Corporate Innovation Strategy and Narrative Disclosures

by

Yixing (Ivee) Che

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Doctor of Philosophy
in
Accounting

Waterloo, Ontario, Canada, 2024

Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner	NAME: Hai Lu Title: McCutcheon Professor in International Business and Professor of Accounting
Supervisor	NAME: Changling Chen Title: Associate Professor of Accounting
Internal Member	NAME: Xin Daniel Jiang Title: Assistant Professor of Accounting
Internal Member	NAME: Theophanis C. Stratopoulos Title: PwC Professor of Accounting
Internal-external Member	NAME: Jean-Paul Lam Title: Associate Professor of Economics

Author’s Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.
I understand that my thesis may be made electronically available to the public.

Abstract

In this thesis, I examine how firms with different prioritizations of innovation strategy utilize narrative disclosures in their 10-K filings to communicate information about their innovation activities. I hypothesize and find that firms with a greater focus on exploratory innovations (versus exploitative innovations) disclose less narrative innovation information based on a cost-benefit tradeoff. Conducting a content analysis of the quality of narrative innovation disclosures, I find that exploration-focused firms tend to disclose fewer details but use a more positive tone in their disclosures compared to exploitation-focused firms. The tendency for exploration-focused firms to employ a more positive tone in narrative disclosures may be due to managerial overconfidence rather than management opportunism or firm performance. I also find that product market competition and technology spillover have opposite effects on narrative innovation disclosures due to their different proprietary cost implications. The negative relation between exploration-focused firms and narrative innovation disclosures is more pronounced when product market competition intensifies, while it becomes less pronounced when technology spillover becomes more prominent. Finally, I find that narrative innovation disclosures enhance investors' understanding of innovative activities and reduce misvaluation and future stock price crash risk for exploration-focused firms. My thesis contributes to the disclosure and innovation literature with insights into how firms' innovation strategies affect their narrative innovation disclosure decisions, which helps investors better evaluate corporate innovation strategy.

Acknowledgments

I would like to express my deepest gratitude to my supervisor, Changling Chen, for her invaluable guidance, mentorship, and support. Her insightful advice and encouragement have been influential in shaping me into a professional academic scholar. Beyond academia, her dedicated spirit and positive attitude have greatly contributed to my personal growth. It is both an honor and a privilege to have her as a role model throughout my Ph.D. journey.

I would also like to thank members of my dissertation committee: Xin Daniel Jiang, Jean-Paul Lam, Hai Lu, and Theophanis C. Stratopoulos for their encouragement, feedback, and directions. Their comments and suggestions have greatly improved this thesis.

I have also benefited from detailed and thoughtful comments from Andrew Bauer, Tim Bauer, Elizabeth Demers, Wenqian Hu, Alan Huang, Ross Lu, Seda Oz, Alan Webb, Mingyue Zhang, and participants at the University of Waterloo seminar and various workshops.

I would also like to thank the faculty and staff at School of Accounting and Finance, University of Waterloo, for their warm-hearted help and support during the Ph.D. program. I also thank fellow doctoral students for all the motivating discussions and encouragement.

Finally, my deepest appreciation goes to my mother, Fengrong, my fiancé, Junqiang, and my beloved family for their invaluable support, unconditional love, and steadfast belief in me every step of the way.

Dedication

I dedicate this dissertation to my father, Zilei, whose memory continues to inspire me. May you always take pride in my accomplishments.

Table of Contents

List of Figures

List of Tables

Chapter 1
Introduction

Corporate innovation strategy varies among firms, with exploration and exploitation at the two ends of the continuum for innovation (Gupta et al., 2006).[1] This spectrum reflects the degree of overlap in which knowledge utilized in innovation is drawn from the firm's existing knowledge pool (Lavie et al., 2010). A lower degree of overlap indicates an emphasis on exploratory innovations, whereas a higher degree of overlap indicates a focus on exploitative innovations (Fitzgerald et al., 2021).[2] Firms with a higher proportion of exploratory innovations are known as exploration-focused firms, while those with a higher proportion of exploitative innovations are known as exploitation-focused firms. Since technological innovation is a primary driver of long-term economic growth (Solow, 1957), the ability of firms to innovate and improve technology is crucial not only for their success but also for their survival (Eisdorfer & Hsu, 2011; Galor & Weil, 2000). Corporate innovation strategy outlines objectives, supports alignment, and concentrates efforts within the firms, which enables managers to make tradeoff decisions and prioritize innovation initiatives effectively (Pisano, 2015). This thesis examines how firms' innovation strategies affect their narrative innovation disclosure decisions and how the implications of innovation disclosures, combined with different innovation strategies, affect investors' valuation.

Firms face challenges in effectively conveying the value of their innovation activities using accounting numbers (Canibano et al., 2000) because the accounting standard requires firms to

[1] Innovation in this thesis is defined as the technological innovation that uses new technologies to improve products, services, or efficiency, to enhance firm operation and performance.
[2] For instance, the transition from manual-wind watches to automatic watches in watch manufacturing represents exploitation, as the knowledge required for manufacturing automatic watches largely stems from existing knowledge about mechanical technology. In contrast, the shift from mechanical watches to battery-powered digital watches represents exploration, as it involves a move from established mechanical technology to quartz technology with minimal overlap with existing knowledge. The degree of overlap between a firm's new technology and existing technology determines the position of the innovation along the exploration-exploitation spectrum (Lavie et al., 2010).

immediately expense (rather than capitalize) the research and development (R&D) investments.[3] This exacerbates the information asymmetry between managers and investors (Lev & Sougiannis, 1999). Moreover, prior research shows that investors tend to overvalue exploration-focused firms compared to exploitation-focused firms (Fitzgerald et al., 2021; Jia, 2018).

Exploitation involves a steady improvement or extension of existing innovative knowledge, while exploration requires firms to venture into unfamiliar territory. The different nature of these two strategies is associated with different financial reporting implications. Exploration has a more uncertain nature and a higher failure rate than exploitative innovation, which likely leads to a higher probability of unsatisfactory earnings performance (Fitzgerald et al., 2021). Therefore, investors face increased information asymmetry when evaluating exploration-focused firms and need to rely on alternative information channels, such as narrative innovation disclosures, for insights into the firm's future growth and competitiveness. Narrative innovation disclosures can play a pivotal role in bridging the gap between a firm's financial statement numbers and its underlying business fundamentals (Merkley, 2014) with information about R&D, products, patents, and other innovation-related activities.

In this thesis, I first explore whether firms with different innovation strategies make different decisions regarding narrative innovation disclosures. The decision of firms to disclose information involves a tradeoff between mitigating information asymmetry and managing proprietary costs (i.e., disclosures related to innovation may attract competition and imitation, potentially eroding the firm's

[3] Under U.S. Generally Accepted Accounting Principles (GAAP) as per Accounting Standards Codification (ASC 730-10-25), firms must expense R&D costs on their financial statements unless certain costs meet criteria for capitalization with alternative future uses. Under International Financial Reporting Standards (IFRS), specifically International Accounting Standard (IAS) 38, research costs are also expensed like U.S. GAAP. However, there is a distinction in the treatment of development costs. Unlike U.S. GAAP, IFRS allows capitalization of development costs only when the technical and commercial feasibility of the asset for sale or use has been established. This implies that firms must have the intent and capability to complete, utilize, or sell intangible assets and demonstrate how the assets will generate future economic benefits.

competitive advantage; Cao et al., 2018).[4] While some firms may opt for more extensive innovation-related disclosures to address information asymmetry between firms and investors, others may restrict disclosures to mitigate proprietary costs, particularly when sensitive or detailed information regarding core operations is at stake (Ryou et al., 2022). The distinct nature of their innovation strategies leads exploration-focused and exploitation-focused firms to make different disclosure decisions.

The extent to which exploration-focused firms benefit from disclosures in alleviating information asymmetry compared to exploitation-focused firms remains uncertain. On the one hand, March's (1991) theoretical framework suggests that exploration-focused firms typically experience higher levels of informational asymmetry and earnings volatility. This volatility reduces the predictability of reported earnings, making it challenging for investors to assess their financial performance accurately (Hayn, 1995). As a result, investors of exploration-focused firms demand more information about innovation activities to better understand future cash flows and associated uncertainty. On the other hand, exploitation-focused firms might benefit more from reducing information asymmetry with investors. Cognitive biases lead investors to pay more attention to radical exploratory innovations than to incremental exploitative innovations (Fitzgerald et al., 2021). This limited attention can result in stock returns that do not fully reflect all available information (e.g., Li & Yu, 2012). Thus, exploitation-focused firms may need to provide substantial investor guidance to signal the profitability of exploitative innovations. However, it remains unclear which type of firm provides a higher quantity of narrative innovation disclosures to mitigate information asymmetry.

However, exploration-focused firms potentially face higher proprietary costs when disclosing detailed information about their innovation activities, compared to exploitation-focused firms (Jia,

[4] Both adverse selection and moral hazard can lead to information asymmetry between insiders (i.e., managers) and outsiders (i.e., investors). Adverse selection occurs when firm managers possess information that investors do not, leading investors to assume that firms lack transparency and, as a result, to assume the worst. Moral hazard, on the other hand, involves managers taking actions that benefit themselves personally, often not observable by investors. Although this thesis does not primarily focus on moral hazard, Section 7.2.3.2 addresses the effect of management opportunism.

2019). This is because such disclosures can provide competitors with valuable insights that may enable them to make entry-exit decisions or imitate products, thereby jeopardizing the competitive position of disclosing firms in the market (Darrough & Stoughton, 1990; Verrecchia, 1983). With limited public information on exploratory innovation, competitors find disclosures from exploration-focused firms more valuable (Kaplan & Tripsas, 2008; Rindova & Petkova, 2007). Prior research shows that exploration-focused firms issue more frequent but less accurate earnings forecasts and provide fewer updates on innovative activities (Jia, 2017, 2019). These findings indicate that for exploration-focused firms, the proprietary costs of disclosures outweigh the potential benefits of reducing information asymmetry. Therefore, I hypothesize that exploration-focused firms may opt to disclose less narrative innovation information to avoid higher proprietary costs compared to exploitation-focused firms.[5]

Second, I examine two factors influencing innovation disclosures in firms with different innovation strategies: product market competition and technology spillover. Product market competition refers to the level of competition among existing rivals for the same product space, whereas technology spillover represents the firm's capacity to gain advantages from the technological knowledge generated by its peers. Although there exists some overlap between peer firms in the product market space (product market competition) and those in the technology space (technology spillover), they are distinct enough to allow for empirical analysis (Bloom et al., 2013). Successful exploration yields a more significant competitive advantage than successful exploitation (Jia, 2019). As product market competition intensifies, exploration-focused firms face higher proprietary costs due to the unique knowledge development inherent in exploratory innovation. In contrast, technology spillover enables more efficient innovation by leveraging research from peers in similar fields (Jaffe,

[5] However, it is important to consider that the cost-benefit tradeoff associated with reducing narrative innovation disclosures may differ from the tradeoff linked to less precise earnings forecasts and fewer news releases. Factors such as the inherent uncertainty in exploration, litigation risks, regulatory obligations, and perceived transparency and credibility can play a role in this variation.

1986), benefiting exploration-focused firms through shared information across industries (Cao et al., 2018). Therefore, I expect that exploration-focused firms tend to provide (1) fewer narrative innovation disclosures when facing intense product market competition to mitigate proprietary costs and (2) more such disclosures when technology spillover is high to benefit from technological synergy than exploitation-focused firms.

My sample includes innovation-intensive firms that applied for at least one patent per year from 1994 to 2018. I obtain cleaned 10-K filings from Bill McDonald's website, available since 1994.[6] I measure the quantity of narrative innovation disclosures as the natural logarithm of the total number of innovation-related sentences in a firm's 10-K filing. I identify innovation-related words by conducting the textual analysis using a modified keyword list from Merkley (2014). I retrieve patent-related data from Stoffman et al. (2022), originally from the United States Patent and Trademark Office (USPTO), spanning 1976 and 2021. My sample ends in 2018, with a three-year buffer before the patent data ends in 2021 to alleviate truncation issues (i.e., patent data becomes incomplete when patent application dates move closer to the end of the dataset). To operationalize the construct of corporate innovation strategy, I follow the literature and employ a continuous ratio by dividing the number of exploratory patents applied for in a year by the total number of patents applied for in that year (Fitzgerald et al., 2021; Jia, 2018). A higher (lower) ratio indicates a greater emphasis on exploratory (exploitative) innovation activities. I collect financial statement data from Compustat and stock return data from the Center for Research in Security Prices (CRSP) for U.S. publicly listed firms. I retrieve analyst data from IBES and executive compensation data from ExecuComp. My final sample consists of 18,560 firm-year observations from 3,107 unique firms.

My results are consistent with my predictions. I find that exploration-focused firms tend to disclose less narrative innovation information compared to their exploitation-focused counterparts. To

[6] I discuss the advantages and features of narrative innovation disclosures within the context of the 10-K filings in Section 2.3.3.

enhance the robustness of my analysis, I incorporate lagged independent variables as well as year, industry, and/or firm fixed effects. My results hold after controlling for potential endogeneity and conducting additional tests to strengthen the causal inference. To address concerns about sample selection bias, omitted correlated variables, and reverse causality (simultaneity), I use various methodologies including propensity score matching, instrumental variables, change specification, and Regulation Fair Disclosure as an exogenous shock. These additional tests help strengthen the validity and reliability of my findings.

I further examine the moderating effects of product market competition (calculated as the cosine similarity of segment sales distribution between the focal firm and its competitors in the product market) and technology spillover (calculated as the cosine similarity of patent distributions across technology classes between the focal firm and its peers) on the relation between a firm's innovation strategy and narrative innovation disclosures. I find that product market competition has a more negative effect on exploration-focused firms than exploitation-focused firms, leading to a reduction in narrative innovation disclosures when competition intensifies. In contrast, technology spillover has a more positive effect on exploration-focused firms than exploitation-focused firms, encouraging firms to increase their narrative innovation disclosures as technology spillover becomes more prominent.

Considering the potential skewness in patent data, I examine extreme cases where firms applied for only one patent in a year and conduct subsample analyses. The results consistently indicate the robust and enduring effect of a firm's innovation strategy on narrative innovation disclosures. Given the substantial variations in innovation across industries, it is crucial to examine innovation-intensive versus non-innovation-intensive industries. To address this concern, I perform a subsample analysis by comparing the top 10 innovation-intensive industries with other industries. Also, considering the significance of firm-specific innovation activities, I conduct subsample analyses by comparing firms above and below the sample mean in patent application activities and size. In addition to proprietary costs, firms may also consider the litigation risk associated with disclosing sensitive information. Exploration-focused firms, which often operate in industries with high litigation risks, may be particularly concerned about these risks and therefore may refrain from disclosing certain information. I compare firms in industries with low litigation risks to those in industries with high litigation risks. My findings suggest that the tendency for exploration-focused firms to disclose less than exploitation-focused firms is generalizable to sample firms in non-innovation-intensive industries, those with lower frequencies of patent application activities, those with smaller sizes, and those operating in industries with low litigation risks.

An alternative explanation could be that firms combine R&D expenses with other expenditures to protect proprietary information (Koh & Reeb, 2015). Firms that do not report R&D might have higher proprietary costs than those that do, which aligns with the traits of exploration-focused firms. I find that whether firms report R&D does not explain the proprietary cost differences between exploration-focused and exploitation-focused firms. Furthermore, I examine the relationship between narrative innovation disclosures and other voluntary disclosure channels, such as management forecasts. The findings suggest that exploration-focused firms are more likely to use management forecasts and narrative innovation disclosures as substitutes compared to exploitation-focused firms, highlighting their concerns about the proprietary costs associated with narrative innovation disclosures.

In robustness checks, I perform several tests to ensure the validity of my measures. Regarding the innovation strategy measure, I extend the search period for a firm’s existing knowledge pool, utilize alternative thresholds to categorize whether a patent is exploratory, and employ alternative measures such as the exploitative ratio. For alternative disclosure measures, I rerun regressions using measures derived from Merkley’s keyword list. In addition, I substitute the sentence count of disclosures with the word count to assess the consistency and robustness of the results.

In evaluating the effect of narrative innovation disclosures on investors’ ability to assess exploration-focused firms, I conduct consequence analyses. These analyses aim to determine whether narrative innovation disclosures aid investors in evaluating firms with different innovation strategies. First, I perform short-term market reaction tests to examine the initial investor reaction to corporate innovation strategy and narrative innovation disclosures. Fitzgerald et al. (2021) observe that investors have a preference bias toward exploratory innovations over exploitative ones, resulting in the undervaluation of exploitation-focused firms. This indicates that exploration-focused firms are more likely to be overvalued by investors. I find some evidence suggesting that narrative innovation disclosures play a role in attracting investors' attention and improving their understanding of firms' innovative activities. This increased transparency enables investors to take corrective actions. Therefore, narrative innovation disclosures serve as a mitigating factor, contributing to the reduction of potential overvaluation associated with exploration-focused firms.

Second, I conduct long-term stock price crash risk tests. Jia (2018) finds that firms with a greater focus on exploratory (exploitative) innovations are positively (negatively) related to stock price crash risk, indicating that investors underestimate the risk of exploration-focused firms that later experience downward corrections in stock prices. The author posits that one reason that leads to crash risk for exploration-focused firms can be through managers withholding interim bad news. Narrative innovation disclosures can inform investors about firms' R&D and in-process innovation activities and the fundamental risk of exploratory innovation. By providing such disclosures, firms prevent managers from withholding interim negative news until the completion of innovative activities, thereby mitigating stock price crash risk. My findings suggest that as exploration-focused firms provide adequate narrative innovation disclosures, investors gain insights into the firm's innovation strategy. This reduction in information asymmetry leads to a decreased likelihood of future stock price crashes.

It is worth considering that firms may also adjust the quality of their narrative innovation disclosures that do not necessarily enhance their relevance. To examine the qualitative characteristics of innovation-related disclosures, I measure the numerical, forward-looking, repetitive, and tone of narrative innovation disclosures (Brown & Tucker, 2011; Henry, 2008; F. Li, 2010; Merkley, 2014). I find that compared to exploitation-focused firms, exploration-focused firms tend to disclose fewer details in numerical, forward-looking, and repetitive terms, aligning with H1 and the baseline findings on innovation disclosure quantity. Moreover, I find that firms with greater exploratory intensity tend to employ a more positive tone in their narrative innovation disclosures. Various factors may contribute to this tone usage, including operational characteristics, management opportunism, and management dispositional characteristics (Luo & Zhou, 2020). My findings are consistent with the third argument: firms with overconfident executive teams are more likely to use a positive tone in disclosures than those with less overconfident executive teams. This suggests that exploration-focused firms tend to use a more positive tone in narrative disclosures, possibly due to managerial overconfidence.

For conditional analyses, I find that the effect of product market competition on the detail of narrative innovation disclosures is more negative for exploration-focused firms than exploitation-focused firms. In contrast, the effect of technology spillover on the detail of narrative innovation disclosures is more positive for exploration-focused firms than exploitation-focused firms. Moreover, the positive effect of exploratory innovation strategy on the tone of innovation disclosures is less pronounced in the presence of increased technology spillover. One possible explanation for this phenomenon is that when technology spillover is high and innovations are more readily shared or accessible across firms, there may be an increased risk of legal disputes over intellectual property and patent infringement. This heightened litigation risk could lead exploration-focused firms to adopt a more cautious or reserved tone in their narrative innovation disclosures (Luo & Zhou, 2020). However, I do not find the effect of product market competition on the relation between corporate innovation strategy and narrative innovation disclosure tone.

In addition to product market competition and technology spillover, I also examine how corporate innovation strategy affects firms' disclosure behaviors when facing technological peer pressure (also known as technology-based product market competition). Technological peer pressure involves firms undertaking R&D initiatives to innovate new products and processes, thereby securing future market competitiveness (Cao et al., 2018). However, limited evidence exists regarding the effect of technological peer pressure on corporate disclosure. Furthermore, there is a gap in understanding how different innovation strategies influence disclosure practices. My findings show that exploration-focused firms tend to disclose more information when faced with high technological peer pressure. This suggests that when competition focuses on technology and innovation, the effect of technological peer pressure aligns with that of technology spillover.

My thesis makes the following contributions. First, my thesis responds to calls from Glaeser and Lang (2024) and Simpson and Tamayo (2020) to study the effect of innovation on financial reporting. Different from prior studies that assume different innovation strategies have an equal effect on disclosure (e.g., Jones, 2007; Merkley, 2014), I extend the literature by investigating how firms with different prioritizations of innovation strategy affect their disclosure decisions. Moreover, prior studies focus on the determinants of firms' choices of innovation strategy between exploration and exploitation (e.g., McGrath, 2001; Smith & Tushman, 2005). Evidence on the consequences of innovation strategy is growing but limited (Fitzgerald et al., 2021; Jia, 2018; Katila & Ahuja, 2002; Uotila et al., 2009; Yang, 2023). My thesis adds insights into how different innovation strategies shape firms' disclosure policies, particularly in the context of narrative innovation disclosures.

Second, my thesis fills a void in the literature by examining how proprietary costs influence firms' disclosure decisions based on their different innovation strategies. Existing research identifies firm characteristics, information asymmetry, and proprietary costs as determinants of innovation disclosures (Gu & Li, 2003; Jones, 2007; Merkley, 2014). Prior studies show initial evidence that exploration-focused (versus exploitation-focused) firms issue more frequent earnings forecasts and less innovation-related news to meet analysts' information demand by avoiding disclosing proprietary information (Jia, 2017, 2019). My thesis examines how product market competition and technology spillover affect the relation between corporate innovation strategy and narrative innovation disclosures differently because of their distinct impacts on proprietary costs. Specifically, my thesis highlights that product market competition functions as a form of proprietary cost, by leading to a reduction in the disclosure of proprietary information. In contrast, technology spillover can motivate exploration-focused firms, which have more proprietary information by nature, to disclose more innovation information. This nuanced perspective adds depth to the current understanding of the determinants of narrative innovation disclosures.

Third, my thesis contributes to the ongoing discussion on enhancing the value-relevance of accounting models in capturing the financial position of innovative firms (Anagnostopoulou, 2008). Previous research highlights the valuation issues of corporate innovation strategy, leading to the potential misallocation of resources among firms with different innovation strategies (Fitzgerald et al., 2021; Jia, 2018). The literature has examined the value relevance of some innovation-related metrics, such as R&D investments and patents, revealing the market's difficulty in evaluating innovative firms (e.g., Cohen et al., 2013; Hirshleifer et al., 2018; Lev et al., 2005). This challenge is exacerbated for firms with different innovation strategies (Jia, 2018). My thesis investigates whether narrative innovation disclosures aid investors in assessing corporate innovation strategy, bringing greater attention to these disclosures in 10-K filings. My findings respond to the call from Fitzgerald et al. (2021) to explore the impact of corporate disclosures on investor perceptions of the value of exploration-focused versus exploitation-focused firms.

My thesis also has practical implications by highlighting the importance of narrative innovation disclosures in 10-K filings. Investors seeking to evaluate firms with varying innovation strategies need to pay closer attention to these narrative disclosures. For standard setters, although current standards mandate the disclosure of some innovation-related information, they still allow firms to exercise discretion. This flexibility enables firms to make rational decisions based on a cost-benefit analysis regarding whether, and to what extent, to disclose narrative innovation information to reflect their innovation strategies.

The rest of this thesis proceeds as follows: Chapter 2 provides a review of relevant literature. Chapter 3 develops hypotheses. Chapter 4 outlines the research designs, including sample selection and research models. Chapter 5 presents the results of how corporate innovation strategy affects narrative disclosures. Chapter 6 examines the stock market consequences of corporate innovation strategy on narrative disclosures. In Chapter 7, I conduct additional analyses. Chapter 8 concludes.

Chapter 2
Background and Literature Review

2.1 Introduction

In this chapter, I provide theoretical and regulatory background about corporate innovation strategy and narrative innovation disclosures. In Section 2.2, I first discuss the notion of exploration and exploitation, followed by discussing the definition of corporate innovation strategy and the difference between innovation strategy and other innovation-related metrics. In addition, I discuss the consequences of corporate innovation strategy. In Section 2.3, I describe innovative firms' disclosure decisions. Then, I discuss innovation-related disclosures. I focus on narrative disclosures in 10-K filings because they are suitable channels for firms to communicate with investors. Section 2.4 discusses product market competition and Section 2.5 discusses technology spillover. At the end of this chapter, I highlight the gap in the literature and the contribution of my thesis.

2.2 Corporate Innovation Strategy: Exploration versus Exploitation

2.2.1 The Notion of Exploration and Exploitation

Since the publication of the seminal paper by March (1991), the concept of exploration and exploitation has been studied in a wide variety of literature, such as organizational learning (Levinthal & March, 1993), strategic management (Uotila et al., 2009), corporate innovation (Katila & Ahuja, 2002), and financial market (Fitzgerald et al., 2021). However, the literature engages in debates regarding the definition and characteristics of exploration and exploitation.

Debates over the definition of exploration and exploitation center on whether these concepts are distinguished by the mere presence versus absence of learning or by the specific types of learning involved (Gupta et al., 2006). The former argument posits that exploration involves active learning and innovation, while exploitation does not (e.g., Rosenkopf & Nerkar, 2001; Vassolo et al., 2004). In contrast, my definition aligns with the latter argument, suggesting that both exploration and exploitation involve learning and innovation, although with differing trajectories or levels of intensity in terms of these activities (e.g., Benner & Tushman, 2002; He & Wong, 2004).

An additional question arises regarding whether the relationship between exploration and exploitation is continuous or orthogonal. Some studies view exploration and exploitation as orthogonal and even complementary strategies (e.g., Tushman & O'Reilly, 1996) due to the different definitions and operationalizations of exploration and exploitation. However, both theoretical frameworks and empirical evidence suggest that the distinction between exploration and exploitation is more a matter of degree than kind (Gupta et al., 2006; Lavie & Rosenkopf, 2006). Therefore, I view exploration and exploitation as two ends of a continuum rather than distinct and separate decisions.[7]

A further debate is whether the balance between exploration and exploitation exists. March (1991) notes that both exploration and exploitation are essential for firms to thrive in the long run, but these two strategies are fundamentally conflicting. Prior studies argue that although it is favorable for firms to maintain an appropriate balance between exploration and exploitation, such balance is difficult to achieve (Jansen et al., 2006; Koryak et al., 2018). This is because any effort (e.g., learning and technological change) to enhance organizational performance and improve competitive advantage involves a tradeoff between exploration and exploitation, which is affected by the allocation of resources in various contexts (March, 1991). First, both strategies are self-reinforcing. For example, exploration-oriented firms may often face failures, which in turn incentivize the firm to search for even newer technologies and ideas, thus becoming more exploratory (Gupta et al., 2006). Second, mindsets and organizational routines of exploration should be different from those needed for exploitation. Exploration requires adaptability and changes, while exploitation requires stability and inertia, which results in opposing cultures and organizational structures (Lavie et al., 2010; Menguc & Auh, 2008). As a result, these two strategies compete for limited resources, compelling firms to

[7] In the previous watch example, the extent of overlap between the firms' mechanical technology (existing knowledge) and new quartz technology (new knowledge) "defines the position of this innovation on the exploration-exploitation continuum" (Lavie et al., 2010, p. 114).

prioritize one over the other at any given time (Fourné et al., 2019).

In addition to debating the existence of a balance between exploration and exploitation, the literature also discusses how such a balance might be achieved. Some studies advocate for ambidexterity, suggesting that firms should pursue both exploration and exploitation simultaneously (Benner & Tushman, 2002). However, resource constraints often force firms to prioritize one strategy over the other (March, 1991). Alternatively, some studies propose punctuated equilibrium, wherein firms alternate between extended periods of exploitation and shorter bursts of exploration (Gupta et al., 2006). Despite these theoretical differences, both perspectives suggest that a firm's prioritization of exploration or exploitation can change over time.

2.2.2 Definition of Corporate Innovation Strategy

A firm's innovation strategy is an internal choice between exploring new technologies and exploiting existing technologies (Manso, 2011; Mueller et al., 2013). Exploration-focused firms pioneer new avenues, aiming for groundbreaking innovations and a potential competitive advantage; exploitation-focused firms, in contrast, focus on refining existing innovations through steady improvements or extensions of current knowledge (Jia, 2018).

Corporate innovation strategy exhibits two key characteristics: relativity and dynamism. A firm's innovation strategy, whether exploration or exploitation, is relative and depends on the focal firm's perspective (Lavie et al., 2010). First, corporate innovation strategy identifies an important relation of a firm's new knowledge relative to its existing knowledge base (Fitzgerald et al., 2021). For example, when Apple first introduced "multipoint touchscreen" technology in the first iPhone, this touchscreen technology could be considered an exploratory innovation for Apple due to the low overlap with its existing technology. However, subsequent enhancements to the touchscreen, characterized by a higher degree of overlap, could be classified as exploitative innovations for Apple. Second, certain technology might be existing knowledge for one firm but new to another. Therefore, what constitutes exploitative innovation for one firm could be viewed as exploratory innovation for another. Continuing with the Apple example, the upgraded touchscreen technology (which represents exploitative innovations for Apple) might still be considered exploratory for an incumbent technology firm that does not possess this knowledge previously.

A firm's innovation strategy is not static but can change along the exploration-exploitation continuum. While debates persist regarding the feasibility and methods of achieving a balance between exploration and exploitation, existing literature recognizes the dynamic nature of a firm's prioritization of these strategies (Benner & Tushman, 2002; Gupta et al., 2006; March, 1991). Furthermore, empirical evidence suggests that a firm's innovation strategy is subject to change and evolves over time (Cao et al., 2023; Gao et al., 2018; Lin et al., 2021).

2.2.3 Innovation-Related Metrics

The literature shows that investors face difficulty evaluating firms across different innovation metrics, including input-based (e.g., R&D intensity and growth) and output-based (e.g., number of patents granted, number of patent citations, innovative originality, innovative efficiency, and innovation strategy). Prior studies show a positive relation between market value and firms' innovative input captured by R&D investment (Chan et al., 2001; Cohen et al., 2013; Lev & Sougiannis, 1996; Sougiannis, 1994). However, input measures, such as R&D expenditures, are subject to limitations. R&D investments involve uncertainty and do not guarantee successful outcomes (Hirshleifer et al., 2018). Moreover, Koh and Reeb (2015) show that R&D investments may not successfully capture the firms' innovative activities as a considerable number of innovation-intensive firms do not report R&D in financial statements.

Prior studies identify patents as output measures for innovation because they capture successful innovative activities (Huang et al., 2021).[8] Gu (2005) finds that the change in patent citations is positively related to firms' future stock returns. Matolcsy and Wyatt (2008) find that technological conditions (e.g., the success rate of past technological investments, technology complexity, and the technology development period) are positively related to market valuation and future firm earnings.

Hirshleifer et al. (2013, 2018) find that investors undervalue the information on innovative efficiency and innovative originality. Innovative efficiency means a firm's ability to generate innovation outputs (e.g., patents and patent citations) relative to its innovation inputs (e.g., R&D investments; Hirshleifer et al., 2013). Although innovative efficiency considers both innovation output and input, it focuses on whether the firm can produce innovation output at a reasonable cost. Firms may generate efficient innovation output at a low R&D cost, but this innovation can be either exploratory or exploitative as innovative efficiency does not factor in the knowledge acquired from each invention.

Hirshleifer et al. (2018) define innovative originality as the "breadth of knowledge used to innovate" (p.2555) and use the diversity of cited technology classes to proxy this measure. Innovative originality only considers the horizontal comparison across firms but not the vertical comparison within the same firm. Exploration and exploitation, on the other hand, focuses on searching for knowledge relative to the same firms' existing technology pool. While a firm may produce an original invention by citing a diverse range of technology classes, the knowledge utilized in this invention remains within the firm's existing knowledge base. Consequently, despite its originality, this invention would be categorized as more exploitative in nature, as it builds upon existing knowledge and technologies within the firm.

A firm's internal choice between exploration-focused and exploitation-focused strategies is

[8] While there are some concerns about patenting metrics in specific scenarios, such as defensive patenting, patent thickets, and potential exploitation by patent trolls (Bessen et al., 2011; Shapiro, 2000), the patent remains a valid proxy for innovation.

conceptually and empirically different from other innovation-related metrics (e.g., R&D intensity, number of patents, innovative efficiency, and innovative originality) studied in the prior literature (Fitzgerald et al., 2021). Corporate innovation strategy focuses on the extent of a firm's new knowledge of the innovation relative to its existing knowledge pool within the same firm (Lavie et al., 2010). Recent findings highlight the difficulty that investors face when understanding the return predictability of a firm's internal choice of innovation strategy between exploration and exploitation (Fitzgerald et al., 2021; Jia, 2018). The predictive power of corporate innovation strategy on return is distinct and incremental to that of other innovation-related variables (Fitzgerald et al., 2021).

2.2.4 Consequence of Corporate Innovation Strategy

While the literature extensively explores the determinants of innovation strategy (e.g., Balsmeier et al., 2017; Brav et al., 2018; Cohen & Levinthal, 1994; Lin et al., 2021; McGrath, 2001; Smith & Tushman, 2005), research on the consequences of corporate innovation strategy is relatively scarce. Some studies examine the effect of innovation strategy on firm performance. Katila and Ahuja (2002) find a positive effect of exploratory innovation on new product introduction. Uotila et al. (2009) find an inverted U-shaped relationship between exploratory innovation and revenue growth.

Studies on the capital market consequences provide initial evidence on how market participants value firms' different innovation strategies. Jia (2018) finds a positive (negative) relation between exploration-focused (exploitation-focused) firms and stock price crash risk. This relation is stronger when firms have higher agency issues and weaker corporate governance. Fitzgerald et al. (2021) show that analysts and investors tend to overvalue exploration-focused firms compared to exploitation-focused counterparts due to cognitive and strategic biases.

Several studies examine how disclosure policy relates to the market implications of innovation strategy. Jia (2017, 2019) finds that exploration-focused firms are associated with lower analyst coverage, higher forecast errors, and higher forecast dispersion than exploitation-focused firms. Moreover, exploration-focused firms are more inclined to issue management earnings forecasts to mitigate information asymmetry.

While the evidence on the consequences of innovation strategy is increasing, it remains limited. My thesis provides insights into how different innovation strategies shape firms' disclosure decisions, especially in the context of narrative innovation disclosures. Specifically, I examine whether narrative innovation disclosures assist investors in evaluating firms with different innovation strategies, thereby highlighting the importance of narrative innovation disclosures in 10-K filings. In addition, my thesis addresses the call made by Fitzgerald et al. (2021) to explore how corporate disclosures concerning innovation strategies affect investors' valuation.

2.3 Narrative Innovation Disclosures

2.3.1 Disclosure Decision by Innovative Firms

Due to the high information asymmetry in innovative-intensive firms, innovation has a negative effect on financial reporting quality (Lobo et al., 2018). It is difficult for investors to understand the financial statements of innovative firms when firms provide limited information on R&D investment and innovation-related activities. The literature discusses how to modify the financial statement model to improve the usefulness of information depicting innovative firms' financial positions. One proposed approach to enhance the value-relevance of accounting information is to mitigate the information asymmetry between innovative firms and investors by disclosing non-financial information. Investors can use such information to augment the financial statement numbers to better evaluate the implications of innovation on both short- and long-term financial performance in innovative firms (Canibano et al., 2000).

Innovative firms face a tradeoff between disclosing proprietary information and mitigating information asymmetry with investors (Ellis et al., 2012; Hayes & Lundholm, 1996; Wagenhofer, 1990). Previous research indicates that firms consider the proprietary costs associated with competition when making disclosure decisions (e.g., Glaeser & Landsman, 2021; Jones, 2007; Merkley, 2014). Cao et al. (2018) find that high-tech firms face heightened proprietary costs when disclosing information that may erode their competitive advantage. Glaeser (2018) finds that firms that pursue trade secrecy also show a higher likelihood of providing earnings guidance and issuing a greater volume of guidance. The findings imply that firms with trade secrets may replace proprietary disclosures with nonproprietary disclosures, as earnings information is considered less proprietary than trade secrets. Huang et al. (2021) find that innovative firms facing heightened competition are less inclined to enhance their issuance of management forecasts after receiving a patent grant.

However, such disclosures offer the benefits of mitigating information asymmetry. For instance, Tasker (1998) shows that R&D-intensive firms hold more conference calls with analysts and receive a majority of questions related to R&D activities during conference calls. Gelb (2002) finds that firms with more intangible assets underline additional disclosures due to the inadequacy of mandated accounting disclosures for firms' performances. Managers face the challenge of weighing the costs and benefits associated with disclosures to effectively serve their information goals. They choose to reveal proprietary information solely when the benefits outweigh the costs (Ellis et al., 2012).

Prior studies typically assume different effects on disclosure decisions between innovative and non-innovative firms; however, they often assume equal effects within innovative firms (e.g., Gu & Li, 2003; Jones, 2007; Merkley, 2014). This implies that firms with different innovation strategies make similar disclosure decisions. However, exploration-focused and exploitation-focused firms may differ in their disclosure decisions due to the tradeoff between the proprietary costs of disclosures and information asymmetry with investors. This thesis contributes to the literature by exploring the dynamics within innovative firms, thereby highlighting the differing effects of innovation strategies on disclosure decisions.

2.3.2 Innovation-Related Disclosures

Firms have the option to disclose information related to innovation in diverse formats, including quantitative financial data and qualitative narrative content. These disclosures can be disseminated through a variety of channels, such as press releases, patents, and regulatory 10-K filings. Prior empirical research typically emphasizes disclosures of quantitative financial metrics, such as management earnings guidance and R&D expenditure, rather than focusing on qualitative information (Healy & Palepu, 2001; Hirst et al., 2008). One possible explanation for this discrepancy is investors' perceived ability to process and interpret quantitative data more readily (Ajinkya & Gift, 1984; Berger & Hann, 2007; Patell, 1976; Penman, 1980). Narrative disclosures contain qualitative and descriptive information, which lacks standardization and may pose challenges for comparison across firms. As a result, investors may find it difficult and costly to extract meaningful insights from such disclosures, potentially undermining their informative value.

Firms often use management earnings guidance as a form of voluntary disclosure to project future performance to market participants (Coller & Yohn, 1997; Goodman et al., 2014; Li & Zhuang, 2012). These earnings forecasts also incorporate managers' expectations regarding the value that a firm can derive from its ongoing innovation projects. Huang et al. (2021) find that innovative firms are more likely to issue management forecasts than non-innovative firms. However, management forecasts do not contain direct proprietary information about firms' innovation activities. Moreover, for exploration-focused firms, it might be more difficult for managers to provide accurate earnings forecasts based on their exploration activities. Jia (2019) finds that compared to exploitation-focused firms, exploration-focused firms are more likely to issue management earnings forecasts. However, these forecasts are generally less optimistic, less accurate, and less precise.

Firms may also disclose quantitative innovation-related information in 10-K filings. SFAS 2 requires firms to recognize total R&D costs in the income statement (FASB, 2010). In practice, managers of innovation-intensive firms exert considerable discretion regarding the materiality and classification of R&D investments and may report R&D expenses together with other expenses as a lump-sum amount in income statements (Koh & Reeb, 2015).

In addition to quantitative information, firms can disclose qualitative information to communicate with stakeholders. Narrative innovation disclosures include quantitative and qualitative descriptions of a firm's innovation activities, including objectives, R&D, patents, and technological collaboration as well as competition. Compared to traditional quantitative disclosures, these disclosures are more future-oriented, more difficult to quantify, and more closely tied to firm strategy (Merkley, 2014). First, narrative disclosures provide a forward-looking perspective, showing a firm's objective and vision for innovation. This is crucial for innovative firms in a dynamic, competitive market. Second, these disclosures go beyond numbers by providing a contextual description of a firm's technological advancements. Third, prior studies find that narrative innovation disclosures complement financial statement numbers (Jones, 2007; Merkley, 2014). This is important when earnings are less predictable and more volatile in innovative firms (Gu & Li, 2003).

Prior studies examine narrative disclosures in different channels. He and Lee (2022) find that firms with more patents are more likely to release patent-related information in 8-K filings. Skinner and Valentine (2024) find a positive relation between firms' green patenting activities and narrative disclosures in conference calls. Cao et al. (2018) examine firm-initiated press releases related to product development, which discuss firms' strategies, allocations, and progress of technological investments in product development. The authors find a negative relation between technological peer pressure and product disclosures. Chu et al. (2023) show the predictive ability of new product announcements in Capital IQ. Firms may also accelerate the publication of their patent applications on the USPTO website before the mandatory publication by the USPTO, which occurs 18 months after the filing date.[9] Glaeser and Landsman (2021) find that patent applicants in more competitive

[9] The USPTO publishes patent applications 18 months after the filing date when the American Inventors Protection Act (AIPA) was enacted on November 29, 1999 (USPTO, 2000).

industries voluntarily accelerate their patent disclosure to deter product market competitors.

2.3.3 Narrative Innovation Disclosures in the 10-K Setting

In this thesis, I examine narrative innovation disclosures in the 10-K setting for several reasons. First, these disclosures are presented alongside financial statements, which are mandated disclosures. This co-presentation of qualitative information complements the quantitative data in financial statements. This integrated approach offers a more comprehensive and credible perspective of a firm's innovation activities. While firms disclose a broad range of nonfinancial information through alternative sources such as press releases and firm websites, 10-K filings still serve as a prominent avenue for innovation-related information (Cohen et al., 2012).

Second, the purpose of these disclosures differs from that of other voluntary narrative innovation disclosures, such as patents. Patents serve two primary purposes: (1) providing legal protections for inventions, granting exclusive rights to the inventor, and (2) documenting innovations to facilitate replication and further development by others. In contrast, 10-K filings are aimed at communicating with financial statement users, including investors. Narrative innovation disclosures within 10-K filings may provide insights into the financial implications of firms' innovation activities, a dimension not addressed in patent documents.

Moreover, Item 101(c) of Regulation S-K (Reg S-K) outlines specific elements for the registrant's disclosures, including new products and intellectual property. This approach helps mitigate selection bias and allows for sampling across diverse industries and timeframes, as all firms with substantial investments in innovation must provide a minimum level of innovation-related disclosures within their 10-K filings (Merkley, 2014). However, it is important to note that while some innovation-related disclosures are mandatory, managers retain discretion regarding the disclosures' level of detail (Rawson, 2022).[10] Appendix A provides examples of narrative innovation disclosures in 10-K filings.

Despite the discretionary nature of narrative innovation disclosures, firms may choose to disclose relevant information in 10-K filings to reduce the information asymmetry with financial reporting users and enhance market value implications (Jones, 2007). Jones (2007) examines the disclosures in conference calls and 10-K filings using a hand-collected sample of R&D-intensive firms and finds that R&D-intensive firms disclose less narrative R&D-related information when proprietary costs are high. In addition, Merkley (2014) shows a negative association between earnings performance and the extent of narrative R&D disclosures, highlighting the added value of such disclosures to investors beyond financial statement figures. However, the author only finds empirical evidence of information demand but fails to find evidence of proprietary costs.

2.4 Product Market Competition

The proprietary cost hypothesis (Verrecchia, 1983, 2001) suggests that revealing proprietary information puts the disclosing firm at risk of losing its competitive edge in the product market if its rivals strategically use the information to the firm's disadvantage. Empirical findings support the theory, indicating that proprietary cost concerns reduce firms' incentive to report their disclosures in various contexts, such as management earnings forecasts (Huang et al., 2021), segment reports (Bens et al., 2011), and nonfinancial information (Ryou et al., 2022). In a survey conducted by Graham et al. (2005), the majority of survey respondents agree that disclosing proprietary information is an important barrier to increased voluntary disclosure. Moreover, a few CFOs show reluctance to explicitly disclose sensitive proprietary information, even if competitors might infer some details

[10] In the 2020 amendments to Reg S-K, Item 101(c) transitioned from a specific list of disclosures to a principle-based approach. It offers a non-exclusive list of information that firms should disclose when it is material for understanding their business. This includes details about the duration and impact of patents, trademarks, licenses, franchises, and concessions within their business descriptions in filings (SEC, 2020). This amendment is outside my sample period, so studying the effect of the amendment is outside the scope of this thesis.

from alternative sources like trade journals or conferences. The survey findings highlight the considerable concerns of proprietary costs in constraining voluntary disclosures.

However, Hughes and Pae (2015) highlight that competition and disclosure involve multifaceted dimensions. The direction of the relation between competition and disclosure depends on the alignment between the nature of competition and the type of disclosure, especially regarding whether product market competitors can gain advantages from such disclosures (Cao et al., 2018). Competition with existing rivals and potential rivals differs, as theoretical frameworks suggest that firms may choose to disclose their innovations as a strategy to deter potential rivals from entering the market (Baker & Mezzetti, 2005).[11] Using patent documents as an example, firms may strategically publish their patent applications on the USPTO website before the mandated publication timeline (Glaeser & Landsman, 2021). The accelerated disclosure allows them to demonstrate their competitive advantage to potential rivals in the product market, potentially influencing competitors' decisions regarding pricing or production strategies. Potential rivals, upon recognizing the unique value and potential cost advantages associated with patents or patented processes, may be discouraged from engaging in direct competition. Glaeser and Landsman (2021) provide empirical evidence supporting that firms voluntarily expedite their patent disclosures to deter potential rivals in the product market.

2.5 Technology Spillover

In contrast to product market competition, which often results in a negative impact through business-stealing among existing rivals, technology spillover generates positive externalities by encouraging collaboration with compatible peers and facilitating exchanges (Cao et al., 2018; Ettredge et al., 2018). Bloom et al. (2013) show that there is an overlap between peer firms in the

[11] Anecdotal evidence suggests that firms disclose information to deter potential product market competitors. For example, Ford Motor publicly announced its adoption of the moving assembly line process, aiming to convey its extremely low production costs to deter potential rivals (Hall et al., 2014).

technology space (technology spillover) and peer firms in the product market space (product market competition), but these aspects are sufficiently different to allow for empirical analysis.[12]

Bloom et al. (2013) identify two conditions necessary for the occurrence of technology spillover: technology proximity and complementarity. First, both the focal firm and its peer firms must share similar technology classes, indicating closeness in the technology space. Second, the knowledge stock of peer firms needs to exceed that of the focal firm, facilitating the knowledge inflow from technology peers to the focal firm and thereby enabling knowledge spillover. Assuming these conditions are met, technology spillover can occur. Firm i, operating in Industry 1, utilizes narrative innovation disclosures to demonstrate its technological competence. This prompts Firm j, from Industry 2, to engage in licensing agreements with Firm i, thereby enabling Firm i to make profits on its innovations. Moreover, such disclosures can serve as signals of willingness for collaboration, attracting potential partners like Firm k in Industry 3 who seek joint ventures. When multiple firms possess similar or related technologies, sharing innovation information can lead to synergies, such as joint research projects. Given that Firms j and k possess larger knowledge stocks, Firm i benefits from the knowledge inflow from Firms j and k through collaboration. However, if firms choose to free ride without disclosing information, they might miss out on potential benefits and synergies. Consequently, the existence of technology spillover enhances firms' motivation to share innovation information and thereby reduces proprietary costs.

Moreover, empirical evidence indicates a positive relationship between technology spillover and firm disclosures. Ettredge et al. (2018) show a positive correlation between technology spillover and the transparency of narrative R&D disclosures. Similarly, Cao et al. (2018) identify a positive association between technology spillover and disclosures related to product announcements.

[12] For example, IBM and Apple, competitors in the personal computer market, also qualify as technology spillover peers. However, IBM and Intel are technology spillover peers, despite not competing directly in the same product market. Phillips and Segway compete in the hard disk market but originate their technologies from different areas. Therefore, Phillips and Segway are product market competitors but are not technology spillover peers. See more details in Appendix D of the Supplemental Material provided by Bloom et al. (2013).

In summary, existing research highlights firm characteristics, information asymmetry, and proprietary costs as key determinants of innovation disclosures (Gu & Li, 2003; Jones, 2007; Merkley, 2014). While some initial evidence suggests that exploration-focused (versus exploitation-focused) firms issue more frequent earnings forecasts and less innovation-related news to meet analysts' information demand by avoiding disclosing proprietary information (Jia, 2017, 2019), the specific role of proprietary costs remains an empirical question. My research aims to address this gap by examining the differential impacts of product market competition and technology spillover on the association between corporate innovation strategy and narrative innovation disclosures. This is particularly important due to their contrasting effects on proprietary costs. This nuanced perspective adds to the literature on determinants of narrative innovation disclosures.

2.6 Conclusion

This chapter reviews the literature on corporate innovation strategy as well as narrative innovation disclosures. I discuss the definition and importance of corporate innovation strategy. I also discuss narrative innovation disclosures in the 10-K setting. Prior studies on corporate innovation strategy focus on its determinants, with increasing interest in its effects. Prior research on narrative disclosures focuses on the firm or institutional factors that may affect firms' disclosure decisions. However, there remains a gap in the literature concerning how firms with different innovation strategies make disclosure decisions and communicate with investors. This thesis aims to bridge these two strands of literature and offer insights into the influence of corporate innovation strategy on narrative innovation disclosure decisions within 10-K filings and to assess whether such disclosures contribute to investors' valuation processes.

Chapter 3
Hypothesis Development

3.1 Introduction

This chapter examines the overall relation between corporate innovation strategy and narrative innovation disclosures. The baseline prediction is that exploration-focused firms provide lower narrative innovation disclosure quantity compared to exploitation-focused firms. Specifically, I hypothesize that firms with different innovation strategies face differing tradeoffs between proprietary costs and information asymmetry. In Section 3.2, I develop this main hypothesis by drawing on the related literature reviewed in Chapter 2 and other related theories. I further hypothesize two moderating factors of the baseline prediction. In Section 3.3, I predict that the effect of product market competition on the quantity of narrative innovation disclosures is more negative for exploration-focused firms than exploitation-focused firms. In Section 3.4, I predict that the effect of technology spillover on the quantity of narrative innovation disclosures is more positive for exploration-focused firms than exploitation-focused firms. I conclude with a summary in Section 3.5.

3.2 Corporate Innovation Strategy and Narrative Innovation Disclosure Quantity (H1)

Firms face a tradeoff between disclosing proprietary information and reducing information asymmetry with investors (Ellis et al., 2012; Hayes & Lundholm, 1996; Wagenhofer, 1990). Narrative innovation disclosures come with associated costs, such as preparation, announcement, potential litigation, and the risk of competitors utilizing disclosed proprietary information (Diamond & Verrecchia, 1991; Leuz & Verrecchia, 2000; X. Li, 2010). Among various forgone information disclosure costs, researchers are particularly concerned with the impact of proprietary costs on managers' disclosure decisions regarding proprietary information (Cao et al., 2018; Glaeser, 2018; Huang et al., 2021). However, narrative innovation disclosures offer benefits, including the reduction of information asymmetry and lower financing costs. For instance, Gu and Li (2003) find that firms disclose more information about innovative activities when current earnings are less value-relevant or future earnings are more uncertain. In order to fulfill the informational purpose of disclosures, managers must weigh the costs and benefits, opting to disclose proprietary information when the benefits outweigh the costs (Ellis et al., 2012). In such scenarios, managers of firms with different innovation strategies may employ different disclosure decisions based on these considerations.

The extent to which exploration-focused firms benefit from disclosures in mitigating information asymmetry relative to exploitation-oriented firms is unclear *ex ante*. On the one hand, March's (1991) theoretical framework suggests that exploration-focused firms face higher information asymmetry with outsiders than do exploitation-focused firms. March (1991) characterizes the payoffs associated with exploratory activities as "uncertain, distant, and often negative" (p. 85). Therefore, exploratory firms tend to have higher levels of informational opacity and experience greater earnings volatility (Jia, 2017). This elevated volatility diminishes the predictive power of reported earnings for future performance, resulting in less reliable earnings (Hayn, 1995). While innovative firms inherently possess higher information asymmetry than less innovative firms, this asymmetry intensifies when firms engage in exploration-focused innovation activities. Moreover, exploration-focused firms typically experience a longer time lag before their exploratory innovations yield tangible results in terms of operating performance. Therefore, these firms often exhibit poorer short-term operating performance compared to their exploitation-focused firms (Fitzgerald et al., 2021). The inherent risk and uncertainty associated with exploratory innovation make it more challenging for investors to accurately predict the financial performance and value of exploration-focused firms (March, 1991; Rindova & Petkova, 2007). Moreover, prior research finds that exploration-focused firms report more conservatively than exploitation-focused firms, as a rational response to uncertainty (Yang, 2023). As a result, investors of exploration-focused firms seek more information about these innovation activities to better gauge future cash flows and associated uncertainty, encouraging managers to provide information.

On the other hand, exploitation-focused firms may benefit more from reducing the information asymmetry with investors compared to exploration-focused firms. Literature in psychology and neuroscience suggests that individuals show a consistent preference for novel and salient information, particularly when confronted with complex issues (Bunzeck et al., 2011; Song & Schwarz, 2010; Wittmann et al., 2007). Due to these cognitive biases, investors tend to pay more attention to radical exploratory innovations than to incremental exploitative innovations (Fitzgerald et al., 2021). This limited attention from investors results in stock returns that may not fully reflect all of the available information (Cohen & Frazzini, 2008; Da et al., 2014; Huberman & Regev, 2001; Klibanoff et al., 1998; Li & Yu, 2012). Consequently, investors place a high value on exploratory innovations, which represent breakthroughs that firms have not previously pursued. In contrast, incremental exploitative innovations fall within a firm's established research trajectory, leading investors to pay less attention and potentially fail to fully understand their economic significance (Fitzgerald et al., 2021). In addition, during a panel discussion on innovation among academics and practitioners organized by the Wall Street Journal, Michel M. Liès, the group chief executive of Swiss Re, highlighted that exploitative incremental innovation can lead to significant improvements and help maintain a firm's market position while being less visible to investors (WSJ, 2013). Fitzgerald et al. (2021) provide empirical evidence supporting this view, indicating that exploitation-focused firms have a greater need to provide detailed investor guidance regarding the profitability associated with exploitative patents. By providing narrative innovation disclosures, exploitation-focused firms can bridge the information gap and signal investors about the potential future profitability arising from successful exploitative innovations.

Based on the mixed theoretical and empirical evidence, it is unclear whether exploration-focused or exploitation-focused firms provide a higher quantity of narrative innovation disclosures to mitigate information asymmetry. It is plausible that exploration-focused firms provide a higher quantity of narrative innovation disclosures than exploitation-focused firms to mitigate information asymmetry if the costs of information disclosure for exploration-focused firms are comparable to or not greater than those for exploitation-focused firms.

However, exploration-focused firms may face higher proprietary costs than exploitation-focused firms. Exploratory innovations are inherently firm-specific, offering a unique market position tailored to the firm's strategic objectives, strengths, and resources. Detailed disclosures about these innovations can enable competitors to adapt them to their own context, thereby diluting the disclosing firm's market standing (Cao et al., 2018). The radical nature of exploratory innovation means that it has a high potential to achieve a competitive edge. Research suggests that successful exploration may result in significant growth in new products and establish a more substantial competitive advantage compared to successful exploitation (Jia, 2019). Given the limited public information on exploratory innovation, competitors find disclosures from exploration-focused firms particularly valuable (Kaplan & Tripsas, 2008; Rindova & Petkova, 2007). Existing competitors may respond to these disclosures by quickly replicating or counteracting the innovations, eroding the disclosing firm's advantage from early market entry (Darrough & Stoughton, 1990; Verrecchia, 1983). Consequently, exploration-focused firms may incur profitability losses from disclosing narrative innovation information. Empirical evidence indicates that exploration-focused firms show lower transparency by issuing more frequent but less accurate earnings forecasts and releasing less media news about innovation progress and objectives (Jia, 2017, 2019). This suggests that for exploration-focused firms, the proprietary costs associated with issuing more innovation details outweigh the benefits of reducing information asymmetry. In contrast, for exploitation-focused firms, the benefits of reducing information asymmetry outweigh the proprietary costs of disclosing information about their incremental innovation activities. Assuming that the tradeoff for narrative innovation disclosures follows a similar pattern to the tradeoff observed for management earnings forecasts and press news, I posit that compared to exploitation-focused firms, exploration-focused firms disclose less narrative innovation information to mitigate their higher proprietary costs.

Nevertheless, this prediction regarding narrative innovation disclosures may not hold for a few reasons. First, it is plausible that managers have incentives to highlight a firm's exploratory innovations to establish their reputation, as these activities attract greater media coverage of both the firm and its managers (Raimondo, 2019). Managers may emphasize significant shifts in the technological direction of a firm's innovative efforts in their 10-K filings to show the management team's successful long-term growth strategy to investors, as well as boost investor confidence and stock prices (Fitzgerald et al., 2021; Kuhnen & Niessen, 2012). Therefore, managers in exploration-focused firms may have the incentive to disclose more narrative innovation disclosures.

Second, the cost-benefit tradeoff for narrative innovation disclosures in the 10-K setting might differ from the findings observed for traditional quantitative disclosures (e.g., earnings forecasts) or other types of narrative disclosures (e.g., media news; Jia, 2017, 2019). Exploration-focused firms face higher litigation risks when disclosing information in 10-K filings rather than using other voluntary channels, such as media news (Ganguly, 2018; Milstead & Foster, 2024). Importantly, regulatory requirements mandate a minimum level of narrative innovation disclosures in 10-K filings for innovative firms. Investors heavily rely on these filings as a primary source for evaluating a firm's future cash flows and growth potential, underlining the crucial role of narrative innovation disclosures in 10-K filings to exhibit transparency. In contrast, while narrative innovation disclosures in media news offer greater content and presentation flexibility with reduced legal liability, they may not consistently ensure the same level of visibility and credibility as audited mandatory 10-K filings.

In summary, I propose that exploration-focused firms may disclose less narrative innovation information compared to exploitation-focused firms. This assumption aligns with patterns observed in management earnings forecasts and press releases (Jia, 2017, 2019). However, due to variances in litigation risks, regulatory environments, and perceived credibility between 10-K filings and other disclosure channels, exploration-focused firms may find 10-K filings a more suitable channel for disclosing innovation-related information. Therefore, my first hypothesis is as follows:

H1: Firms with a greater focus on exploratory (exploitative) innovations disclose a lower (higher) quantity of narrative innovation information.

3.3 Conditional Analysis: Product Market Competition (H2)

Theories predict that product market competition from existing rivals discourages disclosures (Clinch & Verrecchia, 1997; Hughes & Pae, 2015). Consistent with these theories, empirical evidence shows that firms disclose less information as proprietary costs increase due to intensified competition from existing rivals (X. Li, 2010). Narrative innovation disclosures, in contrast to earnings forecasts as a general-purpose measure of voluntary disclosure (Cao et al., 2018), contain more specific proprietary information about their innovation activities, such as objective, progress, expenditure, and other innovation-related information (Merkley, 2014). Competing firms in the product market may closely follow disclosures made by other firms, enabling them to develop similar products and potentially erode the competitive advantage of disclosing firms.

The adverse impact of product market competition on disclosures can be attributed to the motivation of exploration-focused firms to safeguard innovative ideas that are vulnerable to replication by competitors. In highly competitive markets, revealing information can erode their potential competitive advantages (Cao et al., 2018; Ettredge et al., 2018). In contrast, for exploitation-focused firms, competition might still reduce some disclosures, but the incremental nature of their innovations means that the competitive risk of disclosing information is lower. As a result, the impact of competition on reducing disclosures is less pronounced for exploitation-focused firms. Thus, I conjecture that as product market competition becomes more intense, exploration-focused firms may have a greater incentive to reduce their narrative innovation disclosures to mitigate proprietary costs and safeguard their competitive edge. Therefore, I propose the following hypothesis:

H2: The effect of product market competition on the quantity of narrative innovation disclosures is more (less) negative for firms with a greater focus on exploratory (exploitative) innovations.

3.4 Conditional Analysis: Technology Spillover (H3)

Differing from product market competition, which yields a negative business-stealing effect among existing rivals, technology spillover generates positive externalities by attracting compatible partners and facilitating exchanges (Bloom et al., 2013). Futia (1980) posits that product market competition eventually erodes the advantages of innovative firms unless these firms continually innovate. Technology spillover allows a firm to achieve innovation more efficiently by leveraging the research efforts of other firms engaged in similar technologies, thereby reducing the research burden on the firm itself (Jaffe, 1986). Furthermore, technology spillover enhances a firm's research capabilities by providing additional resources to compete effectively in its product market (Cao et al., 2018). Prior research also provides empirical evidence that technology spillover has a positive effect on firms' disclosure decisions (Cao et al., 2018; Ettredge et al., 2018).

I posit that exploration-focused firms benefit more from the decreased proprietary costs associated with technology spillover than exploitation-focused firms. This is because exploration-focused firms engage in more revolutionary, radical, and creative destruction, granting them a competitive advantage in the product market (Jia, 2019). Notably, technology spillover often spans across industries rather than being limited solely to a specific industry, thereby reducing the likelihood of direct product competition with peers experiencing technology spillover. Exploration-focused firms, therefore, find value in disclosing information about their technologies, as they can benefit from knowledge inflow, technology sales, licensing opportunities, and favorable negotiations for strategic alliances when their technology spillover peers possess similar and complementary technologies (Arora & Ceccagnoli, 2006; Bena & Li, 2014; Ettredge et al., 2018). In such cases, exploration-focused firms can leverage the synergy facilitated by technology spillover, thereby reducing their concerns about the proprietary costs of disclosing narrative innovation information. In contrast, exploitation-focused firms tend to conduct more conventional and incremental innovation, which may yield a different level of synergy from technology spillover than exploration-focused firms. Therefore, I propose that as technology spillover increases, exploration-focused firms are likely to have greater incentives to disclose innovation information than exploitation-focused firms to receive the benefits brought by technology spillover. Accordingly, I make the following hypothesis:

H3: The effect of technology spillover on the quantity of narrative innovation disclosures is more (less) positive for firms with a greater focus on exploratory (exploitative) innovations.

3.5 Conclusion

In this chapter, I develop three hypotheses. I present my first hypothesis of a baseline negative association between exploration-focused (versus exploitation-focused) firms and narrative innovation disclosure quantity. I present the next two hypotheses on a negative moderating effect of product market competition and a positive moderating effect of technology spillover on the baseline negative association.

Chapter 4
Research Design

4.1 Introduction

In this chapter, I outline the research design for the hypotheses developed in Chapter 3. Section 4.2 outlines my data sources and sample selection process. Section 4.3 describes the measures of major variables. Section 4.4 introduces the baseline model. Section 4.5 describes the model for conditional hypotheses H2 and H3. I conclude with a summary in Section 4.6.

4.2 Data Sources and Sample Collection

My sample consists of publicly listed U.S. firms that are actively engaged in innovation. I select firms that applied for at least one new patent per year during the period. This selection criterion allows me to concentrate on firms that are consistently engaged in innovative activities as their core business operations. This approach mitigates operationalization validity issues by avoiding assumptions about whether firms without new innovation lean toward exploration or exploitation.[13] I obtain patent-related data from Stoffman et al. (2022).[14] The dataset contains information on all U.S. patents granted by the USPTO between 1976 and 2021, including patent and patent citation numbers, application (filing) and grant (issue) dates, and technology classes. To mitigate the look-ahead bias, I use the patent application year instead of the grant year. Firms have control over the timing of their

---

[13] This method is consistent with prior studies (see Fitzgerald et al., 2021; Jia, 2017, 2018, 2019). One alternative approach is to include firms that applied for at least one patent during the sample period and assign zeros for firms that did not apply for a patent in a year. This method assumes that firms not receiving patents in a particular year prioritized exploitative innovations. A second alternative approach is to include firms that applied for at least one patent for at least three years during the sample period and assign zeros for firms that did not receive a patent in a year. A third alternative approach is to include firms that applied for at least one patent for at least five consecutive years during the sample period and assign zeros for firms that did not receive a patent in a year. In robustness tests, I use these three alternative sample selection methods and the results remain robust across all methods.

[14] I thank the authors of Stoffman et al. (2022) for making the data publicly available on Mike Woeppel's website at: https://www.mikewoeppel.com/data.

patent portfolio applications, but not over when the patents will be granted.[15] To address potential truncation issues with patent data as it becomes incomplete toward the end of the dataset in 2021, I set the last year of my sample period to 2018, providing a three-year buffer.[16] To construct measures of narrative innovation disclosures, I obtain cleaned (post-stage one parsing) 10-K filings from 1994 to 2021, sourced from Bill McDonald's website.[17] I start the sample period from 1994 because it is the earliest year for which cleaned 10-K filings are available. My sample period is from 1994 to 2018.

I collect financial statement data from Compustat, stock return data from CRSP, analyst data from IBES, and executive compensation data from ExecuComp. My initial sample consists of 21,875 firm-year observations from 3,589 unique firms. I exclude 790 observations without positive total assets and book values of equity (Fitzgerald et al., 2021). I remove 348 observations with a year-end share price below $1 (Kim et al., 2011b). I drop 774 financial firms (Standard Industrial Classification [SIC] codes 6000 to 6999) due to industry-specific effects in the financial sector (Fitzgerald et al., 2021; Jia, 2018). After excluding observations lacking essential data for computing variables used in the regression analyses, the final sample consists of 18,560 firm-year observations from 3,107 unique firms. Table 1 outlines the sample selection process.

4.3 Major Variables

4.3.1 Patent-Based Measure of Corporate Innovation Strategy

To operationalize the construct of the innovation strategy, which reflects the extent to which knowledge utilized in innovation is derived from the firm's existing knowledge pool, I adopt the

---

[15] This is consistent with Benner and Tushman (2002) and Gao et al. (2018). However, some studies use grant years to mitigate the truncation issues that patent data increasingly suffers from missing observations when patent application dates move closer to the end of the dataset (Fitzgerald et al., 2021; Jia, 2018). In robustness tests, I replace application years with grant years and the results still hold.
[16] The average time from filing a patent application to receiving a patent grant is three years (Cao et al., 2018).
[17] I thank the authors of Loughran and Mcdonald (2016) for making the data publicly available on Bill McDonald's website at: https://sraf.nd.edu/sec-edgar-data/cleaned-10x-files/.

approach used in prior research (Fitzgerald et al., 2021; Jia, 2018).[18] I measure innovation strategy as the overlap between a firm's citations of new patents applied for in a year and its previous five years' patents and enclosed citations. If the citation in a new patent cannot be matched with past citations or patents, it indicates that the firm acquires new knowledge and the citation is categorized as a "new citation". In contrast, if the citation is matched with past citations or patents, it suggests that the firm utilizes existing knowledge and the citation is labeled as an "old citation". For each patent, if the majority of the enclosed citations are new (i.e., greater than 80%), I categorize it as an exploratory patent. This classification emphasizes patents that primarily draw from new knowledge, reflecting the firm's innovative efforts to expand beyond its existing knowledge base.

To transition from a patent-level measure to a firm-level measure, I use a continuous measure, exploratory patent ratio (*ExploreRatio*), to assess the firm's exploratory intensity. *ExploreRatio* is calculated as the total count of exploratory patents applied for in a year divided by the total number of patents applied for during the same year.[19] This metric indicates a firm's prioritization of exploratory innovations by quantifying the proportion of its patents that are exploratory. A higher (lower) level of *ExploreRatio* indicates a greater focus on exploratory (exploitative) innovations. *ExploreRatio* falls within the range of zero to one, with a value of one (zero) indicating that all patents applied for in a year are exploratory (exploitative), representing an exclusive exploration (exploitation) strategy. Appendix B provides a more comprehensive calculation process and an

[18] While there may be alternative methods to proxy for innovation strategy, the current literature predominantly focuses on patent-based measures (Benner & Tushman, 2002; Gao et al., 2018; Lin et al., 2021). In addition to using patent citations, an alternative method involves examining patents' technology classes (Balsmeier et al., 2017; Fitzgerald et al., 2021). Firms that focus on producing patents in new technological areas are likely to be engaging in more exploratory innovation activities. Conversely, firms that file more patents in familiar technological classes may rely on their previous patent experience, indicating a tendency to avoid exploratory innovation pursuits. Another approach utilizes self-cited patents (Balsmeier et al., 2017; Gao et al., 2018). A higher number of self-citations suggests that the firm primarily innovates within its previously known areas of expertise, implying a more exploitative innovation strategy. Conversely, fewer self-citations indicate a broader exploration into new areas for the firm, indicating a more exploratory innovation strategy.

[19] I use the ratio measure instead of the number of exploratory patents because corporate innovation strategy requires firms to navigate a tradeoff between exploration and exploitation. Relying solely on the count of exploratory or exploitative patents fails to account for this tradeoff decision.

example of Apple's exploratory patent and corporate innovation strategy.[20]

4.3.2 Measure of Narrative Innovation Disclosures

Following Merkley (2014), I extract narrative disclosures relating to innovation from 10-K filings. This involves identifying specific keywords or phrases directly related to innovation activities. The purpose of this dictionary is to capture the diverse aspects of a firm's innovation activities, including objectives, progress, funding, collaboration, and facilities in 10-K filings spanning various industries and an extended timeframe. Such information is primarily prepared for general communications with investors, rather than specialized technological exchanges. To enhance the efficiency of this process, I modify Merkley's (2014) keyword list by stemming and combining keywords to capture terms with similar meanings but differing forms. In addition, I supplement the list with additional keyword phrases based on my review of 10-K filings (e.g., introduce product, technological change). Appendix C provides my keyword list of narrative innovation disclosures.

I measure narrative innovation disclosures (*InvDiscQty*) as the natural logarithm of the total number of innovation-related sentences in a firm's 10-K filing (Merkley, 2014).[21] I conduct textual analysis at the sentence level because of its advantages in capturing variations in tone and content within paragraphs. This approach helps minimize noise and improves classification accuracy.

4.4 Baseline Model

I estimate the following regression model in Equation (1) to test H1, which examines the effect of corporate innovation strategy on firms' narrative innovation disclosure quantity:

---

[20] This patent-based measure is subject to limitations as it only considers backward citations and does not account for the actual influence of the innovation, such as future citations. To improve this measurement, future research may consider adjusting for future citations and the scientific value of patents (Kogan et al., 2017).
[21] In the robustness tests, I measure narrative innovation disclosures as the natural logarithm of one plus the total number of innovation-related sentences in a firm's 10-K filing. The results remain consistent.

$$
\begin{aligned}
InvDiscQty_t = {} & \beta_0 + \beta_1 ExploreRatio_{t-1} + \beta_2 Size_{t-1} + \beta_3 AdjROA_{t-1} + \beta_4 BTM_{t-1} \\
& + \beta_5 CapInt_{t-1} + \beta_6 Lev_{t-1} + \beta_7 Growth_{t-1} + \beta_8 R\&D_{t-1} + \beta_9 R\&DSq_{t-1} \\
& + \beta_{10} FirmAge_{t-1} + \beta_{11} AnalystFollow_{t-1} + \beta_{12} MgmtForecast_{t-1} \\
& + \beta_{13} TotalPatent_{t-1} + \beta_{14} NonInvDisc_t + \beta_{15} PriorInvDisc_t + \sum Year\ FE \\
& + \sum Industry\ FE + \varepsilon \qquad (1)
\end{aligned}
$$

The dependent variable, narrative innovation disclosure quantity (*InvDiscQty*), is the natural logarithm of sentences that contain innovation-related information in the 10-K filing.[22] The variable of interest, exploratory intensity (*ExploreRatio*), is calculated as the number of exploratory patents divided by total patents. Based on the prediction for H1, I expect a negative association between *InvDiscQty* and *ExploreRatio*, i.e., a negative coefficient of β_1. I include control variables that may affect firms' disclosure choices, including firm performance, disclosure environments, investment strategy, and financing incentives. I control for the adjusted return on assets (*AdjROA*, calculated as the net income before R&D expenditure and advertising expenses scaled by lagged total assets) since research evidence shows that firms' narrative R&D disclosures are negatively associated with earnings performance (Merkley, 2014). I also include sales growth (*Growth*, calculated as the year-to-year percentage change in sales) to control for financial performance.

Prior research suggests that firms' size, life cycle (maturity), and external monitoring affect the firms' disclosure environment (Healy & Palepu, 2001; Lang & Lundholm, 1993). I control for the following variables: firm size (*Size*, calculated as the natural logarithm of firms' total assets), firms' life cycle (*FirmAge*, calculated as the natural logarithm of the firm's age), external monitoring (*AnalystFollow*, calculated as the natural logarithm of one plus the number of analysts following), and firms' overall disclosure level, including non-innovation disclosures (*NonInvDisc*, calculated as the natural logarithm of the number of sentences not related to innovation) in 10-K filings and whether firms provide innovation disclosures in their prior year's 10-K filings (*PriorInvDisc*). Research evidence shows that firms with a greater focus on exploratory innovations are more likely to issue

[22] In the robustness tests, I replace the measure of the narrative innovation disclosure quantity with the ratio measure (calculated as the number of narrative innovation sentences divided by the total number of sentences). The results still hold.

earnings forecasts (Jia, 2019). Therefore, I control for the alternative channels of disclosure using the natural logarithm of one plus the number of management forecasts in the reporting period (*MgmtForecast*) and patenting activities (*TotalPatent*, calculated as the number of patents granted to the firm scaled by lagged total assets; Glaeser & Landsman, 2021; Lehavy et al., 2011; Merkley, 2014; Nagar et al., 2003).[23] Research evidence suggests that firms' investment mix affects firms' disclosure behaviors (Entwistle, 1999; Kothari et al., 2002). Thus, I control for R&D expenditures (*R&D*, calculated as the R&D expenditure scaled by lagged total assets) and its squared value (*R&DSq*).[24] I include firms' investment activities, capital intensity (*CapInt*), calculated as the ratio of property, plant, and equipment and inventories to lagged total assets, and book-to-market ratio (*BTM*).

Lastly, firms with different innovation strategies have different financing incentives (Fitzgerald et al., 2021) and prior research suggests that firms adjust their disclosures around capital offerings (Lang & Lundholm, 1993). Thus, I control for financial leverage (*Lev*), calculated as the ratio of debt to lagged total assets. I lag independent and control variables (except for the concurrent variables *NonInvDisc* and *PriorInvDisc*) for one year to alleviate the potential reverse effect of firms' disclosure choices on their innovation strategies.[25] I include year and industry fixed effects to control for time-variant factors at the macro level that may affect firms' disclosure decisions and unobserved time-invariant factors across industries.[26] Appendix D provides detailed definitions of all variables.

---

[23] In the robustness tests, I calculate patenting activities as the natural logarithm of the number of patents granted to the firm and the results still hold.

[24] The innovation literature highlights the value of knowledge stocks (Hall et al., 2005). In the robustness tests, I compute the R&D stock by aggregating cumulative R&D investments with a 15% annual depreciation rate and then scale it by lagged total assets. The patent stock is calculated as the total number of patents applied for up to year $t-1$ scaled by lagged total assets. I replace the "flow of knowledge" variables (*R&D* and *TotalPatent*) with the "stock of knowledge" variables (R&D stock and Patent Stock) and the results remain robust.

[25] The results are still robust if using the concurrent independent and control variables.

[26] I do not use firm fixed effects because they treat all sample years of a firm equally, while for disclosure decisions, a firm's behavior in the previous year holds greater relevance than its earlier years' behavior (Cao et al., 2018). Therefore, I control for whether firms disclose narrative innovation disclosures in their previous year's 10-K filings (*PriorInvDisc*). Moreover, my study focuses more on variations across firms rather than within firms and firm fixed effects would eliminate this cross-firm variation. In the robustness tests, I replace the industry fixed effect with the firm fixed effect to control for the omitted time-invariant firm characteristics. The results remain significant at the 1% level (one-tailed).

4.5 Conditional Analysis: Product Market Competition and Technology Spillover

I estimate the following Equation (2) to examine conditional hypotheses H2 and H3:

$$\begin{aligned} InvDiscQty_t = {} & \beta_0 + \beta_1 ExploreRatio_{t-1} + \beta_2 PMCHigh_{t-1} \text{ or } TSHigh_{t-1} \\ & + \beta_3 ExploreRatio_{t-1} * PMCHigh_{t-1} \textit{ or } TSHigh_{t-1} + \beta_4 Size_{t-1} \\ & + \beta_5 AdjROA_{t-1} + \beta_6 BTM_{t-1} + \beta_7 CapInt_{t-1} + \beta_8 Lev_{t-1} + \beta_9 Growth_{t-1} \\ & + \beta_{10} R\&D_{t-1} + \beta_{11} R\&DSq_{t-1} + \beta_{12} FirmAge_{t-1} + \beta_{13} AnalystFollow_{t-1} \\ & + \beta_{14} MgmtForecast_{t-1} + \beta_{15} TotalPatent_{t-1} + \beta_{16} NonInvDisc_t \\ & + \beta_{17} PriorInvDisc_t + \textstyle\sum Year\ FE + \sum Industry\ FE + \varepsilon \end{aligned} \tag{2}$$

The moderating variables are product market competition (*PMC*) and technology spillover (*TS*). I use a firm-level variable developed by Bloom et al. (2013) to capture product market competition from existing rivalry (*PMC*). Using firm-specific product market competition measures offers several advantages over industry-level measures such as industry concentration ratios and the Herfindahl index (HHI). First, industry-level competition measures may fail to fully account for variations in firm-level disclosure decisions. Second, within an industry, larger firms often experience different levels of competition compared to smaller ones, which may not be accurately reflected in industry-level measures. Third, industry-level measures typically rely on a firm's primary industry classification, potentially overlooking its broader range of operations. For example, while Apple's SEC filing may categorize it under the mobile communication equipment industry (primary SIC code = 36), it also operates in the personal computer industry (secondary SIC code = 35).[27] In contrast, *PMC*, as a firm-specific measure, considers segment sales across both primary and secondary industries, thus providing more comprehensive insights into firms' operations.[28]

I calculate the cosine similarity of sales distribution between the focal firm and its

[27] https://www.naics.com/company-profile-page/?co=9957

[28] Current literature introduces alternative firm-specific competition measures. One measure, LLMCompetition, introduced by Li et al. (2013), counts the number of competition-related words in a firm's 10-K report divided by the total number of words in the report. Another firm-level competition measure, Fluidity, introduced by Hoberg et al. (2014), measures the changes in a firm's product space due to moves made by its competitors by taking the cosine similarity between a firm's own word-usage vector and the absolute aggregate change in all firms' word-usage vectors. Note that LLMCompetition and Fluidity are based on 10-K disclosures, they might overlap with my narrative innovation disclosures. Thus, LLMCompetition and Fluidity might not be ideal measures of competition for testing the relation between competition and disclosure, even though they could be useful in other settings.

competitors in the product market, reflecting the extent of rivalry for the same product space (Bloom et al., 2013). First, I assign a product market distribution vector P_i to each firm i, which is based on the firm's sales distribution across industry sectors (two-digit SIC codes): $P_i = \{p_1, p_2, p_3, \ldots, p_n\}$, where p_1 is the average market share of firm i based on sales in the first industry sector in the previous two years.[29] Second, I calculate the measure of product market similarity $N_{ij} = P_i' P_j \big/ \sqrt{P_i}\sqrt{P_j}$, where N_{ij} is the cosine similarity approach in Jaffe (1986) between firm i's sales distribution (P_i) and firm j's sales distribution (P_j). Third, I multiply product market similarity between firm i and firm j (N_{ij}) with the R&D stock of firm j (G_j). To calculate the R&D stock of firm j's technological knowledge, I use the inventory method employed by Hall et al. (2005). I calculate firm j's imputed R&D stock in year t as the R&D expense in year t plus the depreciated R&D stock in year t −1, where the depreciation rate is 15% (δ = 0.15): $G_{jt} = R\&D_{jt} + (1 - \delta)G_{jt-1}$. Fourth, I aggregate all multiples and take the natural logarithm to construct the product market competition for firm i in year t: $PMC_i = \mathrm{Log}(1 + \sum_{j \neq i} G_j N_{ij})$. A higher *PMC* value indicates a greater overlap between the sales distributions of the focal firm and other firms across product industries, indicating intensified product market competition. To enhance the interpretation of the moderating effect, I rank the sample based on *PMC* and create an indicator variable, *PMCHigh,* with a value of one if *PMC* exceeds the median and zero otherwise. Based on the H2 prediction, I expect a more adverse effect of product market competition on exploration-focused firms, i.e., a negative coefficient of β_3 on the interaction term.

In contrast, technology spillover (*TS*) measures the firm's ability to benefit from the technological knowledge generated by its peers. I follow Bloom et al. (2013) and use a firm-level variable to capture *TS*. Firm i benefits from the technology spillover from firm j when firm i and firm

[29] I use the average market share of firms based on sales in the industry sectors over the previous two years to better reflect fast changes in the product market landscape of R&D firms (Cao et al., 2018). As a robustness check, I use a longer period of the previous five years (Qiu & Wan, 2015) and the result still holds.

j use similar technologies and when the stock of knowledge in firm j is larger than that of firm i ($G_{jt} > G_{it}$). I calculate the technological similarity between firms i and j to measure the ability of firm i to benefit from firm j's technology through learning. I follow Jaffe (1986) and calculate technological similarity based on firm's patent distributions across technology classes. First, I assign a technology distribution vector S_i to firm i, which is based on the firm's patent distribution across 673 technology subclasses in the Cooperative Patent Classification (CPC). $S_i = \{s_1, s_2, s_3, \dots, s_{673}\}$, where s_1 is the proportion of patents held by firm i in the first technology subclass in the previous five years. Second, I calculate the measure of technological similarity $M_{ij} = S_i' S_j \big/ \sqrt{S_i}\sqrt{S_j}$, where M_{ij} is calculated using the cosine similarity approach that measures the ability of firm i to take advantage of technological knowledge developed by firm j. Third, I multiply technological similarity between firm i and firm j (M_{ij}) with the R&D stock of firm j (G_{jt}). Fourth, I aggregate the multiples across all firms j ($j \neq i$), scaled by firm i's own R&D stock, and take the natural logarithm to construct the technology spillover for firm i in year t: $TS_{it} = \text{Log}(1 + \sum_{j \neq i} G_j M_{ij} / G_i)$. A higher TS value suggests that a firm is exposed to greater knowledge inflow and increased technology spillover. *TSHigh* is an indicator that equals one if *TS* exceeds the median and zero otherwise. Based on H3's prediction, I anticipate a more favorable effect of technology spillover on exploration-focused firms (i.e., a positive coefficient of β_3). I lag both explanatory and control variables by one year. All control variables and fixed effects are explained in Section 4.4.

4.6 Conclusion

In summary, this chapter presents the research design for hypotheses. I describe my sample selection process, the measures of major variables, and the regression models for my baseline and conditional hypotheses. Equation (1) is used to test H1 and Equation (2) is used to test H2 and H3.

Chapter 5
Empirical Analysis of the Effect of Corporate Innovation Strategy on Narrative Disclosures

5.1 Introduction

In this chapter, I test my main hypothesis on the association between corporate innovation strategy and narrative innovation disclosures and two conditional hypotheses about the moderating effects of product market competition and technology spillover. Section 5.2 reports the descriptive statistics for the sample firms and the out-of-sample firms. Section 5.3 reports the results of the univariate analysis. Section 5.4 provides the results of the baseline hypothesis (H1). Section 5.5 reports the results of employing propensity score matching, instrumental variables, change specification, and exogenous shock to strengthen causal effects and mitigate endogeneity issues. Section 5.6 provides the results of conditional hypotheses (H2 and H3). In Section 5.7, I perform several tests to ensure the robustness of the measures of innovation strategy and narrative innovation disclosures. I conclude this chapter in Section 5.8.

5.2 Descriptive Statistics

Panel A of Table 2 presents the sample distribution by industry, utilizing the two-digit SIC code. The Electronic and Other Electric Equipment sector (SIC code 36) holds the most significant representation, followed closely by Chemicals and Allied Products (SIC code 28), Instruments and Related Products (SIC code 38), Industrial Machinery and Equipment (SIC code 35), and Business Services (SIC code 73) sectors. These industries are frequently related to intensified innovative activities and patent production.[30] Panel B shows the average (median) *ExploreRatio* across two-digit SIC classifications of industries. The data reveals substantial variations in exploratory intensity across

[30] The distribution of my sample is comparable to that of prior studies (e.g., Jia, 2017, 2018, 2019), which enhances the credibility of my findings in relation to previous research.

these industries, with averages (medians) ranging from 0.381 (0.333) to 0.631 (0.667).[31]

Figure 1 illustrates the sample distribution across years, which reveals a gradual upward trend without notable dominance by a specific year.[32] Figure 2 shows the trends in the average number of total patents and exploratory patents applied for by firms across years. An upward trend in total patents indicates that patenting remains a prevalent method for safeguarding intellectual property. The average number of exploratory patents exhibits relative stability with a gradually increasing trend.

Figure 3 shows the trend of average innovation strategy with exploratory intensity across years. The average exploratory intensity shows a declining trend over time. This pattern aligns with expectations, as obtaining exploratory patents is generally easier when there are relatively few existing patents. As the number of patents increases over the years, the opportunity and ease of securing exploratory patents may diminish, leading to a downward trend in exploratory intensity.

Figure 4 illustrates the trends of the average number of narrative innovation sentences and the average percentage of narrative innovation sentences as a proportion of total sentences in 10-K filings over time. The length of narrative innovation sentences (also the untabulated length of 10-K filings) shows substantial increases over the years. This growth can be attributed partially to the increasing complexity of the operating and reporting environment. Additionally, Reg S-K specifies elements for registrant disclosures, including new products and intellectual property. Moreover, the lengthening of narrative innovation sentences is influenced by the tendency of firms to add new information without necessarily removing outdated content, a phenomenon known as the stickiness of disclosures in 10-K filings (Brown & Tucker, 2011). The trend line of the average narrative innovation sentence ratio also demonstrates an upward trajectory over time.

Panel A of Table 3 presents the summary statistics for the key variables of sample firms over

[31] In untabulated results, I observe differences in the quantity of narrative innovation across various innovation-intensive industries.

[32] I observe a significant increase in sample observations in 2003, which may be due to a surge in 10-K filings.

the period from 1994 to 2018.[33] The average (median) exploratory intensity (*ExploreRatio*) is 0.537 (0.519). The average (median) firm in the sample shows a narrative innovation disclosure quantity of 4.046 (4.094) and a non-narrative innovation disclosure quantity in 10-K filings of 7.237 (7.260). On average, 85.5% of sample firms disclose innovation-related information in their prior year's 10-K filings. The product market competition (*PMC*), which measures the intensity of competition among existing rivals for the same product space, shows a mean (median) of 10.975 (11.895). Technology Spillover (*TS*) measures the positive externality that firms can obtain given the technological investment in patents by peers, with a mean of 5.445 and a median of 6.059. The innovative firms have a mean (median) *Size* of 6.607 (6.479), a book-to-market ratio (*BTM*) of 0.457 (0.369), capital intensity (*CapInt*) of 0.328 (0.296), sales growth (*Growth*) of 0.172 (0.071), and a leverage ratio (*Lev*) of 0.198 (0.149). *R&D* has an average (median) of 0.107 (0.057), while the adjusted return-on-assets (*AdjROA*) has an average (median) of 0.087 (0.094).[34]

Table 3, Panel B provides the summary statistics for raw measures of sample firms. The average (median) of the total number of patents (*CountTotalPatent*) that a firm applied for per year is 60 (7), with 24 (3) exploratory patents (*CountExplorePatent*).[35] The average (median) length of 10-K filings is 1,661 (1,518) sentences (*TotalSent*). I modify the keyword list from Merkley et al. (2014) by stemming and re-ordering keyword combinations, as well as adding new keywords based on reading 10-K filings. The average (median) number of narrative innovation disclosure sentences (*InvSent*) is 98 (60), comprising 5.9% (4.0%) of the total disclosures in 10-K filings. In comparison, firms disclose an average (median) of 43 (25) R&D-related sentences (*InvSentMerkley*) based on Merkley's list, representing 2.6% (1.6%) of the total 10-K disclosures. My modified keyword list captures a

[33] I do not winsorize all continuous variables as this procedure modifies the tail distribution and can affect the randomness of the sample. Instead, to minimize the influence of outliers, I winsorize *BTM* and *Growth* at the *1st* and *99th* percentiles. In the robustness tests, I winsorize all continuous variables and the results still hold.
[34] The sample distribution is consistent with those in prior papers (e.g., Fitzgerald et al., 2021; Jia, 2017, 2018).
[35] Given the potential skewness in patent data, I perform the subsample analysis focusing on extreme cases in Section 5.7.1.

broad range of narrative innovation disclosure sentences, including R&D, product development, and technology enhancement. This shows that narrative innovation disclosures account for a substantial portion of 10-K filings, which is especially significant considering that managers have the discretion to disclose only the minimum amount of information. On average (median), 10 (7) analysts (*AnalystFollowRaw*) follow the sample firms, while managers (*MgmtForecastRaw*) issue 1 (0) forecast per year. These sample firms have been publicly listed (*FirmAgeRaw*) for an average (median) of 24 (18) years. All raw measures are defined in Appendix D.

Panels C and D of Table 3 provide the summary statistics for out-of-sample firms that did not apply for any patents in a year. In Panel C, out-of-sample firms are relatively smaller than sample firms, with an average (median) *Size* of 5.897 (5.826). The average (median) out-of-sample firms disclose less innovation-related information, with 2.803 (2.833) and non-narrative innovation disclosures in 10-K filings of 7.140 (7.166). On average, 81.4% of out-of-sample firms disclose innovation-related information in their prior year's 10-K filings. The product market competition (*PMC*) is also less intense in out-of-sample firms, which have a mean (median) of 9.893 (10.834). In addition, the average (median) out-of-sample firms have a book-to-market ratio (*BTM*) of 0.588 (0.501), capital intensity (*CapInt*) of 0.434 (0.398), sales growth (*Growth*) of 0.309 (0.065), and a leverage ratio (*Lev*) of 0.242 (0.187).[36] The adjusted return-on-assets (*AdjROA*) has an average (median) of 0.050 (0.056). Noticeably, R&D expense (*R&D*) for out-of-sample firms is 0.038 (0), which is significantly lower than that of innovation-active firms.

Table 3, Panel D provides the summary statistics for raw measures of out-of-sample firms. The length of 10-K filings (*TotalSent*) for out-of-sample firms is 1,482 (1,331) sentences, which is comparable to sample firms. The number of narrative innovation disclosures using Merkley's keyword list (*InvSentMerkley*) shows that out-of-sample firms disclose 15 (6) R&D-related sentences, representing 1.0% (0.5%) of the total disclosures in 10-K filings. The number of narrative innovation

[36] *CapInt* is winsorized at the *1st* and *99th* percentiles to minimize the influence of outliers.

disclosure sentences using my modified keyword list (*InvSent*) for out-of-sample firms is 36 (17), representing 2.4% (1.3%) of the total disclosure sentences in 10-K filings. This proportion is significantly lower compared to that of sample firms. These findings align with the notion that out-of-sample firms engage in and disclose fewer innovative activities than their innovation-active counterparts. On average (median), 6 (4) analysts (*AnalystFollowRaw*) follow the out-of-sample firms and managers (*MgmtForecastRaw*) issue 1 (0) forecast per year. These out-of-sample firms have been publicly listed (*FirmAgeRaw*) for an average (median) of 21 (17) years.

In Panel E of Table 3, I categorize firms into three portfolios based on the *30th* and *70th* percentiles of their exploratory intensity (*ExploreRatio*) measured in year $t-1$. On average, these portfolios consist of 5,568, 7,239, and 5,753 firms in the low, middle, and high exploratory-focus categories, respectively. The average *Size* of firms in each portfolio is 6.267, 7.266, and 6.106 respectively. Among firms actively involved in innovation and patent activities, smaller firms tend to be more exploration-focused than larger firms. Moreover, there is significant variation in the exploratory intensity across the portfolios. In particular, the average exploratory intensity in the low *ExploreRatio* group is 0.101, while the average value in the high group is 0.962. Also, I observe that firms with higher exploratory focus tend to exhibit lower R&D intensity (0.085) and produce fewer patents (0.027) compared to firms with higher exploitative focus with R&D intensity of 0.145 and patents of 0.059. These findings align with prior research (Fitzgerald et al., 2021). One plausible explanation is the lower frequency of breakthroughs in exploratory innovation compared to the incremental improvements in exploitative innovation. Exploratory innovation can also be more challenging to scale up and typically carries a higher failure-to-success ratio (Jia, 2017). Narrative innovation disclosures (*InvDiscQty*) are lower in the high exploratory-focus group (3.675) than in the low exploratory-focus group (4.452), which provides preliminary evidence supporting my prediction that exploration-focused firms tend to disclose a lower quantity of narrative innovation information.

Table 4 presents the correlation matrix of major variables. Using Pearson correlation (lower left) as an example, I observe a negative correlation between *ExploreRatio* and *InvDiscQty* with a coefficient of –0.297, which is consistent with my prediction that firms with a greater focus on exploratory activities tend to provide lower narrative innovation disclosure quantity than firms with a greater focus on exploitative activities. I also find a positive but weak correlation between *PMC* and *TS* with a coefficient of 0.089, showing that although there is overlap between peer firms in the technology space and peer firms in the product market space, they are sufficiently different to allow for empirical analysis (Bloom et al., 2013). This preliminary evidence reinforces the notion that PMC and TS represent distinct constructs. Moreover, I find a positive correlation between *R&D* and *InvDiscQty* with a coefficient of 0.497, suggesting that firms with higher R&D expenses tend to disclose more innovation-related information in 10-K filings. I also observe a negative relation between *AdjROA* and *InvDiscQty*, consistent with research evidence that firms' narrative innovation disclosures are negatively associated with earnings performance (Merkley, 2014).[37]

5.3 Univariate Analysis

Table 5 presents the univariate analysis for two sample groups categorized by firms' exploratory intensity and examines the correlation between a firm's innovation strategy and firm characteristics. I divide firms into two groups based on whether their exploratory intensity (*ExploreRatio*) measured in year $t-1$ falls above or below the median (*ExploreHigh*). On average, firms with above-median exploratory intensity report 4.5% of narrative innovation disclosures in 10-K filings, whereas firms below-median report 7.2% of narrative innovation disclosures (untabulated). This comparison suggests that firms with above-median exploratory intensity report 2.7% less narrative innovation disclosure quantity than those below-median (p-value < 0.001). In addition, I observe that firms with above-median exploratory intensity report lower R&D expenses (p-value < 0.001) and hold fewer patents (p-value < 0.001). Overall, the univariate results are consistent with my

[37] The variance inflation factors (VIFs) in my regressions are no greater than 4, which is well below the suggested multicollinearity problem threshold of 10 (Gujarati, 1995).

H1, suggesting that firms with a greater focus on exploratory activities tend to provide lower narrative innovation disclosure quantity than firms with a greater focus on exploitative activities.

5.4 Baseline Result (H1)

My H1 predicts a negative association between firms' innovation strategy of focusing more on exploratory innovations and their narrative innovation disclosures. To test this hypothesis, I estimate an OLS model that regresses the quantity of firms' narrative innovation disclosures (*InvDiscQty*) on firms' exploratory intensity (*ExploreRatio*), using Equation (1). I control factors related to innovation-related disclosures, or both innovation disclosures and innovation strategy.

In Table 6, Columns (1) to (3) report the results for regressions with different control variables and fixed effects. Across all columns, the coefficients on *ExploreRatio* are significantly negative at the 1% level. Column (1) shows the results of the baseline model after controlling for year and industry fixed effects (coefficient = –0.428). Columns (2) and (3) show the results including control variables and further including fixed effects (coefficients = –0.461 and –0.265). The results have economic significance (e.g., Column [3]): for every one percent increase in exploratory innovation intensity, firms decrease their narrative innovation disclosure quantity in 10-K filings by 27%. Overall, the results align with my prediction for H1, suggesting that exploration-focused firms disclose less narrative innovation information compared to exploitation-focused firms.

My regression model includes R&D expenses to control for proprietary costs. In Column (3), the coefficient on *R&D* is positive and significant, while the coefficient on *R&DSq* is significantly negative at the 1% level. The coefficients on the two R&D variables (*R&D* and *R&DSq*) are consistent with Merkley (2014), suggesting a non-linear effect of R&D expenditures on narrative innovation disclosures. Moreover, firms' adjusted return on assets (*AdjROA*), sales growth (*Growth*), and overall disclosure level (*NonInvDisc*) are associated with increased narrative innovation disclosures. Although *AdjROA* and *InvDiscQty* show a negative correlation in Table 4, I observe a positive relation in baseline regression results. This indicates that firms with higher *AdjROA* may be financially robust and more likely to communicate their innovation activities with investors. Firms experiencing high sales growth may find it beneficial to highlight their innovation efforts to sustain the growth. Firms that generally disclose more information may have a more transparent disclosure environment, which leads them to disclose more about their innovation activities.

I find negative relationships between narrative innovation disclosure and firm size (*Size*), book-to-market ratio (*BTM*), capital intensity (*CapInt*), as well as leverage (*Lev*). I observe that firms with larger sizes tend to disclose less narrative innovation information. This phenomenon may be attributed to the prevalence of innovation-intensive industries, such as electronics, chemicals, and measuring (SIC 36, 28, and 38, respectively), where firms typically exhibit smaller sizes relative to the industry average. Firms with higher book-to-market ratios (*BTM*), which are typically more growth-oriented innovative firms, tend to disclose less narrative innovation information. Firms with higher capital intensity (*CapInt*) might invest significantly in technological infrastructure and factories and disclose less to protect their innovation activities. Firms with higher leverage (*Lev*) may disclose less to maintain their financial stability and manage debt obligations. I also find a negative effect of firms' life cycle (*FirmAge*) on narrative innovation disclosures. Older firms, particularly those in mature stages of their life cycle, may prioritize stability over innovation. Firms tend to provide more narrative innovation disclosures under external monitoring as measured by the number of analysts following (*AnalystFollow*).

5.5 Endogeneity Issue of H1

5.5.1 Propensity Score Matching

Although I control for factors that may influence disclosure choices, including firm performance, disclosure environments, investment strategy, and financing incentives, as well as incorporate year, industry, and/or firm fixed effects, I cannot rule out the possibility of potential endogeneity problems caused by selection bias due to observables (Tucker, 2011). It is possible that firms' total patents affect firms' innovation strategy and firms with an exploration focus have fewer patents than firms with an exploitation focus. To reduce the bias of observable factors such as control variables on firms' innovation strategies, I set the indicator variable *ExploreHigh* to identify the treatment group, assigning it a value of one if *ExploreRatio* exceeds the sample median and zero otherwise. Then, I use the propensity score matching (PSM) method to compare two highly similar groups of firms across observable dimensions. To find a control group that is as similar as possible to the treatment group, I use a year-by-year and one-on-one method for matching.[38] I use the control variables from Equation (1) as matching variables and estimate the propensity score for each observation using a logit regression. The single nearest-neighbor approach is utilized to identify the control group, allowing for the calculation of the average treatment effect for the treated value.

Table 7, Panel A compares firm characteristics in a t-test for treatment (firms with higher exploratory intensity, *ExploreHigh* = 1) and matched control firms (firms with higher exploitative intensity, *ExploreHigh* = 0). Insignificant differences in variables between the treatment and control firms in the matched sample confirm the success of the matching process. Panel B shows the H1 results using the PSM sample. Notably, Column (1) shows the result using the indicator *ExploreHigh* as the independent variable, with a coefficient of −0.150 at the 1% level. Column (2) shows the result using the continuous ratio *ExploreRatio* as the independent variable, with a coefficient of −0.273 at the 1% level. I find that exploration-focused firms tend to disclose less narrative innovation information compared to exploitation-focused firms in the matched sample, suggesting that my findings are robust against the endogeneity issue of sample self-selection based on observables.

[38] In an alternative method for PSM, I estimate a logit model to predict firms with higher exploratory intensity versus firms with higher exploitative intensity based on a vector of firm characteristics and controlled by year and industry fixed effects. I then implement nearest-neighbor matching without replacement within a caliper of 0.03 to select benchmark observations. The result is still robust at the 1% level.

5.5.2 Instrumental Variables

To mitigate potential issues related to correlated omitted variables and to enhance the reliability of causal inferences drawn from the baseline results, I implement two instrumental variables (*IVs*): the availability of patent practitioners (attorneys and agents) where the firm's headquarters are located and the industry average of exploratory intensity (Huang et al., 2021). Patent practitioners play a crucial role in advocating for clients' inventions and persuading the USPTO to grant patents. They should have adequate knowledge of technology to understand the invention and protect clients' innovation activities (De Rassenfosse et al., 2023). I posit that the availability of patent practitioners might affect firms' innovation strategy through their involvement in innovation and patent activities. However, it is unlikely that the availability of patent practitioners directly affects firms' innovation disclosures. I use the variable, *PatentPractitioner*, which counts the number of patent practitioners within each state from the USPTO.[39]

Furthermore, I follow a common approach in the accounting literature that uses the industry average of the variable of interest as the second instrument, *ExploreRatioIndAvg* (Huang et al., 2021; Jia, 2017). Industry-level factors may indirectly influence firms' disclosure behaviors through firms' innovation strategies, although there is no direct evidence suggesting that industries prioritizing exploratory innovations provide fewer innovation disclosures. All variables are defined in Appendix D. I estimate the following two-stage least squares (2SLS) model using Equations (3.1) and (3.2):

$$\begin{aligned} ExploreRatio_{t-1} &= \beta_0 + \beta_1 IVs_{t-1} + \beta_2 Size_{t-1} + \beta_3 AdjROA_{t-1} + \beta_4 BTM_{t-1} \\ &+ \beta_5 CapInt_{t-1} + \beta_6 Lev_{t-1} + \beta_7 Growth_{t-1} + \beta_8 R\&D_{t-1} + \beta_9 R\&DSq_{t-1} \\ &+ \beta_{10} FirmAge_{t-1} + \beta_{11} AnalystFollow_{t-1} + \beta_{12} MgmtForecast_{t-1} \\ &+ \beta_{13} TotalPatent_{t-1} + \beta_{14} NonInvDisc_t + \beta_{15} PriorInvDisc_t \\ &+ \sum Year\ FE + \sum Industry\ FE + \varepsilon \end{aligned} \tag{3.1}$$

[39] This data is available from 2006 to 2018 at: https://www.uspto.gov/learning-and-resources/patent-and-trademark-practitioners.

$$
\begin{aligned}
InvDiscQty_t = {} & \beta_0 + \beta_1 \widehat{ExploreRatio}_{t-1} + \beta_2 Size_{t-1} + \beta_3 AdjROA_{t-1} + \beta_4 BTM_{t-1} \\
& + \beta_5 CapInt_{t-1} + \beta_6 Lev_{t-1} + \beta_7 Growth_{t-1} + \beta_8 R\&D_{t-1} + \beta_9 R\&DSq_{t-1} \\
& + \beta_{10} FirmAge_{t-1} + \beta_{11} AnalystFollow_{t-1} + \beta_{12} MgmtForecast_{t-1} \\
& + \beta_{13} TotalPatent_{t-1} + \beta_{14} NonInvDisc_t + \beta_{15} PriorInvDisc_t \\
& + \sum Year\ FE + \sum Industry\ FE + \varepsilon
\end{aligned} \tag{3.2}
$$

Table 8 presents the results of the 2SLS analysis. Both *IVs* are lagged by one year. The first instrument is *PatentPractitioner* and the coefficient on this instrument (−0.006) in the first stage is significantly negative at the 1% level.[40] This aligns with the argument that firms may face higher competition for innovation with a greater number of patent attorneys in a particular area. Thus, firms may be incentivized to protect their current innovations by focusing more on exploitative innovation activities and less on exploratory innovation activities. The second instrument, *ExploreRatioIndAvg*, shows a significantly positive coefficient (0.949) at the 1% level in the first stage. This aligns with the notion that firms have incentives to conduct more exploratory innovation activities if the industry averages also emphasize exploratory innovation activities.

The predicted value of the instrumental variables from the first stage is used in the second stage to examine the relation between firm innovation strategy and narrative innovation disclosures. In the second stage, the coefficient on *ExploreRatio* (−0.195) is negative and significant at the 1% level (one-tailed), which is consistent with my baseline findings.

5.5.3 **Change Specification**

To enhance causal inference and address potential reverse causality issues in my thesis, I employ a change specification analysis. This method allows for the investigation into the dynamic relationship between firms' innovation strategies and their disclosure decisions, focusing on how shifts in innovation strategies relate to changes in disclosure choices over time. Building on prior research highlighting the enduring nature of innovative activities (Nikolaev & Van Lent, 2005), I recognize that a firm's innovation strategy tends to persist longitudinally. Thus, the intensity of

[40] The results still hold if using the patent practitioner measure (PatAttorney) from Huang et al., (2021). I thank the authors for sharing the data.

exploration and exploitation in the current year may be influenced by past trends. To implement this approach, I use a four-year window in Equation (4) of the change specification, examining the connection between shifts in a firm's innovation strategy and corresponding changes in narrative innovation disclosures.[41] The dependent variable represents the change in narrative innovation disclosures from year $t-4$ to year t. Both independent and control variables are lagged by one year, capturing changes from year $t-5$ to year $t-1$.

$$\begin{aligned}\Delta_{t-4}^{t} InvDiscQty \\ &= \beta_0 + \Delta_{t-5}^{t-1}\beta_1 ExploreRatio + \Delta_{t-5}^{t-1}\beta_2 Size + \Delta_{t-5}^{t-1}\beta_3 AdjROA + \Delta_{t-5}^{t-1}\beta_4 BTM \\ &+ \Delta_{t-5}^{t-1}\beta_5 CapInt + \Delta_{t-5}^{t-1}\beta_6 Lev + \Delta_{t-5}^{t-1}\beta_7 Growth + \Delta_{t-5}^{t-1}\beta_8 R\&D + \sum Year\ FE \\ &+ \sum Industry\ FE + \varepsilon \end{aligned} \tag{4}$$

Table 9 reports the results of changes in firms' exploratory intensity and narrative innovation disclosure quantity over four years. In Columns (1) to (3), the coefficients on the overall changes in *ExploreRatio* (−0.093, −0.103, and −0.073, respectively) during this window are negative and significant at the 5% and 1% levels (one-tailed) in Columns (1) and (2), respectively. These results suggest that an increased intensity of exploratory innovation is associated with a subsequent reduction in firms' narrative innovation disclosures. I further divide the sample into cases with positive changes in *ExploreRatio* in Columns (4) to (6) and negative changes in *ExploreRatio* in Columns (7) to (9). Results in Columns (4) to (6) provide some evidence that an increased emphasis on exploratory innovation is associated with a subsequent reduction in firms' narrative innovation disclosures. In Columns (7) and (9), Although I find positive coefficients on negative changes in *ExploreRatio,* they are not statistically significant. The lack of significance may be attributed to the challenges of capturing disclosure behaviors over an extended time frame. Overall, the results indicate that managers become more attentive to proprietary costs when transitioning toward a more exploration-focused strategy, suggesting a dynamic causal relationship is, to some extent, in effect.

[41] In the robustness tests, I also utilize three-year and five-year change window periods. The results are qualitatively hold.

5.5.4 Exogenous Shock: Regulation Fair Disclosure

Private communications serve as a natural alternative to public disclosures and prove particularly valuable when a firm is actively involved in significant innovation activities (Hutton, 2005; Wang, 2007). The enactment of Regulation Fair Disclosure (Reg FD) in October 2000 prevents private disclosures by public firms to market professionals and certain shareholders. Reg FD does not prohibit the disclosure of information but requires that the information is accessible to all parties. Nevertheless, if channels for private disclosures are constrained, the increased demand for information, especially in the context of innovation activities, can only be satisfied through public channels. If narrative innovation disclosures contain lower proprietary costs for exploitation-focused firms relative to exploration-focused firms, I might observe an increase in such disclosures for exploitation-focused firms and a decrease for exploration-focused firms.

Prior studies find evidence of the positive effect of the enactment of Reg FD on corporate disclosures. Bailey et al. (2003) and Heflin et al. (2003) find that issuances of earnings forecasts increase in the post-Reg FD period. Huang et al. (2021) find that there is a notable increase in management forecasts following successful innovation outcomes after the adoption of Reg FD. In line with the concept that limitations on private communications lead to increased disclosures with no or low proprietary costs, investors may expect exploitation-focused firms to provide more transparent and detailed disclosures to validate their incremental and exploitative innovation activities as well as future profitability opportunities. However, exploration-focused firms may be perceived as more risky investments with higher proprietary costs and therefore may not increase disclosures after the enactment of Reg FD.

To examine the impact of Reg FD, I use an indicator variable, *PostRegFD*, which takes the value of one for firm years from 2001 onwards and zero otherwise, and its interactions with *ExploreRatio*. All other variables are defined in Appendix D. I estimate the model in Equation (5):

$$InvDiscQty_t = \beta_0 + \beta_1 ExploreRatio_{t-1} + \beta_2 PostRegFD_t + \beta_3 ExploreRatio_{t-1} * PostRegFD + \beta_4 Size_{t-1} + \beta_5 AdjROA_{t-1} + \beta_6 BTM_{t-1} + \beta_7 CapInt_{t-1} + \beta_8 Lev_{t-1} + \beta_9 Growth_{t-1} + \beta_{10} R\&D_{t-1} + \beta_{11} R\&DSq_{t-1} + \beta_{12} FirmAge_{t-1} + \beta_{13} AnalystFollow_{t-1} + \beta_{14} MgmtForecast_{t-1} + \beta_{15} TotalPatent_{t-1} + \beta_{16} NonInvDisc_t + \beta_{17} PriorInvDisc_t + \sum Year\ FE + \sum Industry\ FE + \varepsilon \quad (5)$$

The results are reported in Table 10. As expected, I observe negative and significant coefficients on the main effect of *ExploreRatio*. Also, the coefficients on *PostRegFD* show an increase in narrative innovation disclosures in the main effect. The coefficients on the interaction term, *ExploreRatio* * *PostRegFD*, are negative and significant. The results suggest that after the adoption of Reg FD, exploitation-focused firms with lower proprietary costs increased their narrative innovation disclosures, while exploration-focused firms with higher proprietary costs decreased their narrative innovation disclosures.

5.6 Conditional Analysis (H2 and H3)

Table 11 reports the results of testing H2 and H3, which predict the moderating effects on the relation between a firm's innovation strategy and narrative innovation disclosures. The main effects of the independent variable, *ExploreRatio*, are significant and negative across all columns (–0.232, –0.352, and –0.314), at the 1% level. Column (1) shows the results of H2, which predicts that the effect of product market competition is more negative on exploration-focused firms than on exploitation-focused firms. The coefficient on the interaction term, *ExploreRatio* * *PMCHigh*, is significantly negative (–0.070) at the 5% level (one-tailed). Column (2) reports the results of H3, which predicts a more positive effect of technology spillover on narrative innovation disclosures for exploration-focused firms than for exploitation-focused firms. The coefficient on the interaction term, *ExploreRatio* * *TSHigh*, is positive (0.170) and significant at the 1% level.

Column (3) presents the results that include both product market competition and technology spillover and their interaction terms with *ExploreRatio*. The coefficient on the interaction term, *ExploreRatio* * *PMCHigh*, is significantly negative (–0.090) at the 1% level (one-tailed) and

*ExploreRatio * TSHigh* is significantly positive (0.179) at the 1% level. These findings hold economic significance, suggesting that as product market competition intensifies from low to high, firms reduce their narrative innovation disclosures in their 10-K filings by 9% for every one percent increase in exploratory innovation intensity. This indicates that when product market competition increases, exploration-focused firms tend to reduce their narrative innovation disclosures to a greater extent compared to exploitation-focused firms. In contrast, as technology spillover increases from low to high, firms increase their narrative innovation disclosures in their 10-K filings by 18% for every one percent increase in exploratory innovation intensity. This indicates that as technology spillover increases, exploration-focused firms tend to increase their narrative innovation disclosures to a greater extent compared to their exploitation-focused counterparts.

Overall, the conditional analyses provide evidence that, when faced with heightened product market competition, exploration-focused firms are more likely to reduce their narrative innovation disclosures compared to exploitation-focused firms. However, with growing technology spillover, exploration-focused firms are more inclined to increase their narrative innovation disclosures compared to exploitation-focused firms.

5.7 Robustness Tests

5.7.1 Subsample Analysis

Considering patent data might be skewed, I look at extreme cases and conduct subsample analyses. Out of 18,560 observations, 3,527 firms have applied for one patent in a year. Within these observations, 1,208 firms have an *ExploreRatio* value of zero, indicating that the patent applied for is exploitative. In addition, among these observations where firms applied for one patent per year, 2,319 observations have an *ExploreRatio* value of one, which means that the patent applied for is exploratory. To examine whether my results are affected by extreme cases, I split the sample based on whether firms applied for more than one patent per year.

Table 12 reports the results of subsample analyses. Panel A shows the results for firms that applied for more than one patent per year (*CountTotalPatent* > 1) in Columns (1) to (3) and firms that applied for only one patent per year (*CountTotalPatent* = 1) in Columns (4) to (6). The coefficients on the variable of interest, *ExploreRatio,* remain significant at the 1% level in both groups, with larger coefficients in the group of firms that applied for more than one patent per year.

Then, I further investigate the group without extreme cases (*CountTotalPatent* > 1). I examine firms with non-exclusive exploitative patents (*ExploreRatio* > 0) in Panel B and firms with non-exclusive exploratory patents (*ExploreRatio* < 1) in Panel C. The coefficients on *ExploreRatio* are negative and significant at the 1% level in all columns. The results consistently show that the effect of a firm's innovation strategy on innovation disclosure is robust and enduring.

Since innovation levels differ across industries, it is essential to examine firms in innovation-intensive industries versus non-innovation-intensive industries. I conduct a subsample analysis by comparing the top 10 innovation-intensive industries with other industries.[42] In untabulated results, the coefficients on *ExploreRatio* are negative and significant at the 1% level in both groups. These findings suggest that the tendency of exploration-focused firms to disclose less than exploitation-focused firms is generalizable to firms in non-innovation-intensive industries.

It is also worth considering firm-specific innovation activities. I conduct a subsample analysis by comparing firms with patent activities above and below the sample mean. In untabulated results, the coefficients on *ExploreRatio* are negative and significant at the 1% level in both groups. This result suggests that the tendency of exploration-focused firms to disclose less than exploitation-focused firms is generalizable to sample firms with lower frequencies in patent activities.

Moreover, I adopt the ratio measure (*ExploreRatio*) instead of using the count of exploratory patents because innovation strategy requires firms to navigate a tradeoff between exploration and

[42] Top 10 industries include SIC2 codes 36, 28, 38, 35, 73, 37, 34, 20, 48, and 26. Details are explained in Section 5.2.

exploitation. Instead, I conduct a subsample analysis based on the sample mean of firm size, comparing large and small firms. In untabulated results, the coefficients on *ExploreRatio* remain significant in both groups at the 1% level, with higher coefficients for the group of larger firms. This finding indicates that the trend of exploration-focused firms disclosing less than exploitation-focused firms holds even for smaller firms.

Besides proprietary costs, firms may also consider the litigation risk of disclosing sensitive information. It is possible that exploration-focused firms generally operate in industries with high litigation risks and have concerns about litigation risks, causing them to refrain from disclosing. Therefore, I include litigation risk (*LitRisk*) by using an indicator variable that equals one if the firm's four-digit SIC code falls within the ranges 2833–2836, 3570–3577, 3600–3674, 5200–5961, or 7370–7374 and zero otherwise (Hsieh et al., 2019; Lafond & Roychowdhury, 2008; Ramalingegowda & Yu, 2012).[43] Table 13, Panel D shows the subsample results of firms that operate in industries with low litigation risks (*LitRisk* = 0) in Columns (1) to (3) and firms that operate in industries with high litigation risks (*LitRisk* = 1) in Columns (4) to (6). The coefficients on the variable of interest, *ExploreRatio*, remain significant at the 1% level in both groups. The findings support my prediction and indicate that it is less likely that litigation risk concerns influence firms' narrative innovation disclosure decisions when they have different innovation strategies.

5.7.2 Alternative Explanations

An alternative explanation could be that firms consolidate R&D expenses with other expenditures to safeguard the proprietary costs of the information (Koh & Reeb, 2015). It is possible that firms that do not report R&D have higher proprietary costs than firms that report R&D, which is consistent with the characteristics of exploration-focused firms. In Table 13, Column (1), the

[43] In industries with high litigation risks, 31.5% of the firms are exploration-focused (those in the 70th percentile or above for *ExploreRatio*), while 28.8% are exploitation-focused (those in the 30th percentile or below for *ExploreRatio*). Specifically, among exploration-focused firms, 58.6% operate in industries with high litigation risks. Conversely, 55.3% of exploitation-focused firms operate in industries with high litigation risks.

coefficients on the main variables, *ExploreRatio* and *MissR&D*, are negative and significant at the 1% level. The results indicate that my main findings hold and firms that do not report R&D expenditure disclose less narrative innovation information. However, the coefficient on the interaction term, *ExploreRatio * MissR&D*, is not significant, suggesting that whether firms report R&D does not explain the differences in proprietary costs between exploration-focused and exploitation-focused firms.[44]

I further examine the relation between narrative innovation disclosures and other voluntary disclosure channels, such as management forecasts. In Table 13, Column (2), the coefficient on the main variable, *ExploreRatio*, is negative and significant. The coefficient on *MgmtForecast* is positive and significant at the 10% level. The results indicate that firms that provide management forecasts are more likely to provide narrative innovation disclosures, reflecting an overall transparent disclosure environment. However, the coefficient on the interaction term, *ExploreRatio * MgmtForecast*, is negative and significant at the 1% level. This finding suggests that exploration-focused firms are more likely to treat management forecasts and narrative innovation disclosures as substitutes compared to exploitation-focused firms, highlighting their concerns about the proprietary costs associated with narrative innovation disclosures.

5.7.3 Measures of Main Variables

To ensure the robustness of the innovation strategy measure, I perform several robustness tests. First, my current search period for a firm's knowledge pool spans the previous five years.[45] As a robustness check, I extend the search period by redefining firm i's past innovation output in year t as all granted patents applied by firm i plus patent citations from 1976 to year $t-1$ (originally from $t-5$ to year $t-1$). This expanded period provides a more comprehensive view of a firm's innovation

[44] In the robustness test, I add *MissR&D* as an additional control in the regression and the results still hold.
[45] Lev and Sougiannis (1996) demonstrate that the duration of the benefits derived from research investments, known as technology cycles, is approximately five years.

activities. Second, I use alternative thresholds (e.g., 50%, 60%, and 90%) to categorize a patent as "exploratory", allowing for sensitivity analysis. I rerun the regressions and find that the results remain robust. Third, from a different perspective, I calculate a firm's focus on exploitative innovation activities, which is the ratio of the total number of a firm's patents applied for in year t that are categorized as "exploitative" to the total number of a firm's patents applied for in that year. A patent is considered "exploitative" if at least 80% of its citations are based on the firm's existing knowledge. The results show opposite signs but similar significances, consistent with my main findings.

For alternative dependent variables, I replace my modified keyword list (*InvDiscQty*) with Merkley's narrative R&D disclosure keyword list (*InvSentMerkley*). Since using a sentence-level measure has the drawback in that the meaning of a sentence can be influenced by its surrounding context, I replace the sentence count of disclosures with the word count. I re-estimate the regressions with alternative measures of the dependent variable and the results still mostly hold.

5.8 Conclusion

In summary, this chapter reports that exploration-focused firms provide lower narrative innovation disclosure quantity in their 10-K filings compared to exploitation-focused firms. The baseline results remain robust even after employing various methods to address endogeneity issues, including propensity score matching, instrumental variables, change specification, and Reg FD as an exogenous shock. Moreover, I conduct subsample analyses to further investigate the baseline relation and perform additional tests to ensure the robustness of the measures of major variables. Furthermore, I conduct conditional analyses. The negative relation observed in the baseline results is more pronounced for firms facing intensified product market competition and less pronounced for firms facing increased technology spillover. As existing evidence on the relation between innovation strategy and disclosure is scarce, my thesis contributes to the literature with evidence from both the baseline and conditional analysis findings.

Chapter 6
Empirical Analysis of Stock Market Consequences of Corporate Innovation Strategy on Narrative Disclosures

6.1 Introduction

In this chapter, I examine the consequences of firms' narrative innovation disclosure decisions based on their innovation strategies. This chapter begins by investigating whether narrative innovation disclosures help investors better evaluate exploration-focused firms. Prior research indicates that exploration-focused firms may be prone to overvaluation by investors due to a preference for exploratory and radical innovation activities (Fitzgerald et al., 2021) and an increased likelihood of future stock price crash risk possibly stemming from a lack of information transparency (Jia, 2018). I argue that narrative innovation disclosures may play a role in better evaluating exploration-focused firms. In section 6.2, I examine the short-term market reaction to the release of narrative innovation disclosures by exploration-focused firms. In Section 6.3, I examine the effect of firms' narrative innovation disclosures on the stock price crash risk for exploration-focused firms. I conclude this chapter in Section 6.4.

6.2 Short-term Market Reaction

Investors face challenges when evaluating innovative firms due to the increased volatility and decreased predictability of their earnings (Gu & Li, 2003). Moreover, recent findings highlight the difficulty investors face in understanding the return predictability associated with a firm's innovation strategy, whether it leans toward exploration or exploitation (Fitzgerald et al., 2021; Jia, 2018). The predictive power of a firm's innovation strategy regarding returns supplements the value offered by other innovation-related metrics such as R&D intensity, patent counts, innovation efficiency, and innovation originality (Fitzgerald et al., 2021).[46] This suggests that information on innovation strategy

[46] Fitzgerald et al. (2021) find that, compared to exploration-focused firms, investors tend to undervalue exploitation-focused firms. The authors also find that exploitation-focused firms are more likely to generate

offers additional insights for investors beyond existing innovation-related metrics.

I conduct short-term market reaction tests to examine initial investor reactions to corporate innovation strategy and narrative innovation disclosures. I estimate the following Equation (6):

$$\begin{aligned} CAR_t \text{ or } sCAR_t = {} & \beta_0 + \beta_1 ExploreRatio_{t-1} + \beta_2 InvDiscQty_t + \beta_3 ExploreRatio_{t-1} \\ & * InvDiscQty_t + \beta_4 Beta_t + \beta_5 MTB_t + \beta_6 Size_t + \beta_7 AdjROA_t + \beta_8 R\&D_t \\ & + \beta_9 SG\&A_t + \beta_{10} ROE_t + \beta_{11} NonInvDisc_t + \sum Year\ FE + \sum Industry\ FE \\ & + \varepsilon \end{aligned} \tag{6}$$

The dependent variables include cumulative abnormal return (*CAR*) and standardized cumulative abnormal return (*sCAR*) during a short-term (−5, +5) event window around the 10-K filing date (Tucker, 2007).[47] I calculate *CAR* as the sum of abnormal returns over the event window, while *sCAR* is derived by scaling *CAR* by the square root of the product of the event window length and the estimated variance of abnormal returns. For the independent variables, I interact exploratory intensity (*ExploreRatio*) with narrative innovation disclosure quantity (*InvDiscQty*). I include controls to account for risk factors, including *Beta*, *Size,* and *MTB*.[48] *Beta* captures the sensitivity of a stock's returns to the overall market returns. I control for financial performance indicators such as adjusted return on assets (*AdjROA*) and return on equity (*ROE*) for profitability. I also control for *R&D* expenses and selling, general, and administrative expenses (*SG&A*) as indicators of proprietary costs (Fitzgerald et al., 2021). Lastly, I control for non-innovation disclosures (*NonInvDisc*) to capture the overall market reaction to the firms' 10-K filing. All additional variables are defined in Appendix D.[49]

The results in Panel A of Table 14 show that the coefficients on the main variable, *ExploreRatio*, are positive and significant. This indicates that investors respond positively to firms

---

superior short-term performance in the future. Furthermore, financial analysts and investors often overlook the significance of a firm's innovation strategy, especially when exploitation-focused firms exceed the market's near-term earnings expectations. The authors also show that exploitation-focused firms are undervalued due to investors' attention biases.

[47] In the robustness tests, I investigate alternative windows. While the results remain consistent, they show weaker significance within the (−3, +3) and (−7, +7) event windows. However, I do not observe significant results within the (−1, +1) event window.

[48] *CAR*, *sCAR*, and *MTB* are winsorized at the *1s*t and *99th* percentiles to mitigate the effects of outliers.

[49] In the placebo tests, I examine pseudo-filing period windows, such as (-25, -15), (-20, -15), and (-20, -10). No significant results are observed across any of these pseudo-event windows, suggesting that the findings are not random.

emphasizing exploratory innovation, interpreting it as a favorable signal for the firms' future performance. This aligns with prior research indicating investor preference for exploratory innovations (Fitzgerald et al., 2021). However, the coefficients on the interaction term, *ExploreRatio* * *InvDiscQty*, are negative in both columns and significant at the 1% level (one-tailed) in Column (1). These findings provide some evidence that narrative innovation disclosures serve to attract investors' attention and enhance their understanding of the firms' innovative activities. As a result, this heightened transparency enables investors to respond with corrective actions, which can potentially mitigate overvaluation concerns associated with exploration-focused firms. In summary, narrative innovation disclosures act as a mitigating factor, helping to alleviate potential overvaluation concerns linked to exploration-focused firms.

Although investors might not be able to observe a firm's innovation strategy from the previous year at the time of the 10-K filing, the literature suggests that they can still obtain related information through other channels (Glaeser & Landsman, 2021). Moreover, research indicates that exploratory intensity tends to be persistent over time (Jia, 2017, 2019).[50] Therefore, I lag the explanatory variable by one more year and rerun the short-term market reaction tests using *ExploreRatio* in year $t-2$.[51] Consistent with the findings in Panel A, the coefficients on the main variable, *ExploreRatio*, are positive in Panel B and significant in Column (1). The coefficients on the interaction term, *ExploreRatio* * *InvDiscQty*, are negative in both columns and significant at the 5% level (one-tailed) in Column (1). These findings provide evidence of the stickiness and persistence of firms' innovation strategies, indicating that investors react to narrative innovation disclosures from firms with different innovation strategies.

---

[50] In untabulated results, the Pearson (Spearman) correlation between *ExploreRatio* in year $t-2$ and *ExploreRatio* in year $t-1$ is 0.5 (0.545) at the 5% level of significance. The average (median) change of *ExploreRatio* between year $t-2$ and year $t-1$ is -0.028 (0) and the average (median) change of *ExploreRatio* between year $t-1$ and year t is -0.031 (0). These statistics provide preliminary evidence of the stickiness of corporate innovation strategy.

[51] I do not include *ExploreRatio* from both years $t-2$ and $t-1$ in the same regression due to high VIFs indicating multicollinearity.

6.3 Stock Price Crash Risk

Jia (2018) finds that firms that prioritize exploratory innovations tend to be positively associated with stock price crash risk, while those that prioritize exploitative innovations tend to be negatively associated with crash risk. This suggests that investors may underestimate the inherent risk associated with exploration-focused firms, which subsequently experience downward corrections in stock prices. The author suggests that the discrepancy in crash risk between firms with different innovation strategies can be attributed to various factors, both direct and indirect.

Directly, certain stock price crash risks arise from the nature of firms' operations (Habib et al., 2018). Exploration, while offering the potential for significant payoff upon success, also involves a higher risk of failure compared to the exploitation strategy (March, 1991). This asymmetry in payoff implies that exploration-focused firms may experience a higher ratio of failures to successes and may encounter more negative news during the innovation process (He & Wong, 2004).

Indirectly, exploration-focused firms can impact crash risk through managerial actions, such as withholding interim bad news (Jia, 2018). The exploratory nature of innovation may widen the information gap between firms and investors, which leads to a less transparent information environment (Kaplan & Tripsas, 2008). Jia (2018) suggests that investors tend to underestimate the fundamental risk associated with exploration-focused firms in the absence of adequate disclosures.

Prior research shows that a lack of information transparency increases stock price crash risk, reflecting a third-moment effect of future extreme returns (Hutton et al., 2009; Kim et al., 2011a). Narrative innovation disclosures can provide investors with insights into a firm's innovation activities and the risk associated with exploratory innovation. By providing timely information, these disclosures prevent managers from withholding negative news until the completion of innovative activities, thereby mitigating stock price crash risk. In addition, narrative innovation disclosures facilitate the communication of contextual information to investors, bridging the gap between a firm's financial statement numbers and its underlying business fundamentals (Merkley, 2014). Investors can leverage this information to supplement financial statement numbers, leading to more accurate projections of firms' future performance and cash flow implications. Thus, I argue that narrative innovation disclosures play a role in reducing stock price crash risk for exploration-focused firms. To investigate this, I first estimate the following Equation (7) to examine the effect of corporate innovation strategy on crash risk, similar to Jia (2018):

$$
\begin{aligned}
CrashRisk_{t+1} = {} & \beta_0 + \beta_1 ExploreRatio_{t-1} + \beta_2 DTurn_t + \beta_3 Sigma_t + \beta_4 MeanRet_t \\
& + \beta_5 Size_t + \beta_6 MTB_t + \beta_7 Lev_t + \beta_8 ROA_t + \beta_9 AccM_t + \beta_{10} R\&D_t \\
& + \beta_{11} FirmAge_t + \beta_{12} AnalystFollow_t + \beta_{13} CrashRisk_t + \textstyle\sum Year\ FE \\
& + \textstyle\sum Industry\ FE + \varepsilon
\end{aligned} \tag{7}
$$

The dependent variables, *CrashRisk*, are a set of variables that measure stock price crash risk in year *t*+1, starting from one month after the 10-K filing date. I follow prior studies (e.g., Chen et al., 2001; Kim et al., 2011a, 2011b) and use two measures of *CrashRisk* based on firm-specific weekly returns estimated as the residuals from the market model. The first measure is the down-to-up volatility (*DUVol*) of the crash likelihood. I use three specifications to measure *DUVol*. *DUVol1* is calculated as the natural logarithm of the standard deviation in the negative weeks divided by the standard deviation in the positive weeks. *DUVol2* and *DUVol3*, each computed as the natural logarithm of the standard deviation during down weeks divided by that of up weeks, involve distinct calculation methods. Second, I use the negative conditional skewness of firm-specific weekly returns over the fiscal year (*NCSkew*), measured as the negative of the third moment of firm-specific weekly returns for each year and normalized by the standard deviation of firm-specific weekly returns raised to the third power (multiplied by negative one for interpretation). Higher values of *CrashRisk* indicate greater stock price crash risk. The independent variable is exploratory intensity (*ExploreRatio*). Based on prior research evidence (Jia, 2018), I anticipate a positive association between firms that emphasize exploratory innovations and stock price crash risk.

I include a set of control variables that affect firm-specific price crash risk, such as firm size (*Size*), leverage (*Lev*), and return on assets (*ROA*; Chen et al., 2001). To account for potential bubbles in glamor stocks or those with high past returns that could lead to significant price declines, I control for the average of firm-specific weekly returns of the year (*MeanRet*) and market-to-book ratio (*MTB*) (Jia, 2018). I also control for *R&D*, life cycle (*FirmAge*), and external monitoring as well as market visibility (*AnalystFollow*). Kim et al. (2014) show that stocks with higher volatility are more prone to crashing. Thus, I control for stock volatility (*Sigma*), calculated as the standard deviation of firm-specific weekly returns over the year. I control for detrended stock trading volume (*DTurn*) for investor heterogeneity, which is calculated as the average monthly share turnover over the fiscal year minus the average monthly share turnover over the previous fiscal year. In addition, I control for the absolute value of performance-matched discretionary accruals (*AccM*) for earnings management, which has predictable power for future crash risk (Chen et al., 2001; Kothari et al., 2005).[52] I also control for the current value of *CrashRisk* to account for potential serial correlation of crash risk (Kim et al., 2011a). Appendix D provides detailed definitions and calculations of additional variables.

Panel A of Table 15 presents the results examining the effect of the firm's innovation strategy and the firm's future stock price crash risk. The coefficients on *ExploreRatio* are positive and significant across all columns. These findings align with existing research (Jia, 2018), which suggests that exploration-focused firms are more likely to experience future stock price crash risk, while exploitation-focused firms are less prone to such risks.

Building on this, I investigate the role of narrative innovation disclosures in influencing the association between exploration-focused firms and stock price crash risk. I estimate Equation (8) to investigate the effect of firms' narrative innovation disclosures on stock price crash risk in the subsample of exploration-focused firms. The dependent variables are stock price crash risk measures (*CrashRisk*) and the independent variable is narrative innovation disclosure quantity (*InvDiscQty*). All other variables are defined in Appendix D.

---

[52] To minimize the influence of outliers, I winsorize *MeanRet* and *DTurn* at the *1st* and *99th* percentiles.

$$CrashRisk_{t+1} = \beta_0 + \beta_1 InvDiscQty_t + \beta_2 DTurn_t + \beta_3 Sigma_t + \beta_4 Ret_t + \beta_5 Size_t + \beta_6 MTB_t + \beta_7 Lev_t + \beta_8 ROA_t + \beta_9 AccM_t + \beta_{10} R\&D_t + \beta_{11} FirmAge_t + \beta_{12} AnalystFollow_t + \beta_{13} CrashRisk_t + \sum Year\ FE + \sum Industry\ FE + \varepsilon \quad (8)$$

Table 15, Panel B presents the effect of innovation disclosure quantity (*InvDiscQty*) on stock price crash risk in the subsample of exploration-focused firms. Although the coefficients on *InvDiscQty* are statistically insignificant, their mixed signs prompt further examination. Therefore, I investigate whether firm characteristics differ between firms categorized by extensive and limited disclosures. In Panel C, a univariate analysis based on *InvDiscHigh* reveals that exploration-focused firms disclosing above the median report significantly higher narrative innovation disclosures than those below the median. On average, exploration-focused firms with above-median disclosure report 8% of narrative innovation disclosures, while those below-median report only 2.1% (untabulated). This finding indicates that exploration-focused firms that provide more disclosures exhibit different characteristics, implying a potential non-linear relationship.

Consequently, I partition the exploration-focused firms into “Disclosure More” (*InvDiscHigh* = 1) and “Disclosure Less” (*InvDiscHigh* = 0) groups, leading to piecewise regressions. Table 15, Panel D provides the results of the effect of narrative innovation disclosures on future stock price crash risk. Columns (1) to (4) show that for exploration-focused firms disclosing below the median, the coefficients on *InvDiscQty* are insignificant. This suggests that inadequate disclosures may lead to a lack of investor understanding regarding a firm’s innovation strategy, potentially failing to mitigate the probability of future stock price crashes. In contrast, Columns (5) to (8) show that the coefficients on *InvDiscQty* for exploration-focused firms disclosing above the median are negative. The coefficients in Columns (5), (7), and (8) are statistically significant (t-statistics = 1.79, 2.28, and 1.62, respectively). These results suggest that as exploration-focused firms provide adequate narrative innovation disclosures, investors gain insights into the firm’s innovation strategy. This reduction in information asymmetry might lead to a decreased likelihood of future stock price crashes.

6.4 Conclusion

In summary, this chapter investigates the stock market consequences of corporate innovation strategy and narrative innovation disclosures. In the short-term event window, I find that investors react positively to exploration-focused firms with fewer disclosures but react negatively to those with more disclosures. This suggests that narrative innovation disclosures act as a mitigating factor, assisting in addressing potential overvaluation concerns associated with exploration-focused firms in the short term. In a long-term window, I find that exploration-focused firms that provide more information about their innovation are less prone to experiencing future stock price crashes compared to those that disclose less. This highlights the importance of adequate narrative innovation disclosures in reducing information asymmetry, enabling investors to gain valuable insights into the firm's innovation strategy, thereby potentially lowering the likelihood of future stock price crashes.

Firms make disclosure decisions based on a cost-benefit analysis, aiming to boost their share price. However, the nature of exploratory innovation poses unique challenges for exploration-focused firms. They often face higher failure-to-success ratios and may withhold interim bad news about their innovations (Jia, 2018). Additionally, investors tend to have a preference bias toward radical and exploratory innovations, leading them to predict overly optimistic future cash flows (Fitzgerald et al., 2021). This overvaluation can increase the risk of future stock price crashes, which leads to negative social influence and impairs the firm reputation. Narrative disclosures can help mitigate risks by enabling investors to project future cash flows more accurately and evaluate the firms based on their fundamental value. Therefore, exploration-focused firms benefit from becoming more transparent, reducing information asymmetry with investors, and thus mitigating the misvaluation issues. Overall, the evidence presented in this chapter corresponds with the motivation and importance of my thesis that narrative innovation disclosures help investors better evaluate exploration-focused firms.

Chapter 7
Additional Analysis

7.1 Introduction

In this chapter, I perform additional analyses on the effect of corporate innovation strategy on narrative disclosures. In Section 7.2, I examine qualitative characteristics of narrative innovation disclosures, including numerical terms, forward-looking statements, repetitiveness, and tone. I also investigate the factors influencing the use of by exploration-focused firms. Section 7.3 examines the moderating effect of technology peer pressure on the relation between corporate innovation strategy and narrative disclosures. Section 7.4 concludes this chapter.

7.2 Narrative Innovation Disclosure Qualitative Characteristics

7.2.1 Research Design for Complementary Tests of H1

It is worth considering that firms may adjust the quality of their narrative innovation disclosures without necessarily improving their relevance. In terms of disclosure content details, exploration-focused firms may choose to provide a higher quantity but vague narrative innovation disclosures in response to higher proprietary costs. I estimate an OLS model using Equations (9), (10), and (11), which regress detailed characteristics (*InvDiscDetail*; i.e., numerical and forward-looking), repetitiveness (*InvDiscRep*), and tone (*InvDiscTone*) of innovation-related disclosures on firms' exploratory intensity (*ExploreRatio*), respectively:

$$\begin{aligned} InvDiscDetail_t \\ &= \beta_0 + \beta_1 ExploreRatio_{t-1} + \beta_2 Size_{t-1} + \beta_3 AdjROA_{t-1} + \beta_4 BTM_{t-1} \\ &+ \beta_5 CapInt_{t-1} + \beta_6 Lev_{t-1} + \beta_7 Growth_{t-1} + \beta_8 R\&D_{t-1} + \beta_9 R\&DSq_{t-1} \\ &+ \beta_{10} FirmAge_{t-1} + \beta_{11} AnalystFollow_{t-1} + \beta_{12} MgmtForecast_{t-1} \\ &+ \beta_{13} TotalPatent_{t-1} + \beta_{14} PriorInvDisc_t + \beta_{15} 10KDiscDetail_t \\ &+ \sum Year\ FE + \sum Industry\ FE + \varepsilon \qquad (9) \end{aligned}$$

$$\begin{aligned} InvDiscRep_t = \beta_0 &+ \beta_1 ExploreRatio_{t-1} + \beta_2 Size_{t-1} + \beta_3 AdjROA_{t-1} + \beta_4 BTM_{t-1} \\ &+ \beta_5 CapInt_{t-1} + \beta_6 Lev_{t-1} + \beta_7 Growth_{t-1} + \beta_8 R\&D_{t-1} + \beta_9 R\&DSq_{t-1} \\ &+ \beta_{10} FirmAge_{t-1} + \beta_{11} AnalystFollow_{t-1} + \beta_{12} MgmtForecast_{t-1} \\ &+ \beta_{13} TotalPatent_{t-1} + \beta_{14} NonInvDisc_t + \beta_{15} PriorInvDisc_t + \sum Year\ FE \\ &+ \sum Industry\ FE + \varepsilon \qquad (10) \end{aligned}$$

$$
\begin{aligned}
InvDiscTone_t = \beta_0 &+ \beta_1 ExploreRatio_{t-1} + \beta_2 Size_{t-1} + \beta_3 AdjROA_{t-1} + \beta_4 BTM_{t-1} \\
&+ \beta_5 CapInt_{t-1} + \beta_6 Lev_{t-1} + \beta_7 Growth_{t-1} + \beta_8 R\&D_{t-1} + \beta_9 R\&DSq_{t-1} \\
&+ \beta_{10} FirmAge_{t-1} + \beta_{11} AnalystFollow_{t-1} + \beta_{12} MgmtForecast_{t-1} \\
&+ \beta_{13} TotalPatent_{t-1} + \beta_{14} NonInvDisc_t + \beta_{15} PriorInvDisc_t \\
&+ \beta_{16} 10KDiscTone_t + \textstyle\sum Year\ FE + \sum Industry\ FE + \varepsilon \qquad (11)
\end{aligned}
$$

To examine qualitative characteristics of innovation-related disclosures, I measure the numerical (*InvDiscNum*), forward-looking (*InvDiscFls*), repetitive (*InvDiscRep*), and tone (*InvDiscTone*) of narrative innovation disclosures (Brown & Tucker, 2011; Henry, 2008; F. Li, 2010; Merkley, 2014). Numerical innovation-related disclosures (*InvDiscNum*) are calculated as the natural logarithm of one plus the number of numerical innovation-related sentences in a firm's 10-K filing. An innovation-related sentence is numerical if it contains numerical information that is not in a date format. I include the control of overall numerical disclosures in a 10-K filing (*10KDiscNum*) and remove the control of non-innovation-related disclosures (*NonInvDisc*) due to multicollinearity between these two control variables. I calculate forward-looking innovation-related disclosures (*InvDiscFls*) as the natural logarithm of one plus the number of forward-looking innovation-related sentences in a firm's 10-K filing. An innovation-related sentence is forward-looking if it contains future tense words, as specified by F. Li (2010). I replace non-innovation-related disclosures (*NonInvDisc*) with the overall usage of the future tense in the 10-K filing (*10KDiscFls*) to mitigate multicollinearity. I calculate repetitive innovation-related disclosures (*InvDiscRep*) as the natural logarithm of one plus the total number of similar innovation-related sentences within the same 10-K filing. Similar disclosures are based on whether the innovation disclosure sentence is similar to other innovation-related sentences in the same 10-K filing (Merkley, 2014).[53]

The tone of innovation-related disclosures is calculated as the total number of positive innovation-related sentences minus the number of negative innovation-related sentences divided by the total number of innovation-related sentences. A sentence is determined to be positive (negative) if

[53] An innovation-related sentence is repetitive if the cosine similarity between the two-word sets of the current sentence and its previous sentence is greater than 0.9 (Merkley, 2014).

it contains more positive (negative) words based on Henry's (2008) word list (*InvDiscTone*).[54] I control for factors related to innovation-related disclosures, or both innovation disclosures and corporate innovation strategy. In addition to the control variables in the baseline model in Equation (1), I include the overall tone of the 10-K filing (*10KDiscTone*) as an additional control. I lag all explanatory and control variables by one year except for concurrent variables (*NonInvDisc*, *PriorInvDisc*, *10KDiscNum*, *10KDiscFls*, and *10KDiscTone*). All additional variables are defined in Appendix D.

7.2.2 Results of Narrative Innovation Disclosure Qualitative Characteristics (Complementing H1)

Table 16 presents the results of regressing detailed (numerical and forward-looking) and repetitive narrative innovation disclosures on *ExploreRatio* using the models in Equations (9) and (10). Columns (1) and (2) provide the regression results of numerical innovation-related disclosures (*InvDiscNum*). The negative coefficients on *ExploreRatio*, significant at the 1% level, align with H1's prediction and the baseline findings on innovation disclosure quantity. Specifically, compared to exploitation-focused firms, exploration-focused firms tend to disclose fewer details in numerical terms. In Columns (3) and (4), the results show a negative relation between corporate innovation strategy and forward-looking innovation-related disclosures (*InvDiscFls*). The coefficients on *ExploreRatio* are negative and significant at the 1% level, suggesting that exploration-focused firms provide less forward-looking information to mitigate proprietary costs.

In Columns (5) and (6), the results reveal a negative association between *ExploreRatio* and the repetition of innovation-related disclosures (*InvDiscRep*), with negative and significant coefficients at the 1% level. However, these results should be interpreted with caution. If I interpret fewer repetitive disclosures as indicative of reduced disclosure detail, the finding aligns with H1,

[54] I also use the Loughran and McDonald's (2011) sentiment word list to calculate an alternative measure of innovation-related disclosure tone and the results majorly hold.

suggesting that exploration-focused firms disclose information with less detail to mitigate the proprietary costs linked to innovative activities, compared to exploitation-focused firms. However, existing literature provides limited guidance on the optimal extent of repetition—what amount is beneficial and what is burdensome. Managers may perceive the utility of repetition for (1) emphasizing important information or (2) redundancy, limited attention, and the mere repetition of vague disclosure information (Merkley, 2014).

Table 17 presents the results of regressing narrative innovation disclosure tone (*InvDiscTone*) on *ExploreRatio* using the model in Equation (11). The coefficients on the innovation-related disclosure tone are significant and positive at the 1% level. This suggests that exploration-focused firms tend to use a more positive tone in their narrative innovation disclosures compared to exploitation-focused firms. Various factors may contribute to this tone usage, including operational characteristics, management opportunism, and management dispositional characteristics (Luo & Zhou, 2020). I conduct further analyses to explore the reasons underlying the relation between exploratory intensity and the tone of narrative innovation disclosures, as shown in the following section.

7.2.3 Explanation of Positive Tone for Exploration-focused Firms

7.2.3.1 Firm Characteristic

One plausible explanation for firms' disclosure choices relates to firm characteristics. This suggests that firms actively engaged in exploratory innovation may perceive such initiatives as promising for their future success, which reflects their confidence. Exploration-focused firms may use optimistic language to convey the potential benefits, opportunities, and achievements associated with their exploratory innovation efforts. This positive tone can attract investor interest and shape perceptions of the firm's innovative potential. Therefore, I test whether the usage of tone is related to future firm performance in the following Equation (12):

$$
\begin{aligned}
FOP_{t+1} = \beta_0 &+ \beta_1 ExploreRatio_{t-1} + \beta_2 InvDiscTone_t + \beta_3 InvDiscQty_t \\
&+ \beta_4 ExploreRatio_{t-1} * InvDiscTone_t + \beta_5 ExploreRatio_{t-1} \\
&* InvDiscQty_t + \beta_6 InvDiscQty_t * InvDiscTone_t + \beta_7 ExploreRatio_{t-1} \\
&* InvDiscQty_t * InvDiscTone_t + \beta_8 \Delta \mathrm{FOP}_t + \beta_9 FOP_t + \beta_{10} BTM_t \\
&+ \beta_{11} CapExp_t + \beta_{12} R\&D_t + \beta_{13} TotalPatent_t + \beta_{14} Lev_t + \beta_{15} FirmAge_t \\
&+ \beta_{16} Cglm_t + \beta_{17} Adv_t + \beta_{18} SG\&A_t + \sum Year\ FE + \sum Industry\ FE + \varepsilon
\end{aligned} \tag{12}
$$

The dependent variable, future operating performance (*FOP*), is defined as either a one-year-ahead return on assets (*ROA*) or one-year-ahead operating cash flow (*OCF*; calculated as income before extraordinary items plus depreciation less changes in working capital, scaled by lagged total assets). Following the literature, I include a variety of control variables that are significant predictors of future operating performance. Variables of interest include the three-way interaction, *ExploreRatio * InvDiscQty * InvDiscTone*, their two-way interactions, and main variables. I control for current firm performance (*ROA* and *OCF*) to account for performance persistence and changes in firm performance (*ΔROA* and *ΔOCF*) to accommodate mean reversion in future operating performance (Fama & French, 2000; Gu, 2005). In addition, I include control variables such as leverage (*Lev*), firm age (*FirmAge*), advertising expenditures (*Adv*), selling, general, and administrative expenditures (*SG&A*), and whether the firm has segments operating in several industries (*Cglm*; Fitzgerald et al., 2021). Furthermore, I control for *R&D*, patenting (*TotalPatent*), capital expenditure (*CapExp*), and book-to-market ratio (*BTM*; Pandit et al., 2011). All additional variables are defined in Appendix D.

Panel A of Table 18 reports the results of regressing firms' future operational performance on the interaction terms of exploratory intensity (*ExploreRatio*), narrative innovation disclosure quantity (*InvDiscQty*), and narrative innovation disclosure tone (*InvDiscTone*). In Columns (1) and (2), the coefficients on *ExploreRatio* remain negative and significant. The results of the interaction term, *ExploreRatio * InvDiscTone*, are negative and significant at the 5% level. The findings suggest that exploration-focused firms tend to use a more positive tone management strategy when firms have lower future performance compared to exploitation-focused firms.

Columns (3) and (4) add the results of the three-way interaction, *ExploreRatio * InvDiscQty **

InvDiscTone. The coefficients on the two-way interaction, *InvDiscQty * InvDiscTone*, are positive and significant. This indicates that when firms prioritize exploitation (*ExploreRatio* = 0), higher future performance is positively associated with increased disclosure and a positive tone in narrative innovation disclosures. The coefficients on the three-way interaction are negative and show a degree of significance, albeit marginal (t statistic = −1.61) in Column (4). The results add to evidence that for exploration-focused firms, narrative innovation disclosure tone is negatively related to future performance even when disclosing more information about innovation activities. In addition, there is a significantly negative association between *R&D* as well as patenting activities and future operating performance, indicating the long-term and uncertain returns associated with investments in innovation. In summary, the findings suggest that exploration-focused firms tend to use a more positive tone in disclosures when anticipating lower future performance compared to exploitation-focused firms This result suggests that the positive tone is less likely to be associated with firm characteristics.[55]

7.2.3.2 Managerial Opportunism

I examine whether exploration-focused firms tend to use a more positive tone due to management opportunism. Managers may have opportunistic incentives to use a positive tone to divert investors' attention away from volatile and unpredictable earnings resulting from a greater uncertainty of exploratory innovation. Prior studies find that managers are more likely to use a tone to bias investors' perceptions when their equity-based compensation is more sensitive to stock price movements (Arslan-Ayaydin et al., 2016; Huang et al., 2014). I split the sample based on two measures of management opportunism, management pay-performance sensitivity (*Delta*) and risk-

[55] F. Li (2010) finds that firms with higher current performance use a more positive tone in their 10-K disclosures. Therefore, I conduct the robustness tests and change the dependent variables from future firms' performance to current firm performance (*ROA* and *OCF*). The results show that exploration-focused firms also tend to employ upward tone management when firms have lower current performance compared to exploitation-focused firms.

taking incentives (*Vega*).

I follow the approach in Coles et al. (2006) and Core and Guay (2002) and calculate *Delta* as the dollar change in the value of the CEO's wealth resulting from a one-percent increase in the firm's stock price at the fiscal year-end. I partition the sample based on whether the CEO falls below or above the sample median of *Delta* (Low *Delta* and High *Delta*, respectively). I calculate *Vega* as the dollar change in the CEO's wealth for a percentage change in the standard deviation of the stock returns. I split the sample based on whether the CEO falls below or above the sample median of *Vega* (Low *Vega* and High *Vega*, respectively). I lag explanatory and control variables (except for concurrent control variables) by one year, using Equation (11) discussed in Section 7.2.1.

Table 18, Panel B reports the results of the subsample analysis for management opportunism by regressing *InvDiscTone* on *ExploreRatio*. The coefficients on *ExploreRatio* are significantly positive at the 1% level for CEOs in both the Low *Delta* group and the High *Delta* group. The results show that the narrative innovation disclosure tone of exploration-focused firms does not vary based on the level of sensitivity of the CEO's equity-based compensation to the stock price (*Delta*) and return volatility (*Vega*).[56] Thus, these results are not consistent with management opportunism argument.[57]

7.2.3.3 Management Dispositional Characteristics

Management dispositional characteristics may affect narrative innovation disclosure tone. Previous research indicates that the managers' optimistic tendencies are associated with the tone of disclosures (Davis et al., 2015). I utilize the average of the CEO and CFO's confidence measure as a proxy for executives' overconfidence (*OC*; *OC67* or *OC100*). CEO (CFO) confidence is an indicator

[56] In additional tests, I examine the effect of the sensitivity of CFO's equity-based compensation. I find no statistically significant differences between CFOs in the Low *Delta* (*Vega*) group and CFOs in the High *Delta* (*Vega*) group.

[57] As a robustness check for the subsample of *Delta* and *Vega*, I regress *InvDiscQty* on *ExploreRatio* and do not observe evidence of managerial opportunism in narrative innovation disclosure quantity.

that equals one if a CEO (CFO) postpones the exercise of vested options that are at least 67% (100%) in the money and zero otherwise. I calculate the average realizable value per option by dividing the total realizable value of the options by the number of options held by the CEO (CFO). The strike price is calculated as the fiscal year-end stock price minus the average realizable value. The ratio is calculated as the stock price divided by the estimated strike price to compute the average moneyness of the CEO's (CFO's) option portfolio for the fiscal year (Campbell et al., 2011; Hirshleifer et al., 2012; Malmendier & Tate, 2005, 2008). I use a subsample split by two measures of executives' overconfidence (*OC67* and *OC100*).[58] I partition the sample based on whether executives fall below or above the sample mean of *OC67* (*OC100*), resulting in Low *OC67* (*OC100*) and High *OC67* (*OC100*) groups, respectively. All additional variables are defined in Appendix D.

Table 18, Panel C reports the results of the subsample analysis for management dispositional characteristics by regressing *InvDiscTone* on *InvDiscQty* using Equation (11). In Columns (1) and (2), the coefficient on *ExploreRatio* is positive but not significant for executives in the Low *OC67* group, while the corresponding coefficient is positive and significant at the 1% level for executives in the High *OC67* group. The results are robust using the threshold of executives delaying the exercise of vested options that are at least 100% in the money in Columns (3) and (4).[59] Overall, the results indicate that executive teams with high overconfidence are more likely to use positive tone in disclosures compared to executive teams with low overconfidence.[60] This suggests that compared to exploitation-focused firms, the tendency of exploration-focused firms to use a more positive tone in narrative disclosures could be attributed to managerial overconfidence.[61]

---

[58] In the robustness tests, I partition the sample into terciles based on whether they fall in the lower tercile or upper tercile of *OC67* (*OC100*) groups and the results still hold.
[59] As a robustness check for the subsample of *OC67* and *OC100*, I regress *InvDiscQty* on *ExploreRatio* and do not find evidence of management dispositional characteristics affecting narrative innovation disclosure quantity.
[60] This managerial overconfidence is a collective executive team characteristic, as I do not observe a leading effect from either CEOs or CFOs.
[61] In additional tests, I explore other management dispositional characteristics, such as CEO and CFO age (Marquez-Illescas et al., 2019), but do not find results.

7.2.4 Research Design for Complementary Tests of H2 and H3

I estimate Equations (13), (14), and (15) to examine conditional hypotheses H2 and H3. The dependent variables, narrative innovation disclosure qualitative characteristics, include disclosure details (*InvDiscDetail*), such as numerical (*InvDiscNum*) and forward-looking (*InvDiscFls*), repetitive narrative innovation disclosures (*InvDiscRep*), as well as tone of narrative innovation disclosures (*InvDiscTone*). All variables are defined in Appendix D.

$$\begin{aligned} InvDiscDetail_t &= \beta_0 + \beta_1 ExploreRatio_{t-1} + \beta_2 PMCHigh_{t-1}\ or\ TSHigh_{t-1} \\ &+ \beta_3 ExploreRatio_{t-1} * PMCHigh_{t-1}\ or\ TSHigh_{t-1} + \beta_4 Size_{t-1} \\ &+ \beta_5 AdjROA_{t-1} + \beta_6 BTM_{t-1} + \beta_7 CapInt_{t-1} + \beta_8 Lev_{t-1} + \beta_9 Growth_{t-1} \\ &+ \beta_{10} R\&D_{t-1} + \beta_{11} R\&DSq_{t-1} + \beta_{12} FirmAge_{t-1} + \beta_{13} AnalystFollow_{t-1} \\ &+ \beta_{14} MgmtForecast_{t-1} + \beta_{15} TotalPatent_{t-1} + \beta_{16} PriorInvDisc_t \\ &+ \beta_{17} 10KDiscDetail_t + \textstyle\sum Year\ FE + \sum Industry\ FE + \varepsilon \end{aligned} \quad (13)$$

$$\begin{aligned} InvDiscRep_t &= \beta_0 + \beta_1 ExploreRatio_{t-1} + \beta_2 PMCHigh_{t-1}\ or\ TSHigh_{t-1} \\ &+ \beta_3 ExploreRatio_{t-1} * PMCHigh_{t-1}\ or\ TSHigh_{t-1} + \beta_4 Size_{t-1} \\ &+ \beta_5 AdjROA_{t-1} + \beta_6 BTM_{t-1} + \beta_7 CapInt_{t-1} + \beta_8 Lev_{t-1} + \beta_9 Growth_{t-1} \\ &+ \beta_{10} R\&D_{t-1} + \beta_{11} R\&DSq_{t-1} + \beta_{12} FirmAge_{t-1} + \beta_{13} AnalystFollow_{t-1} \\ &+ \beta_{14} MgmtForecast_{t-1} + \beta_{15} TotalPatent_{t-1} + \beta_{16} NonInvDisc_t \\ &+ \beta_{17} PriorInvDisc_t + \textstyle\sum Year\ FE + \sum Industry\ FE + \varepsilon \end{aligned} \quad (14)$$

$$\begin{aligned} InvDiscTone_t &= \beta_0 + \beta_1 ExploreRatio_{t-1} + \beta_2 PMCHigh_{t-1}\ or\ TSHigh_{t-1} \\ &+ \beta_3 ExploreRatio_{t-1} * PMCHigh_{t-1}\ or\ TSHigh_{t-1} + \beta_4 Size_{t-1} \\ &+ \beta_5 AdjROA_{t-1} + \beta_6 BTM_{t-1} + \beta_7 CapInt_{t-1} + \beta_8 Lev_{t-1} + \beta_9 Growth_{t-1} \\ &+ \beta_{10} R\&D_{t-1} + \beta_{11} R\&DSq_{t-1} + \beta_{12} FirmAge_{t-1} + \beta_{13} AnalystFollow_{t-1} \\ &+ \beta_{14} MgmtForecast_{t-1} + \beta_{15} TotalPatent_{t-1} + \beta_{16} NonInvDisc_t \\ &+ \beta_{17} PriorInvDisc_t + \beta_{18} 10KDiscTone_t + \textstyle\sum Year\ FE + \sum Industry\ FE \\ &+ \varepsilon \end{aligned} \quad (15)$$

7.2.5 Results of Narrative Innovation Disclosure Qualitative Characteristics (Complementing H2 and H3)

Table 19 provides the regression results on the effect of corporate innovation strategy on narrative innovation disclosure characteristics under the moderating effects of product market competition and technology spillover. Columns (1) to (3) provide the results of numerical (*InvDiscNum*), forward-looking (*InvDiscFls*), and repetitive (*InvDiscRep*) innovation disclosures, using the models in Equations (13) and (14). The coefficients on the interaction term, *ExploreRatio * PMCHigh*, are significantly negative, showing that exploration-focused firms tend to disclose fewer details in numerical, forward-looking, and repetitive terms compared to exploitation-focused firms when product market competition becomes more intense. However, the coefficients on the interaction term, *ExploreRatio* * *TSHigh*, are significantly positive, showing that exploration-focused firms tend to disclose more details in numerical, forward-looking, and repetitive terms when technology spillover is high. Overall, the results show that the effect of product market competition on the detail and repetitiveness of narrative innovation disclosures is more negative for exploration-focused firms and less negative for exploitation-focused firms. In contrast, the effect of technology spillover on the detail and repetitiveness of narrative innovation disclosures is more positive for exploration-focused firms and less positive for exploitation-focused firms.

Column (4) provides the results of narrative innovation disclosure tone, using the model in Equation (15). The coefficient on the interaction term, *ExploreRatio* * *PMCHigh*, is insignificant, showing that product market competition may have a limited deterministic effect on exploration-focused firms when considering the tone of narrative innovation disclosures. The result may indicate that the positive tone is a characteristic associated with exploration-focused firms, irrespective of competitive pressures from the product market. However, I find a negative and significant coefficient on the interaction term of *ExploreRatio* * *TSHigh* at the 1% level, indicating that the positive effect of exploratory innovation on the tone of innovation disclosures is less pronounced in the presence of increased technology spillover. One possible explanation is that when technology spillover is high and innovations are more readily shared or accessible across technology peer firms, there may be an increased risk of legal disputes over intellectual property and patent infringement. This heightened litigation risk could lead exploration-focused firms to adopt a more cautious or reserved tone in their narrative innovation disclosures (Luo & Zhou, 2020).

7.3 Conditional Analysis: Technological Peer Pressure

Prior research has recognized the multidimensional relationship between competition and disclosure across various domains (Bertrand, 1883; Cournot, 1838; Dixit & Stiglitz, 1977; Hotelling, 1929; Schumpeter, 2003; Stahl, 1988). Technological peer pressure involves firms making investments in innovation to develop new products and processes, thereby securing future market competitiveness (Cao et al., 2018). To date, there is limited evidence on the effects of technological peer pressure on corporate disclosures. Cao et al. (2018) introduce a firm-level measure of technology-based product market competition, technological peer pressure (*TPP*). *TPP* assesses the combined technological advancements of firms that compete with the focal firm in the product market compared to the focal firm's technological readiness. A higher *TPP* value indicates that a firm faces more intense technological peer pressure. Even under the same product market pressure (*PMC*), a firm experiences higher technological peer pressure when it has lower technological preparedness. Prior studies find a negative relation between technological peer pressure and product disclosures (Cao et al., 2018) as well as R&D disclosures (Ettredge et al., 2018). However, no prior research simultaneously considers product market competition (*PMC*), technology spillover (*TS*), and technological peer pressure (*TPP*).[62] In addition, there is a lack of evidence within the context of firms' different innovation strategies. To address this gap, I investigate how corporate innovation strategy affects firms' narrative innovation disclosure quantity (*InvDiscQty*) when facing high technological peer pressure (*TPPHigh*), using the following Equation (16):

$$\begin{aligned} InvDiscQty_t = {} & \beta_0 + \beta_1 ExploreRatio_{t-1} + \beta_2 TPPHigh_{t-1} + \beta_3 ExploreRatio_{t-1} \\ & * TPPHigh_{t-1} + \beta_4 Size_{t-1} + \beta_5 AdjROA_{t-1} + \beta_6 BTM_{t-1} + \beta_7 CapInt_{t-1} \\ & + \beta_8 Lev_{t-1} + \beta_9 Growth_{t-1} + \beta_{10} R\&D_{t-1} + \beta_{11} R\&DSq_{t-1} \\ & + \beta_{12} FirmAge_{t-1} + \beta_{13} AnalystFollow_{t-1} + \beta_{14} MgmtForecast_{t-1} \\ & + \beta_{15} TotalPatent_{t-1} + \beta_{16} NonInvDisc_t + \beta_{17} PriorInvDisc_t + \sum Year\ FE \\ & + \sum Industry\ FE + \varepsilon \end{aligned} \tag{16}$$

I follow Cao et al. (2018) to calculate technological peer pressure (*TPP*), which builds upon the measure of product market competition (*PMC*). To calculate *PMC*, Bloom et al. (2013) multiply the product market similarity between firm i and firm j (N_{ij}) by the R&D stock of firm j (G_j) and

[62] Untabulated Pearson (Spearman) correlation matrix shows that the coefficient between *TPP* and *PMC* is 0.687 (0.317). The coefficient between *TPP* and *TS* is 0.21 (0.416).

then aggregate all multiples. Cao et al. (2018) take a step further by dividing the sum by the focal firm's own R&D stock (G_i). *TPP* is calculated as the natural logarithm to construct the technological peer pressure for firm i in year t: $TPP_i = \text{Log}(1 + \sum_{j \neq i} G_j N_{ij} / G_i)$.[63] The numerator of the ratio inside the parentheses is the pool of peers' R&D stock in dollars, which implies the threats posed by rivals' technological developments. The denominator represents the focal firm's own technological preparedness. To enhance the interpretation of the moderating effect, I rank the sample based on *TPP* and create an indicator variable, *TPPHigh*, which takes a value of one if *TPP* exceeds the median and zero otherwise. All variables are defined in Appendix D.

Table 20 reports the results of the moderating effect of technological peer pressure (*TPP*) on the relation between corporate innovation strategy and narrative innovation disclosure by regressing *InvDiscQty* on the interaction of *ExploreRatio* and different moderators (*TPPHigh*, *PMCHigh*, and *TSHigh*). The main variable, *ExploreRatio*, remains significant and negative across all columns, showing a negative effect of firms' exploratory intensity on narrative innovation disclosure quantity. In Column (1), I regress *InvDiscQty* on the interaction term, *ExploreRatio* * *TPPHigh*. The coefficient on the interaction, *ExploreRatio* * *TPPHigh*, is significantly positive at the 1% level. The result shows that the effect of technological peer pressure is more positive on exploration-focused firms than on exploitation-focused firms.

To examine whether technological peer pressure and product market competition capture different aspects of competition, I include the interaction term, *ExploreRatio* * *PMCHigh*, in Column (2). The coefficient on the interaction term, *ExploreRatio* * *TPPHigh*, remains significantly positive at the 1% level and *ExploreRatio* * *PMCHigh* remains significantly negative at the 1% level. To further examine whether technological peer pressure and technology spillover capture different technological effects, I include the interaction term, *ExploreRatio* * *TSHigh*, in Column (3). The

[63] The results remain largely robust when substituting *TPP* with the *TPP* proxy used in Cao et al. (2018). I thank the authors for sharing the data.

coefficient on the interaction term, *ExploreRatio* * *TPPHigh*, remains significantly positive at the 1% level and *ExploreRatio* * *TSHigh* remains significantly positive at the 1% level. Column (4) shows the results including the interaction terms of technological peer pressure, product market competition, and technology spillover and the results are significant at the 1% level.

Overall, these results indicate the nuanced nature of product market competition (*PMC*), technological spillover (*TS*), and technological peer pressure (*TPP*), as well as their distinct impacts on the disclosure behaviors of exploration-focused firms. Exploration-focused firms disclose less information compared to exploitation-focused firms in the presence of high product market competition. This suggests that when faced with intense competition in the product market, exploration-focused firms may adopt a more cautious or reserved approach in their narrative innovation disclosures to mitigate the proprietary costs of the information. Unlike competitive strategies, which focus on gaining an advantage over rivals, technology spillover involves the collaborative diffusion of knowledge across firms and industries. Exploration-focused firms acknowledge the collaborative nature of innovation, leading them to be more open in sharing information to promote collective progress compared to exploitation-focused firms.

In addition to the effect of product market competition and technology spillover, exploration-focused firms disclose more information when confronted with high technological peer pressure. This indicates that when the competition is centered around technology and innovation, the effect of technological peer pressure is consistent with the effect of technological spillover. Therefore, future research should carefully consider the multidimensional relation between competition and disclosure within the context of innovation strategy.

7.4 Conclusion

In summary, I find that compared to exploitation-focused firms, exploration-focused firms tend to disclose fewer details in numerical, forward-looking, and repetitive narrative innovation disclosures, consistent with their overall disclosure decisions regarding quantity. I also find a positive relation between exploratory intensity and disclosure tone, potentially influenced by overconfident executives. Moreover, I find evidence of the moderating effect of technological peer pressure. When product competition revolves around technology and innovation, the effect of technological peer pressure is similar to technology spillover. Overall, the evidence presented in this chapter reinforces and supplements my primary results from Chapter 5.

Chapter 8
Conclusion

Current accounting standards present challenges for innovative firms in effectively communicating the value of their innovation activities through conventional accounting measures, thus creating information asymmetry between firms and investors (Lev & Sougiannis, 1999). Recent research highlights the complexity that investors encounter in understanding the return predictability associated with a firm's internal decision on innovation strategy, whether oriented toward exploration or exploitation (Fitzgerald et al., 2021; Jia, 2018).

This thesis examines the relation between corporate innovation strategy and narrative innovation disclosure decisions, as well as the moderating effects of product market competition and technology spillover. I find that compared to exploitation-focused firms, exploration-focused firms disclose a lower quantity of narrative innovation information due to a cost-benefit tradeoff. I also find that exploration-focused firms tend to disclose fewer numerical, forward-looking, and repetitive narrative innovation disclosures and adopt a more positive tone in their communications compared to exploitation-focused firms. In addition, firms led by overconfident executive teams are more likely to utilize a positive tone in their disclosures.

Moreover, product market competition and technology spillover exhibit opposing effects on both the quantity and the qualitative characteristics of narrative innovation disclosures by exploration-focused firms, emphasizing their differential impacts on proprietary costs. In environments with high levels of product market competition, exploration-focused firms tend to disclose less information in terms of both the quantity and the detail of narrative innovation disclosures compared to exploitation-focused firms. This cautious approach suggests they aim to mitigate the proprietary costs associated with innovation-related information in highly competitive markets. In contrast to competitive strategies, technology spillover encourages collaborative knowledge exchange among firms and across industries. Exploration-focused firms embrace this collaborative nature, leading them to be more open in sharing information to drive collective progress. Therefore, in scenarios with high levels of technology spillover, exploration-focused firms disclose more information with greater detail, potentially signaling their willingness to collaborate. These findings contribute to the disclosure and innovation literature by shedding light on the effect of proprietary costs associated with firms' disclosure decisions within the context of different innovation strategies.

While the existing literature examines the effect of corporate innovation strategy on firm performance and market valuation (Fitzgerald et al., 2021; Jia, 2018), there is limited research on how firms enhance communication with investors and on the value relevance of such communication. My thesis fills the research gap by examining how firms with different innovation strategies utilize narrative innovation disclosures to communicate effectively, reducing information asymmetry and aiding investors in alleviating the valuation challenges associated with their innovation strategy. Narrative innovation disclosures enhance investors' understanding of innovative activities and reduce the potential overvaluation due to preference bias toward exploration-focused firms. These disclosures also inform investors about R&D and ongoing innovation efforts, thereby reducing the risk of managers withholding interim negative news. Eventually, as exploration-focused firms offer more narrative innovation disclosures, investors gain valuable insights into their innovation strategies, leading to reduced information asymmetry and a decreased likelihood of future stock price crashes.

My thesis primarily focuses on public firms that engage in innovation activities, and the findings may have limited generalizability to private firms with a strong emphasis on innovation. Gao et al. (2018) find a significant divergence in exploratory (58%) and exploitative (12%) patents in private firms compared to public firms (48% and 9%, respectively). As a result, the conclusions drawn from my thesis may not be generalizable to private firms.

In addition, my findings may not generalize to firms that rely on trade secrecy rather than patents to protect their intellectual property.[64] Although both types of firms engage in innovation activities, they exhibit systematic differences. Glaeser (2018) finds that firms that opt for trade secrets are less inclined to file patents in the future, indicating that patenting and trade secrets act as substitutes for protecting innovation. However, patents remain a prevalent method for protecting intellectual property, particularly among U.S. firms that receive the highest number of global patents.[65] Given the prominence of patenting and its widespread usage, my thesis holds substantial importance by providing insights into the dynamics of firms' innovation strategies through the lens of patenting activities.

[64] https://ncses.nsf.gov/pubs/nsf21339
[65] https://www.uspto.gov/web/offices/ac/ido/oeip/taf/us_stat.htm

References

Abbott Laboratories. (2002). *Annual Report 2002*. https://www.sec.gov/Archives/edgar/data/1800/000104746903006107/a2102588z10-k.htm

Advanced Micro Devices. (2006). *Annual Report 2006*. https://www.sec.gov/Archives/edgar/data/2488/000119312507044191/d10k.htm

Advanced Micro Devices. (2012). *Annual Report 2012*. https://www.sec.gov/Archives/edgar/data/2488/000119312513069422/d486815d10k.htm

Ajinkya, B. B., & Gift, M. J. (1984). Corporate Managers' Earnings Forecasts and Symmetrical Adjustments of Market Expectations. *Journal of Accounting Research*, *22*(2), 425–444. https://doi.org/10.2307/2490657

Alnylam Pharmaceuticals Inc. (2010). *Annual Report 2010*. https://www.sec.gov/Archives/edgar/data/1178670/000095012311015737/b83541e10vk.htm

Anagnostopoulou, S. C. (2008). R&D expenses and firm valuation: A literature review. *International Journal of Accounting & Information Management*, *16*(1), 5–24. https://doi.org/10.1108/18347640810887735

Analog Devices Inc. (2014). *Anuual Report 2014*. https://www.sec.gov/Archives/edgar/data/6281/000000628114000039/adi-1112014x10k.htm

Analog Devices Inc. (2015). *Annual Report 2015*. https://www.sec.gov/Archives/edgar/data/6281/000000628115000044/adi-10312015x10k.htm

Annett, T. (2007, January 9). The Evening Wrap: Dialing for Dominance. *Wall Street Journal, Eastern Edition*, n/a.

Apple. (2007). *Apple Events (video): Macworld San Francisco 2007 Keynote Address on Apple Podcasts*. Apple Podcasts. https://podcasts.apple.com/us/podcast/macworld-san-francisco-2007-keynote-address/id275834665?i=1000026524322

Arora, A., & Ceccagnoli, M. (2006). Patent Protection, Complementary Assets, and Firms' Incentives for Technology Licensing. *Management Science*, *52*(2), 293–308.

Arslan-Ayaydin, Ö., Boudt, K., & Thewissen, J. (2016). Managers set the tone: Equity incentives and the tone of earnings press releases. *Journal of Banking & Finance*, *72*, S132–S147. https://doi.org/10.1016/j.jbankfin.2015.10.007

Bailey, W., Li, H., Mao, C. X., & Zhong, R. (2003). Regulation Fair Disclosure and Earnings Information: Market, Analyst, and Corporate Responses. *The Journal of Finance*, *58*(6), 2487–2514. https://doi.org/10.1046/j.1540-6261.2003.00613.x

Baker, S., & Mezzetti, C. (2005). Disclosure as a Strategy in the Patent Race. *The Journal of Law and Economics*, *48*(1), 173–194. https://doi.org/10.1086/426879

Balsmeier, B., Fleming, L., & Manso, G. (2017). Independent boards and innovation. *Journal of Financial Economics*, *123*(3), 536–557. https://doi.org/10.1016/j.jfineco.2016.12.005

Bena, J., & Li, K. (2014). Corporate Innovations and Mergers and Acquisitions. *The Journal of Finance*, *69*(5), 1923–1960. https://doi.org/10.1111/jofi.12059

Benner, M. J., & Tushman, M. (2002). Process management and technological innovation: A longitudinal study of the photography and paint industries. *Administrative Science Quarterly*, *47*(4), 676–709.

Bens, D. A., Berger, P. G., & Monahan, S. J. (2011). Discretionary Disclosure in Financial Reporting: An Examination Comparing Internal Firm Data to Externally Reported Segment Data. *The Accounting Review*, *86*(2), 417–449. https://doi.org/10.2308/accr.00000019

Berger, P. G., & Hann, R. N. (2007). Segment Profitability and the Proprietary and Agency Costs of Disclosure. *The Accounting Review*, *82*(4), 869–906.

Bertrand, J. (1883). Review of "Theorie mathematique de la richesse sociale" and of "Recherches sur les principles mathematiques de la theorie des richesses." *Journal de Savants*, *67*, 499.

Bessen, J., Ford, J., & Meurer, M. J. (2011). The Private and Social Costs of Patent Trolls Property. *Regulation*, *34*(4), 26–35.

Bloom, N., Schankerman, M., & Van Reenen, J. (2013). Identifying Technology Spillovers and Product Market Rivalry. *Econometrica*, *81*(4), 1347–1393. https://doi.org/10.3982/ECTA9466

Brav, A., Jiang, W., Ma, S., & Tian, X. (2018). How does hedge fund activism reshape corporate innovation? *Journal of Financial Economics*, *130*(2), 237–264. https://doi.org/10.1016/j.jfineco.2018.06.012

Brown, S. V., & Tucker, J. W. (2011). Large-Sample Evidence on Firms' Year-over-Year MD&A Modifications. *Journal of Accounting Research*, *49*(2), 309–346. https://doi.org/10.1111/j.1475-679X.2010.00396.x

Bunzeck, N., Guitart-Masip, M., Dolan, R. J., & Düzel, E. (2011). Contextual Novelty Modulates the Neural Dynamics of Reward Anticipation. *Journal of Neuroscience*, *31*(36), 12816–12822. https://doi.org/10.1523/JNEUROSCI.0461-11.2011

Campbell, T. C., Gallmeyer, M., Johnson, S. A., Rutherford, J., & Stanley, B. W. (2011). CEO optimism and forced turnover. *Journal of Financial Economics*, *101*(3), 695–712. https://doi.org/10.1016/j.jfineco.2011.03.004

Canibano, L., Garcia-Ayuso, M., & Sanchez, P. (2000). Accounting for intangibles: A literature review. *Journal of Accounting Literature*, *19*, 102–130.

Cao, S. S., Ma, G., Tucker, J. W., & Wan, C. (2018). Technological Peer Pressure and Product Disclosure. *The Accounting Review*, *93*(6), 95–126. https://doi.org/10.2308/accr-52056

Cao, Y., Cheng, S., Tucker, J. W., & Wan, C. (2023). Technological peer pressure and skill specificity of job postings. *Contemporary Accounting Research*, *40*(3), 2106–2139. https://doi.org/10.1111/1911-3846.12870

Chan, L. K. C., Lakonishok, J., & Sougiannis, T. (2001). The Stock Market Valuation of Research and Development Expenditures. *The Journal of Finance*, *56*(6), 2431–2456. https://doi.org/10.1111/0022-1082.00411

Chen, J., Hong, H., & Stein, J. C. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, *61*(3), 345–381. https://doi.org/10.1016/S0304-405X(01)00066-6

Chu, J., He, Y., Hui, K. W., & Lehavy, R. (2023). *New Product Announcements, Innovation Disclosure, and Future Firm Performance* (SSRN Scholarly Paper 3543632). https://doi.org/10.2139/ssrn.3543632

Clinch, G., & Verrecchia, R. E. (1997). Competitive disadvantage and discretionary disclosure in industries. *Australian Journal of Management (University of New South Wales)*, *22*(2), 125–137. https://doi.org/10.1177/031289629702200201

Cohen, J. R., Holder-Webb, L. L., Nath, L., & Wood, D. (2012). Corporate Reporting of Nonfinancial Leading Indicators of Economic Performance and Sustainability. *Accounting Horizons*, *26*(1), 65–90. https://doi.org/10.2308/acch-50073

Cohen, L., Diether, K., & Malloy, C. (2013). Misvaluing Innovation. *The Review of Financial Studies*, *26*(3), 635–666. https://doi.org/10.1093/rfs/hhs183

Cohen, L., & Frazzini, A. (2008). Economic Links and Predictable Returns. *The Journal of Finance*, *63*(4), 1977–2011. https://doi.org/10.1111/j.1540-6261.2008.01379.x

Cohen, W. M., & Levinthal, D. A. (1994). Fortune Favors the Prepared Firm. *Management Science*, *40*(2), 227–251.

Coles, J. L., Daniel, N. D., & Naveen, L. (2006). Managerial incentives and risk-taking. *Journal of Financial Economics*, *79*(2), 431–468. https://doi.org/10.1016/j.jfineco.2004.09.004

Coller, M., & Yohn, T. L. (1997). Management Forecasts and Information Asymmetry: An Examination of Bid-Ask Spreads. *Journal of Accounting Research*, *35*(2), 181–191. https://doi.org/10.2307/2491359

Core, J., & Guay, W. (2002). Estimating the Value of Employee Stock Option Portfolios and Their Sensitivities to Price and Volatility. *Journal of Accounting Research*, *40*(3), 613–630.

Cournot, A. A. (1838). *Recherches sur les principes mathématiques de la théorie des richesses*. L. Hachette.

Da, Z., Gurun, U. G., & Warachka, M. (2014). Frog in the Pan: Continuous Information and Momentum. *The Review of Financial Studies*, *27*(7), 2171–2218.

Darrough, M. N., & Stoughton, N. M. (1990). Financial disclosure policy in an entry game. *Journal of Accounting and Economics*, *12*(1), 219–243. https://doi.org/10.1016/0165-4101(90)90048-9

Davis, A. K., Ge, W., Matsumoto, D., & Zhang, J. L. (2015). The effect of manager-specific optimism on the tone of earnings conference calls. *Review of Accounting Studies*, *20*(2), 639–673. https://doi.org/10.1007/s11142-014-9309-4

De Rassenfosse, G., Jensen, P. H., Julius, T., Palangkaraya, A., & Webster, E. (2023). Is the Patent System an Even Playing Field? The Effect of Patent Attorney Firms. *The Journal of Industrial Economics*, *71*(1), 124–142. https://doi.org/10.1111/joie.12319

Diamond, D. W., & Verrecchia, R. E. (1991). Disclosure, Liquidity, and the Cost of Capital. *The Journal of Finance*, *46*(4), 1325–1359. https://doi.org/10.1111/j.1540-6261.1991.tb04620.x

Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics*, *7*(2), 197–226. https://doi.org/10.1016/0304-405X(79)90013-8

Dixit, A. K., & Stiglitz, J. E. (1977). Monopolistic Competition and Optimum Product Diversity. *The American Economic Review*, *67*(3), 297–308.

Eisdorfer, A., & Hsu, P.-H. (2011). Innovate to Survive: The Effect of Technology Competition on Corporate Bankruptcy. *Financial Management*, *40*(4), 1087–1117. https://doi.org/10.1111/j.1755-053X.2011.01172.x

Ellis, J. A., Fee, C. E., & Thomas, S. E. (2012). Proprietary Costs and the Disclosure of Information About Customers. *Journal of Accounting Research*, *50*(3), 685–727. https://doi.org/10.1111/j.1475-679X.2012.00441.x

Entwistle, G. M. (1999). Exploring the R&D Disclosure Environment. *Accounting Horizons*, *13*(4), 323–342. https://doi.org/10.2308/acch.1999.13.4.323

Ettredge, M., Guo, F., Lisic, L. L., & Tseng, K. (2018). *Technology Spillover and Corporate Technology Disclosures* (SSRN Scholarly Paper 2727933). https://doi.org/10.2139/ssrn.2727933

Fama, E. F., & French, K. R. (2000). Forecasting Profitability and Earnings. *The Journal of Business*, *73*(2), 161–175. https://doi.org/10.1086/209638

Financial Accounting Standards Board (FASB). (2010). *Statement of Financial Accounting Standards No. 2 Accounting for Research and Development Costs*. https://d2x0djib3vzbzj.cloudfront.net/aop_fas2.pdf

Fitzgerald, T., Balsmeier, B., Fleming, L., & Manso, G. (2021). Innovation Search Strategy and Predictable Returns. *Management Science*, *67*(2), 1109–1137. https://doi.org/10.1287/mnsc.2019.3480

Fourné, S. P. L., Rosenbusch, N., Heyden, M. L. M., & Jansen, J. J. P. (2019). Structural and contextual approaches to ambidexterity: A meta-analysis of organizational and environmental contingencies. *European Management Journal*, *37*(5), 564–576. https://doi.org/10.1016/j.emj.2019.04.002

Futia, C. A. (1980). Schumpeterian Competition. *The Quarterly Journal of Economics*, *94*(4), 675–695. https://doi.org/10.2307/1885663

Galor, O., & Weil, D. N. (2000). Population, Technology, and Growth: From Malthusian Stagnation to the Demographic Transition and Beyond. *American Economic Review*, *90*(4), 806–828. https://doi.org/10.1257/aer.90.4.806

Ganguly, A. (2018). *Textual Disclosure in SEC Filings and Litigation Risk*. University of Pittsburgh.

Gao, H., Hsu, P.-H., & Li, K. (2018). Innovation Strategy of Private Firms. *Journal of Financial and Quantitative Analysis*, *53*(1), 1–32. https://doi.org/10.1017/S0022109017001119

Gelb, D. S. (2002). Intangible Assets and Firms' Disclosures: An Empirical Investigation. *Journal of Business Finance & Accounting*, *29*(3–4), 457–476. https://doi.org/10.1111/1468-5957.00438

Glaeser, S. (2018). The effects of proprietary information on corporate disclosure and transparency: Evidence from trade secrets. *Journal of Accounting and Economics*, *66*(1), 163–193. https://doi.org/10.1016/j.jacceco.2018.04.002

Glaeser, S. A., & Landsman, W. R. (2021). Deterrent Disclosure. *The Accounting Review*, *96*(5), 291–315. https://doi.org/10.2308/TAR-2019-1050

Glaeser, S., & Lang, M. H. (2024). A Review of the Accounting Literature on Innovation. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4500800

Goodman, T. H., Neamtiu, M., Shroff, N., & White, H. D. (2014). Management Forecast Quality and Capital Investment Decisions. *The Accounting Review*, *89*(1), 331–365.

Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, *40*(1), 3–73. https://doi.org/10.1016/j.jacceco.2005.01.002

Gu, F. (2005). Innovation, Future Earnings, and Market Efficiency. *Journal of Accounting, Auditing & Finance*, *20*(4), 385–418. https://doi.org/10.1177/0148558X0502000405

Gu, F., & Li, J. Q. (2003). Disclosure of innovation activities by high-technology firms. *Asia-Pacific Journal of Accounting & Economics*, *10*(2), 143–172. https://doi.org/10.1080/16081625.2003.10510623

Gujarati, D. N. (1995). *Basic econometrics* (3rd ed.). McGraw-Hill.

Gupta, A. K., Smith, K. G., & Shalley, C. E. (2006). The Interplay between Exploration and Exploitation. *The Academy of Management Journal*, *49*(4), 693–706. https://doi.org/10.2307/20159793

Habib, A., Hasan, M. M., & Jiang, H. (2018). Stock price crash risk: Review of the empirical literature. *Accounting & Finance*, *58*(S1), 211–251. https://doi.org/10.1111/acfi.12278

Hall, B. H., Jaffe, A., & Trajtenberg, M. (2005). Market Value and Patent Citations. *The RAND Journal of Economics*, *36*(1), 16–38.

Hall, B., Helmers, C., Rogers, M., & Sena, V. (2014). The Choice between Formal and Informal Intellectual Property: A Review. *Journal of Economic Literature*, *52*(2), 375–423. https://doi.org/10.1257/jel.52.2.375

Hayes, R. M., & Lundholm, R. (1996). Segment Reporting to the Capital Market in the Presence of a Competitor. *Journal of Accounting Research*, *34*(2), 261–279. https://doi.org/10.2307/2491502

Hayn, C. (1995). The information content of losses. *Journal of Accounting and Economics*, *20*(2), 125–153. https://doi.org/10.1016/0165-4101(95)00397-2

He, J., & Lee, D. (2022). *Say More to Return Less? Disclosure Subsequent to Successful Technological Innovation* (SSRN Scholarly Paper 4050189). https://doi.org/10.2139/ssrn.4050189

He, Z.-L., & Wong, P.-K. (2004). Exploration vs. Exploitation: An Empirical Test of the Ambidexterity Hypothesis. *Organization Science*, *15*(4), 481–494. https://doi.org/10.1287/orsc.1040.0078

Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, *31*(1), 405–440. https://doi.org/10.1016/S0165-4101(01)00018-0

Heflin, F., Subramanyam, K. R., & Zhang, Y. (2003). Regulation FD and the financial information environment: Early evidence. *The Accounting Review*, *78*(1), 1–38.

Henry, E. (2008). Are Investors Influenced By How Earnings Press Releases Are Written? *The Journal of Business Communication (1973)*, *45*(4), 363–407. https://doi.org/10.1177/0021943608319388

Hirshleifer, D., Hsu, P.-H., & Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics*, *107*(3), 632–654. https://doi.org/10.1016/j.jfineco.2012.09.011

Hirshleifer, D., Hsu, P.-H., & Li, D. (2018). Innovative Originality, Profitability, and Stock Returns. *The Review of Financial Studies*, *31*(7), 2553–2605. https://doi.org/10.1093/rfs/hhx101

Hirshleifer, D., Low, A., & Teoh, S. H. (2012). Are Overconfident CEOs Better Innovators? *The Journal of Finance*, *67*(4), 1457–1498. https://doi.org/10.1111/j.1540-6261.2012.01753.x

Hirst, D. E., Koonce, L., & Venkataraman, S. (2008). Management Earnings Forecasts: A Review and Framework. *Accounting Horizons*, *22*(3), 315–338.

Hoberg, G., Phillips, G., & Prabhala, N. (2014). Product Market Threats, Payouts, and Financial Flexibility. *The Journal of Finance*, *69*(1), 293–324. https://doi.org/10.1111/jofi.12050

Hotelling, H. (1929). Stability in Competition. *The Economic Journal*, *39*(153), 41–57. https://doi.org/10.2307/2224214

Hsieh, C.-C., Ma, Z., & Novoselov, K. E. (2019). Accounting conservatism, business strategy, and ambiguity. *Accounting, Organizations and Society*, *74*, 41–55. https://doi.org/10.1016/j.aos.2018.08.001

Huang, S., Ng, J., Ranasinghe, T., & Zhang, M. (2021). Do Innovative Firms Communicate More? Evidence from the Relation between Patenting and Management Guidance. *The Accounting Review*, *96*(1), 273–297. https://doi.org/10.2308/tar-2017-0082

Huang, X., Teoh, S. H., & Zhang, Y. (2014). Tone Management. *The Accounting Review*, *89*(3), 1083–1113. https://doi.org/10.2308/accr-50684

Huberman, G., & Regev, T. (2001). Contagious Speculation and a Cure for Cancer: A Nonevent That Made Stock Prices Soar. *The Journal of Finance*, *56*(1), 387–396.

Hughes, J. S., & Pae, S. (2015). Discretionary disclosure, spillovers, and competition. *Review of Accounting Studies*, *20*(1), 319–342. https://doi.org/10.1007/s11142-014-9299-2

Hutton, A. P. (2005). Determinants of Managerial Earnings Guidance Prior to Regulation Fair Disclosure and Bias in Analysts' Earnings Forecasts. *Contemporary Accounting Research*, *22*(4), 867–914. https://doi.org/10.1506/6QUR-CR5M-AQQX-KX1A

Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R2, and crash risk. *Journal of Financial Economics*, *94*(1), 67–86. https://doi.org/10.1016/j.jfineco.2008.10.003

International Business Machines Corporation. (2017). *Annual Report 2017*. https://www.sec.gov/Archives/edgar/data/51143/000104746918001117/a2233835z10-k.htm

Jaffe, A. B. (1986). Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value. *The American Economic Review*, *76*(5), 984–1001.

Jansen, J. J. P., Bosch, F. A. J. V. D., & Volberda, H. W. (2006). Exploratory innovation, exploitative innovation, and performance: Effects of organizational antecedents and environmental moderators. *Management Science*, *52*(11), 1661–1675.

Jia, N. (2017). Corporate Innovation Strategy, Analyst Forecasting Activities and the Economic Consequences. *Journal of Business Finance & Accounting*, *44*(5–6), 812–853. https://doi.org/10.1111/jbfa.12242

Jia, N. (2018). Corporate innovation strategy and stock price crash risk. *Journal of Corporate Finance*, *53*, 155–173. https://doi.org/10.1016/j.jcorpfin.2018.10.006

Jia, N. (2019). Corporate innovation strategy and disclosure policy. *Review of Quantitative Finance and Accounting*, *52*(1), 253–288. https://doi.org/10.1007/s11156-018-0709-6
Jones, D. A. (2007). Voluntary Disclosure in R&D-Intensive Industries. *Contemporary Accounting Research*, *24*(2), 489–522. https://doi.org/10.1506/G3M3-2532-514H-1517
Kaplan, S., & Tripsas, M. (2008). Thinking about technology: Applying a cognitive lens to technical change. *Research Policy*, *37*(5), 790–805. https://doi.org/10.1016/j.respol.2008.02.002
Katila, R., & Ahuja, G. (2002). Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction. *Academy of Management Journal*, *45*(6), 1183–1194. https://doi.org/10.5465/3069433
Kim, J.-B., Li, Y., & Zhang, L. (2011a). CFOs versus CEOs: Equity incentives and crashes. *Journal of Financial Economics*, *101*(3), 713–730. https://doi.org/10.1016/j.jfineco.2011.03.013
Kim, J.-B., Li, Y., & Zhang, L. (2011b). Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics*, *100*(3), 639–662. https://doi.org/10.1016/j.jfineco.2010.07.007
Kim, Y., Li, H., & Li, S. (2014). Corporate social responsibility and stock price crash risk. *Journal of Banking & Finance*, *43*, 1–13. https://doi.org/10.1016/j.jbankfin.2014.02.013
Klibanoff, P., Lamont, O., & Wizman, T. A. (1998). Investor Reaction to Salient News in Closed-End Country Funds. *The Journal of Finance*, *53*(2), 673–699.
Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological Innovation, Resource Allocation, and Growth. *The Quarterly Journal of Economics*, *132*(2), 665–712. https://doi.org/10.1093/qje/qjw040
Koh, P.-S., & Reeb, D. M. (2015). Missing R&D. *Journal of Accounting and Economics*, *60*(1), 73–94. https://doi.org/10.1016/j.jacceco.2015.03.004
Koryak, O., Lockett, A., Hayton, J., Nicolaou, N., & Mole, K. (2018). Disentangling the antecedents of ambidexterity: Exploration and exploitation. *Research Policy*, *47*(2), 413–427. https://doi.org/10.1016/j.respol.2017.12.003
Kothari, S. P., Laguerre, T. E., & Leone, A. J. (2002). Capitalization versus Expensing: Evidence on the Uncertainty of Future Earnings from Capital Expenditures versus R&D Outlays. *Review of Accounting Studies*, *7*(4), 355.
Kothari, S. P., Leone, A. J., & Wasley, C. E. (2005). Performance matched discretionary accrual measures. *Journal of Accounting and Economics*, *39*(1), 163–197. https://doi.org/10.1016/j.jacceco.2004.11.002
Kuhnen, C. M., & Niessen, A. (2012). Public Opinion and Executive Compensation. *Management Science*, *58*(7), 1249–1272. https://doi.org/10.1287/mnsc.1110.1490
Lafond, R., & Roychowdhury, S. (2008). Managerial Ownership and Accounting Conservatism. *Journal of Accounting Research*, *46*(1), 101–135. https://doi.org/10.1111/j.1475-679X.2008.00268.x
Lang, M., & Lundholm, R. (1993). Cross-Sectional Determinants of Analyst Ratings of Corporate Disclosures. *Journal of Accounting Research*, *31*(2), 246–271. https://doi.org/10.2307/2491273
Lavie, D., & Rosenkopf, L. (2006). Balancing Exploration and Exploitation in Alliance Formation. *The Academy of Management Journal*, *49*(4), 797–818.
Lavie, D., Stettner, U., & Tushman, M. L. (2010). Exploration and Exploitation Within and Across Organizations. *The Academy of Management Annals*, *4*(1), 109–155. https://doi.org/10.1080/19416521003691287
Lehavy, R., Li, F., & Merkley, K. (2011). The Effect of Annual Report Readability on Analyst Following and the Properties of Their Earnings Forecasts. *The Accounting Review*, *86*(3), 1087–1115.

Leuz, C., & Verrecchia, R. E. (2000). The Economic Consequences of Increased Disclosure. *Journal of Accounting Research*, *38*, 91–124. https://doi.org/10.2307/2672910

Lev, B., Sarath, B., & Sougiannis, T. (2005). R&D Reporting Biases and Their Consequences. *Contemporary Accounting Research*, *22*(4), 977–1026. https://doi.org/10.1506/7XMH-QQ74-L6GG-CJRX

Lev, B., & Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of R&D. *Journal of Accounting and Economics*, *21*(1), 107–138. https://doi.org/10.1016/0165-4101(95)00410-6

Lev, B., & Sougiannis, T. (1999). Penetrating the Book-to-Market Black Box: The R&D Effect. *Journal of Business Finance & Accounting*, *26*(3–4), 419–449. https://doi.org/10.1111/1468-5957.00262

Levinthal, D. A., & March, J. G. (1993). The myopia of learning. *Strategic Management Journal*, *14*(S2), 95–112. https://doi.org/10.1002/smj.4250141009

Li, F. (2010). The Information Content of Forward-Looking Statements in Corporate Filings—A Naïve Bayesian Machine Learning Approach. *Journal of Accounting Research*, *48*(5), 1049–1102. https://doi.org/10.1111/j.1475-679X.2010.00382.x

Li, F., Lundholm, R., & Minnis, M. (2013). A Measure of Competition Based on 10-K Filings. *Journal of Accounting Research*, *51*(2), 399–436. https://doi.org/10.1111/j.1475-679X.2012.00472.x

Li, J., & Yu, J. (2012). Investor attention, psychological anchors, and stock return predictability. *Journal of Financial Economics*, *104*(2), 401–419. https://doi.org/10.1016/j.jfineco.2011.04.003

Li, O. Z., & Zhuang, Z. (2012). Management Guidance and the Underpricing of Seasoned Equity Offerings. *Contemporary Accounting Research*, *29*(3), 710–737. https://doi.org/10.1111/j.1911-3846.2011.01120.x

Li, X. (2010). The impacts of product market competition on the quantity and quality of voluntary disclosures. *Review of Accounting Studies*, *15*(3), 663–711. https://doi.org/10.1007/s11142-010-9129-0

Lin, C., Liu, S., & Manso, G. (2021). Shareholder Litigation and Corporate Innovation. *Management Science*, *67*(6), 3346–3367. https://doi.org/10.1287/mnsc.2020.3626

Lobo, G. J., Xie, Y., & Zhang, J. H. (2018). Innovation, financial reporting quality, and audit quality. *Review of Quantitative Finance and Accounting*, *51*(3), 719–749. http://dx.doi.org.proxy.lib.uwaterloo.ca/10.1007/s11156-017-0686-1

Loughran, T., & McDonald, B. (2011). When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *The Journal of Finance*, *66*(1), 35–65. https://doi.org/10.1111/j.1540-6261.2010.01625.x

Loughran, T., & McDonald, B. (2016). Textual Analysis in Accounting and Finance: A Survey. *Journal of Accounting Research*, *54*(4), 1187–1230. https://doi.org/10.1111/1475-679X.12123

Luo, Y., & Zhou, L. (2020). Textual tone in corporate financial disclosures: A survey of the literature. *International Journal of Disclosure and Governance*, *17*(2–3), 101–110. https://doi.org/10.1057/s41310-020-00077-y

Malmendier, U., & Tate, G. (2005). CEO Overconfidence and Corporate Investment. *The Journal of Finance*, *60*(6), 2661–2700. https://doi.org/10.1111/j.1540-6261.2005.00813.x

Malmendier, U., & Tate, G. (2008). Who makes acquisitions? CEO overconfidence and the market's reaction. *Journal of Financial Economics*, *89*(1), 20–43. https://doi.org/10.1016/j.jfineco.2007.07.002

Manso, G. (2011). Motivating Innovation. *The Journal of Finance*, *66*(5), 1823–1860. https://doi.org/10.1111/j.1540-6261.2011.01688.x

March, J. G. (1991). Exploration and Exploitation in Organizational Learning. *Organization Science*, *2*(1), 71–87. https://doi.org/10.1287/orsc.2.1.71

Marquez-Illescas, G., Zebedee, A. A., & Zhou, L. (2019). Hear Me Write: Does CEO Narcissism Affect Disclosure? *Journal of Business Ethics*, *159*(2), 401–417.

Matolcsy, Z. P., & Wyatt, A. (2008). The Association between Technological Conditions and the Market Value of Equity. *The Accounting Review*, *83*(2), 479–518. https://doi.org/10.2308/accr.2008.83.2.479

McGrath, R. G. (2001). Exploratory learning, innovative capacity, and managerial oversight. *Academy of Management Journal*, *44*(1), 118–131.

Menguc, B., & Auh, S. (2008). The asymmetric moderating role of market orientation on the ambidexterity–firm performance relationship for prospectors and defenders. *Industrial Marketing Management*, *37*(4), 455–470. https://doi.org/10.1016/j.indmarman.2007.05.002

Merkley, K. J. (2014). Narrative Disclosure and Earnings Performance: Evidence from R&D Disclosures. *The Accounting Review*, *89*(2), 725–757.

Milstead, V., & Foster, M. (2024, January 24). Beware of potential securities litigation over risk-factor disclosures. *Reuters*. https://www.reuters.com/legal/legalindustry/beware-potential-securities-litigation-over-risk-factor-disclosures-2024-01-24/

Mueller, V., Rosenbusch, N., & Bausch, A. (2013). Success Patterns of Exploratory and Exploitative Innovation: A Meta-Analysis of the Influence of Institutional Factors. *Journal of Management*, *39*(6), 1606–1636. https://doi.org/10.1177/0149206313484516

Nagar, V., Nanda, D., & Wysocki, P. (2003). Discretionary disclosure and stock-based incentives. *Journal of Accounting and Economics*, *34*(1), 283–309. https://doi.org/10.1016/S0165-4101(02)00075-7

Nikolaev, V., & Van Lent, L. (2005). The endogeneity bias in the relation between cost-of-debt capital and corporate disclosure policy. *European Accounting Review*, *14*(4), 677–724. https://doi.org/10.1080/09638180500204624

Pandit, S., Wasley, C. E., & Zach, T. (2011). Information Externalities along the Supply Chain: The Economic Determinants of Suppliers' Stock Price Reaction to Their Customers' Earnings Announcements. *Contemporary Accounting Research*, *28*(4), 1304–1343. https://doi.org/10.1111/j.1911-3846.2011.01092.x

Patell, J. M. (1976). Corporate Forecasts of Earnings Per Share and Stock Price Behavior: Empirical Test. *Journal of Accounting Research*, *14*(2), 246–276. https://doi.org/10.2307/2490543

Penman, S. H. (1980). An Empirical Investigation of the Voluntary Disclosure of Corporate Earnings Forecasts. *Journal of Accounting Research*, *18*(1), 132–160. https://doi.org/10.2307/2490396

Pisano, G. P. (2015, June 1). You Need an Innovation Strategy. *Harvard Business Review*. https://hbr.org/2015/06/you-need-an-innovation-strategy

Qiu, J., & Wan, C. (2015). Technology spillovers and corporate cash holdings. *Journal of Financial Economics*, *115*(3), 558–573. https://doi.org/10.1016/j.jfineco.2014.10.005

Raimondo, C. (2019). The Media and the Financial Markets: A Review. *Asia-Pacific Journal of Financial Studies*, *48*(2), 155–184. https://doi.org/10.1111/ajfs.12250

Ramalingegowda, S., & Yu, Y. (2012). Institutional ownership and conservatism. *Journal of Accounting and Economics*, *53*(1–2), 98–114. https://doi.org/10.1016/j.jacceco.2011.06.004

Rawson, C. (2022). Manager perception and proprietary investment disclosure. *Review of Accounting Studies*, *27*(4), 1493–1525. https://doi.org/10.1007/s11142-021-09629-1

Rindova, V. P., & Petkova, A. P. (2007). When Is a New Thing a Good Thing? Technological Change, Product Form Design, and Perceptions of Value for Product Innovations. *Organization Science*, *18*(2), 217–232. https://doi.org/10.1287/orsc.1060.0233

Rosenkopf, L., & Nerkar, A. (2001). Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal*, *22*(4), 287–306. https://doi.org/10.1002/smj.160

Ryou, J. W., Tsang, A., & Wang, K. T. (2022). Product Market Competition and Voluntary Corporate Social Responsibility Disclosures. *Contemporary Accounting Research*, *39*(2), 1215–1259. https://doi.org/10.1111/1911-3846.12748

Schumpeter, J. A. (2003). *Capitalism, Socialism and Democracy* (5th ed.). Routledge. https://doi.org/10.4324/9780203202050

SEC. (2020). *Modernization of Regulation S-K Items 101, 103, and 105*. https://www.sec.gov/rules/final/2020/33-10825.pdf

Shapiro, C. (2000). Navigating the Patent Thicket: Cross Licenses, Patent Pools, and Standard Setting. *Innovation Policy and the Economy*, *1*, 119–150. https://doi.org/10.1086/ipe.1.25056143

Simpson, A., & Tamayo, A. (2020). Real effects of financial reporting and disclosure on innovation. *Accounting and Business Research*, *50*(5), 401–421. https://doi.org/10.1080/00014788.2020.1770926

Skinner, A. N., & Valentine, K. (2024). *Green Patenting and Voluntary Innovation Disclosure* (SSRN Scholarly Paper 4321932). https://doi.org/10.2139/ssrn.4321932

Skyworks Solutions Inc. (2014). *Annual Report 2014*. https://www.sec.gov/Archives/edgar/data/4127/000000412714000046/fy1410k1032014.htm

Smith, W. K., & Tushman, M. L. (2005). Managing Strategic Contradictions: A Top Management Model for Managing Innovation Streams. *Organization Science*, *16*(5), 522–536. https://doi.org/10.1287/orsc.1050.0134

Solow, R. M. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, *39*(3), 312–320. https://doi.org/10.2307/1926047

Song, H., & Schwarz, N. (2010). If it,s easy to read, it,s easy to do, pretty, good, and true. *Psychologist*. https://www.semanticscholar.org/paper/If-it%2Cs-easy-to-read%2C-it%2Cs-easy-to-do%2C-pretty%2C-and-Song-Schwarz/a25cec946b2ff47a9513789a5415058992bd4d68

Sougiannis, T. (1994). The Accounting Based Valuation of Corporate R&D. *The Accounting Review*, *69*(1), 44–68.

Stahl, D. O. (1988). Bertrand Competition for Inputs and Walrasian Outcomes. *The American Economic Review*, *78*(1), 189–201.

Stoffman, N., Woeppel, M., & Yavuz, M. D. (2022). Small innovators: No risk, No return. *Journal of Accounting and Economics*, *74*(1), 101492. https://doi.org/10.1016/j.jacceco.2022.101492

Tasker, S. C. (1998). Bridging the Information Gap: Quarterly Conference Calls as a Medium for Voluntary Disclosure. *Review of Accounting Studies*, *3*(1), 137–167. https://doi.org/10.1023/A:1009684502135

Tucker, J. W. (2007). Is Openness Penalized? Stock Returns around Earnings Warnings: Accounting Review. *The Accounting Review*, *82*(4), 1055–1087. https://doi.org/10.2308/accr.2007.82.4.1055

Tucker, J. W. (2011). Selection Bias and Econometric Remedies in Accounting and Finance Research. *Journal of Accounting Literature*. https://papers.ssrn.com/abstract=1756911

Tushman, M. L., & O’Reilly, C. A. (1996). Ambidextrous Organizations: Managing Evolutionary and Revolutionary Change. *California Management Review*, *38*(4), 8–29. https://doi.org/10.2307/41165852

Uotila, J., Maula, M., Keil, T., & Zahra, S. A. (2009). Exploration, exploitation, and financial performance: Analysis of S&P 500 corporations. *Strategic Management Journal*, *30*(2), 221–231. https://doi.org/10.1002/smj.738

USPTO. (2000). *American Inventors Protection Act—Summary* [Text]. https://www.uspto.gov/patents/laws/american-inventors-protection-act-1999/american-inventors-protection-a-2

Vassolo, R. S., Anand, J., & Folta, T. B. (2004). Non-additivity in portfolios of exploration activities: A real options-based analysis of equity alliances in biotechnology. *Strategic Management Journal*, *25*(11), 1045–1061. https://doi.org/10.1002/smj.414

Verrecchia, R. E. (1983). Discretionary disclosure. *Journal of Accounting and Economics*, *5*, 179–194. https://doi.org/10.1016/0165-4101(83)90011-3

Verrecchia, R. E. (2001). Essays on disclosure. *Journal of Accounting and Economics*, *32*(1), 97–180. https://doi.org/10.1016/S0165-4101(01)00025-8

Wagenhofer, A. (1990). Voluntary disclosure with a strategic opponent. *Journal of Accounting and Economics*, *12*(4), 341–363. https://doi.org/10.1016/0165-4101(90)90020-5

Wang, I. Y. (2007). Private Earnings Guidance and Its Implications for Disclosure Regulation. *The Accounting Review*, *82*(5), 1299–1332.

Wittmann, B. C., Bunzeck, N., Dolan, R. J., & Düzel, E. (2007). Anticipation of novelty recruits reward system and hippocampus while promoting recollection. *NeuroImage*, *38*(1), 194–202. https://doi.org/10.1016/j.neuroimage.2007.06.038

WSJ. (2013, September 17). Do Companies Spend Too Much Time Searching for Groundbreaking Innovations? *Wall Street Journal (Online)*. http://www.proquest.com/docview/1433125714/citation/422BF308B4A64E30PQ/11

Yang, J. (2023). *Essays on corporate innovation strategy and corporate disclosure* [Thesis, Loughborough University]. https://doi.org/10.26174/thesis.lboro.22121933.v1

Appendices

Appendix A

Examples of Narrative Innovation Disclosures in 10-K Filings

Strategy

"Our markets are characterized by rapid technological changes and advances. Accordingly, we make substantial investments in the design and development of new products and manufacturing processes, and the improvement of existing products and manufacturing processes. We spent approximately $560 million during fiscal 2014 on the design, development and improvement of new and existing products and manufacturing processes, compared to approximately $513 million during fiscal 2013 and approximately $512 million during fiscal 2012. Our research and development strategy focuses on building technical leadership in core technologies of converters, amplifiers and RF and microwave, MEMS, power management, and DSP. In support of our research and development activities, we employ thousands of engineers involved in product and manufacturing process development throughout the world" (Analog Devices Inc, 2014, p.6).

Patent

"On December 31, 2002, the FDA approved Humira for the treatment of rheumatoid arthritis. Worldwide sales of Humira are forecasted to be more than $150 million in 2003. The expiration of patent protection can affect the future revenues and operating income of Abbott. Significant patent expirations and activities in the next three years are as follows. The original U.S. compound patent on clarithromycin expires in 2005. Approximately 50% of the U.S. sales of clarithromycin in 2002 were made under a form covered by patents that expire later than 2005. U.S. sales of clarithromycin were $487 million in 2002. Abbott markets TriCor in the U.S. under a license agreement. Patents covering TriCor are being challenged by competitors. Abbott is vigorously defending the patents. U.S. sales of TriCor were $403 million in 2002. An NDA for Synthroid, which is not protected by a patent, was approved by the FDA in 2002. The FDA is studying the conditions under which competitors may rely on Abbott's NDA to market a competitive product. U.S. sales of Synthroid were $489 million in 2002" (Abbott Laboratories, 2002, p.27).

"We have obtained a substantial number of patents and trademarks in the United States and in other countries. As of October 31, 2015, we held approximately 2,280 U.S. patents and approximately 635 non-provisional pending U.S. patent applications with expiration dates ranging from 2015 through 2034" (Analog Devices Inc, 2015, p.6).

R&D Expense

"Research and development expenses of $1.4 billion in 2012, decreased by $99 million, or 7%, compared to $1.5 billion in 2011. The decrease was due to a $60 million decrease in research and development expenses attributable to our Graphics segment and a $45 million decrease in research and development expenses attributable to our Computing Solutions segment, partially offset by a $6 million increase in stock-based compensation expense recorded in the All Other category. Research and development expenses attributable to our Graphics segment decreased as a result of a $36 million decrease in product engineering and design costs, a $16 million decrease in other employee compensation and benefit expense and a $9 million decrease in manufacturing process technology expenses. The decrease in research and development expenses attributable to our Computing Solutions segment was primarily due to a $26 million decrease in other employee compensation and benefit expense, an $11 million decrease in manufacturing process technology expenses related to GF for our future products and a $9 million decrease in product engineering and design costs" (Advanced Micro Devices, 2012, p.51).

"IBM's research and development (R&D) operations differentiate the company from its competitors. IBM annually invests 7 to 8 percent of total revenue for R&D, focusing on high-growth, high-value opportunities. IBM Research works with clients and the company's business units through global labs on near-term and mid-term innovations. It delivers many new technologies to IBM's portfolio every year and helps clients address their most difficult challenges. IBM Research scientists are conducting pioneering work in artificial intelligence, quantum computing, blockchain, security, cloud, nanotechnology, silicon and post-silicon computing architectures and more—applying these technologies across industries including healthcare, IoT, education and financial services" (International Business Machines Corporation, 2017, p.7) .

Collaboration
"We conduct our microprocessor manufacturing process development activities primarily through our joint development agreement with IBM. Under this agreement, we jointly develop new process technologies, including 45-nanometer, 32-nanometer, 22-nanometer and certain other advanced technologies, to be implemented on silicon wafers. Our relationship also includes laboratory-based research of emerging technologies such as new transistor, interconnect, lithography and die-to-package connection technologies. We pay fees to IBM for joint development projects" (Advanced Micro Devices, 2006, p.15).

Employee
"At January 31, 2011, we had 172 employees, 142 of whom were engaged in research and development. None of our employees are represented by a labor union or covered by a collective bargaining agreement, nor have we experienced work stoppages. We believe that relations with our employees are good" (Alnylam Pharmaceuticals Inc, 2010, p.42).

Competition
"The competitive environment in the semiconductor industry is in a constant state of flux, with new products continually emerging and existing products approaching technological obsolescence. We compete on the basis of time-to-market, new product innovation, quality, performance, price, compliance with industry standards, strategic relationships with customers and baseband vendors, personnel and protection of our intellectual property. We participate in highly competitive markets against numerous competitors that may be able to adapt more quickly than we can to new or emerging technologies and changes in customer requirements, or may be able to devote greater resources to the development, promotion and sale of their products than we can. Erosion of average selling prices of established products is typical of the semiconductor industry. Consistent with trends in the industry, we anticipate that average selling prices for our established products will continue to decline at a normalized rate of five to ten percent per year. As part of our normal course of business, we mitigate the gross margin impact of declining average selling prices with efforts to increase unit volumes, reduce material costs and lower manufacturing costs of existing products and by introducing new and higher value-added products" (Skyworks Solutions Inc, 2014, p.9).

Facility
"At December 29, 2012, we owned principal research and development, engineering, manufacturing, warehouse and administrative facilities located in the United States, Canada, China, Singapore and Malaysia. These facilities totaled approximately 2.4 million square feet. Our main facility with respect to our graphics and chipset products is located in Markham, Ontario, Canada. This facility

consists of approximately 240,000 square feet of office and research and development space" (Advanced Micro Devices, 2012, p.35).

Appendix B

Patent-Based Measure of Corporate Innovation Strategy

A firm initiates the patent process by filing a patent application, which is assigned a unique patent application number. Upon approval, the application transforms into a patent, and the USPTO issues a patent document containing both the patent number and the original patent application number. The document also includes citations to existing patents or patent applications, which serve as references that contribute to the development of the innovation. These citations can originate from patents or patent applications generated by the firm itself or from those produced by other firms. A firm incurs high learning costs to acquire the knowledge in the citation and to produce its own innovation as a new patent that builds on those citations. Therefore, I consider citations as part of the firms' own knowledge and use them as a measure to assess the firm's knowledge base.

Therefore, I start with the citation level of each patent granted to a firm.[66] To build up the firm's existing knowledge pool in year t, I identify all patents applied for by firm i plus citations made by those patents in year $t-5$ to $t-1$ to account for the depreciation of patent stock. For a patent p applied for by firm i in year t, I consider all citations made by this patent as knowledge utilized in innovation. To determine the extent to which knowledge utilized in innovation is derived from the firm's existing knowledge pool, I compare each citation in patent p with every patent and citation in the firm's existing knowledge pool in year t. If there is a match, it means that the citation has been used before (or the firm cites its own patent), which indicates that the firm refers to existing knowledge that requires less time and effort to learn and apply. Thus, this citation is defined as an "old citation." If there is no match, it means that the citation has never been used before, which indicates that the firm spends substantial time and effort to acquire the new knowledge in order to cite it in the patent. Thus, the citation is defined as a "new citation."

[66] It is empirically unfeasible to analyze a firm's innovation strategy at the product level, such as the iPhone, due to the data limitation.

Next, at the patent level, if patent p exhibits a higher "new citation ratio" (calculated as the total number of new citations divided by the total number of citations), it indicates that the knowledge utilized in innovation mainly originates from outside the firm's existing knowledge. This reflects the firm's efforts to expand beyond its existing technology base. I follow the literature (Fitzgerald et al., 2021; Jia, 2018) and flag patent p as "exploratory" if it contains 80% or more new citations (new citation ratio ≥ 80%).

The final step involves transitioning from a patent-level measure to a firm-level measure. If firm i generates a higher proportion of exploratory patents out of total patents, it indicates that the firm prioritizes an exploration strategy. To operationalize the construct of corporate innovation strategy at the firm level, I calculate a continuous measure, exploratory patent ratio (*ExploreRatio*), to assess the firm's exploratory intensity. *ExploreRatio* is calculated as the total number of firm i's patents applied for in year t that are flagged as "exploratory," divided by the total number of firm i's patents applied for in year t. A higher (lower) value of *ExploreRatio* indicates that the firm relatively focuses more (less) on exploratory (exploitative) innovations.

Taking the "multipoint touchscreen" in the first iPhone as an example, when Steve Jobs, the former CEO of Apple, announced the first iPhone in 2007, he introduced a core technology called "multipoint touchscreen," enabling users to perform multi-finger gestures directly on the screen without the need for a stylus (Apple, 2007). This technology was applied for a patent in 2004 and was granted patent number US7663607 in 2010. From a theoretical perspective, this patent is considered exploratory because the introduction of the multi-touch iPhone revolutionized the phone production and led a phenomenal revolution in user interfaces (Annett, 2007). This suggests that the knowledge utilized in screen technology primarily originates from outside Apple's existing knowledge pool.

To operationalize the measure based on my definition, I first identify Apple's existing knowledge in the application year 2004, which includes all patents applied for by Apple plus patents or patent applications produced by other firms that were cited by those patents from 1999 to 2003.

At the citation level of the patent “multipoint touchscreen” (US7663607), Apple’s knowledge utilized in innovation includes all citations within this patent. Among the total of 223 citations, I identify 166 U.S. citations, 24 foreign citations, and 33 patent applications, which are consistent with the original patent document. Then, I compare each citation with patents and citations within the existing knowledge pool and identify 183 new citations and 40 old citations.

At the patent level, I calculate the “new citation ratio” as 0.82 (183/223). I follow the literature and flag this patent as “exploratory” because more than 80% of its citations are based on new knowledge (new citation ratio ≥ 80%). Therefore, I identify the patent “multipoint touchscreen” as an exploratory patent.

To transition from patent-level measure to firm-level measure for Apple in the application year 2004, I calculate the exploratory intensity (*ExploreRatio*) as the total number of Apple’s patents applied for in the year 2004 that are flagged as “exploratory,” divided by the total number of Apple’s patents applied for in the year 2004. The *ExploreRatio* measure for 2004 is 0.55 (162/294).

Appendix C

Narrative Innovation Disclosure Keywords Modified from Merkley (2014)

Application Pending
Breakthrough
Clinic Candidate
Clinic Data
Clinic Development
Clinic Program
Clinic Study
Collaboration
Continue Development
Develop Product
Develop Proprietary Technology
Develop Technology
Drug Candidate
Enter Development
Enhance Product
Evaluate Potential
Innovation
Introduce Product
Improve Product
Joint Venture Development
Milestone
New Product
New Technology
Patent
Pending Application
Pilot Study
Preclinical Data
Preclinical Development
Product Candidate
Product Development
Product Engineering
Product Enhance
Product Improvement
Product Introduction
Project Development
Proprietary Technology
R&D
Research
Safety Study
Technical Development
Technological Advance
Technological Change
Technology Development

Appendix D

Variable Definitions

Variable	Definition
	Measure of Corporate Innovation Strategy in Equation (1)
ExploreRatio	Exploratory patent ratio that shows a firm's innovation strategy on exploratory intensity, calculated as the total number of firm i's patents applied for in a year that is flagged as "exploratory," divided by the total number of firm i's patents applied for in the same year. A patent is "exploratory" if at least 80% of its citations are based on new knowledge outside of a firm's existing knowledge (i.e., not citing the firm's existing patents or the citations made by those patents). See the detailed calculation in Appendix B.
	Measure of Narrative Innovation Disclosure Quantity in Equation (1)
InvDiscQty	Narrative innovation disclosure quantity, calculated as the natural logarithm of the number of innovation-related sentences in a firm's 10-K filing.
	Control Variables in Equation (1)
Size	Firm size, calculated as the natural logarithm of a firm's book value of total assets in a year.
AdjROA	Adjusted return on asset, calculated as net income before R&D expenditure and advertising expenses scaled by lagged total assets.
BTM	Book-to-market ratio, calculated as the book value of equity divided by the market value of equity at the fiscal year-end.
CapInt	Capital intensity, calculated as the ratio of property, plant, and equipment (PP&E) and inventories scaled by lagged total assets.
Lev	Financial leverage, calculated as total debt scaled by lagged total assets.
Growth	Sales growth, calculated as the year-to-year percentage change in sales.
R&D	Research and development (R&D) expenditure, calculated as R&D expenditure scaled by lagged total assets.
R&DSq	Square of R&D expenditure scaled by lagged total assets.
FirmAge	Firm age, calculated as the natural logarithm of the number of years the firm exists in the Compustat annual fundamental file.
AnalystFollow	Analyst following, calculated as the natural logarithm of one plus the number of analysts that issue earnings forecasts for the firm in a year.
MgmtForecast	Management forecast frequency, calculated as the natural logarithm of one plus the number of management forecasts issued in a year.
TotalPatent	Number of granted patents, calculated as the number of patents granted to the firm scaled by lagged total assets.
NonInvDisc	Non-innovation disclosure quantity, calculated as the natural logarithm of the number of sentences in the 10-K filing that are not related to innovation.
PriorInvDisc	Prior innovation disclosure, an indicator that equals one if the firm discloses narrative innovation information in the prior 10-K filing.
	Conditional Variables in Equation (2)
PMC	Product market competition from existing rivalry, measured as a firm-level variable from Bloom et al. (2013). First, I assign a product market distribution vector P_i to each firm i, which is based on the firm's sales distribution across industry sectors (two-digit SIC codes): $P_i = \{p_1, p_2, p_3, \dots, p_n\}$, where p_1 is the average market share of firm i based on sales in the first industry sector in the

	previous two years. Second, I calculate the measure of product market similarity $N_{ij} = P_i' P_j / \sqrt{P_i}\sqrt{P_j}$, where N_{ij} is the cosine similarity approach in Jaffe (1986) between firm i's sales distribution (P_i) and firm j's sales distribution (P_j). Third, I multiply product market similarity between firm i and firm j (N_{ij}) with the R&D stock of firm j (G_j). To calculate R&D stock of firm j's technological knowledge, I use the inventory method employed by Hall et al. (2005). I calculate firm j's imputed R&D stock in year t as the R&D expense in year t plus depreciated R&D stock in year t −1, where the depreciation rate is 15% (δ = 0.15): $G_{jt} = R\&D_{jt} + (1 - \delta)G_{jt-1}$. Fourth, I aggregate all multiples and take the natural logarithm to construct the product market competition for firm i in year t: $PMC_i = \text{Log}(1 + \sum_{j \neq i} G_j N_{ij})$.
PMCHigh	High *PMC*, an indicator equals one if *PMC* is above the sample median and zero otherwise.
TS	Technology spillover, measured a firm-level variable from Bloom et al. (2013) by highlighting the significance of technological closeness and complementarity as essential components of the technology spillover. Firm i benefits from the technology spillover from firm j when firm i and firm j use similar technologies and when the stock of knowledge in firm j is larger than firm i ($G_{jt} > G_{it}$). I calculate the technological similarity between firms i and j to measure the ability of firm i to benefit from firm j's technology through learning. I follow Jaffe (1986) and calculate technological similarity based on the firm's patent distributions across technology classes. First, I assign a technology distribution vector S_i to firm i, which is based on firm's patent distribution across 673 technology subclasses in the Cooperative Patent Classification (CPC). $S_i = \{s_1, s_2, s_3, \ldots, s_{673}\}$, where s_1 is the proportion of patents held by firm i in the first technology subclass in the previous five years. Second, I calculate the measure of technological similarity $M_{ij} = S_i' S_j / \sqrt{S_i}\sqrt{S_j}$, where M_{ij} is the cosine similarity approach that measures the ability of firm i to take advantage of technological knowledge developed by firm j. Third, I multiply technological similarity between firm i and firm j (M_{ij}) with the R&D stock of firm j (G_{jt}). Fourth, I aggregate the multiples across all firms j ($j \neq i$), scaled by firm i's own R&D stock, and take the natural logarithm to construct the technology spillover for firm i in year t: $TS_{it} = \text{Log}(1 + \sum_{j \neq i} G_j M_{ij} / G_i)$.
TSHigh	High *TS*, an indicator equals one if *TS* is above the sample median and zero otherwise.
	Raw Measures of Major Variables in Table 3
CountExplorePatent	Count of exploratory patents. A patent is "exploratory" if at least 80% of its citations are based on new knowledge outside of a firm's existing knowledge (i.e., not citing the existing patents or the citations made by those patents). See a detailed definition and calculation in Appendix B.
CountTotalPatent	Count of total patents applied for in a year.
InvSentMerkley	Count of narrative R&D sentences in a firm's 10-K filing using Merkley's keyword list.
InvSent	Count of narrative innovation sentences in a firm's 10-K filing using the modified keyword list.

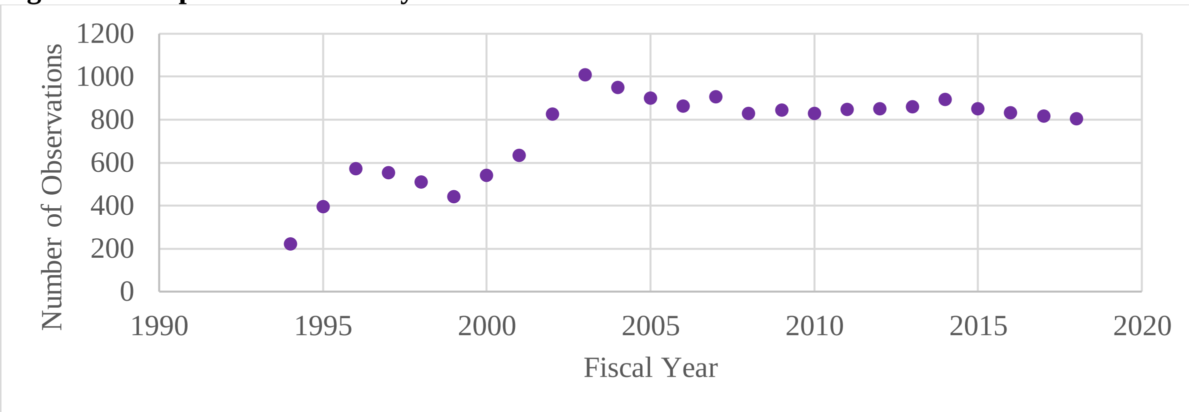
TotalSent	Count of total sentences in a firm's 10-K filings.
FirmAgeRaw	Count of years the firm exists in the Compustat annual fundamental file.
AnalystFollowRaw	Count of analysts that issue earnings forecasts for the firm in a year.
MgmtForecastRaw	Count of management earnings forecasts issued in a year.
	Additional Independent Variable in Table 5
ExploreHigh	High exploratory intensity, an indicator equals one if *ExploreRatio* is above the sample median and zero otherwise.
	Instrumental Variables in Equation (3.1) and Equation (3.2)
PatentPractitioner	Total number of patent practitioners (agents and attorneys) within each state (divided by 1000 for interpretation).
ExploreRatioIndAvg	Industry average of *ExploreRatio*.
	Exogenous Shock Study Variable in Equation (5)
PostRegFD	Post-Regulation Fair Disclosure period, an indicator that equals one for firm-years from 2001 onwards and zero otherwise.
	Additional Alternative Explanation Variables in Table 13
LitRisk	Litigation risks, an indicator equals one if the firm's four-digit SIC code falls within the ranges 2833–2836, 3570–3577, 3600–3674, 5200–5961, or 7370–7374 and zero otherwise.
MissR&D	Missing R&D, an indicator equals one if the firm does not report R&D expenditure and zero otherwise.
	Short-term Consequence Variables in Equation (6)
CAR	Cumulative abnormal return, calculated as the sum of abnormal returns over the event window, using filing date as trading day within (−5, +5) event window.
sCAR	Standardized cumulative abnormal return, calculated as *CAR* scaled by the square root of the product of the event window length and the estimated variance of abnormal returns using filing date as trading day within (−5, +5) event window.
Beta	Beta coefficient on the market factor, which captures the sensitivity of a stock's returns to the overall market returns.
MTB	Market-to-book ratio during fiscal year t, calculated as the market value of equity divided by book value of equity at the fiscal year-end.
SG&A	Selling, general, and administrative expenses scaled by lagged total assets.
ROE	Return on equity, calculated as income before extraordinary items divided by lagged book value of shareholder's equity.
	Stock Price Crash Risk Variables in Equation (7) and Equation (8)
DUVol1	Down-to-up volatility, calculated as the natural logarithm of the standard deviation in the negative weeks divided by the standard deviation in the positive weeks.
DUVol2	Down-to-up volatility, calculated as the natural logarithm of the standard deviation in the down weeks divided by the standard deviation in the up weeks. Down weeks are determined as weeks with firm-specific weekly returns below the annual mean and up weeks are those with firm-specific weekly returns above the period mean. Standard deviation is calculated separately in down week and up week subsamples. *DUVol2* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks: $DUVol2 = \log\{(n_u - 1)\sum_{Down} W_{i,\tau}^2$ /

	$(n_d - 1)\sum_{Up} W_{i,\tau}^2\}$ where n_u and n_d are the number of up and down weeks in year t, respectively.
DUVol3	Down-to-up volatility, calculated as the natural logarithm of the standard deviation in the down weeks divided by the standard deviation in the up weeks. Down weeks are determined as weeks with firm-specific weekly returns below the annual mean and up weeks are those with firm-specific weekly returns above the period mean. Standard deviation is calculated separately in down week and up week subsamples. *DUVol3* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks: $DUVol3 = \log\,(Std_{UP}/Std_{DOWN})$.
NCSkew	Negative conditional skewness of firm-specific weekly returns over the year, calculated as the negative of the third moment of firm-specific weekly returns for each year and normalizing it by the standard deviation of firm-specific weekly returns raised to the third power. For each firm i in year t, $NCSkew = -\left[n(n-1)^{2/3}\sum W_{i,\tau}^3\right]/[(n-1)(n-2)\left(\sum W_{i,\tau}^2\right)^{2/3}]$ where n is the number of weekly returns during year t. The negative sign is put in front of the third moment for the interpretation that a higher value of *NCSkew* indicates a higher crash risk. The firm-specific weekly return for firm i in week τ ($W_{i,\tau}$) is calculated as the natural logarithm of one plus the residual return from the following regression using firm-specific returns: $r_{i,\tau} = \alpha_j + \beta_{2,i}r_{m,\tau-2} + \beta_{2,i}r_{m,\tau-1} + \beta_{3,i}r_{m,\tau} + \beta_{4,i}r_{m,\tau+1} + \beta_{5,i}r_{m,\tau+2} + \varepsilon_{i,\tau}$ where $r_{i,\tau}$ is the return on stock i in week τ and $r_{m,\tau}$ is the return on the CRSP value-weighted market index in week τ. The lead and lag terms of the market index return allow for nonsynchronous trading (Dimson, 1979).
DTurn	Detrended average monthly stock turnover, calculated as the average monthly share turnover over the fiscal year minus the average monthly share turnover over the previous fiscal year, where monthly share turnover is calculated as the monthly trading volume divided by the number of shares outstanding during the month.
Sigma	The standard deviation of firm-specific weekly returns over the year.
MeanRet	The average of firm-specific weekly returns of the year (multiplied by 100 for interpretation).
ROA	Return on assets, calculated as income before extraordinary items scaled by lagged total assets.
AccM	Absolute value of discretionary accruals, calculated as the absolute value of the estimated residuals derived from the methodology proposed by Kothari et al. (2005).
	Qualitative Disclosure Variables in Equation (9)
InvDiscNum	Numerical innovation-related disclosures, calculated as the natural logarithm of one plus the number of numerical innovation-related sentences in a firm's 10-K filing. An innovation-related sentence is numerical if it contains numerical information that is not in a date format.
InvDiscFls	Forward-looking innovation-related disclosures, calculated as the natural logarithm of one plus the number of forward-looking innovation-related sentences in a firm's 10-K filing. An innovation-related sentence is forward-looking if it contains future tense words, as specified by F. Li (2010).
10KDiscNum	Numerical information in the 10-K disclosures, calculated as the natural

	logarithm of one plus the number of numerical sentences in a firm's 10-K filing. A 10-K sentence is numerical if it contains numerical information that is not in a date format.
10KDiscFls	Forward-looking information in the 10-K disclosures, calculated as the natural logarithm of one plus the number of forward-looking sentences in a firm's 10-K filing. A 10-K sentence is forward-looking if it contains future tense words, as specified by F. Li (2010).
	Additional Qualitative Disclosure Variable in Equation (10)
InvDiscRep	Repetitive innovation-related disclosures, calculated as the natural logarithm of one plus the total number of similar innovation-related sentences in the same 10-K filing. Similar disclosures are based on whether the innovation disclosure sentence is similar to other innovation-related sentences in the same 10-K filing (Merkley, 2014). An innovation-related sentence is repetitive if the cosine similarity between the two-word sets of the current sentence and its previous sentence is greater than 0.9.
	Additional Qualitative Disclosure Variables in Equation (11)
InvDiscTone	Tone of innovation-related disclosures, calculated as the total number of positive innovation-related sentences minus the number of negative innovation-related sentences divided by the total number of innovation-related sentences. A sentence is determined as positive (negative) if it contains more positive (negative) words based on the word lists in Henry (2008).
10KDiscTone	Tone of the 10-K disclosures, calculated as the total number of positive sentences minus the number of negative sentences divided by the total number of sentences in 10-K. A sentence is determined as positive (negative) if it contains more positive (negative) words based on the word lists in F. Li (2010).
	Additional Variables in Equation (12)
OCF	Operating cash flow, calculated as income before extraordinary items plus depreciation less changes in working capital (defined as changes in current assets minus changes in current liabilities) scaled by lagged total assets.
CapExp	Capital expenditure scaled by lagged total assets.
Cglm	Conglomerate, indicator equals one if a firm has segments with positive sales in more than one industry during the year and zero otherwise.
Adv	Advertising expenses scaled by lagged total assets.
	Management Dispositional Characteristics Variables in Table 17
Delta	Executive pay-performance sensitivity, calculated as the dollar change in the value of the CEO's wealth resulting from a one percent increase in the firm's stock price at the fiscal year-end (Coles et al., 2006; Core & Guay, 2002).
Vega	Executive risk-taking incentives, calculated as the dollar change in the CEO's wealth for a 0.01 change in the standard deviation of the stock returns (Coles et al., 2006; Core & Guay, 2002).
OC (OC67 or *OC100)*	Executive overconfidence, an average of the CEO and CFO's confidence measure. CEO (CFO) confidence is an indicator that equals one if a CEO (CFO) delays the exercise of vested options that are at least 67% (100%) in the money, i.e., degree of option-in-money exceeds 0.67(1), zero otherwise. The degree of option-in-money by using the ratio between the average value per option (i.e., the value of unexercised exercisable options divided by a number of unexercised exercisable options) and the average exercise price per option

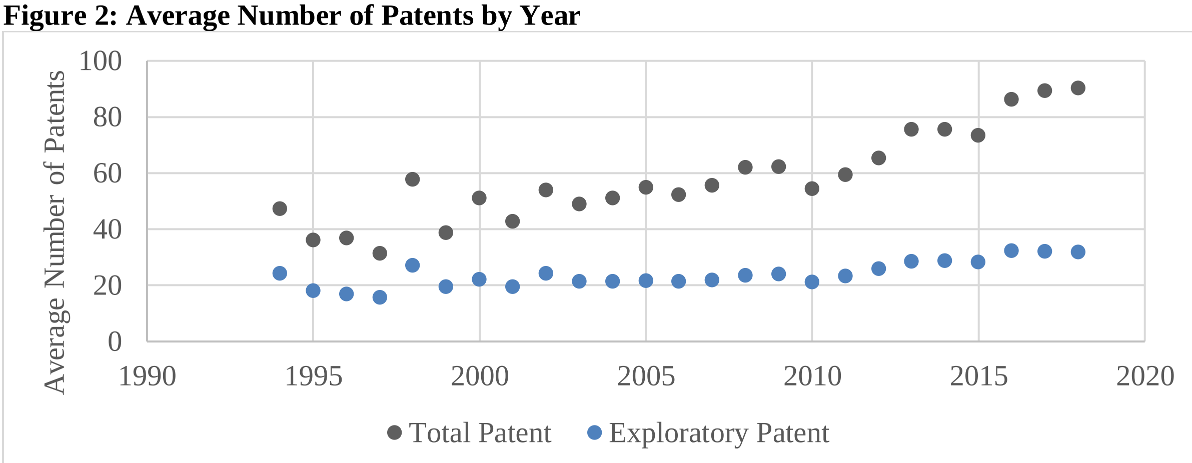
	(i.e., the difference between the stock price at fiscal year-end and the average value per option; Campbell et al., 2011; Hirshleifer et al., 2012).
	Technology Peer Pressure Variables in Equation (16)
TPP	Technological peer pressure, a firm-level measure of technology-based product market competition (Cao et al., 2018). First, I assign a product market distribution vector P_i to each firm i, which is based on the firm's sales distribution across industry sectors (two-digit SIC codes): $P_i = \{p_1, p_2, p_3, \ldots, p_n\}$, where p_1 is the average market share of firm i based on sales in the first industry sector in previous two years. Second, I calculate the measure of product market similarity $N_{ij} = P_i' P_j \big/ \sqrt{P_i}\sqrt{P_j}$, where N_{ij} is the cosine similarity approach in Jaffe (1986) between firm i's sales distribution (P_i) and firm j's sales distribution (P_j). Third, I multiply the product market similarity between firm i and firm j (N_{ij}) with the R&D stock of firm j (G_j). Next, I aggregate all multiples and divide the sum by the firm's own R&D stock (G_i). Finally, I take the natural logarithm to construct the technological peer pressure for firm i in year t: $TPP_i = \text{Log}(1 + \sum_{j \neq i} G_j N_{ij} / G_i)$.
TPPHigh	High *TPP*, an indicator equals one if *TPP* is above the sample median and zero otherwise.

Figure 1: Sample Distribution by Year



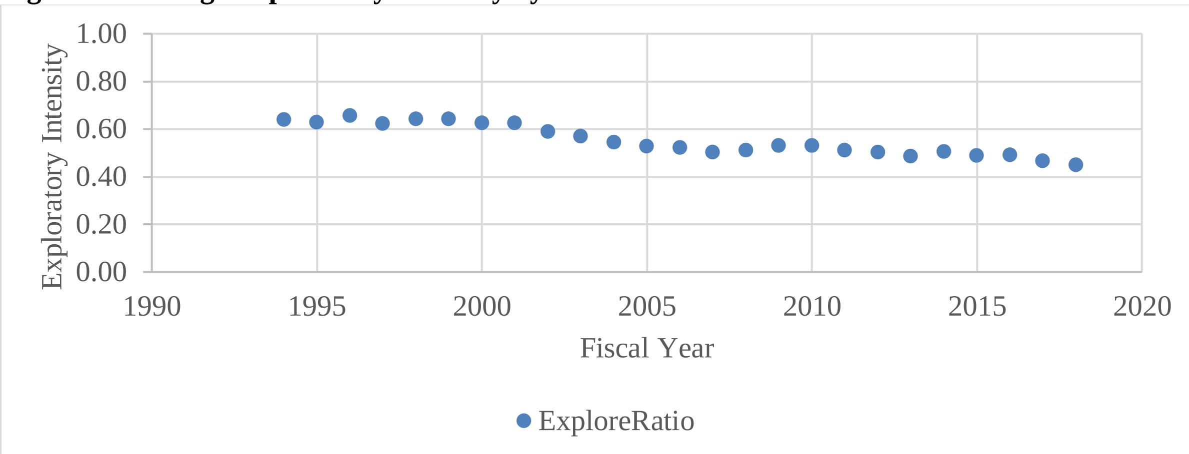
Note: This figure illustrates the sample distribution across fiscal years of 10-K filings. The horizontal axis represents the fiscal years. The vertical axis shows the number of observations in each year, depicted by the purple dots.

Figure 2: Average Number of Patents by Year



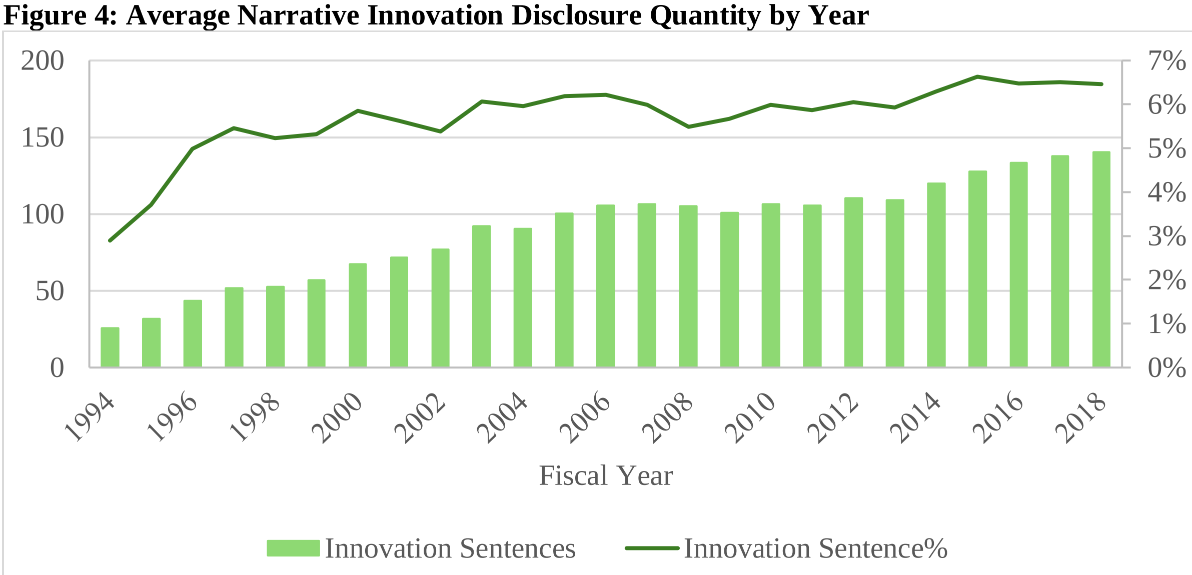
Note: This figure shows the trends in the average number of total patents and exploratory patents applied for by firms across fiscal years of 10-K filings. The horizontal axis represents the fiscal years. The vertical axis shows the average number of patents applied for by a firm in each year. The average number of total patents is depicted by the dark grey dots, while the average number of exploratory patents is represented by the light blue dots.

Figure 3: Average Exploratory Intensity by Year



Note: This figure illustrates the trend of average exploratory intensity across fiscal years of 10-K filings. The horizontal axis represents the fiscal years. The vertical axis shows the firm's average exploratory intensity measured by the exploratory ratio *(ExploreRatio*), represented by the light blue dots.

Figure 4: Average Narrative Innovation Disclosure Quantity by Year



Note: This figure shows the trends of the average number of narrative innovation sentences and the average percentage of narrative innovation sentences as a proportion of total sentences in 10-K filings over time (narrative innovation disclosure ratio). The horizontal axis shows the fiscal years of 10-K filings. The left vertical axis shows the average length (i.e., total number of sentences) of innovation disclosures in 10-K filings filed each year, represented by the light green vertical bars. The right vertical axis shows the ratio of narrative innovation disclosures, as a percentage of innovation-related sentences in the 10-K filings, represented by the dark green line.

Table 1: Sample Selection Process

	Firm-Year	Unique Firm
Firms that applied for at least one new patent per year during the period from 1994 to 2018	21,875	3,589
Less: observations without positive total assets and book value of equity	(790)	
	21,085	3,543
Less: observations with a year-end share price below $1	(348)	
	20,737	3,495
Less: financial firms (SIC codes 6000 to 6999)	(774)	
	19,963	3,364
Less: observations without data necessary to compute key variables	(1,403)	
Final sample	18,560	3,107

Note: This table describes the sample selection process. I construct the initial sample starting with firms that applied for at least one new patent per year during the period from 1994 to 2018. The sample consists of 21,875 firm-year observations (representing 3,589 unique firms). Next, I exclude firm-year observations without positive total assets and book value of equity, observations with a year-end share price below $1, and financial firms (SIC codes 6000 to 6999). Finally, I exclude observations without data necessary to compute test variables and control variables. The final sample consists of 18,560 firm-year observations (representing 3,107 unique firms).

Table 2: Sample Distribution by Industry

Panel A: Frequency Distribution by Industry

SIC2	Industry	Frequency	Percent
36	Electronic & Other Electrical Equipment & Components	3,173	17.10%
28	Chemicals and Allied Products	3,127	16.85%
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	2,541	13.69%
35	Industrial and Commercial Machinery and Computer Equipment	2,348	12.65%
73	Business Services	2,041	11.00%
37	Transportation Equipment	840	4.53%
34	Fabricated Metal Products	461	2.48%
20	Food and Kindred Products	349	1.88%
48	Communications	338	1.82%
26	Paper and Allied Products	298	1.61%
	Others	3,044	16.39%
Total		18,560	100.00%

Panel B: Exploratory Intensity Distribution by Industry

SIC2	Industry	Mean	Median	SD
36	Electronic & Other Electrical Equipment & Components	0.612	0.629	0.307
28	Chemicals and Allied Products	0.381	0.333	0.346
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	0.470	0.480	0.353
35	Industrial and Commercial Machinery and Computer Equipment	0.569	0.556	0.317
73	Business Services	0.583	0.611	0.379
37	Transportation Equipment	0.604	0.600	0.282
34	Fabricated Metal Products	0.631	0.667	0.345
20	Food and Kindred Products	0.618	0.657	0.328
48	Communications	0.626	0.631	0.331
26	Paper and Allied Products	0.497	0.487	0.343

Note: This table provides the sample distribution by industry. Panel A presents the distribution of frequency. Panel B presents the distribution of average, median, and standard deviation of the variable of interest, *ExploreRatio*, across two-digit SIC classifications of industries.

Table 3: Summary Statistics

Panel A: Key Variables of Sample Firms

	N	Mean	SD	P25	Median	P75
ExploreRatio	18,560	0.537	0.353	0.250	0.519	0.895
InvDiscQty	18,560	4.046	1.054	3.401	4.094	4.644
PMC	18,560	10.975	3.011	11.219	11.895	12.370
TS	18,560	5.445	2.750	4.347	6.059	7.293
Size	18,560	6.607	2.079	5.073	6.479	7.980
AdjROA	18,560	0.087	0.205	0.030	0.094	0.169
BTM	18,560	0.457	0.365	0.219	0.369	0.595
CapInt	18,560	0.328	0.233	0.145	0.296	0.467
Lev	18,560	0.198	0.238	0.004	0.149	0.303
Growth	18,560	0.172	0.666	-0.013	0.071	0.207
R&D	18,560	0.107	0.169	0.015	0.057	0.136
FirmAge	18,560	2.881	0.787	2.303	2.890	3.555
AnalystFollow	18,560	1.993	0.952	1.386	2.079	2.708
MgmtForecast	18,560	0.490	0.755	0.000	0.000	1.099
TotalPatent	18,560	0.042	0.101	0.005	0.015	0.040
NonInvDisc	18,560	7.237	0.489	6.956	7.260	7.541
PriorInvDisc	18,560	0.855	0.352	1.000	1.000	1.000

Panel B: Raw Measures of Sample Firms

	N	Mean	SD	P25	Median	P75
CountExplorePatent	18,560	24	90	1	3	12
CountTotalPatent	18,560	60	278	2	7	27
InvSentMerkley	18,560	43	61	11	25	44
InvSent	18,560	98	125	30	60	104
TotalSent	18,560	1,661	856	1,124	1,518	2,004
FirmAgeRaw	18,560	24	17	10	18	35
AnalystFollowRaw	18,560	10	9	3	7	14
MgmtForecastRaw	18,560	1	2	0	0	2

Panel C: Key Variables of Out-of-Sample Firms

	N	Mean	SD	P25	Median	P75
InvDiscQty	23,960	2.803	1.253	1.946	2.833	3.689
PMC	23,960	9.893	3.211	9.154	10.834	12.073
Size	23,960	5.897	1.819	4.570	5.826	7.157
AdjROA	23,960	0.050	0.264	0.009	0.056	0.114
BTM	23,960	0.588	6.259	0.289	0.501	0.800
CapInt	23,960	0.434	0.316	0.158	0.398	0.649
Lev	23,960	0.242	0.299	0.014	0.187	0.367
Growth	23,960	0.309	11.177	-0.014	0.065	0.201
R&D	23,960	0.038	0.155	0.000	0.000	0.022
FirmAge	23,960	2.782	0.761	2.197	2.833	3.401
AnalystFollow	23,960	1.466	0.995	0.693	1.609	2.197
MgmtForecast	23,960	0.331	0.638	0.000	0.000	0.000
NonInvDisc	23,960	7.140	0.529	6.823	7.166	7.480
PriorInvDisc	23,960	0.814	0.389	1.000	1.000	1.000

Panel D: Raw Measures of Out-of-Sample Firms

	N	Mean	SD	P25	Median	P75
InvSentMerkley	23,960	15	34	2	6	16
InvSent	23,960	36	64	7	17	40
TotalSent	23,960	1,482	832	949	1,331	1,816
FirmAgeRaw	23,960	21	15	9	17	30
AnalystFollowRaw	23,960	6	6	1	4	8
MgmtForecastRaw	23,960	1	2	0	0	0

Panel E: Firm Characteristics of Exploratory Intensity Portfolios

	Low			*Middle*			*High*		
	N = 5,568			N = 7,239			N = 5,753		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
ExploreRatio	0.101	0.041	0.113	0.535	0.510	0.123	0.962	1.000	0.072
InvDiscQty	4.452	4.431	1.104	4.028	4.078	0.916	3.675	3.784	1.025
NonInvDisc	7.276	7.293	0.459	7.287	7.302	0.474	7.136	7.170	0.518
Size	6.267	6.021	2.124	7.266	7.252	2.047	6.106	5.952	1.844
AdjROA	0.071	0.090	0.237	0.106	0.105	0.178	0.078	0.084	0.201
BTM	0.408	0.317	0.344	0.444	0.365	0.348	0.522	0.434	0.395
CapInt	0.283	0.238	0.221	0.333	0.308	0.208	0.366	0.338	0.264
Lev	0.184	0.109	0.248	0.210	0.182	0.216	0.195	0.133	0.252
Growth	0.236	0.081	0.920	0.131	0.067	0.510	0.159	0.070	0.530
R&D	0.145	0.081	0.223	0.096	0.056	0.139	0.085	0.037	0.134
FirmAge	2.782	2.773	0.744	3.032	3.045	0.790	2.786	2.833	0.793
AnalystFollow	1.971	2.079	0.921	2.222	2.303	0.910	1.726	1.792	0.962
MgmtForecast	0.483	0.000	0.758	0.570	0.000	0.797	0.397	0.000	0.684
TotalPatent	0.059	0.021	0.145	0.039	0.017	0.078	0.027	0.009	0.063

Note: This table presents the summary statistics. Panel A reports the descriptive statistics of the key variables of sample firms. *BTM* and *Growth* are winsorized at the *1*st and *99th* percentiles. Panel B reports the descriptive statistics of raw measures of sample firms. Panel C reports the descriptive statistics of the key variables of out-of-sample firms. *CapInt* is winsorized at the *1st* and *99th* percentiles. Panel D reports the descriptive statistics of raw measures of out-of-sample firms. Panel E provides the descriptive statistics of the key variables for three portfolios. Firms are categorized into three portfolios based on the *30th* and *70th* percentiles of their exploratory intensity (*ExploreRatio*) measured in year *t*−1. All variables are defined in Appendix D.

Table 4: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) *ExploreRatio*		**-0.287**	**-0.130**	**-0.179**	**-0.107**	-0.003	0.001	**0.143**	**0.155**	**0.044**	**-0.019**	**-0.183**	**0.018**	**-0.081**	**-0.036**	**-0.195**	**-0.087**
(2) *InvDiscQty*	**-0.297**		**0.481**	**0.207**	**0.261**	**-0.274**	**0.045**	**-0.247**	**-0.529**	**-0.295**	**0.082**	**0.706**	**-0.388**	**0.023**	**-0.049**	**0.423**	**0.089**
(3) *PMC*	**-0.046**	**0.280**		**0.106**	**0.179**	**-0.076**	**0.044**	**-0.123**	**-0.439**	**-0.183**	0.012	**0.438**	**-0.112**	**0.068**	**0.015**	**0.147**	**0.171**
(4) *TS*	**-0.225**	**0.190**	**0.089**		**-0.070**	**-0.357**	**-0.104**	-0.005	**-0.147**	**-0.189**	**0.049**	**0.200**	**-0.286**	**-0.238**	**-0.132**	**0.272**	**-0.036**
(5) *NonInvDisc*	**-0.108**	**0.293**	**-0.050**	0.008		**0.441**	**-0.091**	**-0.074**	**-0.165**	**0.203**	**-0.020**	**-0.067**	**0.096**	**0.389**	**0.231**	**-0.268**	**0.205**
(6) *Size*	-0.004	**-0.237**	**-0.197**	**-0.173**	**0.441**		**0.113**	**-0.017**	**0.191**	**0.457**	**-0.035**	**-0.457**	**0.519**	**0.728**	**0.387**	**-0.563**	**0.192**
(7) *AdjROA*	**0.024**	**-0.029**	-0.002	**-0.051**	**-0.055**	**0.154**		**-0.266**	**0.041**	**-0.160**	**0.248**	**0.198**	**0.078**	**0.223**	**0.119**	**0.137**	**0.051**
(8) *BTM*	**0.120**	**-0.206**	**-0.019**	**-0.020**	**-0.071**	**-0.057**	**-0.153**		**0.187**	**-0.038**	**-0.210**	**-0.292**	**0.099**	**-0.235**	**-0.089**	**-0.164**	**-0.043**
(9) *CapInt*	**0.150**	**-0.496**	**-0.193**	**-0.103**	**-0.153**	**0.156**	**0.036**	**0.130**		**0.345**	**0.075**	**-0.439**	**0.303**	**-0.028**	**-0.025**	**-0.166**	**-0.098**
(10) *Lev*	**0.021**	**-0.169**	**-0.113**	**-0.077**	**0.160**	**0.307**	**-0.065**	**-0.068**	**0.315**		0.014	**-0.396**	**0.291**	**0.200**	**0.188**	**-0.364**	0.012
(11) *Growth*	**-0.052**	**0.146**	**0.052**	**0.049**	**0.018**	**-0.085**	**-0.043**	**-0.095**	0.013	**0.062**		**0.131**	**-0.134**	**0.088**	**0.017**	**0.096**	**-0.019**
(12) *R&D*	**-0.151**	**0.497**	**0.194**	**0.118**	**-0.020**	**-0.361**	**-0.036**	**-0.198**	**-0.263**	**-0.102**	**0.216**		**-0.407**	**-0.088**	**-0.200**	**0.605**	**-0.034**
(13) *FirmAge*	**0.016**	**-0.360**	**-0.150**	**-0.163**	**0.093**	**0.510**	**0.114**	**0.044**	**0.240**	**0.164**	**-0.143**	**-0.307**		**0.228**	**0.242**	**-0.332**	**0.157**
(14) *AnalystFollow*	**-0.083**	**0.051**	**-0.053**	**-0.065**	**0.386**	**0.694**	**0.176**	**-0.252**	**-0.038**	**0.129**	0.005	**-0.097**	**0.199**		**0.314**	**-0.284**	**0.170**
(15) *MgmtForecast*	**-0.038**	**-0.034**	**-0.078**	**-0.066**	**0.240**	**0.385**	**0.103**	**-0.107**	**-0.052**	**0.123**	**-0.062**	**-0.184**	**0.255**	**0.312**		**-0.256**	**0.154**
(16) *TotalPatent*	**-0.126**	**0.189**	**0.082**	**0.162**	**-0.139**	**-0.339**	**-0.102**	**-0.105**	**-0.070**	**-0.109**	**0.085**	**0.361**	**-0.201**	**-0.199**	**-0.147**		**-0.127**
(17) *PriorInvDisc*	**-0.086**	**0.099**	-0.003	-0.007	**0.211**	**0.191**	**0.066**	**-0.056**	**-0.104**	0.011	**-0.034**	**-0.039**	**0.165**	**0.179**	**0.163**	**-0.084**	

Note: This table reports the correlation matrix. Pearson (Spearman) correlations of the key variables are reported lower left (upper right) of the diagonal. Correlation coefficients with significance at the 5% level are boldfaced. All variables are defined in Appendix D.

Table 5: Univariate Analysis

	ExploreHigh = 1		*ExploreHigh* = 0		Difference			
	N = 9,280		N = 9,280					
	Mean	Median	Mean	Median	Mean	p-value	Median	p-value
InvDiscQty	3.777	3.871	4.315	4.317	-0.538	0.000	-0.446	0.000
Size	6.590	6.521	6.623	6.431	-0.033	0.288	0.090	0.332
AdjROA	0.090	0.093	0.084	0.096	0.006	0.051	-0.003	0.812
BTM	0.494	0.409	0.421	0.330	0.073	0.000	0.079	0.000
CapInt	0.357	0.332	0.299	0.263	0.058	0.000	0.069	0.000
Lev	0.201	0.158	0.194	0.141	0.007	0.034	0.017	0.000
Growth	0.141	0.068	0.202	0.075	-0.061	0.000	-0.007	0.011
R&D	0.087	0.043	0.127	0.071	-0.040	0.000	-0.028	0.000
FirmAge	2.886	2.890	2.875	2.890	0.011	0.337	0.000	0.083
TotalPatent	0.031	0.012	0.052	0.020	-0.021	0.000	-0.008	0.000

Note: This table provides univariate analysis by comparing the mean and median of firm characteristics in two sample groups determined by firms' exploratory intensity. All variables are defined in Appendix D.

Table 6: Baseline Result (H1)

DV = *InvDiscQty*$_t$	(1)	(2)	(3)
ExploreRatio$_{t-1}$	**-0.428*****	**-0.461*****	**-0.265*****
	(0.030)	**(0.026)**	**(0.021)**
Size$_{t-1}$		-0.106***	-0.058***
		(0.013)	(0.011)
AdjROA$_{t-1}$		0.163***	0.143***
		(0.039)	(0.032)
BTM$_{t-1}$		-0.101***	-0.063**
		(0.025)	(0.025)
CapInt$_{t-1}$		-1.071***	-0.787***
		(0.070)	(0.066)
Lev$_{t-1}$		-0.113**	-0.127***
		(0.049)	(0.040)
Growth$_{t-1}$		0.037***	0.032***
		(0.011)	(0.008)
R&D$_{t-1}$		2.653***	1.786***
		(0.173)	(0.142)
R&DSq$_{t-1}$		-0.442***	-0.302***
		(0.122)	(0.089)
FirmAge$_{t-1}$		-0.176***	-0.243***
		(0.018)	(0.018)
AnalystFollow$_{t-1}$		0.098***	0.112***
		(0.019)	(0.015)
MgmtForecast$_{t-1}$		0.025	-0.003
		(0.018)	(0.015)
TotalPatent$_{t-1}$		-0.122	0.083
		(0.112)	(0.116)
NonInvDisc$_t$		0.660***	0.535***
		(0.024)	(0.023)
PriorInvDisc$_t$		0.151***	-0.002
		(0.019)	(0.016)
Constant	4.276***	0.522***	1.297***
	(0.022)	(0.173)	(0.168)
Observations	18,557	18,560	18,557
R-squared	0.496	0.561	0.697
Industry & Year FE	Yes	No	Yes

Note: This table reports the results of regressing narrative innovation disclosure quantity (*InvDiscQty*) on exploratory innovation intensity (*ExploreRatio*), using the model in Equation (1). Column (1) shows the baseline results with fixed effects. Column (2) shows the results with control variables. Column (3) shows the results with control and fixed effects. The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 7: Propensity Score Matching (H1)

Panel A: Comparison of Firm Characteristics between Treatment and Control groups

	ExploreHigh = 1		*ExploreHigh* = 0		Difference			
	N = 2,429		N = 2,429					
	Mean	Median	Mean	Median	Mean	p-value	Median	p-value
InvDiscQty	4.020	4.094	4.258	4.277	-0.238	0.000	-0.183	0.000
Size	6.696	6.678	6.723	6.494	-0.027	0.657	0.184	0.497
AdjROA	0.086	0.099	0.087	0.097	-0.001	0.919	0.002	0.686
BTM	0.429	0.351	0.430	0.342	-0.001	0.929	0.009	0.352
CapInt	0.298	0.261	0.304	0.272	-0.006	0.339	-0.011	0.421
Lev	0.195	0.143	0.192	0.142	0.003	0.629	0.001	0.457
Growth	0.156	0.077	0.152	0.072	0.004	0.752	0.005	0.321
R&D	0.115	0.067	0.112	0.065	0.003	0.591	0.002	0.653
FirmAge	2.899	2.890	2.882	2.833	0.017	0.450	0.057	0.332
TotalPatent	0.043	0.014	0.043	0.018	0.000	0.886	-0.004	0.000

Panel B: Propensity Score Matched Regression (H1)

DV = $InvDiscQty_t$	(1)	(2)
$\boldsymbol{ExploreHigh_{t-1}}$	**-0.150***** **(0.021)**	
$\boldsymbol{ExploreRatio_{t-1}}$		**-0.273***** **(0.031)**
Observations	4,854	4,854
R-squared	0.690	0.693
Controls	Yes	Yes
Industry & Year FE	Yes	Yes

Note: This table reports the results for the PSM sample. Panel A compares variables using a t-test for treatment (*ExploreHigh* = 1) and matched control firms (*ExploreHigh* = 0). Panel B shows the results of regressing *InvDiscQty* on exploratory intensity, using the model in Equation (1), with controls and fixed effects. Column (1) shows the results using *ExploreHigh* as the independent variable. Column (2) shows the results using *ExploreRatio* as the independent variable. The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 8: Instrumental Variables (H1)

DV = *InvDiscQty*$_t$	(1) First Stage	(2) Second Stage
PatentPractitioner$_{t-1}$	**-0.006***** **(0.001)**	
ExploreRatioIndAvg$_{t-1}$	**0.949***** **(0.037)**	
ExploreRatio$_{t-1}$		**-0.195**** **(0.078)**
Observations	18,557	18,560
R-squared	0.162	0.697
Controls	Yes	Yes
Industry & Year FE	Yes	Yes

Note: This table reports the results of the 2SLS analysis. Column (1) reports the results of the first stage by regressing instrumental variables, including patent practitioners (*PatentPractitioner*) and the industry average of the variable of interest (*ExploreRatioIndAvg*), on *ExploreRatio*, using the model in Equation (3.1). Column (2) shows the results of the second stage by regressing *InvDiscQty* on the predicted value in the first stage using Equation (3.2). Control variables and fixed effects are included. The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 9: Change Specification (H1)

DV = Δ*InvDiscQty*	(1) Total Δ	(2) Total Δ	(3) Total Δ	(4) Positive Δ	(5) Positive Δ	(6) Positive Δ	(7) Negative Δ	(8) Negative Δ	(9) Negative Δ
ΔExploreRatio	**-0.093****	**-0.103***	**-0.073**	**-0.220****	**-0.405*****	**-0.217**	**0.051**	**0.150**	**0.046**
	(0.043)	**(0.054)**	**(0.054)**	**(0.111)**	**(0.141)**	**(0.139)**	**(0.096)**	**(0.119)**	**(0.111)**
ΔSize		-0.006	0.024*		-0.021	0.026		-0.014	0.016
		(0.009)	(0.013)		(0.022)	(0.022)		(0.020)	(0.017)
ΔAdjROA		0.056**	0.042**		0.310***	0.239**		0.045*	0.036**
		(0.024)	(0.018)		(0.120)	(0.098)		(0.024)	(0.014)
ΔBTM		0.088*	0.083		0.042	0.026		0.098	0.083
		(0.053)	(0.052)		(0.104)	(0.108)		(0.068)	(0.063)
ΔCapInt		-0.061	0.010		0.016	0.049		-0.064	0.029
		(0.039)	(0.043)		(0.046)	(0.040)		(0.090)	(0.078)
ΔLev		0.075**	0.029		-0.007	-0.024		0.146**	0.082
		(0.032)	(0.036)		(0.060)	(0.051)		(0.061)	(0.056)
ΔGrowth		-0.007*	-0.008		0.009	0.006		-0.005	-0.008
		(0.004)	(0.007)		(0.015)	(0.011)		(0.010)	(0.009)
ΔR&D		0.867***	0.580***		0.900***	0.617***		0.821***	0.572***
		(0.061)	(0.113)		(0.246)	(0.212)		(0.186)	(0.163)
Constant	2.580***	2.531***	2.369***	2.580***	2.668***	2.351***	2.645***	2.657***	2.453***
	(0.015)	(0.059)	(0.083)	(0.046)	(0.154)	(0.161)	(0.042)	(0.133)	(0.121)
Observations	5,621	4,281	4,276	2,000	1,536	1,530	2,980	2,280	2,275
R-squared	0.203	0.057	0.222	0.193	0.070	0.230	0.202	0.056	0.218
Industry & Year FE	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes

Note: This table reports the results of regressing changes in narrative innovation disclosure (*ΔInvDiscQty*) on changes in exploratory innovation intensity (*ΔExploreRatio*), using a four-year window change model in Equation (4). Columns (1) to (3) show the results of overall changes. Columns (4) to (6) show the results of positive changes. Columns (7) to (9) show the results of negative changes. The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 10: Exogenous Shock Impact of Reg FD (H1)

DV = $InvDiscQty_t$	(1)	(2)	(3)
$ExploreRatio_{t-1}$	-0.244***	-0.318***	-0.174***
	(0.056)	(0.049)	(0.044)
$PostRegFD_t$	0.263**	0.384***	0.054
	(0.103)	(0.046)	(0.077)
$ExploreRatio_{t-1}$ * $PostRegFD_t$	**-0.215*** **	**-0.153*** **	**-0.106** **
	(0.060)	**(0.054)**	**(0.047)**
Observations	18,557	18,560	18,557
R-squared	0.497	0.568	0.698
Controls	No	Yes	Yes
Industry & Year FE	Yes	No	Yes

Note: This table reports the results for the effect of post-Reg FD (*PostRegFD*) on the relation between narrative innovation disclosure quantity (*InvDiscQty*) and exploratory intensity (*ExploreRatio*), using the model in Equation (5). The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 11: Conditional Analysis (H2 and H3)

DV = $InvDiscQty_t$	(1)	(2)	(3)
$ExploreRatio_{t-1}$	-0.232***	-0.352***	-0.314***
	(0.028)	(0.033)	(0.036)
$PMCHigh_{t-1}$	0.137***		0.147***
	(0.033)		(0.033)
$ExploreRatio_{t-1}$ * $PMCHigh_{t-1}$	**-0.070***		**-0.090** **
	(0.038)		**(0.038)**
$TSHigh_{t-1}$		-0.064**	-0.070**
		(0.032)	(0.032)
$ExploreRatio_{t-1}$ * $TSHigh_{t-1}$		**0.170*** **	**0.179*** **
		(0.038)	**(0.038)**
Observations	18,557	18,557	18,557
R-squared	0.699	0.698	0.700
Controls	Yes	Yes	Yes
Industry & Year FE	Yes	Yes	Yes

Note: This table reports the results for the conditional analyses of how ranked product market competition (*PMCHigh*) and ranked technology spillover (*TSHigh*) influence the relation between *InvDiscQty* and *ExploreRatio*, using the model in Equation (2). Column (1) reports the results of regressing *InvDiscQty* on the interaction term, *ExploreRatio * PMCHigh*. Column (2) reports the results of regressing *InvDiscQty* on the interaction term, *ExploreRatio * TSHigh*. Column (3) presents the results of regressing *InvDiscQty* on both interaction terms, *ExploreRatio * PMCHigh* and *ExploreRatio * TSHigh*. The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 12: Subsample Analysis

Panel A: Whether Firms Applied for More Than One Patent Per Year

DV = *InvDiscQty*$_t$	*CountTotalPatent* > 1			*CountTotalPatent* = 1		
	(1)	(2)	(3)	(4)	(5)	(6)
ExploreRatio$_{t-1}$	**-0.505*****	**-0.529*****	**-0.313*****	**-0.199*****	**-0.174*****	**-0.102*****
	(0.040)	**(0.032)**	**(0.028)**	**(0.032)**	**(0.030)**	**(0.024)**
Observations	15,026	15,033	15,026	3,525	3,527	3,525
R-squared	0.483	0.567	0.696	0.547	0.605	0.724
Controls	No	Yes	Yes	No	Yes	Yes
Industry & Year FE	Yes	No	Yes	Yes	No	Yes

Panel B: Firms Applied for More Than One Patent Per Year with Non-Exclusive Exploitative Patents

DV = *InvDiscQty*$_t$	*CountTotalPatent* > 1 & *ExploreRatio* > 0		
	(1)	(2)	(3)
ExploreRatio$_{t-1}$	**-0.527*****	**-0.657*****	**-0.407*****
	(0.046)	**(0.039)**	**(0.033)**
Observations	13,548	13,554	13,548
R-squared	0.445	0.549	0.675
Controls	No	Yes	Yes
Industry & Year FE	Yes	No	Yes

Panel C: Firms Applied for More Than One Patent Per Year with Non-Exclusive Exploratory Patents

DV = *InvDiscQty*$_t$	*CountTotalPatent* > 1 & *ExploreRatio* < 1		
	(1)	(2)	(3)
ExploreRatio$_{t-1}$	**-0.558*****	**-0.516*****	**-0.327*****
	(0.056)	**(0.043)**	**(0.039)**
Observations	12,967	12,972	12,967
R-squared	0.476	0.560	0.692
Controls	No	Yes	Yes
Industry & Year FE	Yes	No	Yes

Panel D: Firms Operate in Industries with High Litigation Risks

DV = *InvDiscQty*$_t$	*LitRisk* = 0			*LitRisk* = 1		
	(1)	(2)	(3)	(4)	(5)	(6)
ExploreRatio$_{t-1}$	**-0.398*****	**-0.320*****	**-0.223*****	**-0.266*****	**-0.616*****	**-0.200*****
	(0.035)	**(0.033)**	**(0.026)**	**(0.036)**	**(0.037)**	**(0.028)**
Observations	10,684	10,687	10,684	7,873	7,873	7,873
R-squared	0.464	0.523	0.636	0.620	0.511	0.763
Controls	No	Yes	Yes	No	Yes	Yes
Industry & Year FE	Yes	No	Yes	Yes	No	Yes

Note: This table reports the results of regressing narrative innovation disclosure (*InvDiscQty*) on exploratory innovation intensity (*ExploreRatio*) in subsamples, using the model in Equation (1). Panel A reports the results based on whether firms applied for more than one patent per year. Panel B shows the results of firms without extreme cases (*CountTotalPatent* > 1) and with non-exclusive-exploitative patents (*ExploreRatio* > 0). Panel C shows the results of firms without extreme cases (*CountTotalPatent* > 1) and with non-exclusive-exploratory patents (*ExploreRatio* < 1). Panel D shows the results of firms that operate in industries with low litigation risks (*LitRisk* = 0) and those in industries with high litigation risks (*LitRisk* = 1). The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 13: Alternative Explanations

DV = $InvDiscQty_t$	(1)	(2)
$ExploreRatio_{t-1}$	-0.228***	-0.228***
	(0.022)	(0.023)
$MissR\&D_t$	-0.599***	
	(0.061)	
$ExploreRatio_{t-1}$ * $MissR\&D_t$	**-0.007**	
	(0.060)	
$MgmtForecast_{t-1}$	-0.010	0.043*
	(0.015)	(0.022)
$ExploreRatio_{t-1}$ * $MgmtForecast_{t-1}$		**-0.090*** **
		(0.028)
Observations	18,557	18,557
R-squared	0.720	0.698
Controls	Yes	Yes
Industry & Year FE	Yes	Yes

Note: This table reports the results of examining alternative explanations by regressing narrative innovation disclosure (*InvDiscQty*) on exploratory innovation intensity (*ExploreRatio*) and its interactions with alternative explanatory variables, using the model in Equation (1). Column (1) reports the results of *MissR&D*. Column (2) reports the results of *MgmtForecast*. The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 14: Consequence Analysis of Short-term Market Reaction

Panel A: Short-term Market Reaction to Narrative Disclosures and Exploratory Intensity in Year $t-1$

	(1)	(2)
DV =	CAR_t	$sCAR_t$
$ExploreRatio_{t-1}$	2.207***	14.038*
	(0.843)	(8.205)
$InvDiscQty_t$	0.041	-0.725
	(0.154)	(1.442)
$ExploreRatio_{t-1}$ * $InvDiscQty_t$	**-0.516****	**-2.971**
	(0.212)	**(1.954)**
$Beta_t$	-0.483**	-5.629***
	(0.202)	(1.628)
MTB_t	-0.017	-0.094
	(0.014)	(0.126)
$Size_t$	-0.049	0.271
	(0.050)	(0.488)
$AdjROA_t$	2.300***	18.242***
	(0.586)	(4.724)
$R\&D_t$	-1.301*	-7.901
	(0.746)	(5.109)
$SG\&A_t$	-0.335	-0.767
	(0.394)	(3.047)
ROE_t	-0.010**	-0.035
	(0.004)	(0.059)
$NonInvDisc_t$	-0.123	-0.238
	(0.219)	(2.092)
Constant	1.647	11.286
	(1.446)	(13.839)
Observations	15,561	15,561
R-squared	0.017	0.016
Industry & Year FE	Yes	Yes

Panel B: Short-term Market Reaction to Narrative Disclosures and Exploratory Intensity in Year $t-2$

	(1)	(2)
DV =	CAR_t	$sCAR_t$
$ExploreRatio_{t-2}$	1.876*	15.245
	(1.072)	(10.247)
$InvDiscQty_t$	0.068	-0.618
	(0.182)	(1.724)
$ExploreRatio_{t-2}$ * $InvDiscQty_t$	**-0.494***	**-3.364**
	(0.269)	**(2.444)**
Observations	12,828	12,828
R-squared	0.019	0.019
Controls	Yes	Yes
Industry & Year FE	Yes	Yes

Note: This table reports the results of the short-term event study, which examines the market reaction to the firm's exploratory intensity (*ExploreRatio*) and narrative innovation disclosure quantity (*InvDiscQty*), using the model in Equation (6). Panel A reports the results of *ExploreRatio* in year $t-1$. Panel B reports the results of *ExploreRatio* in year $t-2$. *CAR*, *sCAR*, and *MTB* are winsorized at the *1st* and *99th* percentiles. The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 15: Consequence Analysis of Stock Price Crash Risk

Panel A: Exploratory Intensity and Stock Price Crash Risk

	(1)	(2)	(3)	(4)
DV =	$DUVol1_{t+1}$	$DUVol2_{t+1}$	$DUVol3_{t+1}$	$NCSkew_{t+1}$
$\boldsymbol{ExploreRatio_{t-1}}$	**0.036****	**0.042****	**0.021***	**0.054****
	(0.016)	**(0.016)**	**(0.011)**	**(0.027)**
$DTurn_t$	-0.043***	-0.049***	-0.032***	-0.080***
	(0.010)	(0.010)	(0.007)	(0.016)
$Sigma_t$	-0.782**	-1.612***	0.141	-0.788
	(0.336)	(0.399)	(0.231)	(0.609)
$MeanRet_t$	-0.470***	-0.781***	-0.217***	-0.904***
	(0.013)	(0.016)	(0.009)	(0.022)
$Size_t$	0.010*	0.007	0.007**	0.014
	(0.005)	(0.005)	(0.004)	(0.008)
MTB_t	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Lev_t	-0.014	-0.012	0.001	-0.005
	(0.025)	(0.025)	(0.017)	(0.043)
ROA_t	0.148***	0.146***	0.116***	0.236***
	(0.033)	(0.036)	(0.023)	(0.055)
$AccM_t$	0.055	0.042	0.031	0.076
	(0.052)	(0.056)	(0.037)	(0.093)
$R\&D_t$	0.125***	0.128**	0.107***	0.243***
	(0.046)	(0.050)	(0.033)	(0.079)
$FirmAge_t$	-0.002	0.003	0.001	0.006
	(0.009)	(0.010)	(0.007)	(0.016)
$AnalystFollow_t$	0.052***	0.054***	0.037***	0.080***
	(0.009)	(0.009)	(0.006)	(0.014)
$DUVol1_t$ or $DUVol2_t$	-0.001	-0.027***	0.009	-0.011
or $DUVol3_t$ or $NCSkew_t$	(0.010)	(0.009)	(0.010)	(0.010)
Constant	-0.207***	-0.157***	-0.183***	-0.291***
	(0.044)	(0.050)	(0.031)	(0.078)
Observations	13,512	13,519	13,519	13,530
R-squared	0.150	0.295	0.086	0.185
Industry & Year FE	Yes	Yes	Yes	Yes

Panel B: Narrative Innovation Disclosures and Stock Price Crash Risk in Exploration-focused Firms

	Exploration-focused Firms			
	(1)	(2)	(3)	(4)
DV =	*$DUVol1_{t+1}$*	*$DUVol2_{t+1}$*	*$DUVol3_{t+1}$*	*$NCSkew_{t+1}$*
$InvDiscQty_t$	**0.005**	**0.009**	**-0.003**	**-0.010**
	(0.013)	**(0.014)**	**(0.009)**	**(0.022)**
Observations	4,084	4,086	4,086	4,086
R-squared	0.170	0.319	0.103	0.203
Controls	Yes	Yes	Yes	Yes
Industry & Year FE	Yes	Yes	Yes	Yes

Panel C: Univariate Analysis of Narrative Innovation Disclosures in Exploration-focused Firms

	InvDiscHigh = 1		*InvDiscHigh* = 0		Difference			
	N = 1,615		N = 2,481					
	Mean	Median	Mean	Median	Mean	p-value	Median	p-value
InvDiscQty	4.688	4.522	3.142	3.296	1.546	0.000	1.226	0.000
Size	0.080	0.064	0.025	0.021	0.055	0.000	0.043	0.000
MTB	5.597	5.497	6.652	6.618	-1.055	0.000	-1.121	0.000
Lev	4.827	2.934	3.284	2.088	1.543	0.000	0.846	0.000
ROA	0.144	0.018	0.234	0.204	-0.090	0.000	-0.186	0.000
R&D	-0.082	0.003	0.034	0.051	-0.116	0.000	-0.048	0.000
FirmAge	0.166	0.120	0.039	0.013	0.127	0.000	0.107	0.000
AnalystFollow	2.535	2.485	3.052	3.091	-0.517	0.000	-0.606	0.000

Panel D: Piece-wise Regression of Narrative Innovation Disclosures in Exploration-focused Firms

	Exploration-focused Firms							
	Disclose Less (*InvDiscHigh* = 0)				Disclose More (*InvDiscHigh* = 1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DV =	$DUVol1_{t+1}$	$DUVol2_{t+1}$	$DUVol3_{t+1}$	$NCSkew_{t+1}$	$DUVol1_{t+1}$	$DUVol2_{t+1}$	$DUVol3_{t+1}$	$NCSkew_{t+1}$
InvDiscQty$_t$	**0.005**	**-0.002**	**-0.003**	**-0.011**	**-0.077***	**-0.049**	**-0.072****	**-0.125**
	(0.016)	**(0.017)**	**(0.012)**	**(0.027)**	**(0.043)**	**(0.045)**	**(0.031)**	**(0.077)**
Observations	2,475	2,475	2,475	2,475	1,604	1,606	1,606	1,606
R-squared	0.174	0.318	0.108	0.214	0.201	0.349	0.132	0.216
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the results of the consequences of the firm's future stock price crash risk. Panel A reports the effect of the firm's innovation strategy and future stock price crash risk by regressing *CrashRisk* variables (*DUVol1*, *DUVol2*, *DUVol3*, and *NCSkew*) on *ExploreRatio*, using Equation (7). Panel B shows the results of the subsample analysis for exploration-focused firms by regressing *CrashRisk* variables on *InvDiscQty*, using Equation (8). Panel C shows the results of the univariate analysis based on exploration-focused firms disclosing above the median compared to those below the median (*InvDiscHigh*). Panel D presents the results of piecewise regression by regressing *CrashRisk* variables on *InvDiscQty*, using Equation (8). The subsample is based on exploration-focused firms disclosing above the median compared to those below the median (*InvDiscHigh*). The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. *MeanRet* and *DTurn* are winsorized at 1^{st} and 99^{th} percentiles. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 16: Exploratory Intensity and Narrative Innovation Disclosure Details and Repetitiveness (Complementing H1)

	(1)	(2)	(3)	(4)	(5)	(6)
DV =	*InvDiscNum*$_t$	*InvDiscNum*$_t$	*InvDiscFls*$_t$	*InvDiscFls*$_t$	*InvDiscRep*$_t$	*InvDiscRep*$_t$
***ExploreRatio*$_{t-1}$**	**-0.489***** **(0.032)**	**-0.321***** **(0.024)**	**-0.425***** **(0.033)**	**-0.246***** **(0.021)**	**-0.489***** **(0.037)**	**-0.290***** **(0.027)**
Observations	18,557	18,557	18,557	18,557	18,557	18,557
R-squared	0.427	0.616	0.462	0.706	0.511	0.691
Controls	No	Yes	No	Yes	No	Yes
Industry & Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the results of regressing detailed and repetitive innovation-related disclosures (*InvDiscNum*, *InvDiscFls*, and *InvDiscRep*) on exploratory intensity (*ExploreRatio*). Columns (1) and (2) provide the regression results of numerical innovation-related disclosures (*InvDiscNum*), using the model in Equation (9). Columns (3) and (4) provide the regression results of forward-looking innovation-related disclosures (*InvDiscFls*), using the model in Equation (9). Columns (5) and (6) provide the regression results of repetitive innovation-related disclosures (*InvDiscRep*), using the model in Equation (10). The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 17: Exploratory Intensity and Narrative Innovation Disclosure Tone (Complementing H1)

DV = *InvDiscTone*$_t$	(1)	(2)
***ExploreRatio*$_{t-1}$**	**0.046***** **(0.007)**	**0.032***** **(0.006)**
Observations	18,557	18,557
R-squared	0.117	0.254
Controls	No	Yes
Industry & Year FE	Yes	Yes

Note: This table reports the results of regressing innovation-related disclosures tone (*InvDiscTone*) on firms' exploratory intensity (*ExploreRatio*), using the model in Equation (11). The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 18: Explanation of Positive Tone for Exploration-focused Firms

Panel A: Future Operational Performance and Narrative Innovation Disclosure Tone

DV =	(1) ROA_{t+1}	(2) OCF_{t+1}	(3) ROA_{t+1}	(4) OCF_{t+1}
$ExploreRatio_{t-1}$	-0.013**	-0.046***	0.004	-0.007
	(0.006)	(0.013)	(0.022)	(0.042)
$InvDiscTone_t$	0.042***	0.079***	-0.060*	-0.148***
	(0.014)	(0.027)	(0.033)	(0.056)
$InvDiscQty_t$			-0.007	0.004
			(0.006)	(0.011)
$ExploreRatio_{t-1}$ * $InvDiscTone_t$	**-0.050****	**-0.091****	**0.040**	**0.088**
	(0.020)	**(0.036)**	**(0.045)**	**(0.075)**
$ExploreRatio_{t-1}$ * $InvDiscQty_t$			**-0.006**	**-0.012**
			(0.007)	**(0.013)**
$InvDiscQty$ * $InvDiscTone_t$			**0.026****	**0.060*****
			(0.012)	**(0.020)**
$ExploreRatio_{t-1}$ * $InvDiscQty_t$ * $InvDiscTone_t$			**-0.023**	**-0.044**
			(0.017)	(0.027)
ΔROA or ΔOCF	-0.223***	-0.139***	-0.220***	-0.136***
	(0.041)	(0.032)	(0.041)	(0.031)
ROA_t or OCF_t	0.580***	0.092***	0.578***	0.091***
	(0.036)	(0.031)	(0.036)	(0.031)
BTM_t	-0.038***	0.023**	-0.041***	0.020*
	(0.007)	(0.011)	(0.006)	(0.010)
$CapExp_t$	0.066*	0.421***	0.051	0.397***
	(0.040)	(0.083)	(0.040)	(0.083)
$R\&D_t$	-0.049	-0.507***	-0.025	-0.477***
	(0.072)	(0.122)	(0.073)	(0.126)
$TotalPatent_t$	-0.157***	-0.516***	-0.158***	-0.515***
	(0.052)	(0.116)	(0.051)	(0.117)
Lev_t	0.008	0.039**	0.006	0.037**
	(0.009)	(0.016)	(0.009)	(0.016)
$FirmAge_t$	0.029***	0.060***	0.023***	0.054***
	(0.004)	(0.007)	(0.003)	(0.007)
$Cglm_t$	0.022***	0.016*	0.019***	0.012
	(0.005)	(0.008)	(0.004)	(0.008)
Adv_t	0.168**	0.316***	0.165**	0.308***
	(0.082)	(0.115)	(0.082)	(0.114)
$SG\&A_t$	0.049***	0.009	0.044***	0.004
	(0.014)	(0.028)	(0.014)	(0.029)
Constant	-0.081***	-0.124***	-0.027	-0.103**
	(0.019)	(0.035)	(0.023)	(0.044)
Observations	14,173	14,173	14,173	14,173
R-squared	0.472	0.230	0.474	0.232
Industry & Year FE	Yes	Yes	Yes	Yes

Panel B: Management Opportunism and Narrative Innovation Disclosure Tone

DV = *InvDiscTone*$_t$	(1) Low *Delta*	(2) High *Delta*	(3) Low *Vega*	(4) High *Vega*
***ExploreRatio*$_{t-1}$**	**0.045***** **(0.014)**	**0.027***** **(0.007)**	**0.049***** **(0.014)**	**0.028***** **(0.007)**
Observations	3,582	14,969	3,579	14,975
R-squared	0.239	0.273	0.222	0.282
Controls	Yes	Yes	Yes	Yes
Industry & Year FE	Yes	Yes	Yes	Yes

Panel C: Management Dispositional Characteristics and Narrative Innovation Disclosure Tone

DV = *InvDiscTone*$_t$	(1) Low *OC67*	(2) High *OC67*	(3) Low *OC100*	(4) High *OC100*
***ExploreRatio*$_{t-1}$**	**0.017** **(0.014)**	**0.036***** **(0.007)**	**0.013** **(0.014)**	**0.038***** **(0.007)**
Observations	5,888	12,662	6,399	12,154
R-squared	0.244	0.269	0.247	0.264
Controls	Yes	Yes	Yes	Yes
Industry & Year FE	Yes	Yes	Yes	Yes

Note: This table reports the results of the determinants of narrative innovation disclosure tone. Panel A reports the results of regressing firms' future operational performance on the interaction terms of *ExploreRatio*, *InvDiscQty*, and *InvDiscTone*, using the model in Equation (12). Panel B reports the results of the subsample analysis for management opportunism by regressing *InvDiscTone* on *ExploreRatio*, using the model in Equation (11). I partition the sample based on whether the CEO falls below or above the sample median of *Delta* and *Vega*. Panel C reports the results of the subsample analysis for management dispositional characteristics by regressing *InvDiscTone* on *ExploreRatio*, using the model in Equation (11). I split the sample based on whether executives fall below or above the sample mean of *OC67* and *OC100*. The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 19: Narrative Innovation Disclosure Qualitative Characteristics (Complementing H2 and H3)

DV =	(1) *InvDiscNum$_t$*	(2) *InvDiscFls$_t$*	(3) *InvDiscRep$_t$*	(4) *InvDiscTone$_t$*
ExploreRatio$_{t-1}$	-0.387***	-0.261***	-0.361***	0.050***
	(0.041)	(0.036)	(0.045)	(0.013)
ExploreRatio$_{t-1}$ * PMCHigh$_{t-1}$	**-0.106****	**-0.145*****	**-0.093***	**-0.011**
	(0.044)	**(0.038)**	**(0.048)**	**(0.012)**
PMCHigh$_{t-1}$	0.170***	0.174***	0.198***	0.006
	(0.038)	(0.033)	(0.041)	(0.010)
ExploreRatio$_{t-1}$ * TSHigh$_{t-1}$	**0.225*****	**0.159*****	**0.221*****	**-0.025***
	(0.044)	**(0.038)**	**(0.047)**	**(0.013)**
TSHigh$_{t-1}$	-0.098***	-0.084***	-0.101**	0.011
	(0.036)	(0.031)	(0.039)	(0.010)
Observations	18,557	18,557	18,557	18,557
R-squared	0.619	0.708	0.694	0.254
Controls	Yes	Yes	Yes	Yes
Industry & Year FE	Yes	Yes	Yes	Yes

Note: This table reports the results of the conditional analysis on how ranked product market competition (*PMCHigh*) and ranked technology spillover (*TSHigh*) influence the relation between narrative innovation disclosure quality and *ExploreRatio*. Column (1) shows the results of *InvDiscNum* using the model in Equation (13). Column (2) shows the results of *InvDiscFls* using the model in Equation (13). Column (3) shows the results of *InvDiscRep* using the model in Equation (14). Column (4) shows the results of *InvDiscTone* using the model in Equation (15). The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).

Table 20: Conditional Analysis of Technological Peer Pressure

DV = $InvDiscQty_t$	(1)	(2)	(3)	(4)
$ExploreRatio_{t-1}$	-0.400***	-0.362***	-0.428***	-0.386***
	(0.038)	(0.039)	(0.042)	(0.042)
$ExploreRatio_{t-1}$ * $TPPHigh_{t-1}$	**0.212*** **	**0.248*** **	**0.189*** **	**0.229*** **
	(0.042)	**(0.043)**	**(0.042)**	**(0.043)**
$TPPHigh_{t-1}$	-0.228***	-0.261***	-0.234***	-0.270***
	(0.037)	(0.037)	(0.037)	(0.037)
$ExploreRatio_{t-1}$ * $PMCHigh_{t-1}$		**-0.127*** **		**-0.136*** **
		(0.039)		**(0.039)**
$PMCHigh_{t-1}$		0.187***		0.193***
		(0.034)		(0.034)
$ExploreRatio_{t-1}$ * $TSHigh_{t-1}$			**0.097*** **	**0.096*** **
			(0.037)	**(0.037)**
$TSHigh_{t-1}$			0.011	0.015
			(0.031)	(0.030)
Observations	18,557	18,557	18,557	18,557
R-squared	0.700	0.702	0.701	0.703
Controls	Yes	Yes	Yes	Yes
Industry & Year FE	Yes	Yes	Yes	Yes

Note: This table presents the results of regressing *InvDiscQty* on the interaction of *ExploreRatio* and different moderators (*TPPHigh*, *PMCHigh*, and *TSHigh*). The fixed effects refer to SIC's two-digit industry and year fixed effects. All variables are defined in Appendix D. Robust standard errors are clustered at the firm level and displayed in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (two-tailed).