixed effects to control time-invariant differences across firm-peer pairs and year-quarter fixed effects to control any specific time effects (e.g. wide economic shock) that may coincide with peer redacted disclosures and explain future firm investment behavior. Even with this fixed effect structure, documenting a causal relation between redacted disclosures and peer learning is challenging due to the *reflection problem*, as discussed in Leuz and Wysocki (2016) and Roychowdhury et al. (2019). The reflection problem may arise mainly because the selection of a firm and its peers competing in a similar product space is not random. Time-varying common latent factors, such as a shock in growth opportunity to a particular industry, may affect both peer redaction choice and firm investment behavior. In this case, private information of the firm and its peers is correlated, and the positive association between peer redacted filings, and the firm's future investment behavior may not necessarily be a result of active firm response to peer disclosures.

In order to overcome this challenge and sharpen my identification, for only R&D analyses, I include firm-peer#year fixed effects to control any common shocks to both firm and its peers in a given year in a particular product space. In this case, the variation comes from the quarters with confidential filings in a given firm-peer-year. By this, I am able to test the effect of the peer confidential filings on a firm's future R&D investment, abstract from any time-varying firm-peer specific characteristics that may confound the learning effect.[71] I cluster standard errors in firm-peer level.[72]

This setting allows me to identify whether firms chose to become more similar (distant) to redacting peers but not to non-redacting peers in a given year. Moreover, it also allows me to identify when firms choose to become similar (distant) to a specific peer while keeping time-invariant firm-peer-specific factors constant.

4.4. Empirical Results

4.4.1. Redacted Filings and Subsequent Investment Decisions

4.4.1.1. Main Results

Table 3 shows the results of peer effects on future R&D investments, both in the absence and presence of firm#peer#year fixed effects.[73] Upon observing redacted disclosures, firms, on average, seem to increase their R&D spending in the subsequent quarter and year. However, the coefficients are relatively small, especially when firm#peer#year fixed effects are included. For instance, Column 3 suggests that firms experience a 4.9% increase in average R&D spending (0.0034/0.07) following redactions by rival firms. However, this effect diminishes to 0.5% increase when fixed effects are included (Column 4). Although the magnitude of the effect may appear modest, it is crucial to acknowledge that firm#peer#year fixed effects might subsume a considerable portion of the variation. Nevertheless, it still highlights a significant change in rivals' investment behavior after redactions.

[71] I cannot use firm-peer#year fixed effects for similarity analyses because in this case no variation remains in product similarity between firm-peers since the measure is available only yearly basis. I alternatively use firm#year fixed effects to control for a shock to firms' growth opportunity that may explain firms' future investment behavior and that may coincide with peer redaction choice

[72] For R&D analyses, the dependent variable (R&D intensity) stays the same in a given quarter across different peers. This makes the correlation of residuals higher within firm clusters. For this reason, I alternatively cluster standard errors at the firm level. The results remain qualitatively similar, although clustering at the firm level slightly decreases the significance levels.

[73] Untabulated analyses show that the results are qualitatively similar when a dummy for innovation related confidential contracts is used instead of the dummy for confidential filings.

Remarkably, the results in Table 4 reveal that firms move towards redacting peers in product space despite rivals' efforts to protect their private information. The coefficient on the confidential dummy is consistently positive and significant across columns. This supports the notion that firms actively learn from redacted disclosures and strategically choose to enter similar markets with redacting peers. The coefficient is economically meaningful with redacted peer disclosures leading to an increase of up to 2.7% (0.0016/0.06) increase in average product similarity for the baseline regression when no fixed effects are included (Column 3). However, the effect is substantially influenced by fixed effects, resulting in a significant decrease in the effect to only 1%. Nevertheless, the persistence of the effect over a 1- to 3-year horizon in product similarity, along with its robustness to various fixed effects reinforces the reliability of the observed association, providing strong evidence of firm learning from redacted disclosures.[74]

4.4.1.2. Redacting Firm Performance

In this section, I test my assumption that rivals' redaction choice stems from protecting proprietary information (e.g., Boone et al., 2016; Glaeser, 2018) that is valuable to the peers rather than the intention to conceal bad contracting terms (Bao et al., 2021). For these analyses, I focus on redacting firms and test whether they show superior performance and become more innovative after redactions.[75]

[74] In untabulated analyses, I also control firm#year together with peer fixed effects to mitigate any possibility that firms respond a economy-wide shoch that can also explain peer's redaction choice. The results are qualitatively similar to using different fixed effects structure. Moreover, regarding any reverse causality concerns, I also use the lagged change in product similarity (from t-1 to t) as the outcome variable. For instance, firms may choose to redact filings when the product market is dynamic (Tian and Yu, 2018), i.e., when other firms become closer to disclosing firms. In this case, the positive change observed in product similarity might be a cause but not the result of peer redaction choice. The untabulated results show that this is not the case i.e. firms do approach redacting peers in product space after their confidential filing but not before (the coefficient is negative).

[75] Using proprietary data on licensing contracts, Kankanhalli et al. (2021) suggest that firms redact to protect their impending innovations and redactions are followed by greater innovative activity. They also show that the redaction choice is well received by the capital market, especially by *innovation-oriented* investors.

First, I test whether redacting firms show higher future profitability relative to non-redacting counterparts. In contrast, using cross-sectional within industry analyses, Bao et al. (2021) show that redacting firms, on average, show negative 1-year future profitability, which supports the idea that firms exploit confidential treatments to conceal unfavorable contracting terms. However, firms that invest in R&D tend to be smaller, less profitable, and, at the same time, have higher proprietary costs; therefore, they are more likely to redact (e.g., Glaeser, 2018). Since increasing R&D spending may suppress the bottom-line profitability even more for younger and innovative firms that also redact more, similar to earlier studies, I use operating income before R&D instead as my dependent variable for future profitability (e.g., Merkley, 2014). For the reasons explained above, I also conduct within-firm analyses to control for any cross-sectional differences between redacting and non-redacting firms.

The results in Table 5 show that redacting firms show higher operating profitability (Column 1) starting the year when they disclose redacted agreements, and this effect mainly comes from the innovation related redacted contracts (Column 3).[76] Interestingly, although still positive, the effect of innovative contracts becomes less significant after one year (Column 4). Further analyses show that the overall effect on future profitability is partly offset for firms with higher product market fluidity, a measure of rivals becoming closer to redacting firms in product space (Column 5). These results suggest a wealth transfer between redacting firms and their competitors that join a similar market after observing redacted agreements.

Furthermore, the main analyses have shown that product similarity between firms and redacting rivals increase in the future. However, this may also raise concerns regarding its origin. While I posit that rivals approach redacting peers, an alternative possibility also exists: Redacting firms may also become closer to rivals, resulting in the observed higher product

[76] Untabulated results show that confidential agreements is not positively associated with one-year lagged operating profitability that further mitigates concerns for reverse causality.

similarity identified in the main analyses. To strengthen the robustness of my inferences, I test whether the product market fluidity of redacting firms changes after redactions since this measure relies on rival movements towards the firm, offering valuable insights into the dynamics of observed product similarity. The results in Table 5 (Columns 6-7) show that the coefficient on the confidential dummy is significant and positive for one year ahead fluidity after redaction but not for the current year market fluidity while controlling lagged fluidity. This reinforces my main inferences that rivals invest in similar markets and become more similar to redacting firms in the future but not vice versa.

Finally, I investigate whether redacting firms demonstrate an increase in innovative activity, reflected in their product descriptions over time. Chapter 2 of my dissertation introduces a novel text-based innovation measure using 10-K business descriptions that explain future sales growth and profitability. Using the innovation measure, I test whether redacting firms exhibit more innovative activity and introduce novel products and services in their business descriptions in the aftermath of redactions. For this analysis, I specifically focus on the impact of licensing and R&D types of confidential contracts. The results (Columns 8-9) provide compelling evidence that redacting firms indeed become more innovative after redactions. This finding suggests that firms conceal information that is proprietary in nature, consistent with the results in Kankanhalli et al. (2021).

4.4.1.3. Robustness Checks

I conduct a battery of robustness tests to check whether my results are susceptible to several factors relating to my research design choices. To ensure the observed relation is not simply due to the treatment variable choice, I use an alternative variable to measure the effect of redacted disclosures on firm learning. Specifically, I use the natural logarithm of the number of confidential filings instead of using a dummy variable. The results in Column 1 of Table 6 show that my inferences hold and are not sensitive to the choice of my treatment variable.

Moreover, to ensure the robustness of the findings and address potential biases related to customer-supplier relationships, I remove from my sample firm-peers that have a customer-supplier relationship. Chen, Tian and Yu (2022) provide evidence that supplier firms redact filings in line with their customer disclosure policies, indicating a potential influence of such relationships on disclosure behavior. At the same time, firms may make adjustments to their product portfolio in response to customer-supplier relationships without necessarily learning from each other's disclosures.

While firm-peer fixed effects account for static relationships between firms, it may fail to control for time-varying relationships. As a conservative approach, I remove firm-peer-years with customer-supplier relationships from my sample to mitigate any potential impact of dynamic customer-supplier relationships on firms' product market decisions without learning. Utilizing the supplier-customer data by WRDS to remove firm-peer pairs, I rerun my analyses. Column 2 demonstrates that the results are also robust to this exclusion.

Another concern might be the joint projects or collaboration agreements undertaken by firm-peer pairs. It is possible that the increased product similarity between firms and redacting rivals may be a result of collaborative work rather than learning from disclosures. To this end, I exclude all 'peer' types of confidential contracts from my sample to remove such effects. My inferences remain unchanged as well (Column 3).[77]

Finally, I categorize the redacted filings based on their types. I decompose the confidential filings into their contract types and check which type of contracts might be useful for peer learning, similar to the literature (e.g., Boone et al.; 2016). For example, contracts with more proprietary data might be more informative to firms than other contracts. To determine the type of contract, I download the text of confidential filings and conduct keyword searches

[77] The contracts with titles including ‘collaborative’, ‘collaboration’, ‘cooperation’, ‘cooperative’, ‘joint’, and ‘strategic alliance’ and their variants.

using regular expressions. Unlike prior studies, however, I combine innovation-related contracts (such as R&D, patent, royalty etc.) into one category as "License & RD". This consolidation enables a more comprehensive analysis of the impact of innovation-related contracts. In line with the literature, I observe that "Purchase & Sale" and "License & RD" contracts are the most prevalent, followed by "Credit & Lease", "Investment & Merger", and "Employment" contracts.

I regress the future product similarity between pairs on the type of the confidential agreement. It seems that the innovation-related (licensing, R&D) contracts significantly contribute to the positive coefficient on the confidential dummy. This finding highlights the importance of innovation-related information in driving rivals' subsequent investment decisions. Interestingly, however, the results also reveal that finance and employment types of contracts play a noteworthy role in explaining the positive association. The result for financing agreements is consistent with Bernard (2013), which suggests that rivals may exhibit predating behavior and force financially constrained firms to exit the market. Learning from confidential financing agreements, firms may seize opportunities to gain a competitive advantage over rivals facing financial constraints. Moreover, confidential employment agreements appear to convey valuable information to firms regarding peers' human capital investments beyond financial statements, providing insights into peers' human capital investments.

Overall, the findings further strengthen my inferences that firms actively extract valuable information from peers' redacted disclosures and adapt their investment strategies, underscoring the existence of a learning effect.

4.4.1.4. Additional Analyses and Moderating Effects

This section analyzes whether the learning effect is sensitive to some specific firm and firm-peer-specific characteristics, including competition.

The increase in R&D spending in main analyses may depend on some firm-specific characteristics. I test whether the observed R&D increase changes with the firm size. On the one hand, firms may undertake additional investments to join a profitable market that they learn from their peers. This would manifest in an increase in R&D spending, at least in the short term. On the other hand, firms may substitute the *new* profitable market with the *old* non-profitable ones or projects with a high probability of failure or uncertainty. In this case, a rise in R&D spending for the new market would be offset by a decrease in expenditures for other existing projects firms decide to forgo, making the R&D increase unobservable. Ciftci and Cready (2011) show that larger firms with R&D investments enjoy lower earnings volatility compared to smaller firms due to the ability to diversify R&D investment risk better. Having many projects in their pipeline, larger firms have the ability to substitute an opportunity that they learn from peers with their existing projects, making the change in R&D investments less visible.

To check whether an increase in R&D changes with firm size, I interact the confidential dummy with the firm size. It seems that the effect on R&D is attenuated for larger firms (Table 7, Column 1), consistent with the idea that larger firms are better able to substitute the opportunities learned from peer disclosures with the ones in their existing portfolio.

Next, I examine whether the increasing similarity between a firm and redacting peers depend on the characteristic of firm-peer-specific relationships and the competitive forces. For example, firms may find it challenging to compete with stronger rivals (Zhang, 2020) even if they are able to decipher the signal they receive regarding profitable markets. To test this, I create a dummy variable, *strong rival*, which takes the value of one when the peer size is larger than the firm size (in terms of market value). This variable allows me to identify instances where peers might be strong rivals for a subset of firms while being weaker rivals for others based on their relative market positions. The result in Column 2 demonstrates that the interaction effect of the strong rival dummy is negative and significant. This finding suggests that firms indeed do not prefer to join the same market when disclosures come from strong rivals. This implies that firms can still learn from rival disclosures, but instead, they are deterred from investing in similar markets.[78]

Second, firms may consider the current market structure of peers before making investment decisions based on what they learn from redacting peers. For example, firms may find it less attractive to join already crowded markets where too many players compete. To test this, I use the *Total Similarity* measure by Hoberg and Philips (2016), which measures the aggregate similarity of rivals for a given firm in a year. The result in Column 3 shows that firms find it less attractive if redacted disclosures come from a peer with greater total similarity, i.e., when the market is already crowded, and the competition is too high. One possible explanation is that firms may find it less worthy to enter a market where the profit margins are relatively small. In Column 4, I also find that confidential filings are especially informative for peers when the redactions accompany an increase in R&D spending in the same quarter.

Finally, I check whether the location of firms and their peers play a role in subsequent investment decisions in response to redactions. The literature shows that the distance between rivals may play an essential role in technology spillovers due to, e.g., the interfirm mobility of inventors (Almeida and Kogut, 1999). Managers may possess greater knowledge of other firms in the same geographic area (Jaffe, Trajtenberg, and Henderson 1993). On the one hand, local firms may have a better capacity or resources (e.g., due to less information frictions) regarding rivals than non-local firms, making it easier to unravel what is hidden in redacted disclosures, increasing the learning effect. On the other hand, local firms may already be informed about

[78] A natural question may arise why firms choose to redact in the first place if the disclosure can deter rivals. Given the heterogeneity in rival characteristics (the mixture of weak and strong rivals), firms may still find it optimal to redact to protect their intangible capital against strong rivals.

the underlying technology that rivals attempt to hide. In this case, the learning effect would be attenuated for local firms.

Using the state of incorporation data from Compustat, I generate a dummy variable *same state* to identify instances where a firm and its particular peer are located in the same state. [79] The results presented in Column 5 suggest that being in the same state has a negative effect, if any (t-stat = 1.70), on firm learning from redacted disclosures. This finding supports the notion that firms located in the same state may already possess superior knowledge about the concealed information in the contracts compared to non-local firms. As a result, the negative relation between same-state firms provides further assurance against a possible concern that the observed relation is merely a result of a common demand shock.

4.4.2. Attention Mechanism

In this section, I explore the role of increasing awareness and attention as a potential mechanism to facilitate peer learning from redacted disclosures. In the first analysis, I examine whether there is higher information demand for redacted filings compared to non-redacted contracts. Understanding the level of information demand can provide valuable insights into the importance of redacted disclosures for competitors and their motivation to extract valuable information from these contracts.

Next, I employ a unique approach by exploiting two plausibly exogenous shocks to firm attention. External factors that may distract or redirect firm attention from redacted disclosures enable me to test whether a disruption in firm attention impairs their ability to learn from redacted disclosures provided by peers.

[79] One way to collect state of incorporation is to look at company filings to get historical information since Compustat only keep the latest records regarding state information but fail to provide historical changes. Since my sample covers relatively small time period, I do not think that collecting data from company filings may alter my inferences.

4.4.2.1. Information Demand and Download Analyses

For information demand analyses, I leverage the detailed information from EDGAR log files, which provide granular data on the download of public firms' filings at the SEC. Unlike prior studies on SEC downloads (e.g., Drake et al., 2015; Bernard et al., 2020; Hollander and Litjens, 2020), which capture downloads based on document accession numbers, the EDGAR log files' unique feature allows for a more refined analysis at the 'extension' level. This enables me to compare the downloads of confidential exhibits with their non-confidential counterparts, even within the same filing/accession (e.g., 10-K or 10-Q).

This comparison, however, requires additional effort to identify exhibits' links (filename), including those of non-redacted ones, since EDGAR log files do not provide information about the nature of exhibits. In order to identify all material exhibits (redacted + non-redacted) and their ‘extention’ (filename), I use EDGAR index pages of each 10-K and 10-Q filing. I merge the data from index files with EDGAR log files using the accession and filename (extention) and only keep material exhibits. By this, I identify the information regarding the number of downloads and the nature of each material exhibit.

To mimic downloads by competitors, I first followed a procedure similar to the literature, excluding machine downloads (e.g., Drake et al., 2015). Second, I only use downloads of exhibits in human-readable forms (i.e., .html, .htm, or .pdf), excluding the text files containing html codes such as complete submission files. This should further eliminate possible downloads by sophisticated investors. Although it is not possible to completely rule out the inclusion of downloads by other parties (e.g., retail investors), this approach allows me to reasonably mimic competitor downloads. Investors are more likely to use other platforms (i.e., Bloomberg terminals) or information intermediaries to access company filings (Drake et al., 2015) relative to competitors. Moreover, there appears to be no reason why competitor demand would significantly deviate from the demand pattern observed in the data.

The first descriptive evidence for greater attention to redacted filings is depicted in Figure 1. Figure 1.a shows the cumulative downloads of redacted vs. non-redacted material exhibits up until six months after their filing. The figure clearly demonstrates that redacted material exhibits receive more attention than non-redacted material counterparts starting from day zero and continue to follow a similar pattern during the six months. Figure 1.b, on the other hand, depicts the cumulative downloads of material contracts relative to the publication date of confidential treatment order (CTO) by the SEC after the original (redacted) contracts are published by firms. It is interesting to see that there is a clear jump in the downloads for confidential exhibits at the time of CTO, which includes no information other than the location of the filing.[80] Although the contracts are already published in the EDGAR system, there seems to be an additional attention effect at the time of the CTO grant. This difference in download patterns around CTO grants alleviates concerns that the observed relation is not because of greater attention but simply because of the nature of contracts that are more likely to be redacted and downloaded.

Still, in order to alleviate concerns that the depicted figure may arise because of certain characteristics of firms that file redacted exhibits or time-varying firm disclosure behavior that correlates with the number of downloads, I conduct regression analyses. To control the effect of other confounding factors, I regress the logarithm of the number of downloads to a dummy variable that takes the value of one if the material contract is redacted. Here the unit of analysis is the contract (exhibit) level.

[80] The SEC publishes CTO grants usually within several months after the original filing (and redaction). As can be seen in Appendix B, this document includes information about the firm that files redacted contract, the location of the filing, and exhibit number together with the expiration date of the CTO grant. The document gives no additional information about the nature or the type of the contract.

In different models, I use a variety of fixed effects to control omitted correlated variables that may affect both filing downloads and firms' disclosure choices. I use firm and year-quarter fixed effects to control for any time-invariant firm characteristics and timing effects. Moreover, for concerns regarding time-varying firm characteristics driving both the downloads of firms and their disclosure choices, I use firm#year-quarter fixed effects. For instance, innovative and growing firms may both receive more attention (downloads) and at the same time, choose to redact filings due to proprietary concerns. Finally, to further sharpen the identification, I include filing FE in the model and conduct *within-filing* analyses to compare the attention to redacted filings to their non-redacted counterparts within the same filing (e.g., 10-K) while keeping any filing-related factors constant.

The results reported in Table 8 align with what is depicted in Figure 1. The positive coefficients on confidential exhibits in Columns 1-4 show that redacted material contracts receive, on average, 43-52% more attention compared to their non-redacted counterparts. The documented effect is robust to a variety of firm and time-specific characteristics, including total downloads of the main filing (e.g., the text of 10-K). Notably, redacted exhibits receive 43% more attention than non-redacted exhibits, even if they are attached to the very same filing (Column 4).

One might argue that redactions may simply capture some firm-specific characteristics, such as higher agency costs, which might explain higher downloads for redacted exhibits. If so, one should observe a similar pattern for the downloads of main filings containing redactions. The results in Columns 7-8 show that this is not the case: There is no evidence that main filings with redacted exhibits receive more attention compared to filings with no confidential exhibits. The coefficient on main filings with redacted exhibits is even negative and becomes insignificant when controlled for only firm fixed effects.[81] Taken together, the results show that redacted material exhibits receive significantly greater attention compared to non-redacted material exhibits abstract from the firm-, time-, and filings-related factors.

Finally, similar to the main analyses, I decompose the confidential dummy to its contract type to test whether the type of contract is a determinant of greater attention to these filings. Results in Columns 5-6 show that confidential filings receive greater attention independent of their type (except Service & Consult contracts). This further supports the notion of the Streisand effect and mitigates concerns that confidential filings receive greater attention simply because of the type of contracts that are more likely to be redacted (such as R&D-related contracts) and downloaded.

While I cannot entirely rule out the potential influence of the nature of the contract on downloads, I believe attention plays a crucial role in determining the downloads of these filings. As explained in Section 2 in detail, competitors are already aware of which exhibits are redacted even before accessing the actual document. Since rivals cannot ascertain the true usefulness of the contract until they access it, their download decisions are likely guided by *perceived importance* of the contract rather than its actual significance or nature. This observation underscores the crucial role of attention in driving competitors to focus on filings they perceive as significant, providing compelling evidence of the attention mechanism at play.

4.4.2.2. Quasi-natural Experiments on Firm Attention

To provide further empirical support for the attention argument, I employ a quasi-natural experiment that leverages CEO departures as an exogenous shock affecting the attention levels of competitors. However, CEO departures from rival firms may not be

[81] This is consistent with the idea that smaller firms are more likely to redact filings while also suffering from lower downloads for their filings overall. It is possible that higher demand for main filings in case of a redaction is offset by the size of firm, leading to a coefficient not different from zero.

exogenous to firms' redaction choice. For instance, firms replace CEOs for performance reasons relative to peers (Eisfeldt and Kuhnen, 2013) or in result of a competition shock (Dasgupta, Li, and Wang, 2018) that may, at the same time, co-determine peers' disclosure (redaction) choice. To address these endogeneity concerns, I focus on exogenous CEO departures due to death or health reasons, which the literature suggests do not significantly impact corporate policies such as investment decisions, in contrast to departures due to performance reasons (Fee et al., 2013). By leveraging these exogenous CEO departures (and subsequent new hiring) as a temporary and firm-specific shock to attention, I aim to isolate the effects of attention dynamics on firms' ability to learn from peer disclosures.

To this end, I use the data provided by Gentry et al. (2021) on CEO departures of S&P 1500 firms between 2000 and 2018. The authors identify all kinds of CEO departures and classify all voluntary and involuntary departures into eight distinct categories. Following a similar categorization approach as in Fee et al. (2013), I construct a dummy variable E*xo_CEO_shock,* a value of one for three quarters following the announcement of CEO replacement decisions.[82] I also control for any other CEO departures (*other_CEO_shock*) in my analyses.

Table 9 reports the results regarding the attention mechanism. Notably, the coefficient on the interaction of E*xo_CEO_shock* and confidential dummy is negative and significant both for future R&D investments and product similarity between firm-peers (Columns 1-2). This suggests that the learning effect is attenuated by exogenous CEO departures due to decreased attention to rival disclosures. These results suggest that firm attention plays a role in the extent

[82] Particularly, I use following four categories as *exogenous* types of departures: Category 1: Involuntary—CEO death, Category 2: Involuntary—CEO illness, Category 4: Involuntary—CEO dismissed for personal issues, and Category 5: Voluntary—CEO retired. Other categories (endogenous departures) include; Category 3: Involuntary—CEO dismissed for job performance, Category 6: Voluntary—New Opportunity, Category 7: Other, and Category 8: missed. See Gentry et al. (2021) for details.

to how firms learn from rival disclosures, which has not yet been explored in the disclosure literature.

Second, I use the financial crisis of 2008 as an economy-wide shock to firm attention. In a survey study, Campello et al. (2010) show that firms, even unconstrained firms, cut spending on technology, employment, etc., and stay irresponsive to attractive investment opportunities during the financial crisis. I argue that the financial crisis arguably caused firms to focus on other issues, such as liquidity management or reorganization, rather than seeking new investment opportunities.

To test whether an economy-wide attention shock affects firm learning from redacted disclosures, first, I manually collect data on confidential material agreements before the crisis since CT Orders are only available after May 2008 on the SEC EDGAR website.[83] I create a dummy variable *Post_fincrisis,* which takes a value of one for seven quarters between the 3rd quarter of 2008 and the first quarter of 2010 to measure the effect of the financial crisis. I restrict my sample to three years around the crisis, i.e., from the third quarter of 2005 to the 3rd quarter of 2011. For a possible concern that post-crisis investment behavior might drive the effect in future R&D spending and product market decisions that might correlate with peer disclosures, I also control the interaction of *Post_fincrisisxR&D* in my regressions.

The results in Table 9 (Columns 3-4) show that the interaction effect of a temporary financial crisis shock and confidential dummy is negative and significant for predicting future R&D investment and product similarity between the firm and its peers. The results suggest that an economy-wide shock that averts firm attention to matters other than future investment opportunities reduces the effect of firm learning, confirming the moderating effect of firm attention on peer learning. However, the results regarding the financial crisis should be treated

[83] I collect data on confidential material agreements starting from 2005 by only searching 10-K and 10-Q files for convenience due to additional effort for manual collection. I first identify all material agreement before 2008 and search the text of these agreements for 'confidential treatment' and its variations to further determine whether the material agreement in question is redacted or not.

with caution since the crisis may affect firm investment behavior in dimensions other than firm attention that I failed to control, and that may correlate with peer redaction choice.

Taken together, the results in this section suggest that attention plays an important role and might be a potential mechanism on peer learning from disclosures.

4.5. Discussion and Conclusion

In this study, I examine whether firms can extract valuable information from their peers' redacted disclosures for their subsequent investment decisions. I find that competitors change their investment behavior upon observing such disclosures, suggesting a learning effect. Next, I show that there is greater information demand for redacted disclosures, suggesting an increase in attention to these filings. Finally, using CEO departures and the financial crisis as an exogenous shock to firm attention, I show that firm attention might be a potential underlying mechanism that can explain the learning effects documented in the literature. The results shown in this paper are robust to various static and time-varying confounding factors that may explain the observed association.

Despite my efforts to document a causal relation between redacted disclosures and peer investment behavior, several caveats are worth mentioning. First, one of the challenges in studying the relations in peer settings is the reflection problem, as explained in previous sections. A possible scenario that might explain the observed association is that peers simply respond to the same growth opportunity shock. I attempt to overcome this problem by using highly granular fixed effects to control such shocks. However, since there is a time difference between an observed redacted filing and rivals' future investments, I still may fail to control confounding effects that might explain the observed association. Second, the information leakage may not necessarily originate from a redacted contract but from other information sources regarding the same underlying activity concealed in redacted contracts. For instance, rivals may gather information through common suppliers or other information networks instead of redacted filings. Unfortunately, it is challenging to disentangle those effects without knowing the actual information flow between rivals. However, it is still more likely that firms first observe redacting filings that may increase the awareness of such opportunities and only then use other information sources to extract more information.

Another caveat relates to the attention mechanism I attempt to document in my study. Although descriptive analyses show that redactions receive significantly more downloads, pinpointing the underlying reason is still challenging since the choice of redaction is endogenous to the firm- and filing-specific characteristics. Despite my attempts to control those factors in my regression analyses, it is still possible that these filings are downloaded more, not because of the unconditional greater attention but because they simply have different characteristics than unredacted material agreements. This concern is partly mitigated in my analyses since greater attention to redacted contracts seems independent from the contract type. Moreover, competitors are already aware that a contract is redacted before accessing it, further alleviating this concern. One alternative solution might be to collect additional information regarding the type of unredacted contracts that make it possible to compare redacted and non-redacted filings of the same type. However, even in this case, the underlying redactions are not observable, whether they relate to just one word, a number, or an entire paragraph that makes these contracts potentially different. Furthermore, even if the underlying information can be observed, the importance or, in other words, the true proprietary nature of the information concealed is private information and unknown to researchers. Nevertheless, whether it is due to greater attention or the characteristics of these filings, this still does not alter my main inferences that rivals respond to redacting filings.

Finally, observing the results, one might naturally ask why firms redact in the first place if they anticipate that rivals can increase their attention to these filings and subsequently learn from them. The results in the paper suggest that redacting firms, on average, fail to protect proprietary information by censoring them. However, this does not necessarily mean that these redactions do not work for some subset of firms. On the contrary, redacting firms may find it best to increase the acquisition cost for rivals by putting a barrier with redactions while inadvertently decreasing rivals' awareness costs. The average effect seems to result from the interplay between these two opposing forces.

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4.7. Appendix

Appendix A. Description of Variables

Dependent variables	
$Similarity_{ij,t+T}$	Product similarity measure firm *i* and peer *j*.
$R\&D\ investment_{i,q+1}$	One quarter ahead R&D intensity calculated as $xrdq_{q+1}/at_q$
$R\&D\ investment_{i,y+1}$	Subsequent four-quarter R&D intensity calculated as: $\frac{\sum_{i=1}^{4}(xrdq_{q+i})}{at_q}$
Treatment Variables	
$confidential\ dummy_{ijt}$	An indicator variable that takes the value of one if the firm *i* observes at least one confidential exhibit by its peer *j* in a given quarter
$\log(confidential)_{ijt}$	The number of confidential exhibits filed by peer *j* of firm *i* in the current quarter
$License - R\&D\ dummy_{ijt}$	An indicator variable that takes the value of one if the confidential exhibit is of type licensing or R&D related
$Supply\ dummy_{ijt}$	An indicator variable that takes the value of one if the confidential exhibit is a supply agreement
$Financing\ dummy_{ijt}$	An indicator variable that takes the value of one if the confidential exhibit is a credit agreement
$Employment\ dummy_{ijt}$	An indicator variable that takes the value of one if the confidential exhibit is an employment related agreement
$Investment\ dummy_{ijt}$	An indicator variable that takes the value of one if the confidential exhibit is an investment agreement
$Peer\ dummy_{ijt}$	An indicator variable that takes the value of one if the confidential exhibit is a joint agreement
$Other\ confidential\ dummy_{ijt}$	An indicator variable that takes the value of one if the confidential exhibit is of another type
Control Variables	
$SizeQ_{i(j)t}$	The natural logarithm of the quarterly market value of equity: $cshoq\ x\ prccq$
$R\&DQ_{i(j)t}$	R&D intensity calculated as $xrdq_q/at_q$ where $xrdq_q$ is set to zero if missing
$missing\ R\&DQ_{i(j)t}$	An indicator variable that takes the value one if $xrdq_q$ is missing
$MBQ_{i(j)t}$	Market-to-book value calculated as $(cshoq\ x\ prccq)/ceqq$
$LeverageQ_{i(j)t}$	The sum of long-term and short-term debt scaled by total assets $(dlttq + dlcq)/at$ where missing variables in nominator is set to zero.
$ROAQ_{i(j)t}$	The earnings before extraordinary items scaled by total assets: ibq/at_q
$LOSSQ_{i(j)t}$	An indicator variable that takes the value of one if the firm (peer) reports a loss $(niq < 0)$
$\log(main\ filing)$	The natural logarithm of the number of downloads of the main filing (i.e.,10-K or 10-Q) to which a material exhibit is attached;.

Additional Variables

$Exo\_CEO\_departures_{ijt}$	An indicator variable that takes the value one for three quarters following peer *j* of firm *i* experiences an exogenous CEO turnover
$Other\_CEO\_departures_{ijt}$	An indicator variable that takes the value one for three quarters following peer *j* of firm *i* experiences other types of CEO turnover
$\log(other\ material\ exhibits)_{ijt}$	The number of non-confidential material exhibits filed by peer *j* of firm *i* in the current quarter
$Post_{ijt}$	An indicator variable for the financial crisis that takes the value one for the quarters between 2008Q3 and 2010Q1
$ROAOP_{jt}$	Operating profitability before R&D and depreciation scaled by total assets for the year: $(oiadp\ +\ dp\ +\ xrd)/at$
$Market\ Fluidity_{jt}$	The product market fluidity measure by Hoberg et al., (2014) capturing the rival movements towards firm in product space.
$Innovation_{jt}$	Textual innovation measure by Ahci and Joos (2019)

Appendix B.1. Confidential Treatment Order

UNITED STATES
SECURITIES AND EXCHANGE COMMISSION
September 13, 2017

ORDER GRANTING CONFIDENTIAL TREATMENT
UNDER THE SECURITIES EXCHANGE ACT OF 1934

Tesla, Inc. Filer name

File No. 1-34756 - CF#35364

Tesla, Inc. submitted an application under Rule 24b-2 requesting confidential treatment for information it excluded from the Exhibits to a Form 10-Q filed on August 4, 2017.

Form type Filing date

Based on representations by Tesla, Inc. that this information qualifies as confidential commercial or financial information under the Freedom of Information Act, 5 U.S.C. 552(b)(4), the Division of Corporation Finance has determined not to publicly disclose it. Accordingly, excluded information from the following exhibit(s) will not be released to the public for the time period(s) specified:

Redacted Exhibits			Expiration dates
	Exhibit 10.4	through December 31, 2019	
	Exhibit 10.5	through December 31, 2019	
	Exhibit 10.7	through December 31, 2019	
	Exhibit 10.8	through December 31, 2019	

For the Commission, by the Division of Corporation Finance, pursuant to delegated authority:

Brent J. Fields
Secretary

Appendix B.2. Confidential Treatment Order (Extension and several filings)

UNITED STATES
SECURITIES AND EXCHANGE COMMISSION
April 23, 2015

ORDER GRANTING CONFIDENTIAL TREATMENT
THE SECURITIES EXCHANGE ACT OF 1934

Ligand Pharmaceuticals Incorporated

File No. 1-33093 - CF#32050

Ligand Pharmaceuticals Incorporated submitted an application under Rule 24b-2 requesting an extension of prior grants of confidential treatment for information it excluded from the Exhibits to Forms 10-K filed on March 3, 2011 and February 23, 2012.

Based on representations by Ligand Pharmaceuticals Incorporated that this information qualifies as confidential commercial or financial information under the Freedom of Information Act, 5 U.S.C. 552(b)(4), the Division of Corporation Finance has determined not to publicly disclose it. Accordingly, excluded information from the following exhibits will not be released to the public for the time periods specified:

Exhibit	to Form	Filed on	Confidential Treatment Granted
10.114	10-K	March 3, 2011	through March 5, 2018
10.131	10-K	February 23, 2012	through February 23, 2018
10.132	10-K	February 23, 2012	through February 23, 2018
10.133	10-K	February 23, 2012	through February 23, 2018

For the Commission, by the Division of Corporation Finance, pursuant to delegated authority:

Brent J. Fields
Secretary

Appendix C. Excerpt from a confidential filing (redacted exhibit)

Exhibit 10.15 of 10-K filed on 2019-03-18 by Arcturus Therapeutics Ltd.

*(*Highlights are my own)*

EX-10.15 4 arct-ex1015_582.htm EX-10.15

Exhibit 10.15

*****Text Omitted and Filed Separately**
with the Securities and Exchange Commission.
Confidential Treatment Requested
Under 17 C.F.R. Sections 200.80(b)(4) and Rule 24b-2

RESEARCH COLLABORATION AGREEMENT

This Research Collaboration Agreement is entered into and effective as of March 8, 2019 (the ***"Effective Date"***), by and between **Arcturus Therapeutics, Inc.** (***"Arcturus"***), a Delaware corporation, having offices at 10628 Science Center Drive, Suite 250, San Diego, CA 92121 and **MILLENNIUM PHARMACEUTICALS, INC.** (***"Takeda"***), a wholly owned subsidiary of Takeda Pharmaceutical Company Limited and a Delaware corporation organized under the laws of Delaware, having offices at 40 Landsdowne Street, Cambridge, MA 02139, collectively the ***"Parties"*** and respectively the "***Party***".

Whereas, Arcturus (i) owns a proprietary lipid nanoparticle technology referred to as LUNAR technology (the ***"LUNAR Technology"***) which is useful in delivering therapeutic nucleic acid molecules to various cells in vivo, including hepatocytes, (ii) possesses expertise in producing lipid nanoparticle formulated therapeutic nucleic acid molecules, including mRNA, and (iii) has developed proprietary protein modification expertise, mRNA designs and processes to produce therapeutic mRNA molecules […***…][1] and any data pertaining thereto), (the "***Arcturus mRNA Technology"***).

Whereas, Takeda possesses expertise in the pre-clinical and clinical development of therapeutic compounds to treat various conditions, including non-alcoholic steatohepatitis (NASH).

Whereas, the Parties have completed the Research Program to discover siRNA medicines under the Research Agreement executed by the Parties as of December 6, 2016, as amended (the "***2016 Research Agreement***") with US $[…***…][2] of the research funding which was paid by Takeda to Arcturus and remains unspent or uncommitted by Arcturus at the time of completion (the ***"Remaining Funds"***).

Whereas, notwithstanding Section 3.2 of the 2016 Research Agreement providing Arcturus' obligation to reimburse the Remaining Funds to Takeda, the Parties desire to collaboratively conduct the research set forth in **Exhibit A** hereto (the ***"Research Plan"***), by using the Remaining Funds for the purpose of generating, producing and/or optimizing therapeutic mRNA molecules […***…][3] (collectively, the ***"Materials"***) for their evaluation in […***…][4] (the ***"Studies"***) to inform the Parties as to whether or not to further develop the Materials for the treatment of […***…][5].

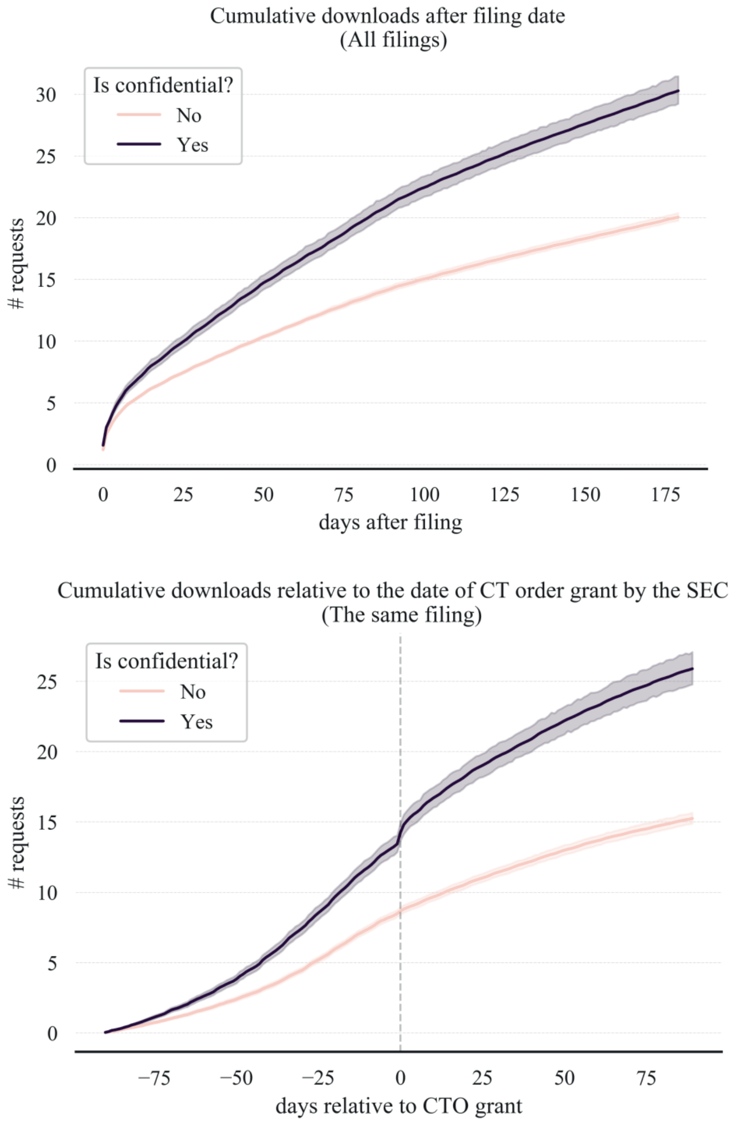

Figure 1. Number of downloads of material agreements

The Figure 1.A plots the cumulative number of requests/downloads of material exhibits (EX-10.XXs) up until 6 months after their filing and figure 1.B plots the downloads relative to the filing of confidential treatment order (CTO) grants by the SEC. Material exhibits in this figure are filed with either 10-Qs or 10-Ks between 2008 and 2017. Confidential material exhibits are identified from confidential treatment orders made public by the SEC after May 1, 2008.

Table 1. Sample Construction

Panel A: Selection of Confidential Treatment Orders	
Description	**# CT Orders**
Total downloaded CT Orders filed between 2008 and 2018	12,664
After dropping CTOs with extensions or denial	11,255
After dropping CT Orders for filings other than 10-K, 10-Q, and 8-K	9,625

Panel B: Selection of redacted firms and filings

Description	**# filings**	**# exhibits**
Number of filings and exhibits in 9,625 CT Orders	9,729	16,397
After dropping number of unidentified filings and exhibits	8,549	14,712
After dropping firms according to sample selection criteria (dropping firms not in CRSP/Compustat and/or TNIC3 industry data; dropping financials and utility firms and firms with missing variables)	6,319	10,757

Panel C: Disclosing Peers by year

Year	#sample firms	#redacting firms	#redacted filing	#redacted exhibit
2008	3,354	455	663	1,119
2009	3,179	434	627	1,151
2010	3,059	431	626	1,062
2011	2,954	400	589	980
2012	2,874	375	539	874
2013	2,929	374	559	930
2014	3,058	386	547	902
2015	3,014	385	549	955
2016	2,887	357	533	932
2017	2,883	352	533	977
2018	2,893	371	554	875
TOTAL	**33,084**	**4,320**	**6,319**	**10,757**

Table 2. Descriptive Statistics for sample firms

Panel A: Overall Descriptives

	N	Mean	Sd	p25	p50	p75
Confidential	33,084	0.13	0.34	0.00	0.00	0.00
Redact at least once	33,084	0.35	0.48	0.00	0.00	1.00
Similarity	33,084*	0.06	0.56	0.02	0.05	0.09
SIZE	33,084	6.29	2.15	4.74	6.31	7.75
R&D	33,084	0.07	0.15	0.00	0.01	0.08
MB	33,084	3.14	5.78	1.13	2.04	3.79
LEVERAGE	33,084	0.23	0.23	0.01	0.18	0.36
ROAOP	33,084	0.09	0.20	0.05	0.12	0.19
Cash	33,084	0.41	0.43	0.08	0.25	0.59
ACQUISITION	33,084	0.02	0.06	0.00	0.00	0.01
CapEX	33,084	0.05	0.06	0.01	0.03	0.06
SGA	33,084	0.20	0.26	0.06	0.15	0.30
TANGIBILITY	33,084	0.24	0.24	0.06	0.14	0.35
log(Innovation)	28,603	5.32	0.85	4.91	5.41	5.86

Panel B: Firms With At Least One vs. Never Redaction

	Non-redactors		Redactors			
	N	Mean	N	Mean	Diff.	t-stat
Confidential	21,343	0.00	11,741	0.37	**-0.37**	-111.46
Redact at least once	21,343	0.00	11,741	1.00	**-1.00**	.
log(MVE)	21,343	6.33	11,741	6.22	**0.10**	4.11
R&D	21,343	0.04	11,741	0.13	**-0.09**	-52.66
MB	21,343	2.91	11,741	3.54	**-0.63**	-9.46
LEVERAGE	21,343	0.23	11,741	0.22	**0.01**	2.52
ROAOP	21,343	0.10	11,741	0.06	**0.04**	19.02
Cash	21,343	0.33	11,741	0.57	**-0.24**	-50.60
ACQUISITION	21,343	0.02	11,741	0.02	**0.00**	4.98
CAPEX	21,343	0.05	11,741	0.04	**0.01**	8.70
SGA	21,343	0.22	11,741	0.17	**0.05**	17.05
TANGIBILITY	21,343	0.25	11,741	0.21	**0.05**	17.19
log(Innovation)	18,486	5.18	10,117	5.58	**-0.40**	-38.78

Panel C: Industry Distribution

	#Firms	#redacted contracts	#redacting firms	at least once	R&D
Top 15 Industries					
Pharmaceutical Products	4,065	3,981	0.394	0.780	0.306
Transportation	1,026	936	0.186	0.380	0.000
Business Services	1,979	772	0.120	0.352	0.025
Computer Software	3,032	703	0.107	0.320	0.097
Communication	1,031	648	0.156	0.351	0.016
Electronic Equipment	2,244	537	0.099	0.332	0.124
Medical Equipment	1,400	491	0.182	0.516	0.134
Retail	1,795	320	0.099	0.339	0.002
Computer Hardware	704	197	0.108	0.426	0.129
Chemicals	859	238	0.094	0.265	0.030
Wholesale	1,221	225	0.087	0.242	0.002
Petroleum and Natural Gas	2,007	204	0.055	0.208	0.002
Electrical Equipment	617	163	0.112	0.350	0.060
Healthcare	699	145	0.109	0.361	0.018
Personal Services	444	120	0.099	0.279	0.004

Table reports the descriptive statistics. While Panel A demonstrates the overall distribution of variables for whole sample firms, Panel B partition the sample based on redactions and reports the difference of variables between the subsamples. I define redactors as the firms with a redacted filing at least once during the sample period. Similarly, non-redactor firms are those who never filed a redacted contract during the sample period. Panel C reports the redaction statistics across industries. Top 15 industries is defined based on the number of redacted contracts in a given industry during the sample period. Confidential is a dummy variable taking the value of one for non-zero confidential contract by a firm in given year. *At least once* is dummy variable taking the value of one for firms that issued at least one redacted contract during the sample period. Similarity is the Hoberg and Philips (2016)'s product market similarity score between firm-peer pairs based on business text descriptions (The statistics are given for firm-peer pairs for sample firms). SIZE represents the natural logarithm of the market value of equity (MVE). R&D represents research and development expenses scaled by total assets. MB is the ratio of market capitalization and book value of equity. ROAOP denotes the operating income before R&D and depreciation scaled by total assets. Cash is the cash holdings scaled by total assets. ACQUISITION refers to acquisitions from the cash flow statement. CAPEX denotes capital expenditures, and SGA denotes the SG&A expenses before R&D, advertising, and depreciation, all scaled by total assets. log(Innovation) is the natural logarithm of innovation word usage in business descriptions by Ahci and Joos (2019). The definitions of variables are also detailed in the Appendix A.

Table 3. Future R&D Investments

	$RDQ_{i,q+1}$	$RDQ_{i,q+1}$	$RDY_{i,y+1}$	$RDY_{i,y+1}$
	(1)	(2)	(3)	(4)
Confidential dummy	**0.0008*** **	**0.0002*** **	**0.0034*** **	**0.0004*** **
	(19.31)	**(3.46)**	**(20.64)**	**(2.97)**
Similarity score	0.0292***	0.0237***	0.1871***	-0.0178***
	(115.89)	(22.65)	(122.52)	(-5.66)
RDQ_{firm}	0.8297***	-0.0197***	3.2644***	1.1341***
	(1615.80)	(-20.57)	(1302.33)	(251.26)
Missing $R\&DQ_{firm}$	-0.0041***	0.0101***	-0.0212***	0.0390***
	(-119.00)	(74.13)	(-143.28)	(85.33)
$MBQ_{\_firm}$	0.0001***	0.0002***	0.0014***	0.0008***
	(56.15)	(42.17)	(136.03)	(57.83)
$LEVERAGEQ_{\_firm}$	-0.0041***	-0.0064***	-0.0383***	0.0343***
	(-78.58)	(-25.72)	(-132.34)	(37.05)
$ROAQ_{\_firm}$	0.0098***	-0.0067***	-0.0191***	-0.1427***
	(41.08)	(-23.12)	(-16.60)	(-138.08)
$LOSSQ_{\_firm}$	0.0059***	0.0005***	0.0264***	-0.0083***
	(233.44)	(18.85)	(210.50)	(-91.96)
$Size_{firm}$	-0.0012***	-0.0042***	-0.0003***	-0.0315***
	(-178.20)	(-75.31)	(-8.60)	(-192.78)
$Size_{peer}$	0.0001***	-0.0002***	0.0006***	0.0085***
	(11.58)	(-6.16)	(18.25)	(72.10)
$RDQ_{\_peer}$	0.0124***	0.0025***	0.0153***	0.0092***
	(40.37)	(4.06)	(9.71)	(5.23)
Missing RDQ_{peer}	-0.0036***	0.0004***	-0.0158***	0.0009***
	(-108.59)	(4.71)	(-103.39)	(3.87)
MBQ_{peer}	0.0000***	-0.0000**	0.0002***	-0.0000
	(8.08)	(-3.18)	(25.11)	(-1.12)
$LEVERAGEQ_{peer}$	0.0005***	0.0002	0.0009***	-0.0017**
	(11.67)	(0.78)	(3.33)	(-2.88)
$ROAQ_{peer}$	-0.0013***	0.0004	-0.0140***	0.0045***
	(-8.13)	(1.61)	(-18.12)	(7.26)
$LOSSQ_{peer}$	0.0010***	-0.0001*	0.0056***	0.0000
	(40.43)	(-2.29)	(44.97)	(0.18)
Firm#Peer FE	No	No	No	No
Firm#Peer#Year FE	No	Yes	No	Yes
Year#Quarter FE	No	No	No	No
#Observations	9,513,761	9,513,761	8,791,287	8,791,287
Adj. R^2	0.78	0.86	0.84	0.93

The Table reports the effect of confidential filings by rivals on firms' future R&D investments. While Columns 1 and 3 reports the results without fixed effects, Columns 2 and 4 include firm-peer-year fixed effects for one-quarter and one-year ahead R&D investments, respectively. Confidential dummy takes the value of one when a rival issues at least one redacted filing in a given quarter. See Appendix A for the description of variables. *, **, *** show the significance levels at 10%, 5%, 1%, respectively. The standard errors are clustered at the firm-peer level and t-statistics are reported in parantheses.

Table 4. Future Product Similarity

	$Similarity_{ij,t+1}$		$Similarity_{ij,t+2}$		$Similarity_{ij,t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Confidential dummy	**0.0010***	**0.0003***	**0.0016***	**0.0006***	**0.0016***	**0.0004***
	(23.13)	**(10.54)**	**(25.34)**	**(16.66)**	**(18.51)**	**(7.43)**
Similarity score	0.8608***	0.7595***	0.8036***	0.6839***	0.7580***	0.6386***
	(259.06)	(186.10)	(206.59)	(165.09)	(163.25)	(141.01)
RDQ_{firm}	0.0258***	-0.0012***	0.0373***	0.0017***	0.0412***	0.0010*
	(35.12)	(-3.76)	(39.78)	(4.31)	(34.19)	(2.00)
Missing $R\&DQ_{firm}$	0.0022***	-0.0000	0.0037***	0.0002**	0.0047***	-0.0001
	(22.90)	(-0.45)	(28.06)	(2.81)	(26.56)	(-1.02)
MBQ_{firm}	0.0000***	0.0000***	0.0000***	-0.0000**	0.0000	0.0000***
	(3.94)	(3.65)	(3.59)	(-3.07)	(0.12)	(4.43)
$LEVERAGEQ_{firm}$	-0.0019***	-0.0016***	-0.0028***	-0.0008***	-0.0033***	-0.0020***
	(-19.34)	(-12.53)	(-18.86)	(-4.12)	(-15.81)	(-11.01)
$ROAQ\_{firm}$	0.0053***	-0.0006***	0.0073***	0.0006***	0.0075***	-0.0009***
	(21.90)	(-4.48)	(20.47)	(3.66)	(14.71)	(-4.70)
$LOSSQ\_{firm}$	0.0021***	-0.0001***	0.0027***	0.0001***	0.0031***	0.0001*
	(28.93)	(-3.65)	(29.98)	(3.33)	(27.12)	(2.46)
$Size_{firm}$	0.0001***	-0.0000	0.0000*	0.0001**	-0.0001***	-0.0004***
	(10.76)	(-1.80)	(1.96)	(3.11)	(-3.45)	(-10.60)
$Size_{peer}$	0.0002***	0.0006***	0.0001***	0.0007***	-0.0000	0.0002***
	(13.45)	(24.37)	(4.19)	(18.11)	(-1.85)	(4.01)
RDQ_{peer}	0.0255***	0.0075***	0.0368***	0.0108***	0.0400***	0.0066***
	(36.27)	(19.41)	(40.50)	(17.97)	(34.21)	(7.85)
Missing RDQ_{peer}	0.0020***	-0.0004***	0.0034***	-0.0006***	0.0043***	-0.0003
	(22.17)	(-4.48)	(27.27)	(-3.94)	(25.48)	(-1.27)
MBQ_{peer}	0.0000*	0.0000	0.0000	-0.0000***	-0.0000	-0.0000
	(1.99)	(1.20)	(1.15)	(-4.05)	(-0.37)	(-1.00)
$LEVERAGEQ_{peer}$	-0.0020***	-0.0014***	-0.0029***	-0.0023***	-0.0034***	-0.0038***
	(-19.76)	(-12.81)	(-18.84)	(-13.21)	(-15.98)	(-15.76)
$ROAQ_{peer}$	0.0053***	0.0022***	0.0071***	0.0026***	0.0067***	-0.0008*
	(23.03)	(13.51)	(20.55)	(10.75)	(13.51)	(-2.47)
$LOSSQ_{peer}$	0.0023***	0.0001	0.0029***	0.0002***	0.0032***	-0.0003***
	(30.91)	(1.68)	(31.29)	(5.07)	(26.94)	(-5.20)
Firm#Peer FE	No	Yes	No	Yes	No	Yes
Year#Quarter FE	No	Yes	No	Yes	No	Yes
#Observations	7,197,977	7,197,977	5,052,505	5,052,505	3,498,230	3,498,230
Adj. R^2	0.81	0.90	0.71	0.89	0.64	0.89

The Table reports the effect of confidential filings by rivals on future product similarity between firm and peers. Columns 1, 3, and 5 report the results without fixed effects, while Columns 2, 4, and 6 include firm-peer and year-quarter fixed effects for one-year, two-year, and three-year ahead product similarity, respectively. Confidential dummy takes the value of one when a rival issues at least one redacted filing in a given quarter. See Appendix A for the description of variables. *, **, *** show the significance levels at 10%, 5%, 1%, respectively. The standard errors are clustered at the firm-peer level and t-statistics are reported in parantheses.

Table 5. Redacting Peer Analyses

	$ROAOP_t$	$ROAOP_{t+1}$	$ROAOP_t$	$ROAOP_{t+1}$	$ROAOP_{t+1}$	$Fluidity_t$	$Fluidity_{t+1}$	$Innovation_t$	$Innovation_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Confidential	0.0066**	0.0009				0.0476	0.0820**		
	(2.23)	(0.25)				(1.22)	(2.08)		
License- R&D			0.0148**	0.0155*	0.0761**			0.0135	0.0321**
			(2.59)	(1.95)	(2.17)			(0.84)	(2.23)
License - R&D #					-0.0254*				
log(Fluididity)					(-1.68)				
Supply			-0.0064*	-0.0108**	-0.0106**				
			(-1.72)	(-2.01)	(-1.96)				
Financing			-0.0059	-0.0026	-0.0024				
			(-1.43)	(-0.40)	(-0.38)				
Employment			0.0066	0.0016	0.0005				
			(0.60)	(0.11)	(0.04)				
Investment			-0.0058	0.0050	0.0047				
			(-0.73)	(0.48)	(0.45)				
Peer			0.0089	0.0027	0.0054				
			(1.19)	(0.25)	(0.48)				
Service			-0.0141	-0.0087	-0.0088				
			(-1.33)	(-0.49)	(-0.50)				
#Observation	30,851	28,305	30,851	28,305	28,305	30,891	28,328	28,603	24,120
Adj. R	0.76	0.72	0.84	0.72	0.72	0.86	0.84	0.77	0.79
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the effect of confidential filings on future performance of redacting firm. ROAOP is the operating income before R&D and depreciation scaled by total assets. Fluidity is the product market rivalry by Hoberg et al. (2014) based on rival movements in product space. Innovation (in logarithm) is the text-based innovation measure by Ahci and Joos (2019). See Appendix A for the description of variables. *, **, *** show the significance levels at 10%, 5%, 1%, respectively. The standard errors are clustered at the firm level and t-statistics are reported in parantheses.

Table 6. Robustness Tests

	$Similarity_{ij,t+1}$	$Similarity_{ij,t+1}$	$Similarity_{ij,t+1}$	$Similarity_{ij,t+1}$
	(Alternative)	(no customer-supplier)	(no joint agreements)	(decomposition)
	(1)	(2)	(3)	(4)
Confidential dummy		0.0001***	0.0001***	
		(3.60)	(4.29)	
Log(confidential)$_{\text{peer}}$	0.0002***			
	(6.56)			
Log(other exhibits)$_{\text{peer}}$	-0.0000			
	(-0.25)			
License - R&D				0.0004***
				(9.36)
Supply				-0.0000
				(-0.48)
Financing				0.0007***
				(8.80)
Employment				0.0008***
				(4.48)
Investment				-0.0006***
				(-4.49)
Peer				-0.0003***
				(-4.47)
Service				0.0005**
				(2.43)
Others				-0.0005***
				(-11.00)
Controls Firm	Yes	Yes	Yes	Yes
Controls Peer	Yes	Yes	Yes	Yes
Firm#Peer FE	Yes	Yes	Yes	Yes
Year#Quarter FE	Yes	Yes	Yes	Yes
#Observations	7,197,977	7,176,044	7,042,226	7,197,977
Adj. R^2	0.90	0.90	0.90	0.90

The table reports the robustness test results of the effect of confidential filings on future product similarity between firm and peers with alternative treatment variable (Column 1), removing customer-supplier firms from the sample (Column 2), removing collaboration contracts (Column 3), and the decomposition of contract types (Column 4). See Appendix A for the description of variables. *, **, *** show the significance levels at 10%, 5%, 1%, respectively. The standard errors are clustered at the firm-peer level and t-statistics are reported in parantheses.

Table 7. Additional Analyses and Moderating Effects

	$RDY_{i,y+1}$	$Similarity_{ij,t+1}$	$Similarity_{ij,t+1}$	$Similarity_{ij,t+1}$	$Similarity_{ij,t+1}$
	(1)	(2)	(3)	(4)	(5)
Confidential dummy	0.0029***	0.0004***	0.0004***	0.0001***	0.0002***
	(6.21)	(8.86)	(9.16)	(4.19)	(3.32)
Confidential # ***$Size_{firm}$***	-0.0004***				
	(-6.53)				
Confidential # ***Strong rival***		-0.0005***			
		(-8.75)			
Confidential # ***$TotalSimilarity_{peer}$***			-0.0000***		
			(-8.34)		
Confidential # ***ΔRDQ_{peer}***				0.0035***	
				(6.38)	
Confidential # ***Same state***					-0.0001
					(-1.70)
Strong rival		0.0001			
		(0.96)			
$TotalSimilarity_{peer}$			0.0001***		
			(17.63)		
ΔRDQ_{peer}				-0.0022***	
				(-6.51)	
Same state					0.0004**
					(2.20)
#Observations	8,791,287	7,197,977	7,197,977	7,197,977	7,197,977
Adj. R^2	0.93	0.90	0.90	0.90	0.90
Firm & Peer controls	Yes	Yes	Yes	Yes	Yes
Firm#Peer#(Year) FE	Yes	Yes	Yes	Yes	Yes
Year-Q FE	Yes	Yes	Yes	Yes	Yes

The table reports the moderating effects of size, relationship between firm-peers and current market structure of redacting peers on the effect of redactions on peers' investment. See Appendix A for the description of variables. *, **, *** show the significance levels at 10%, 5%, 1%, respectively. The standard errors are clustered at the firm-peer level and t-statistics are reported in parantheses.

Table 8. Information Demand for Confidential Filings

	All material exhibits (Exhibits 10.XX)						Main filings	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Confidential dummy	*0.456****	*0.517****	*0.431****	*0.430****				
	(15.35)	*(27.05)*	*(24.05)*	*(21.09)*				
Confidential filing							-0.117***	-0.020
							(-4.35)	(-1.27)
Log(main filing)	0.095***	-0.033***	-0.118***		-0.033***			
	(6.44)	(-3.49)	(-4.25)		(-3.50)			
License-RD dummy					0.544***	0.445***		
					(15.17)	(11.41)		
Supply dummy					0.079*	0.092**		
					(2.24)	(2.59)		
Financing dummy					0.667***	0.516***		
					(18.35)	(11.15)		
Employment dummy					0.103*	0.169**		
					(2.43)	(2.45)		
Investment dummy					0.510***	0.370***		
					(9.62)	(5.56)		
Peer dummy					0.416***	0.393***		
					(9.92)	(6.82)		
Service Consult					0.053	0.095		
					(0.58)	(0.86)		
Other					0.433***	0.345***		
					(16.44)	(14.00)		
# Observations	144,454	144,454	144,454	144,454	144,454	144,454	51,125	51,125
Adj. R^2	0.04	0.46	0.63	0.60	0.46	0.60	0.00	0.47
Firm FE	No	Yes	No	Yes	Yes	Yes	No	Yes
Year#Quarter FE	No	Yes	No	Yes	Yes	Yes	No	No
Firm#YearQ FE	No	No	Yes	No	No	No	No	No
Form Type FE	No	Yes	Yes	No	Yes	No	No	No
Filing FE	No	No	No	Yes	No	Yes	No	No

The Table shows the downloads of confidential exhibits (columns 1-6) and the main filings to which confidential exhibits are attached (columns 7-8) compared to their non-confidential counterparts. Confidential dummy takes the value of one when the material exhibit contains confidential contract. Similarly, confidential filing takes the value of one when any redacted material exhibit is attached to the form type of 10-Q or 10-K. See Appendix A for the description of variables. *, **, *** show the significance levels at 10%, 5%, 1%, respectively. The standard errors are clustered at the firm level and t-statistics are reported in parantheses.

Table 9. Attention Mechanism Tests

	$\Delta Similarity_{ij,t+2}$	$RDY_{t+1,\ firm}$	$\Delta Similarity_{ij,t+2}$	$RDY_{t+1,\ firm}$
	(1)	(2)	(3)	(4)
Confidential dummy	0.0004***	0.0004***	0.0002***	0.0006**
	(0.000)	(0.000)	(0.000)	(0.000)
Confidential # Exo_CEO_shock	-0.0018***	-0.0024**		
	(0.000)	(0.001)		
Confidential # Post_fincrisis			-0.0003***	-0.0044***
			(0.000)	(0.000)
Exo_CEO_shock	-0.0011***	-0.0037***		
	(0.000)	(0.000)		
Other_CEO_shock	0.0005**	-0.0014***		
	(0.000)	(0.000)		
Post_fincrisis # $RDQ_{q+1,\ firm}$			0.0075***	-0.0210***
			(0.001)	(0.005)
#Observations	4,272,576	4,272,576	2,790,512	4,416,351
Adj. R^2	0.61	0.89	0.63	0.90
Firm and Peer Controls	Yes	Yes	Yes	Yes
Firm#Peer FE	Yes	No	Yes	No
Year_quarter FE	Yes	No	Yes	No
Firm-peer#year	No	Yes	No	Yes

The Table reports the results for attention mechanism tests using two quasi-natural experiments, namely exogenous CEO departures of firms and 2008 financial crisis. See Appendix A for the description of variables. *, **, *** show the significance levels at 10%, 5%, 1%, respectively. The standard errors are clustered at the firm-peer level and t-statistics are reported in parantheses.

Scientific summary

This dissertation comprises three essays investigating corporate disclosures and their impact on corporate investments, particularly investments in innovation. The study delves into the critical role of innovation, a driver of economic growth and business success, which also sparks debates on the value-relevance of accounting disclosures.

The first essay develops a text-based innovation measure based on financial statement text, filling the gap of inability of conventional proxies, such as R&D investments and patents, in measuring the broad array of firms' innovative activities. This measure proves valuable in understanding firms' strategic assets and predicting future growth, market performance, and net income. The second essay explores the implications of innovation-related disclosures on managerial decisions and how the separation or bundling of information releases affects firms' ability to gather information from stock prices. The third essay investigates firms' incentives to disclose innovation-related investments while considering proprietary costs and their potential benefits for rival firms. Overall, this dissertation contributes to understanding the dynamics of corporate disclosures, their effects on capital markets and firms' investment choices, and the complexities surrounding proprietary costs of these disclosures.

Wetenschappelijke samenvatting

Dit proefschrift bestaat uit drie essays over corporate disclosures en hun impact op bedrijfsinvesteringen. Het proefschrift onderzoekt de cruciale rol van innovatie, een drijvende kracht achter economische groei en zakelijk succes, wat tevens debatten aanwakkert over de waarde-relevantie van disclosures.

Het eerste essay ontwikkelt een innovatiemaatstaf op basis van tekst uit financiële overzichten zonder de gebreken van bestaande maatstaven zoals R&D-investeringen en patenten. Deze maatstaf helpt om inzicht te krijgen in de strategische activa van bedrijven en om toekomstige groei, marktprestaties en nettowinst te voorspellen. Het tweede essay onderzoekt de implicaties van innovatie-disclosures op investeringen en hoe het scheiden of bundelen van informatieverstrekking van invloed is op het vermogen van bedrijven om informatie uit aandelenkoersen te halen. Het derde essay onderzoekt de prikkels van bedrijven om investeringen in innovatie bekend te maken, waarbij rekening wordt gehouden met de kosten van het vrijgeven van informatie en de potentiële voordelen voor concurrerende bedrijven. Over het geheel genomen draagt dit proefschrift bij aan de kennis van de dynamiek van corporate disclosures, hun effecten op kapitaalmarkten en de investeringen van bedrijven, en de complexiteit rond de kosten van deze disclosures.

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This dissertation comprises three essays investigating corporate disclosures and their impact on corporate investments, particularly investments in innovation. The study delves into the critical role of innovation, a driver of economic growth and business success, which also sparks debates on the value-relevance of accounting disclosures.

The first essay develops a text-based innovation measure based on financial statement text, filling the gap of inability of conventional proxies, such as R&D investments and patents, in measuring the broad array of firms' innovative activities. This measure proves valuable in understanding firms' strategic assets and predicting future growth, market performance, and net income. The second essay explores the implications of innovation-related disclosures on managerial decisions and how the separation or bundling of information releases affects firms' ability to gather information from stock prices. The third essay investigates firms' incentives to disclose innovation-related investments while considering proprietary costs and their potential benefits for rival firms. Overall, this dissertation contributes to understanding the dynamics of corporate disclosures, their effects on capital markets and firms' investment choices, and the complexities surrounding proprietary costs of these disclosures.

Mustafa Ahçı (Istanbul, Turkey) is an assistant professor of accounting at the Rotterdam School of Management, Erasmus University. He completed his BSc degree in Electrical & Electronics Engineering before pursuing his passion for finance and accounting. Mustafa earned his MSc (research) degree in Business (Finance) from Bilkent University and graduated with distinction form Research Master's degree in Business (Accounting) from Tilburg University. Before embarking on his academic journey, Mustafa worked for seven years as a government professional in the Ministry of Treasury and Finance of Turkey. In 2019, he began his PhD in Accounting, and during this academic pursuit, he had the privilege of visiting Columbia Business School in New York as a visiting scholar.

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