The Mitigating Effect of Pending Patent Disclosure on Myopic R&D Underinvestment

Abstract

Guided by prior theoretical studies of real effects of disclosure, we investigate whether pending patent disclosure under the American Inventor's Protection Act (AIPA) can mitigate managerial myopic underinvestment in R&D. When there is limited information on R&D payoff, investors tend to fixate on earnings when valuing firms, which motivates managers to underinvest in R&D myopically. The AIPA requires pending patent disclosure within 18 months of patent application. Such disclosure provides timely, detailed, and credible information on R&D payoff and can serve as an additional signal of firm value, reduce investors' fixation on earnings, and mitigate R&D underinvestment. We find that pending patent disclosure under the AIPA significantly mitigates R&D underinvestment, especially for firms that face greater pressure to meet or beat earnings targets. We also find that the mitigating effect is stronger for firms with more analysts following, higher institutional ownership, and more unique technologies.

Keywords: Managerial Myopia, R&D Investments, AIPA, Pending Patent Disclosure

1. Introduction

Managerial myopia, defined as actions that boost short-term performances at the expense of long-term value creation, has attracted attention from academic researchers and industry practitioners for the past several decades (e.g., Narayanan, 1985; Stein, 1988, 1989; Porter, 1992; Kanodia and Mukherji, 1996; Graham et al., 2005; Asker et al., 2015; Kanodia and Sapra, 2016). One of the most important drivers of managerial myopia is the market pressure to maintain or increase short-term stock price.[1] While prior empirical studies on managerial myopia usually treat the stock price pressure as exogenous (e.g., Asker et al., 2015; Kothari et al., 2016; Edmans et al., 2017) , recent theoretical studies on real effects of disclosure argue that public disclosure can simultaneously affect market pricing and corporate decisions (Kanodia, 1980; Stein, 1989; Kanodia and Mukherji, 1996; Kanodia and Sapra, 2016). In this study, we examine whether pending patent disclosure as mandated by the American Inventor's Protection Act (AIPA) can mitigate myopic R&D underinvestment, by enhancing R&D payoff disclosure and reducing investors' reliance on short term performances.

The motivation for our research question is twofold. First, the AIPA accelerated the patent disclosures from the patent grant date to within 18 months of the patent filing date, by twenty months on average. The timely disclosure of R&D payoff can serve as an additional signal of firm value and influence market pricing. Hence this is an ideal setting to test the real effects of disclosure through the channel of influencing capital market pricing. Second, the AIPA is one of

[1]Barton and Wiseman (2014) provide survey evidence that most executives and board members feel that they are under market pressure to deliver short-term financial performance even though they believe that using longer time horizon to make business decisions can be beneficial in the long run. Other drivers of managerial myopia include contracts based on earnings performance (Dechow and Sloan, 1991) and managers' career concern, i.e., the risk of losing the job because of poor performance of risky investments (Aghion et al., 2013; Chen et al., 2015).

the most significant policy changes in the U.S. patent law history. It is therefore important to understand the AIPA's effect on R&D investment, which drives patent generation and innovation.

Our empirical prediction is based on the theoretical studies of real effects of disclosure (hereafter the real effects theory) (Kanodia, 1980; Stein, 1989; Kanodia and Mukherji, 1996; Kanodia and Sapra, 2016). The main idea of the real effects theory is as follows. The information available to investors in the capital market will determine the equilibrium pricing rule, i.e., the stock price as a function of different information available to investors. Managers, bearing the equilibrium pricing rule in mind, choose the investment level to generate the information signals that maximizes short-term stock price. Specifically, if investors put more weights on short-term performances (e.g., earnings or cash flows), managers will behave more myopically to boost short-term performances (e.g., by cutting R&D). Conversely, if investors put more weights on long-term performances, managers are incentivized to invest more. The weights on different information in the equilibrium pricing rule depend on the information set that is available to investors and the relative precision of the information in predicting future cash flows.

The AIPA was passed by the U.S. Congress on November 29, 1999 and became effective one year later. The objective of the AIPA is to facilitate knowledge diffusion, reduce duplicative research, promote innovation activities, and harmonize U.S. patent disclosure rules with other major countries. Before the AIPA became effective, U.S. patents were disclosed by the U.S. Patent and Trademark Office (USPTO) at the time of the patent grant, which was on average 38 months after the patent application. Following the AIPA, patents are required to be disclosed within 18 months of the application. Therefore, the AIPA accelerates the patent disclosure by about 20 months on average. The mandatory pending patent disclosure under the AIPA provides investors with timely, detailed, and credible information on the output of recent R&D investments, which is useful for predicting future cash flows (Hegde et al., 2018; Beyhaghi et al., 2019; Blanco et al., 2020). As a result, investors will take pending patent disclosure into account when valuing the firm and put relatively less weight on current earnings. The former encourages managers to invest in R&D and generate more patent applications to signal firm value, and the latter alleviates the pressure on managers to increase current earnings by cutting R&D. Both lead to the prediction that pending patent disclosure under the AIPA mitigates R&D underinvestment and the mitigating effect increases with the amount of pending patent disclosure.[2]

Our sample includes U.S. publicly listed firms that have high R&D investment intensity and a patent application history. The sample period is 1996-2007 (i.e., from 5 years before the AIPA till 7 years after the AIPA). We regress abnormal R&D on pending patent disclosure under the AIPA, controlling for all pending patents, granted patents and other related variables. Following prior studies (e.g., Roychowdhury 2006; Gunny 2010), we use abnormal R&D to capture the amount of discretionary R&D investments that are not explained by factors such as industry trend and technology development. Abnormal R&D is measured as the residual from Gunny (2010)'s model.[3] Pending patent disclosure under the AIPA is zero before the AIPA and the number (economic value) of disclosed pending patents after the AIPA. In order to control for the influence of the underlying innovation intensity on R&D investments, we include the total pending patents and granted patents in the previous 5 years. We also control for various firm characteristics such as financial conditions following prior studies (Biddle and Hilary, 2006; Biddle et al., 2009). We further include firm fixed effects and industry-year fixed effects in the regressions to control for

[2] While theoretically firms can voluntarily disclose pending patent information before the AIPA, firms rarely do so in practice because of proprietary cost concerns. After the AIPA, pending patent disclosure is effectively legally protected. For patents that are granted, firms are granted monopoly rights retroactively from the date of disclosure.

[3] Note that we use Gunny (2010)'s model here to capture industry R&D norm and not to model optimal R&D investments. Hence abnormal R&D is meant to reflect discretionary R&D and is not used to measure deviation from optimal R&D.

time-invariant firm characteristics and industry and time trends.

As predicted, we find that pending patent disclosure is significantly positively associated with abnormal R&D, consistent with the disclosure mitigating myopic R&D underinvestment. The effect is economically significant: when a firm moves from zero disclosure prior to the AIPA to the average level of disclosed pending patents after the AIPA, abnormal R&D increases by 3.29% (4.57%) relative to the median value of R&D in the pre-AIPA period, when patent disclosure is measured as the number (economic value) of disclosed pending patents. Time trend analysis further shows that the effect of pending patent disclosure on abnormal R&D persists after the AIPA. In addition, we perform placebo tests by assuming the pending patents before the AIPA as disclosed. We find that the assumed pending patent disclosure before the AIPA does not affect abnormal R&D, suggesting that the effect of pending patent disclosure after the AIPA arises from public disclosures.

To reinforce our main finding and provide additional insights, we develop and test several cross-sectional predictions. First, it is well documented in the literature that managers have strong incentives to just meet or beat earnings targets by decreasing discretionary spending (Graham et al., 2005). "Habitual beaters," in particular, face greater pressure to meet or beat earnings targets in order to enjoy the "meet/beat" return premium and avoid disappointing the market (Kasznik and McNichols, 2002). Hence we expect the mitigation effect of pending patent disclosure on R&D underinvestment to be stronger for firms that have a higher frequency of just meeting or beating analyst consensus forecast in the pre-AIPA period. The empirical analyses provide supportive evidence. Second, patent applications are full of technical and legal jargons that require sophisticated knowledge to understand. We predict and find that the effect of pending patent disclosure on R&D is stronger when firms are followed by more analysts or have larger institutional ownership. Third, firms that use more unique technologies face larger information asymmetry regarding R&D payoff because investors cannot easily infer their innovation outputs from peer firms' information. Therefore, we predict and find that the effect of pending patent disclosure on R&D is stronger for firms with more unique technology.

We also perform the following additional tests. (i) To substantiate that pending patent disclosure indeed changes the market pricing, we document that pending patent disclosure is positively associated with stock return and at the same time decreases the earnings response coefficient, consistent with investors fixating less on earnings when there is pending patent disclosure. (ii) Our paper takes the stand that public firms generally underinvest in R&D based on the results in Asker et al. (2015) that public firms have lower investment level and investment-q sensitivity compared with private firms, and the survey evidence in Barton and Wiseman (2014). In order to make a stronger efficiency inference, we examine investment-q sensitivity. We find that pending patent disclosure increases R&D investment-q sensitivity. This suggests that the increase in abnormal R&D after the AIPA disclosure is more consistent with the mitigation of R&D underinvestment than with R&D overinvestment, since R&D investment becomes more responsive to investment opportunities when there is more pending patent disclosure under the AIPA.

Lastly, we conduct analyses to ensure that our findings are not driven by the following alternative explanations. First, it is possible that the increase in abnormal R&D after the AIPA is caused by the greater transparency and lower cost of capital brought by pending patent disclosure. We find that the effect of pending patent disclosure on abnormal R&D is concentrated in the subsample of firms that have fewer financial constraints. This result is more consistent with our story, since firms with fewer financial constraints have more flexibility to increase their R&D

investments in response to the capital market pricing. Second, another alternative explanation is that pending patent disclosure facilitates more effective monitoring of managers, which forces "lazy" managers to innovate. We find that the effect of pending patent disclosure on abnormal R&D is stronger in the subsample of firms that face greater product market competition. This is more consistent with our story, since this subsample of firms have fewer agency problems due to the external governance role played by the market competition (Giroud and Mueller, 2011) but higher stock price pressure due to the takeover threat associated with the market competition. Third, several recent studies document that pending patent disclosure mandated by the AIPA can both encourage innovation through knowledge spillover from peer firms and discourage innovation due to concerns with leakage of proprietary information to peer firms (Hegde et al., 2020; Kim and Valentine, 2021). Our argument is different from theirs – we focus on the role of capital market pricing, instead of the interaction between peer firms, in affecting innovation after the AIPA implementation. After we control for the measures of peer firm interactions as in Kim and Valentine (2021) and Bloom et al. (2013), our findings continue to hold.

This paper makes several contributions. First, it contributes to the literature on the real effects of disclosure. Prior studies on how disclosure affects corporate decisions usually fit into the framework proposed by Roychowdhury et al. (2019) -- the effect is through resolving information asymmetry between firms and investors or through decreasing information uncertainty. This paper directly tests and supports the recent theoretical studies on real effects of disclosure, which propose that disclosure can have significant impact on firms' investment decisions through affecting capital market pricing (Kanodia, 1980; Stein, 1989; Kanodia and Mukherji, 1996; Kanodia and Sapra, 2016).

Second, this paper contributes to the literature on the effects of the AIPA, an important milestone regarding patent disclosure in the history of U.S. patent law. It extends prior studies that find that mandatory pending patent disclosure under the AIPA provides useful information to the capital market and affects firms' innovation through knowledge spillover and proprietary information leakage (Hegde et al., 2018; Beyhaghi et al., 2019; Blanco et al., 2020; Kim and Valentine, 2021). Different from those studies, we provide evidence that pending patent disclosure encourages firms to invest in R&D through the channel of capital market pricing.

Third, this paper also contributes to the literature on managerial myopia. Prior literature often attributes managerial myopia to exogeneous short-term market pressure (Asker et al., 2015; Kothari et al., 2016; Edmans et al., 2017) . Our analyses suggest that market pricing is endogenous to firms' information environment and can be influenced by firms' disclosure. Our findings shed light on a potential solution to managerial myopia -- timely disclosure of R&D payoff can act as a positive signal of firm value and mitigate investors' fixation on earnings. Therefore, we also provide empirical support to recent practitioners' calls for and regulators' deliberation of the disclosure of long-term firm performance metrics.[4]

The rest of this paper is organized as follows. Section 2 provides background information on the AIPA and develops the hypotheses. Section 3 discusses the sample and data. Section 4 reports the main results and the cross-sectional tests. Section 5 reports the additional analyses, and section 6 concludes.

[4] Practitioners argue that the disclosure of long-term performance metrics can help investors understand the drivers of sustainable firm value creation, fixate less on earnings, and mitigate managerial myopia induced by capital market pressure. For example, Barton and Wiseman (2014) state that "focusing on metrics like 10-year economic value added, R&D efficiency, patent pipelines, multiyear return on capital investments, and energy intensity of production is likely to give investors more useful information than basic GAAP accounting in assessing a company's performance over the long haul." On August 26th, 2020, the SEC adopted amendments to Regulation S-K, including requirement of firms to provide a description of their human capital investment policy, in response to the Human Capital Rulemaking Petition, which argues that "there is broad consensus that long-term investing strategies are needed to stabilize and improve our markets and to affect the efficient allocation of capital. Human capital management metrics are precisely the type of information that enables investors to take the long view."

2. Institutional Background and Hypothesis Development

2.1 The American Inventor's Protection Act (AIPA)

The American Inventor's Protection Act (AIPA) was signed into law by Bill Clinton on November 29, 1999 after an extremely convoluted process that spanned three congresses.[5] The most important part of the AIPA is the 18-month disclosure rule, which mandates disclosure of the patent application documents within 18 months of the patent application, in order to harmonize patent disclosure rule in the U.S. with virtually all the other major countries (Graham and Hegde, 2015).

According to the AIPA, all patent applications filed on or after November 29th, 2000 are required to be disclosed within18 months of the first filing date, or on the patent grant date if it's earlier. [6,7] The patent documents are posted on the USPTO website and are easily accessible and searchable by applicant name or technology class. Before the AIPA, patent applications were disclosed only upon grant, which happened on average 38 months after the application date (Hegde et al., 2018). Therefore, the AIPA significantly accelerated the public access to patent information by 20 months on average and expanded the scope of publicly available patent information to pending patents.[8] The policy change is summarized in Figure 1. The pending patent publication

[5] See Ergenzinger (2006) for the detailed history on the legislation of the AIPA. Proponents of the AIPA argued that early patent disclosure could facilitate knowledge spillover and reduce duplicated innovation effort, while opponents of the AIPA, including 26 Nobel laureates in Economics, Physics, Chemistry, and Medicine, argued that the AIPA would harm independent and small inventors who are less able to obtain redress if a larger firm infringes and are less able to keep pace if a larger firm attempts to invent around the patent.

[6] The determination of the first filing date can be somewhat complicated. In most cases, it is the first filing date (including foreign filing dates) of the patent application. See https://www.ipwatchdog.com/2015/08/03/the-myth-of-the-18-month-delay-in-publishing-patent-applications/id=60185/ for details. Patent applicants can choose to have their applications published by the USPTO prior to the publication deadline if they submit an early disclosure request.

[7] Patents without parallel foreign applications can opt out of the 18-month disclosure requirement, but only 15% of patents that are eligible for the opt out option actually opt out (Graham and Hegde, 2015).

[8] Before the AIPA, U.S. patent applications with parallel foreign applications were disclosed after 18 months of the application by the relevant foreign patent office. However, as argued by Hegde and Luo (2018) and Saidi and Zaldokas (2020), patent publication

does not leave the inventors exposed to infringement without recourse. The inventors can seek reasonable royalties for infringement that occurred between patent publication and grant if the patent application satisfies several conditions (35 U.S.C. section 154). In addition, when the patent is granted, the monopoly rights are retroactively applied from the date of disclosure. [9]

Pending patent disclosure is closely followed not only by inventors but also by investors. For example, on Dec. 26th, 2019, USPTO published a patent application from Amazon about a touchless scanning system that would identify individuals not by their faces but by features associated with the palms of their hands, including wrinkles and veins.[10] On the same day, Recode, a technology news website owned by Vox Media, Inc., reported this application and discussed its potential use.[11] The Wall Street Journal covered this application on Jan. 19th, 2020, discussing how the technology is related to Amazon's business strategy, the progress of the related projects, the benefits the technology will bring and the challenges its application will face.[12,13]

2.2 Hypothesis Development

Our hypothesis relies on the real effects theory, as elaborated below. There are two important

---

by a foreign patent office is not the same as patent publication by the USPTO, because there were no public records available prior to the AIPA that linked U.S. applications to their foreign counterparts. Furthermore, foreign counterparts might have been published in foreign languages, while U.S.-based entities would typically only search the USPTO's databases due to resource and time constraints (Luck et al., 2020). Moreover, it was common for the U.S. patent applicants who sought foreign protection to file foreign applications approximately one year after the U.S. filing date, in order to keep the patentability of the invention and lengthen the patent secrecy period. In such cases, prior to the AIPA, patent publications by the relevant foreign patent office were approximately within 30 months of the US patent application. Therefore the AIPA accelerated the patent publication by about one year even after considering publications by the foreign patent offices (Johnson et al., 2003).

[9] See https://www.law.cornell.edu/uscode/text/35/154 for details.

[10] http://appft1.uspto.gov/netacgi/nph-Parser?Sect1=PTO1&Sect2=HITOFF&d=PG01&p=1&u=/netahtml/PTO/srchnum.html&r=1&f=G&l=50&s1=20190392189.PGNR.

[11] https://www.vox.com/recode/2019/12/26/21037923/amazon-go-hand-scanning-patent-biometrics-whole-foods-identity

[12] https://www.wsj.com/articles/cash-plastic-or-hand-amazon-envisions-paying-with-a-wave-11579352401?mod=searchresults

[13] See Hegde et al. (2018) for other examples of how investors use the information in published pending patent applications to better understand firms' innovation potential.

assumptions in the real effects theory (Kanodia, 1980; Stein, 1989; Kanodia and Mukherji, 1996; Kanodia and Sapra, 2016). First, managers want to maximize the short-term stock price due to various reasons, such as takeover threat (Stein, 1988), market-based compensation (Edmans et al., 2017), seasoned equity issuing (Kothari et al., 2016), and the pressure from short-term investors (Bushee, 1998). Second, there is information asymmetry between managers and investors regarding investments and managers cannot credibly convey their private information to investors. As a result, market prices and corporate decisions are jointly determined – managers will use the stock price to guide their investment decisions with the understanding that their decisions will influence the stock price. How efficient investments are depends upon how well the stock price reflects firm fundamentals. Specifically, if investors put more weights on short-term oriented information, such as cash flows, managers will myopically underinvest in order to report higher short-term cash flows. In contrast, if investors put more weights on long-term oriented information, such as investments, managers are motivated to invest more. Furthermore, public disclosures affect both market pricing and firm decisions. The market pricing rule depends on the information signals available in the capital market and the signals' relative precision in predicting future cash flows. Public disclosures hence influence investment decisions through the market pricing.

R&D investment fits well into the framework of the real effects theory. First, R&D investment reduces short-term earnings and cash flows but creates value in the long run. R&D expenditures are immediately expensed when incurred.[14] Second, R&D investment is associated with high information asymmetry between managers and investors. Even though R&D expense is reported on the income statement, given the firm-specificity and complexity of R&D investment

[14] As required by SFAS No.2, R&D expenditures are expensed when incurred except for certain software development expenditures.

and the limited information available about firms' innovation (Aboody and Baruch, 2000), investors tend to underreact to R&D investment and fixate on bottom-line earnings (Eberhart et al., 2004; Oswald et al., 2020). Therefore, managers are incentivized to cut R&D investment when they are under the pressure of delivering short-term performance (Graham et al., 2005). [15]

The AIPA mandates timely, credible, and detailed disclosure of pending patent information. First, pending patent disclosure provides timely information on the payoff of the most recent R&D projects. Second, pending patent disclosure is also credible because inventors may risk delay or denial of their patent applications by making false claims in the applications. Third, pending patent disclosure is detailed because USPTO requires the applications to be detailed enough to enable someone "skilled in the art" to replicate and extend the invention (35 U.S.C. section 112). Besides, the information can be easily found in the centralized repository of USPTO and compared across firms (Hegde and Luo, 2018). The pending patent information is thus very useful for investors to understand the outcome of recent R&D investments and forecast future cash flows. Previous studies of the AIPA provide empirical and anecdotal evidence on the value of the information in pending patent disclosure to investors (Hegde et al., 2018), analysts (Beyhaghi et al., 2019), and institutional investors (Blanco et al., 2020).

According to the real effects theory, pending patent disclosure, by providing information on the payoff of recent R&D investments, acts as a positive signal when investors price the firm. The disclosure provides investors with more insights into recent R&D investments, such as how

[15] Market inefficiency is not a necessary condition for the real effects theory to work. Even when investors are rational, myopic underinvestment can still arise as long as managers have private information on investments that outside investors cannot perfectly observe. Given the information asymmetry, managers do not have incentive to deviate to more efficient investment decisions, because investors' off-equilibrium beliefs about firm value do not vary with the actual investment decisions. At the equilibrium, price efficiency is achieved while economic efficiency is not achieved (Kanodia and Sapra, 2016). If investors are not totally rational, the fixation on earnings by irrational investors can further strengthen our prediction, based on the real effects theory.

efficient the R&D expenditures are in generating profitable outputs, and thus allows investors to better understand firms' operating performance, strategy, and competitive advantage. In addition, the disclosure will reduce investors' fixation on the bottom-line earnings. The information value of pending patent disclosure encourages managers to invest in R&D to generate more patent applications to signal firm value and the reduced weight on earnings alleviates the pressure on managers to deliver higher earnings through cutting R&D. Both lead to the following prediction:

H1: The pending patent disclosure mandated by the AIPA mitigates myopic R&D underinvestment and the effect is increasing in the amount of the disclosure.

It is well documented in the literature that managers face more conflicts between long-term investments and short-term earnings when they try to meet or beat earnings targets (Bushee, 1998; Graham et al., 2005; Roychowdhury, 2006; Zang, 2012). Graham et al. (2005) report that 80% of their survey participants would decrease discretionary spending on R&D, advertising, and maintenance in order to meet short-term earnings targets and more than 50% of the survey participants would forego projects with positive net present values if undertaking such projects would temporarily depress reported earnings. Bartov et al. (2002) and Kasznik and McNichols (2002) document a stock price premium for firms that consistently meet or beat analyst forecasts, i.e., "habitual beaters." Hence habitual beaters are likely under stronger pressures to manage earnings to meet or beat analyst forecasts, compared to the other firms. After the AIPA, such pressures become less. Therefore, we predict that pending patent disclosure has a stronger mitigation effect on R&D underinvestment for habitual beaters than for the other firms:

H2: The mitigating effect of pending patent disclosure on myopic R&D underinvestment is stronger for firms with a high frequency of just meeting or beating analyst forecasts in the pre-

AIPA period than for the other firms.[16]

Patent applications are full of technical and legal jargons such that readers need to have sophisticated knowledge to understand the contents, infer the implications for firms' strategies, operations and future performances, and incorporate the information into firm valuation. There is anecdotal evidence that faculty and Ph.D. graduates of scientific fields have been employed as sell-side and buy-side financial analysts to provide advices on investments in science-based industries (Swarup, 2008). Beyhaghi et al. (2019) and Blanco et al. (2020) find that pending patent disclosure under the AIPA increases analyst forecast accuracy and attracts institutional investors. Hegde et al. (2018) document that there is an increase in the efficiency of stock price discovery associated with pending patent disclosure under the AIPA and the increase is greater for firms with more analysts following and larger institutional holdings. The above findings are consistent with financial analysts and institutional investors being more capable of understanding pending patent disclosure and incorporating the relevant information into firm valuation, compared to the other investors. Accordingly, we have the following predictions:

H3a: The mitigating effect of pending patent disclosure on myopic R&D underinvestment is stronger for firms followed by more analysts.

H3b: The mitigating effect of pending patent disclosure on myopic R&D underinvestment is stronger for firms with larger institutional holdings.

There is potentially more information asymmetry between investors and management when firms have more unique technologies, because investors cannot infer firms' innovation prospects

[16] We use the frequency of *just* meeting or beating analyst forecasts to define "habitual beaters," instead of the frequency of meeting or beating analyst forecasts, in order to exclude the cases where firms truly perform well and beat analyst forecasts consistently by nontrivial amounts.

from peer firms' information (Aboody and Baruch, 2000). Therefore, the information provided by pending patent disclosure is likely more useful and has a larger effect on myopic R&D underinvestment for firms that have more unique technologies, leading to the following prediction:

H4: The mitigating effect of pending patent disclosure on myopic R&D underinvestment is stronger for firms with more unique technologies.

3. Sample, Variables, and Summary Statistics

3.1 Data and Sample Selection

The sample includes all U.S. publicly listed firms with high R&D intensity and a patent application history in the pre-AIPA period 1996-2000 (i.e., five years prior to the AIPA implementation in November 2000). Specifically, we require that firms have an average R&D intensity (R&D expenditures divided by sales) of above 1% and at least one patent application in the pre-AIPA period.[17] The sample period is from 1996 to 2007, including 5 years before the AIPA and 7 years after the AIPA. We include two more years in the post-AIPA period – AIPA is applicable to patent applications after November 2000 and it can take up to 18 months after this date for inventors to provide pending patent disclosure. Following prior research, we exclude financial companies (SIC between 6000 and 6999) and utility companies (SIC between 4900 and 4999). We also exclude firm-years that have missing values for the regression variables. The main sample consists of 13,670 firm-years, and the samples used for different regressions vary due to different specifications, control variables, and partition variables.

The patent data is obtained from Kogan et al. (2017), who provide information on all utility

[17] The selection criteria are based on firm characteristics in the pre-AIPA period to alleviate survivorship bias. Since these R&D-intensive firms consistently report R&D expenditures (only 2.17% firm-years have missing R&D in our sample period), the missing R&D problem discussed in Koh and Reeb (2015) is not a significant concern for our sample.

patents granted by USPTO between 1926 and 2010.[18] We extend the patent citation data to the end of 2017 using the UVA Darden Global Corporate Patent Dataset, in order to alleviate the concern of citation truncation for patents granted in the later years of the sample period.[19,20] We obtain financial data from Compustat, stock market data from CRSP, analyst data from Thomson Reuter I/B/E/S, and institutional holding data from Thomson Reuter 13F dataset. We use the 10-K text-based financial constraint measure developed by Hoberg and Maksimovic (2015) and the 10-K text-based industry concentration measure from the Hoberg-Phillips data library.[21,22] We winsorize the continuous variables at 1% and 99%.

3.2 Dependent Variable: Abnormal R&D Expenditures

It is important to distinguish the R&D expenditure changes due to managers' discretionary R&D strategy from the changes due to other reasons, such as industry landscape and technology development. Following the prior literature (Gunny, 2010; Bereskin et al., 2018), we use the model developed by Gunny (2010) to split the R&D expenditures into the "normal" part, which is the average R&D expenditures estimated for similar firms in the same industry (i.e., the industry-year "norm"), and the "abnormal" part, which is the discretionary R&D expenditure. Specifically,

[18] We thank the authors for making the data available at https://iu.app.box.com/v/patents. USPTO issues three different types of patents: utility patents, design patents, and plant patents. Utility patents, also known as "patents for invention," are related to new or improved product, process, or machine and are the most common patents. This dataset covers all the patents that were granted between 1926 and 2010 and our last sample year is 2007. Since the average time lag between patent application and grant is 38 months, this dataset should cover almost all the successful patents that were filed during our period. While this dataset may miss some of the successful patent applications that were filed before 2007 and granted after 2010, this should not be a big issue. Our use of scaled measures helps alleviate this concern. In addition, all our results continue to hold if our sample period stops in 2005 or 2006.

[19] The data is available at https://patents.darden.virginia.edu/ and is used in Bena et al. (2017).

[20] Patents that are granted later may have fewer citations simply because there is less time for them to receive citations (Hall et al., 2001).

[21] We thank the authors for making the data available at http://hobergphillips.tuck.dartmouth.edu/industryconcen.htm.

[22] We thank the authors for making the data available at http://faculty.marshall.usc.edu/Gerard-Hoberg/MaxDataSite/index.html.

abnomal R&D is estimated from the following regression:

$$\frac{RD_{i,t}}{A_{i,t-1}} = \alpha_0 + \alpha_1 \frac{1}{A_{i,t-1}} + \beta_1 MV_{i,t} + \beta_2 Tobin's\ Q_{i,t} + \beta_3 \frac{INT_{i,t}}{A_{i,t-1}} + \beta_4 \frac{RD_{i,t-1}}{A_{i,t-1}} + \varepsilon_{i.t}^{R\&D}, \tag{1}$$

where $RD_{i,t}$ is the R&D expense of firm *i* in year *t*, $A_{i,t-1}$ is total assets of firm *i* in year *t-1*, $MV_{i,t}$ is the natural logarithm of firm *i*'s market value at the end of year *t*, $Tobin's\ Q_{i,t}$ is firm *i*'s Tobin's Q at the end of year *t*, and $INT_{i,t}$ is the internal funds of firm *i* in year *t*. Detailed variable definitions are provided in the Appendix. We estimate Equation (1) for each year (1996-2007) and industry (based on 2-digit SIC) combination with at least 15 observations, using all firm-year observations with non-missing R&D expense. The residual $\varepsilon_{i.t}^{R\&D}$ is the abnormal R&D expenditure (*Ab_RD*).

3.3 Independent Variable of Interest: Disclosed Pending Patents

We use the disclosed pending patents to measure the additional information provided under the AIPA, while holding the underlying innovation intensity constant (i.e., controlling for pending and granted patents over the previous five years). We define *Ln_n_discl* (*Ln_eco_discl*) as the number (economic value) of the disclosed pending patents after the AIPA; and they are zero before the AIPA. The number of the patents is a commonly used measure of a firm's innovation activity (Hall et al., 2001; Lerner and Seru, 2017). The economic value of the patents is a market-based measure developed and estimated by Kogan et al. (2017) based on the market reaction to patent issuance.[23] This measure complements the number of the patents and can be potentially more relevant because it directly estimates the economic value of the patents as perceived by investors.[24]

---

[23] For the main tests, we do not use the citation-weighted number of patents as in some of the previous studies, because Lerner and Seru (2017) show that citation truncation is a significant concern even after adjustments.

[24] Please see Kogan et al. (2017) for details of this measure. Briefly speaking, the measure is calculated based on the market reaction at patent issuance, under the assumption that the economic value of a patent is observable to the market participants before the grant of the patent and the share price reaction up until patent issuance also considers the ex ante probability assessment that the

We measure the total number (economic value) of disclosed pending patents at the end of the third fiscal quarter for each firm-year. We choose the third quarter because at this point managers likely have a relatively accurate expectation of annual earnings and can still adjust R&D investments (Bushee, 1998).[25] We focus only on patents that are eventually granted, in order to keep the definitions of patent-related variables (i.e., pending and granted patents) consistent before and after the AIPA, since information on patent applications that were unsuccessful was not available before the AIPA. This is justified by Hegde et al.'s (2018) finding that the disclosure of unsuccessful pending patents conveys little information compared to the disclosure of pending patents that are eventually granted.

In order to adjust for the time trend of patenting due to the market condition and different patent intensity in different patent classes, we first scale the patent by the median number of patents in the same class and filed in the same year by a firm across all sample firms and scale the patent's economic value by the median aggregated economic value of patents in the same class and filed in the same year by a firm across all sample firms. We then sum the scaled number (economic value) of disclosed pending patents in each firm-year and take the natural log of one plus the sum in order to mitigate the skewness. We provide detailed variable definitions in the Appendix.

3.4 Control Variables

In order to control for the influence of the underlying innovation intensity on R&D investments, we include the following measures of the firm's concurrent patent portfolio in the

---

patent application is successful. Kogan et al. (2017) provides evidence that this measure is strongly positively related to forward citations of patents as well as strongly associated with firm growth and reallocation of resources across firms.

[25] Our results are similar if we choose to measure the disclosed pending patents at the beginning of the fiscal year or at the end of the fiscal year.

regression – the number (economic value) of all the pending patents and granted patents over the previous five years measured at the end of the third fiscal quarter. We use 15% annual discount rate as in Hall et al. (2005). These patent variables are also first scaled and log transformed following the same procedure as calculating the disclosed pending patents. Following Biddle and Hilary (2006) and Biddle et al. (2009), we also control for firm size, market-to-book ratio, profitability, cash flow volatility, bankruptcy risk, asset tangibility, firm leverage, industry leverage, operating cash flow, cash slack, and dividend payout ratio. These are measured at the beginning of the fiscal year or over the current fiscal year (Roychowdhury 2006). We provide detailed variable definitions in the Appendix. We include firm fixed effects and industry-year fixed effects in the regression to control for the influence of time-invariant firm characteristics and time-variant industry shocks.

3.5 Summary Statistics

Table 1 presents the summary statistics of the main variables used in the analyses. The number and the economic value of disclosed pending patents are zero before the AIPA and are positive after the AIPA due to the mandatory 18-month disclosure requirement under the AIPA. Due to the sample selection criteria, the sample firms are on average R&D-intensive. R&D (scaled by total assets) has a mean of 14% in the pre-AIPA period and 12.3% in the post-AIPA period. The firm-years after the AIPA on average have a larger patent portfolio, as indicated by the larger value of the number and economic value of pending patents and granted patents.[26] Firm-years in the post-AIPA period have lower market-to-book ratio, larger size, and lower ROA. The summary statistics of the other control variables are comparable to those in Biddle and Hilary (2006) and Biddle et

[26] Note that the economic value of patents has smaller number of observations than the number of patents because not all patents have economic value in Kogan et al.'s (2017) database.

al. (2009).

4. Empirical Models and Results

4.1 Main Tests

To test the main prediction that the pending patent disclosure mandated by the AIPA mitigates myopic R&D underinvestment (H1), we employ the following regression specification:

$$Ab\_RD_{i,t} = \beta_0 + \beta_1 Ln\_n(eco)\_discl_{i,t} + \beta_2 Ln\_n(eco)\_pend_{i,t} + \beta_3 Ln\_n(eco)\_grant_{i,t} + \sum \gamma X + firm\ fixed\ effects + industry\_year\ fixed\ effects + \varepsilon_{i,t}, \quad (2)$$

where *i* stands for firm *i* and *t* for fiscal year *t*. The dependent variable is abnormal R&D ($Ab\_RD_{i,t}$) discussed in Section 3.2. The main independent variable of interest is the number (economic value) of disclosed pending patents ($Ln\_n(eco)\_discl_{i,t}$) discussed in Section 3.3. The rest of the independent variables include variables for patent portfolio, including pending patents and granted patents, control variables X, firm fixed effects, and industry-year fixed effects as discussed in Section 3.4. The standard errors are clustered at firm level. H1 predicts β_1 to be positive.

The regression results are reported in Table 2, Column (1) and Column (2). The significantly positive coefficients on the disclosed pending patents in Column (1) (*Ln_n_discl*) and Column (2) (*Ln_eco_discl*) indicate that pending patent disclosure mandated by the AIPA is associated with an increase in abnormal R&D, and the effect is increasing in the amount of the disclosure, consistent with H1. The effect is economically significant: moving from zero disclosure prior to the AIPA to an average level of disclosed pending patents after the AIPA, a firm increases the abnormal R&D by 3.29% (4.57%), relative to the median value of R&D in the pre-AIPA period, when the information disclosure is measured by the number (economic value) of disclosed pending patents.[27] In Table 2, Column (3) and (4), we use R&D expenditures (RD) as the dependent variable. The coefficient on the number of disclosed pending patents is positive but not significant in Column (3). The coefficient on the economic value of disclosed pending patents is significantly positive in Column (4). The stronger results when abnormal R&D is used as the dependent variable suggest that abnormal R&D indeed filters out some noises in R&D not related to managers' discretion. With respect to the control variables, total pending patents are significantly positive. Total granted patents are significantly negative. One possible explanation is that firms with more mature technology are under greater pressure to convince investors that they can effectively convert the scientific outcomes contained in the granted patents to economic profits, which motivates managers to underinvest in R&D to deliver higher earnings. The pressure is less for on-going R&D projects. The positive coefficients on market-to-book ratio and the negative coefficients on size and ROA are consistent with the regression results in Biddle and Hilary (2006). The significantly positive coefficients on Z-score and the significantly negative coefficients on K-structure suggest that financially healthy firms and firms with low leverage invest more in R&D.

In Panel A of Table 3, we examine the time trend by separately testing the disclosed pending patents for each sample year after the AIPA. Specifically, we construct a series of variables $Ln\_n(eco)\_discl_{i,s}$ as the natural logarithm of one plus the scaled number (economic value) of the disclosed pending patents in event year *s* and set it to be 0 in all other years. *s* denotes the *sth* year after *Year 0*, the year when firm *i* discloses its first pending patent under the AIPA. As reported, the coefficients on the disclosed pending patents are insignificant in *Year 0*, which is consistent with the fact that few pending patents are disclosed in *Year 0*. When more and more

[27] This is calculated as 0.002*1.498/0.091 or 0.003*1.387/0.091, where 0.002 (0.003) is the coefficient on the disclosed pending patents in column (1) (column (2)), 1.498 (1.387) is the average value of the number (economic value) of disclosed pending patents after the AIPA, and 0.091 is the median value of R&D in the pre-AIPA period.

pending patents are disclosed under the AIPA as time passes by, the effect of disclosed pending patents on abnormal R&D becomes greater.

In Panel B of Table 3, we report the placebo tests. Specifically, we construct two placebo disclosure variables $Ln\_n(eco)\_pbo\_discl_{i,-1}$ and $Ln\_n(eco)\_pbo\_discl_{i,-2}$ by applying the 18-month disclosure rule to the pending patents filed before Nov 29th, 2000 in firm *i*'s patent portfolio in the two years before year 0, the first year firm *i* disclosed its pending patent under the AIPA. The coefficients on the two placebo disclosure variables are insignificant, supporting that it is the actual pending patent disclosure under the AIPA that is associated with an increase in abnormal R&D.

4.2 Cross-sectional Tests

To test H2 that the mitigating effect of pending patent disclosure on myopic R&D underinvestment is stronger for firms with a higher frequency of just meeting or beating analyst forecasts in the pre-AIPA period than for the other firms, we split the sample according to each firm's frequency of just meeting or beating quarterly analyst consensus forecast (MBE hereafter) in the pre-AIPA period. Just meeting or beating analyst consensus forecast is defined as when quarterly EPS less analyst consensus forecast is between 0 and 1 cent.[28] The frequency of MBE is calculated as the number of times of MBE divided by the total number of quarters with non-missing actual EPS and analyst forecasts in the pre-AIPA period. We only keep those firms that have at least 10 quarters with non-missing actual EPS and analyst forecasts in the pre-AIPA period to alleviate noises introduced by small denominators. The summary statistics in Table 1 show that on average firms just meet or beat analyst consensus forecast 23% of the times.

[28] We use the actual EPS in I/B/E/S to keep the definition of actual EPS and that of analyst consensus forecast consistent.

We report the tests of H2 in Table 4. In Panel A of Table 4, we partition the sample by the median of the frequency of MBE in each 2-digit SIC industry. The firms with the above-median frequency of MBE in the corresponding industry are included in the "high MBE" subsample and those with the below-median frequency of MBE in the corresponding industry are included in the "low MBE" sample. In the Panel B of Table 4, we partition the sample by the 3rd quartile of the frequency of MBE in each industry and define "high MBE" and "low MBE" subsamples accordingly. Panel A show that the effect of pending patent disclosure on abnormal R&D is larger for firms with the above-median MBE frequency than for firms with the below-median MBE frequency. The differences in the coefficients on pending patent disclosure between the subsamples are not significant at the conventional levels. Panel B show that the effect of pending patent disclosure on abnormal R&D is larger for firms with the above-3rd-quartile MBE frequency than for firms with the below-3rd-quartile MBE frequency. The differences in the coefficients on pending patent disclosure between the subsamples are statistically significant. The stronger results in Panel B than in Panel A are consistent with that firms in the top-quartile MBE frequency group better represent "habitual beaters." Overall, the results in Table 4 are consistent with H2 that "habitual beaters" who face greater market pressure to deliver short term performance are affected more by pending patent disclosure, since pending patent disclosure can serve as an additional signal of firm value and reduce investors' fixation on earnings.

Next, we test H3a and H3b that the mitigating effect of pending patent disclosure on myopic R&D underinvestment is stronger for firms followed by more analysts and with larger institutional holdings. The results are reported in Table 5. In Panel A, we split the sample according to the average number of analysts following in each year during the pre-AIPA period. The "High analyst" subsample includes firms followed by an above-median number of analysts in the industry, and the "Low analyst" subsample includes firms followed by a below-median number of analysts in the industry. Similarly, in Panel B of Table 5, we split the sample according to the average institutional ownership in the pre-AIPA period. The "High inst" subsample includes firms with an above-median institutional ownership in the industry, and the "Low inst" subsample includes firms with a below-median institutional ownership in the industry. As reported, the effect of disclosed pending patents on abnormal R&D is significantly larger in the subsample with more analysts following and with higher institutional ownership.[29] These results are consistent with H3a and H3b and support that sophisticated market participants are better able to incorporate pending patent disclosure into firm valuation and fixate less on earnings when timely pending patent information is available after the AIPA.

Lastly, to test H4 that the mitigating effect of pending patent disclosure on myopic R&D underinvestment is stronger for firms with more unique technologies, we proxy the uniqueness of the technologies using the self-citation ratio. A firm's self-citation ratio is calculated as the proportion of the total citations that are from the firm itself, among the total citations received by the firm's patents granted during the pre-AIPA period. When the firm's inventions are mainly cited by its own other patents, the firm's inventions are considered more unique. We partition the sample according to the median value of self-citation ratio in the industry. The results are reported in Table 6. As reported, the effect of pending patent disclosure is only significant in the subsample with the above-median self-citation ratio, though the coefficient differences between the two subsamples are not statistically significant at conventional levels.

[29] The differences in the coefficients on the disclosed pending patents between the "High inst" and "Low inst" subsamples become more significant when we partition the sample by the dedicated institutional ownership. This is consistent with the finding in Hegde et al. (2018) that the increase in the efficiency of price discovery after the AIPA is larger for firms with higher dedicated institutional holding because dedicated investors are fundamental information acquirers, compared to quasi-indexers and transient investors.

5. Additional Analyses

5.1 Value-relevance Test

To substantiate our argument that pending patent disclosure changes the capital market pricing, we conduct a value-relevance test using the following regression:

$$Ab\_Ret_{i,t} = \beta_0 + \beta_1 SUE_{i,t} * Ln\_n(eco)\_discl_{i,t} + \beta_2 Ln\_n(eco)\_discl_{i,t} + \beta_3 Ln\_n(eco)\_pend_{i,t} + \beta_4 Ln\_n(eco)\_grant_{i,t} + \beta_5 SUE_{i,t} + \beta_6 Size_{i,t} + \beta_7 MTB_{i,t} + \beta_8 Loss_{i,t} + firm\ fixed\ effects + year\ fixed\ effects + \varepsilon_{i,t} \quad (3)$$

$Ab\_Ret_{i,t}$ is the abnormal buy-and-hold return during the 12-month period ended on the earnings announcement month, where the benchmark return is the equal-weighted buy-and-hold return of the size and market-to-book ratio matched portfolio constructed using the Fama-French six size/book-to-market portfolio construction method. The definitions of the patent variables ($Ln\_n(eco)\_discl_{i,t}$, $Ln\_n(eco)\_pend_{i,t}$, $Ln\_n(eco)\_grant_{i,t}$) are similar to those in the main tests, except that the time of measurement is changed to the earnings announcement date in order to be consistent with the definition of the earnings surprise. The earnings surprise ($SUE_{i,t}$) is the difference between the actual EPS and the analyst consensus EPS forecast scaled by the share price at the end of the year. We also control for firm size ($Size_{i,t}$), market-to-book ratio ($MTB_{i,t}$), and loss indicator ($Loss_{i,t}$). We provide detailed variable definitions in the Appendix. We include firm and year fixed effects to control for time-invariant firm characteristics and time trend. The standard errors are clustered at firm level.[30]

[30] The results are robust if we also include the interactions between the earnings surprise and the control variables in the regression.

The regression results are reported in Table 7. As shown, the earnings surprise is significantly positive, and the coefficients on the interactions between the earnings surprise and pending patent disclosure are significantly negative, confirming that the pending patent disclosure reduces investors' fixation on earnings when valuing the firm. The economic value of the pending patent disclosure is significantly positive (Column (2)), consistent with pending patent disclosure conveying positive information to the capital market. The number of disclosed pending patents is positive but not significant (Column (1)), possibly because the number of disclosed pending patents is a noisier measure of the value of the pending patents compared to the economic value of disclosed pending patents. In summary, the results in Table 7 confirm the market pricing mechanism underlying our hypothesis.

5.2 Investment-q sensitivity Test

To provide evidence on the efficiency implication of the increase of R&D investments associated with the pending patent disclosure under the AIPA, we conduct the following investment-q sensitivity test:

$$RD\_inv_{i,t} = \beta_0 + \beta_1 Ln\_n(eco)\_discl_{i,t} * Totalq_{i,t-1} + \beta_2\, Totalq_{i,t-1} + \beta_3 Ln\_n(eco)\_discl_{i,t} + \beta_4 Ln\_n(eco)\_pend_{i,t} + \beta_5 Ln\_n(eco)\_grant_{i,t} + \sum \gamma X + firm\ fixed\ effects + industry\_year\ fixed\ effects + \varepsilon_{i,t} \quad (4)$$

Peters and Taylor (2017) demonstrate that the neoclassical q-theory, which is mainly used for fixed asset investments, can be extended to intangible investments after the Tobin's q is adjusted to account for intangible capital. Specifically, the new Tobin's q proxy, called "Total q", includes the on-balance-sheet and off-balance-sheet intangible capital in the capital stock calculation. $RD\_inv_{i,t}$ is the R&D expenditure in year *t* divided by the sum of tangible and intangible capital in year t-1. We use it as the dependent variable to be consistent with the definition in Peters and Taylor (2017). We also report the results using $Ab\_RD_{i,t}$ as the dependent variable. $Totalq_{i,t-1}$ is the "Total q" defined in Peters and Taylor (2017), calculated by dividing firm value by the sum of tangible and intangible capital. The patent variables are defined in the same way as those in the main tests. X is the same series of controls as those in the main tests, excluding market-to-book ratio since it is conceptually similar to the Total q. Higher investment-q sensitivity means that firms' investments are more responsive to investment opportunities, implying higher investment efficiency (e.g., Asker et al., 2014).

The results are reported in Table 8. As reported, the coefficient on the interaction of Total q and disclosed pending patents is significantly positive in all the columns. That is, more disclosed pending patents are associated with higher investment-q sensitivity, implying that the investment efficiency increases with pending patent disclosure after the AIPA. This test provides corroborative evidence that the increase in abnormal R&D investments after the AIPA is a mitigation of underinvestment, as opposed to an aggravation of overinvestment.

5.3 Alternative Explanations and Robustness Tests

We conduct a series of additional tests to rule out alternative explanations that may drive the results. First, it is possible that the increase in abnormal R&D after the AIPA is caused by the greater transparency and lower cost of capital brought by pending patent disclosure. However, when we split the sample into two groups based on the median of the average financial constraint faced by firms during the pre-AIPA period in each industry (Hoberg and Maksimovic, 2015), the results are only significant in the subsample of firms facing fewer financial constraints, as shown in Panel A of Table 9. This is more consistent with our story because less financially constrained firms have more feasibility to adjust their R&D investment in response to the capital market's lower fixation on earnings and larger weight on pending patent disclosure after the AIPA. In contrast, the above alternative story predicts that the results should be stronger for firms facing more financing constraints because such firms will benefit more from lower cost of capital after the AIPA.

Second, the results can be driven by more effective monitoring of investors because there is more information about the outputs of managers' innovation effort after the AIPA, which can in turn force the "lazy" managers to innovate. Similar to Aghion et al. (2013), we use the different predictions on the interaction between the pending patent disclosure and product market competition to differentiate our argument from this alternative story. We partition the sample according to the median of the average Herfindahl-Hirschmann Index in the pre-AIPA period using the 10-K text-based industry classification (Hoberg and Phillips, 2016). The results in Panel B of Table 9 show that the effect of pending patent disclosure on abnormal R&D is stronger in the subsample of firms that face greater product market competition. This is more consistent with our story, since this subsample of firms have fewer agency problems due to the external governance role played by the market competition but face greater stock price pressure due to the takeover threat associated with the market competition (Giroud and Mueller, 2011).

Third, several recent studies find that the pending patent disclosure mandated by the AIPA can both encourage innovation through the knowledge spillover from peers and discourage innovation because of the leakage of proprietary information to peers (Hegde et al., 2020; Kim and Valentine, 2021). We explicitly control for these mechanisms in the same way as in Kim and Valentine (2021) by including the interaction of the firm's relative spillover position and an indicator for the post-AIPA period. In addition, Bloom et al. (2013) find that R&D expenditures of technology peers can encourage the focal firm's innovation through the knowledge spillover and R&D expenditures of product peers can discourage the focal firm's innovation through the business competition. We also control for these spillover and competition effects by including the technology and product market closeness-weighted R&D of peer firms for each firm-year, defined as in Bloom et al. (2013) and Lucking et al. (2017). Panel A of Table 10 shows that our results are robust to the inclusion of these additional variables.

Fourth, in order to ensure that our results are not confounded by the Dot-Com bubble, we exclude high-tech firms following Ljungqvist and Wilhelm (2003).[31] The first two columns of Panel B of Table 10 show that the effect of pending patent disclosure is still positively significant in this subsample. Lastly, the USPTO digitalized all granted patent information and made it publicly available on its website starting from June 1998. Before that, only granted patent bibliographic data and abstracts were digitally available. This event facilitated public access to granted patent information and can potentially lead to greater influence of granted patents. Our results are robust when we exclude firm-years before 1998, as shown in Column (3) and Column (4) of Panel B of Table 10.

6. Conclusion

In this paper, we study whether timely, detailed, and credible disclosure of R&D payoff under the AIPA can mitigate managerial myopic underinvestment in R&D through the capital market pricing, as predicted by the real effects theory (Kanodia, 1980; Stein, 1989; Kanodia and Mukherji, 1996; Kanodia and Sapra, 2016). We find that pending patent disclosure under the AIPA

[31] Specifically, we exclude firms in the following (four-digit) SIC industries: 3571, 3572, 3575, 3577, 3578 (computer hardware), 3661, 3663, 3669 (communications equipment), 3674 (electronics), 3812 (navigation equipment), 3823, 3825, 3826, 3827, 3829 (measuring and controlling devices), 4899 (communication services), and 7370, 7371, 7372, 7373, 7374, 7375, 7378, and 7379 (software).

significantly mitigates managerial myopic R&D underinvestment. We also find that the mitigating effect of pending patent disclosure on managerial myopia is stronger for “habitual beaters” who face a greater pressure to deliver short-term earnings performance and for firms followed by more analysts, held by more institutional investors and using more unique technologies. R&D investment efficiency also increases with pending patent disclosure under the AIPA. Our value-relevance tests corroborate the underlying market pricing mechanism by showing that pending patent disclosure sends a positive signal of firm value and reduces the market’s fixation on earnings. Moreover, the results cannot be explained by alternative stories such as the decrease of cost of capital or the increase of investors’ monitoring after the AIPA.

Corporate investments have changed significantly over the past few decades. Firms spend less on physical assets and more on intangibles, such as R&D, brand developments, and employee training (Ewens et al., 2019). These types of investments are usually long-term and firm-specific, involving large information asymmetry. Moreover, the related expenditures are usually expensed when incurred. As a result, investors cannot value these investments correctly and may tend to fixate on earnings, which induces managerial myopia and harms the economy in the long-run. In response to this, there is a great demand of information disclosure on intangible investments and long-term performance metrics from investors and regulators in order to enable investors to take the long-term view and, as a result, mitigate managerial myopia. Our results provide empirical support to this call for long-term oriented information disclosure as well as provide evidence on the economic impact of AIPA, a milestone in the U.S. patent law history.

Reference

Aboody, D., & Baruch, L. (2000). Information asymmetry, R&D, and insider gains. *Journal of Finance, 55*(6), 2747–2766.

Aghion, P., Van Reenen, J., & Zingales, L. (2013). Innovation and institutional ownership. *American Economic Review*, *103*(1), 277–304.

Asker, J., Farre-Mensa, J., & Ljungqvist, A. (2015). Corporate investment and stock market listing: A puzzle? *Review of Financial Studies*, *28*(2), 342–390.

Barton, D., & Wiseman,M. (2014). Focusing capital on the long term. *Harvard Business Review, (January-Feburary*), 48–55.

Bartov, E., Givoly, D., & Hayn, C. (2002). The rewards to meeting or beating earnings expectations. *Journal of Accocunting and Economics*, *33*(2), 173–204.

Bena, J., Ferreira, M. A., Matos, P., & Pires, P. (2017). Are foreign investors locusts? The long-term effects of foreign institutional ownership. *Journal of Financial Economics*, *126*(1), 122–146.

Bena, J., & Li, K. (2014). Corporate innovations and mergers and acquisitions. *Journal of Finance, 69*(5), 1923–1960.

Bereskin, F. L., Hsu, P. H., & Rotenberg, W. (2020). The real effects of real earnings management: Evidence from innovation. *Contemporary Accounting Research*, *35*(1), 525–557.

Beyhaghi, M., Khashabi, P., & Mohammadi, A. (2019). Pre-Grant patent disclosure and analyst forecast accuracy : Evidence from The American Investor's Protection Act. *SSRN Electronic Journal*.

Blanco, I., Garcca, S., & Wehrheim, D. (2020). Mandated disclosure, institutional investors and stock price informativeness: Evidence from a quasi-natural experiment. *SSRN Electronic Journal*.

Bloom, N., Schankerman, M., & Reenen, J.V. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, *81*(4),1347-1393.

Biddle, G., & Hilary G. (2006). Accounting quality and firm-level capital investment. *The Accounting Review, 81*(5), 963–982.

Biddle, G., Hilary, G., & Verdi, R. S. (2009). How does financial reporting quality relate to investment efficiency? *Journal of Accounting and Economics, 48*(2–3), 112–131.

Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review,73*(3), 305-333.

Chen, X., Cheng, Q., Lo, A. K., & Wang, X. (2015). CEO contractual protection and managerial short-termism. *The Accounting Review*, *90*(5), 1871–1906.

Dechow, P. M., & Sloan, R. G. (1991). Executive incentives and the horizon problems. *Journal of Accounting & Economics*, *14*, 51-89.

Eberhart, A. C., Maxwell, W. F., & Siddique, A. R. (2004). An examination of long-term abnormal stock returns and operating performance following R&D increases. *Journal of Finance*, *59*(2), 623–650.

Edmans, A., Fang, V. W., & Lewellen, K. A. (2017). Equity vesting and investment. *The Review of Financial Studies*, *30*(7), 2229–2271.

Ergenzinger, E. R. (2006) The American Inventor's Protection Act: A legislative history. W*ake Forest Intellectual Property Law J. 7*(1): 145–172.
Ewens, M., Peters, R. H., & Wang, S. (2019). Acquisition prices and the measurement of intangible capital. *SSRN Electronic Journal*, *September 2019*.
Giroud, X., & Mueller, H. M. (2011). Corporate governance, product market competition, and equity prices. *Journal of Finance*, *66*(2), 563–600.
Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, *40*(1–3), 3–73.
Graham, S., & Hegde, D. (2015). U.S. patents and their disclosure status. *Science*, *347*(6219), 236–237.
Gunny, K. A. (2010). The relation between earnings management using real activities manipulation and future performance: Evidence from meeting earnings benchmarks. *Contemporary Accounting Research*, *27*(3), 855–888.
Hall, B. H., Haffe, A. B., & Trajtenberg, M. (2001). The NBER patent citation data file: Lessons, insights and methodological tools. *NBER Working Paper*.
Hall, B. H., Haffe, A. B., & Trajtenberg, M. (2005). Market value and patent citations. *Rand Journal of Economics*, *36*(1).
Hegde, D., Herkenhoff, K., & Zhu, C. (2020). Patent publication and innovation. *SSRN Electronic Journal*.
Hegde, D., Lev, B. I., & Zhu, C. (2018). Patent disclosure and price discovery. *SSRN Electronic Journal*.
Hegde, D., & Luoc, H. (2018). Patent publication and the market for ideas. *Management Science*, *64*(2), 652–672.
Hirshleifer, D., Hsu, P. H., & Li, D. (2018). Innovative originality, profitability, and stock returns. *Review of Financial Studies*, *31*(7), 2553–2605.
Hoberg, G., & Maksimovic, V. (2015). Redefining financial constraints: A text-based analysis. *Review of Financial Studies*, *28*(5), 1312–1352.
Hoberg, G., & Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, *124*(5), 1423–1465.
Jaffe, A. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *American Economic Review 76 (5)*, 984-1001.
Johnson, D. K. N., & Popp, D. (2003). Forced out of the closet: The impact of the American Inventors Protection Act on the timing of patent disclosure. *The RAND Journal of Economics, 34*(1), 96–112.
Kanodia, C. (1980). Effects of shareholder information on corporate decisions and capital market equilibrium. *Econometrica*, *48*(4), 923-953.
Kanodia, C., & Mukherji, A. (1996). Real effects of separating investment and operating cash flows. *Review of Accounting Studies*, *1*(1), 51–71.
Kanodia, C., & Sapra, H. (2016). A real effects perspective to accounting measurement and disclosure: Implications and insights for future research. *Journal of Accounting Research*, *54*(2), 623–676.
Kasznik, R., & McNichols, M. F. (2002). Does meeting earnings expectations matter? Evidence from analyst forecast revisions and share prices. *Journal of Accounting Research, 40*(3), 727-759.

Kim, J., & Valentine, K. (2021). The innovation consequences of mandatory patent disclosures. *Journal of Accounting and Economics, 71*(2), 1) 1013812.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technologyical innovation, resource allocation and growth. *The Quarterly Journal of Economics, 132*(2), 665–712.

Koh, P. S., & Reeb, D. M. (2015). Missing R&D. *Journal of Accounting and Economics*, *60*(1), 73–94.

Kothari, S. P., Mizik, N., & Roychowdhury, S. (2016). Managing for the moment: The role of earnings management via real activities versus accruals in SEO valuation. *The Accounting Review*, *91*(2), 559–586.

Lerner, J., & Seru, A. (2017). The use and misuse of patent data: Issues for corporate finance and beyond. *SSRN Electronic Journal*.

Ljungqvist, A., & Wilhelm, W. J. (2003). IPO pricing in the Dot-com bubble. *Journal of Finance, 58*(2), 723–752.

Lück, S., Balsmeier, B., Seliger, F., & Fleming, L. (2020). Early disclosure of invention and reduced duplication: An empirical test. *Management Science, 66*(6), 2677–2685.

Lucking, B., Bloom, N., & Van Reenen, J. (2017). Have R&D spillovers changed? *SSRN Electronic Journal*.

Merkley, K. J. (2014). Narrative disclosure and earnings performance: Evidence from R&D disclosures. *The Accounting Review*, *89*(2), 725–757.

Narayanan, M. P. (1985). Managerial incentives for short-term results. *The Journal of Finance, 40*(5), 1469-1484.

Oswald, D., Simpson, A., & Zarowin, P. (2020). The information benefits of R&D capitalization. *SSRN Electronic Journal*.

Peters, R. H., & Taylor, L. A. (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics*, *123*(2), 251–272.

Porter, M. E. (1992). Capital disadvantage: America's failing capital investment system. *Harvard Business Review*, *70*(5), 65–82.

Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, *42*(3), 335–370.

Roychowdhury, S., Shroff, N., & Verdi, R. S. (2019). The effects of financial reporting and disclosure on corporate investment: A review. *Journal of Accounting and Economics*, *68*(2–3), 101246.

Saidi, F., & Žaldokas, A. (2020). How does firms' innovation disclosure affect their banking relationships? *Management Science,* September.

Securities and Exchange Commission. (2020). Final Rule, Modernization of Regulation S-K Items 101, 103, and 105.

Stein, J. C. (1988). Takeover threats and managerial myopia. *Journal of Political Economy*, *96*(1), 61–80.

Stein, J. C. (1989). Efficient capital markets, inefficient firms: A model of myopic corporate behavior. *The Quarterly Journal of Economics*, *104*(4), 655–669.

Swarup, A. (2008). Analyzing scientific investments. *Science*. 322 (5905): 1266-1267.

Zang, A. Y. (2012). Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *The Accounting Review*, *87*(2), 675–703.

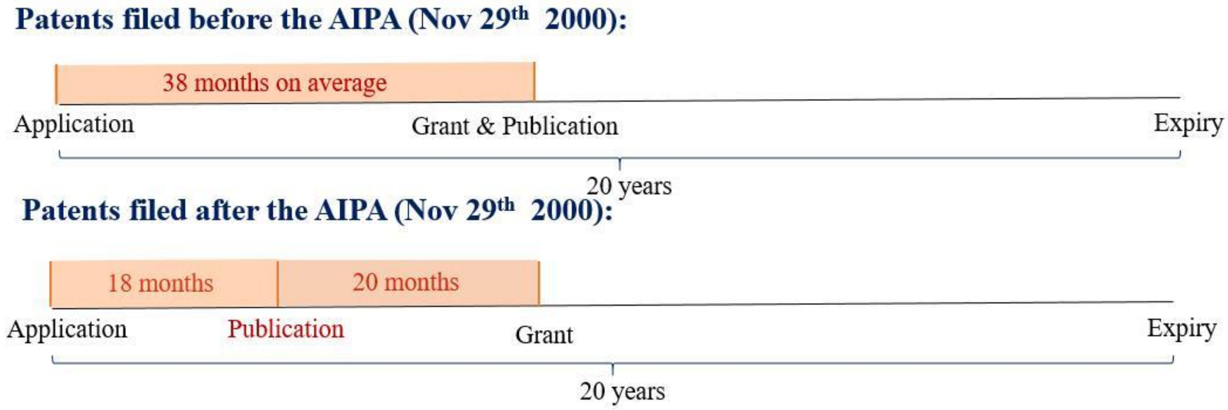
Appendix

Variable	Definition (Compustat items in parentheses where applicable)
Variables used in the main test	
Ab_RD	The residuals from the regression by industry (2-digit SIC) and fiscal year following the model developed by Gunny (2010) as below, where at least 15 observations are available in each industry-year regression: $\frac{RD_{i,t}}{A_{i,t-1}} = \alpha_0 + \alpha_1 \frac{1}{A_{i,t-1}} + \beta_1 MV_{i,t} + \beta_2 Tobin's\ Q_{i,t} + \beta_3 \frac{INT_{i,t}}{A_{i,t-1}} + \beta_4 \frac{RD_{i,t-1}}{A_{i,t-1}} + \varepsilon_{i.t}^{R\&D}$
$Patent$ $- related\ variables$	All the patent measures are scaled in three steps as in Bena and Li (2014). First, for each technology class *k* and patent application year *t*, we compute the median value of the number (the aggregated economic value) of patents in technology class *k* and application year *t* across all firms that have at least one patent in technology class *k* and application year *t*. Second, we scale each patent (its economic value) by the corresponding technology class and application year median value from the first step. Third, we sum up the scaled number (economic value) of all patents that satisfy a certain status at a certain time point for each firm.
$Ln\_n(eco)\_discl$	The natural logarithm of one plus the scaled number (economic value) of the disclosed pending patents at the end of the third fiscal quarter.
$Ln\_n(eco)\_pend$	The natural logarithm of one plus the scaled number (economic value) of all the pending patents at the end of the third fiscal quarter.
$Ln\_n(eco)\_grant$	The natural logarithm of one plus the scaled number (economic value) of all the granted patents over the previous 5 years until the end of the third fiscal quarter, applying 15% annual discount rate as in Hall et al. (2005).
$Ln\_n(eco)\_pbo\_discl$	The natural logarithm of one plus the scaled number (economic value) of the placebo disclosed pending patents at the end of the third fiscal quarter. The placebo disclosure measure is constructed by applying 18-month disclosure rule to the patents filed before the AIPA assuming the disclosure date is 18 months after the patent application.
$Size$	The natural logarithm of total assets (AT).
MTB	The ratio of the market value of total assets (AT+CSHO*PRCC_F-CEQ-TXDITC) to book value of total assets (AT).
ROA	Earnings before extraordinary items (IB) scaled by the total assets at the beginning of the fiscal year (AT).
Std_CFO	The standard deviation of cash flows from operations (OANCF) deflated by average total assets (AT) in the previous 5 years.
Z_score	Z-score calculated as in Biddle and Hilary (2006) and Biddle et al. (2009) ([3.3*PI+SALE+0.25*RE+0.5*(ACT-LCT)]/AT).
$Tangibility$	The ratio of PPE (PPENT) to total assets (AT).
$K\_structure$	The ratio of long-term debt (DLTT) to the sum of long-term debt and the market value of equity (DLTT+ CSHO*PRCC_F).
$IndK\_structure$	Mean K-structure for firms in the same 3-digit SIC industry and year.
CFO_Asset	The ratio of CFO to assets (OANCF/AT).

Slack	The ratio of cash (CHE) to PPE (PPENT).
Dividend	An indicator variable that takes the value of one if the firm paid a dividend (i.e., if DVC>0 or DV>0), and zero otherwise
Variables used in the cross-sectional tests	
MBE	The frequency of just meeting or beating analyst forecasts in the pre-AIPA period, calculated as the number of times of just meeting or beating analyst consensus forecast divided by the total number of quarters with non-missing EPS and analyst consensus forecast. Just meeting or beating analyst consensus forecast means that quarterly EPS minus analyst consensus forecast is between 0 and 1 cent. We only keep firms that have at least 10 quarters with non-missing actual EPS and analyst forecasts in the pre-AIPA period to alleviate noises introduced by small denominators.
High (low)_MBE	Firms whose frequency of just meeting or beating analyst forecasts in the pre-AIPA period is above (below) the corresponding industry median value. An alternative definition uses industry 3rd quartile.
analyst	The average number of analysts following the firm during the pre-AIPA period.
High (low)_analyst	Firms whose average number of analysts following the firm during the pre-AIPA period is above (below) the corresponding industry median value.
inst	The average institutional ownership during the pre-AIPA period.
High (low)_inst	Firms whose average institutional ownership during the pre-AIPA period is above (below) the corresponding industry median value.
self_cite	The self-citation ratio of all the patents granted to the firm in the pre-AIPA period, which is calculated as the proportion of the total citations received from the firm itself.
High (low)_self_cite	Firms whose self-citation ratio in the pre-AIPA period is above (below) the corresponding industry median value.
Variables used in the additional tests	
Ab_Ret	The buy-and-hold abnormal return of the 12-month period ended in the annual earnings announcement month. Abnormal return is calculated as raw buy-and-hold return minus the equal-weighted buy-and-hold return of the corresponding size and book-to-market ratio matched portfolio constructed following the Fama-French methodology outlined on Ken French website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/six_portfolios.html.
SUE	$\frac{Actual\ EPS - concensus\ EPS\ forecasted\ by\ analysts}{Closing\ price\ at\ year\ t}$, where the consensus EPS is the median value of the latest forecast issued by each analyst in the 180 days before the earnings announcement date.
RD_inv	R&D expenditure divided by the sum of tangible and intangible capital at the beginning of the year; see Peter and Taylor (2017) for the detailed definitions.
Totalq	Firm value scaled by the sum of tangible and intangible capital; see Peter and Taylor (2017) for the detailed definitions.

$High\ (low)\_constraint$	Firms whose average financial constraint during the pre-AIPA period is above (below) the corresponding industry median value. We use the 10-K text-based financial constraint measure developed by Hoberg and Maksimovic (2015), which is available for 1997-2015. The higher the value is, the more financial constraints the firm faces.
$High\ (low)\_competition$	Firms whose average $tnic3hhi$ during the pre-AIPA period is below (above) the corresponding industry median value. $tnic3hhi$ is the Herfindahl-Hirschmann index, calculated as the sum of squared market shares based on the 10-K text-based industry classification developed by Hoberg and Phillips (2016), which is available for 1996-2017.
$Spillover\_naics4 * post$	The interaction between the firm's relative spillover position and the post-AIPA indicator; See Kim and Valentine (2021) for the detailed definition of spillover position.
$ln\ \_spilltec$	The natural logarithm of weighted sum of R&D of all technology peers, available for 1970-2017. The weight is the Mahalanobis Closeness in technology space. See Bloom et al. (2013) and Lucking et al. (2017) for the detailed definition.
$ln\ \_spillsic$	The natural logarithm of weighted sum of R&D of all product market peers, available for 1970-2017. The weight is the Mahalanobis Closeness in product space market. See Bloom et al. (2013) and Lucking et al. (2017) for the detailed definition.
Variables used in the calculation of Ab_RD	
RD	R&D expense [XRD].
A	Total assets [AT].
MV	The natural logarithm of market value [PRCC_F*CSHO].
$Tobin's\ Q$	Tobin's Q [(PRCC_F*CSHO+ PSTK + DLTT + DLC)/AT].
INT	Internal funds [IB+XRD+DP].

Figure 1: The AIPA pending patent disclosure rule



This figure compares the patent disclosure rule before and after the AIPA. Before the AIPA, patents were disclosed when granted, which on average happened 38 months after the filing date. After the AIPA, patent applications are required to be disclosed within 18 months from the earliest filing date.

Table 1: Summary statistics

Panel A: Firm characteristics in the pre- and post- AIPA period (firm-year level)

	Pre-AIPA period: 1996-2000			Post-AIPA period: 2001-2007		
variable	N	mean	median	N	mean	median
Ab_RD_t	5,680	-0.002	-0.010	7,990	0.001***	-0.004***
RD_t	5,680	0.140	0.091	7,990	0.123***	0.086***
$Ln\_n\_discl_t$	5,680	0.000	0.000	7,990	1.498***	1.099***
$Ln\_n\_pend_t$	5,680	2.030	1.705	7,990	2.300***	1.992***
$Ln\_n\_grant_t$	5,680	2.001	1.679	7,990	2.349***	2.019***
$Ln\_eco\_discl_t$	5,680	0.000	0.000	7,831	1.387***	0.513***
$Ln\_\mathrm{eco}\_pend_t$	5,528	1.767	0.862	7,799	2.036***	1.239***
$Ln\_\mathrm{eco}\_grant_t$	5,606	1.628	0.767	7,915	2.129***	1.412***
$Size_{t-1}$	5,680	5.191	4.846	7,990	5.783***	5.528***
MTB_{t-1}	5,680	2.987	1.998	7,990	2.509***	1.861***
ROA_t	5,680	-0.047	0.037	7,990	-0.063***	0.018***
Std_CFO_{t-1}	5,680	0.090	0.068	7,990	0.088	0.065**
Z_score_{t-1}	5,680	0.956	1.366	7,990	0.518***	0.956***
$Tangibility_{t-1}$	5,680	0.213	0.187	7,990	0.167***	0.130***
$K\_structure_{t-1}$	5,680	0.089	0.026	7,990	0.091	0.017***
$IndK\_structure_{t-1}$	5,680	0.105	0.075	7,990	0.102**	0.077***
CFO_Asset_t	5,680	0.013	0.070	7,990	0.012	0.066***
$Slack_{t-1}$	5,680	3.652	0.832	7,990	6.478***	1.966***
$Dividend_t$	5,680	0.321	0.000	7,990	0.270***	0.000***

Panel B: Average firm characteristics in the pre-AIPA period (firm-level)

variable	N	mean	std	p25	p50	P75
MBE	664	0.230	0.160	0.100	0.200	0.310
$analyst$	939	8.090	8.580	2.330	4.800	10.80
ins	990	0.400	0.250	0.170	0.410	0.620
$self\_cite$	892	0.090	0.120	0.010	0.040	0.110

Panel A reports the descriptive statistics of firm-year characteristics during the pre-AIPA and post-AIPA periods. Panel B reports the descriptive statistics of firm-level partition variables used in the cross-sectional tests. The partition variables are measured at firm-level using the pre-AIPA period. *, **, *** denotes significant difference in the mean/median difference between firm characteristics in the pre-AIPA and in the post-AIPA period at the 10%, 5% and 1% level (two-tail), respectively. Please see the Appendix for variable definitions.

Table 2: Main tests - H1

	(1)	(2)	(3)	(4)
	Ab_RD_t		RD_t	
$Ln\_n\_discl_t$	0.002***		0.001	
	(3.431)		(1.213)	
$Ln\_n\_pend_t$	0.004***		0.012***	
	(2.926)		(6.490)	
$Ln\_n\_grant_t$	-0.004***		-0.004***	
	(-3.230)		(-2.613)	
$Ln\_eco\_discl_t$		0.003***		0.002**
		(4.863)		(2.336)
$Ln\_\text{eco}\_pend_t$		0.005***		0.017***
		(3.589)		(8.526)
$Ln\_\text{eco}\_grant_t$		-0.002*		-0.001
		(-1.956)		(-0.735)
$Size_{t-1}$	-0.017***	-0.018***	-0.062***	-0.064***
	(-9.505)	(-9.241)	(-20.325)	(-20.118)
MTB_{t-1}	0.003***	0.003***	0.008***	0.008***
	(6.061)	(5.430)	(11.228)	(10.019)
ROA_t	-0.118***	-0.121***	-0.150***	-0.153***
	(-13.779)	(-13.874)	(-11.945)	(-11.882)
Std_CFO_t	-0.004	-0.001	0.015	0.021
	(-0.212)	(-0.052)	(0.530)	(0.731)
Z_score_{t-1}	0.020***	0.020***	0.001	0.001
	(15.856)	(15.073)	(0.852)	(0.980)
$Tangibility_{t-1}$	-0.011	-0.014	0.046**	0.047**
	(-0.880)	(-1.066)	(2.387)	(2.375)
$K\_structure_{t-1}$	-0.015**	-0.014**	-0.038***	-0.032***
	(-2.328)	(-2.096)	(-3.869)	(-3.129)
$IndK\_structure_{t-1}$	-0.012	-0.013	-0.014	-0.011
	(-0.897)	(-0.964)	(-0.563)	(-0.424)
CFO_Asset_t	-0.003	-0.002	-0.020	-0.021
	(-0.346)	(-0.159)	(-1.427)	(-1.511)
$Slack_{t-1}$	-0.000	-0.000	-0.001***	-0.001***
	(-0.394)	(-0.346)	(-4.216)	(-4.040)
$Dividend_t$	0.003	0.004	0.005	0.007*
	(1.238)	(1.519)	(1.434)	(1.818)
$Constant$	0.068***	0.070***	0.421***	0.422***
	(6.240)	(6.000)	(22.781)	(22.062)
Firm fixed effects	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y
N	13670	13172	13670	13172
R^2	0.399	0.406	0.822	0.823

This table reports the effect of pending patent disclosure on R&D investments. Column (1) and Column (2) use the abnormal R&D as the dependent variable.

Column (3) and Column (4) use R&D (scaled by total assets) as the dependent variable. The main variable of interest is $Ln\_n(eco)\_discl_{i,t}$, which is measured as the natural algorithm of one plus the scaled number (economic value) of disclosed pending patents. Detailed variable definitions are in the Appendix. The t-statistics are reported in parentheses and are computed based on standard errors clustered by firm. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels (two-tail), respectively.

Table 3: Time trend and placebo tests

Panel A: Time trend

	(1)	(2)
	Ab_RD_t	
$Ln\_n\_discl_0$	0.001	
	(0.697)	
$Ln\_n\_discl_1$	0.001	
	(0.661)	
$Ln\_n\_discl_2$	0.002*	
	(1.912)	
$Ln\_n\_discl_3$	0.003***	
	(3.004)	
$Ln\_n\_discl_{4+}$	0.003***	
	(3.990)	
$Ln\_eco\_discl_0$		0.001
		(0.778)
$Ln\_eco\_discl_1$		0.002*
		(1.720)
$Ln\_eco\_discl_2$		0.002**
		(2.319)
$Ln\_eco\_discl_3$		0.003***
		(4.367)
$Ln\_eco\_discl_{4+}$		0.004***
		(5.310)
Pending, granted patents	Y	Y
Other controls	Y	Y
Firm fixed effects	Y	Y
Industry-year fixed effects	Y	Y
N	13670	13172
R^2	0.399	0.406

Panel B: Placebo test

	(1)	(2)
	Ab_RD_t	
Ln_pbo_n_discl_{-2}	-0.000	
	(-0.320)	
Ln_pbo_n_discl_{-1}	-0.001	
	(-1.588)	
$Ln\_n\_discl_{0+}$	0.003***	
	(3.512)	
Ln_pbo_eco_discl_{-2}		-0.001
		(-1.359)
Ln_pbo_eco_discl_{-1}		-0.001
		(-1.205)
$Ln\_eco\_discl_{0+}$		0.003***
		(5.020)

Pending, granted patents	Y	Y
Other controls	Y	Y
Firm fixed effects	Y	Y
Industry-year fixed effects	Y	Y
N	13670	13076
R^2	0.399	0.408

Panel A reports the effect of pending patent disclosure on abnormal R&D, separating disclosed pending patents into the individual years after the AIPA. $Ln\_n(eco)\_discl_{i,s}$ is the natural logarithm of one plus the scaled number (economic value) of the disclosed pending patents in event year s and 0 in all the other years. *Year 0* is the year when firm i discloses its first pending patent under the AIPA. Panel B reports the results of placebo tests, where the 18-month disclosure rule is applied to pending patents in firm i's patent portfolio in the two years before *Year 0*. $Ln\_n(eco)\_pbo\_discl_{i,-1}$ and $Ln\_n(eco)\_pbo\_discl_{i,-2}$ are defined accordingly. Detailed variable definitions are in the Appendix. The t-statistics are reported in parentheses and are computed based on standard errors clustered by firm. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels (two-tail), respectively.

Table 4 – Cross sectional tests - H2

Panel A: Sample partitioned by the median of MBE in each industry

	(1)	(2)	(3)	(4)
		Ab_RD_t		
	Low MBE	*High MBE*	*Low MBE*	*High MBE*
$Ln\_n\_discl_t$	0.002	0.004***		
	(1.425)	(3.152)		
$Ln\_n\_pend_t$	0.006*	0.001		
	(1.801)	(0.580)		
$Ln\_n\_grant_t$	-0.004*	-0.004		
	(-1.753)	(-1.603)		
$Ln\_eco\_discl_t$			0.002**	0.004***
			(2.390)	(3.917)
$Ln\_\mathrm{eco}\_pend_t$			0.004	0.001
			(1.335)	(0.593)
$Ln\_\mathrm{eco}\_grant_t$			-0.002	-0.002
			(-0.947)	(-0.790)
Controls	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y
N	2996	2774	2929	2719
R^2	0.424	0.415	0.421	0.420
Coeff diff- Chow test	0.003 (1.54)		0.002 (1.46)	

Panel B: Sample partitioned by the 3rd quartile of MBE in each industry

	(1)	(2)	(3)	(4)
		Ab_RD_t		
	Low MBE	*High MBE*	*Low MBE*	*High MBE*
$Ln\_n\_discl_t$	0.001	0.006***		
	(1.396)	(3.529)		
$Ln\_n\_pend_t$	0.005**	-0.005		
	(2.482)	(-1.573)		
$Ln\_n\_grant_t$	-0.004**	-0.003		
	(-2.142)	(-1.061)		
$Ln\_eco\_discl_t$			0.002**	0.005***
			(2.444)	(3.807)
$Ln\_\mathrm{eco}\_pend_t$			0.004**	-0.003
			(2.052)	(-0.999)
$Ln\_\mathrm{eco}\_grant_t$			-0.002	-0.003
			(-1.080)	(-0.700)
Controls	Y	Y	Y	Y

Firm fixed effects	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y
N	4474	1298	4396	1260
R^2	0.410	0.467	0.409	0.471
Coeff diff- Chow test	0.004** (2.09)		0.003* (1.85)	

This table reports the effect of disclosed pending patents on abnormal R&D in subsamples with high and low MBE frequency in the pre-AIPA period. Panel A partitions the sample by the median of MBE frequency in each 2-digit SIC industry. Panel B partitions the sample by the 3rd quartile of MBE frequency in each 2-digit SIC industry. The tests of the coefficient difference on $Ln\_n(eco)\_discl_{i,t}$ between the subsamples are displayed at the bottom of each panel. Detailed variable definitions are in the Appendix. The t-statistics are reported in parentheses and are computed based on standard errors clustered by firm. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels (two-tail), respectively.

Table 5 – Cross sectional tests – H3

Panel A: Sample partitioned by the median number of analysts following

	(1)	(2)	(3)	(4)
	Ab_RD_t			
	Low analyst	*High analyst*	*Low analyst*	*High analyst*
$Ln\_n\_discl_t$	-0.001	0.004***		
	(-0.538)	(3.861)		
$Ln\_n\_pend_t$	0.006***	0.003		
	(2.824)	(1.587)		
$Ln\_n\_grant_t$	-0.004**	-0.003**		
	(-2.016)	(-2.149)		
$Ln\_eco\_discl_t$			-0.003	0.004***
			(-1.375)	(4.940)
$Ln\_\text{eco}\_pend_t$			0.010***	0.003**
			(3.506)	(2.023)
$Ln\_\text{eco}\_grant_t$			-0.001	-0.001
			(-0.229)	(-0.993)
Controls	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y
N	5944	6390	5675	6249
R^2	0.414	0.416	0.421	0.424
Coeff diff- Chow test	0.004*** (2.59)		0.006*** (2.58)	

Panel B: Sample partitioned by the median institutional ownership

	(1)	(2)	(3)	(4)
	Ab_RD_t			
	Low inst	*High inst*	*Low inst*	*High inst*
$Ln\_n\_discl_t$	-0.001	0.003***		
	(-0.641)	(3.262)		
$Ln\_n\_pend_t$	0.008***	0.002		
	(3.098)	(0.966)		
$Ln\_n\_grant_t$	-0.005*	-0.003*		
	(-1.927)	(-1.742)		
$Ln\_eco\_discl_t$			-0.001	0.004***
			(-0.600)	(4.894)
$Ln\_\text{eco}\_pend_t$			0.013***	0.003*
			(3.441)	(1.875)
$Ln\_\text{eco}\_grant_t$			-0.004	-0.001
			(-1.110)	(-0.410)
Controls	Y	Y	Y	Y

Firm fixed effects	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y
N	5710	6592	5427	6409
R^2	0.399	0.441	0.405	0.452
Coeff diff- Chow test	0.004* (1.72)		0.004* (1.66)	

Panel A reports the effect of disclosed pending patents on abnormal R&D in subsamples with high and low average number of analysts following in the pre-AIPA period. Panel A partitions the sample by the median number of analysts following in each 2-digit SIC industry. Panel B reports the effect of disclosed pending patents on abnormal R&D in subsamples with high and low average institutional holdings in the pre-AIPA period. Panel B partitions the sample by the median of institutional ownership in each 2-digit SIC industry. The tests of the coefficient difference on $Ln\_n(eco)\_discl_{i,t}$ between the subsamples are displayed at the bottom of each panel. Detailed variable definitions are in the Appendix. The t-statistics are reported in parentheses and are computed based on standard errors clustered by firm. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels (two-tail), respectively.

Table 6 – Cross sectional tests – H4

	(1)	(2)	(3)	(4)
	Ab_RD_t			
	Low Self_cite	*High Self_cite*	*Low Self_cite*	*High Self_cite*
$Ln\_n\_discl_t$	0.001	0.003***		
	(0.672)	(3.138)		
$Ln\_n\_pend_t$	0.003	0.005**		
	(1.437)	(2.363)		
$Ln\_n\_grant_t$	-0.003	-0.005***		
	(-1.363)	(-2.627)		
$Ln\_eco\_discl_t$			0.002	0.003***
			(1.250)	(4.403)
$Ln\_\text{eco}\_pend_t$			0.004*	0.005**
			(1.811)	(2.347)
$Ln\_\text{eco}\_grant_t$			-0.003	-0.001
			(-1.240)	(-0.473)
Controls	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y
N	5425	5722	5188	5630
R^2	0.422	0.396	0.426	0.399
Coeff diff- Chow test	0.002 (0.87)		0.001 (0.75)	

This table reports the effect of disclosed pending patents on abnormal R&D in subsamples with high and low self-citation ratio of patents granted in the pre-AIPA period. The sample is partitioned by the median of the self-citation ratio in each 2-digit SIC industry. The tests of the coefficient difference on $Ln\_n(eco)\_discl_{i,t}$ between the subsamples are displayed at the bottom of each panel. Detailed variable definitions are in the Appendix. The t-statistics are reported in parentheses and are computed based on standard errors clustered by firm. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels (two-tail), respectively.

Table 7 Value-Relevance test

	(1)	(2)
	Ab_Ret_t	
$SUE_t * Ln\_n\_discl_t$	-1.276***	
	(-3.335)	
$Ln\_n\_discl_t$	0.007	
	(0.785)	
$Ln\_n\_pend_t$	-0.000	
	(-0.019)	
$Ln\_n\_grant_t$	0.000	
	(0.015)	
$SUE_t * Ln\_eco\_discl_t$		-1.277***
		(-3.057)
$Ln\_eco\_discl_t$		0.021***
		(2.974)
$Ln\_\mathrm{eco}\_pend_t$		0.092***
		(6.425)
$Ln\_\mathrm{eco}\_grant_t$		-0.126***
		(-8.171)
SUE_t	3.235***	2.789***
	(7.996)	(6.969)
$Size_t$	-0.082***	-0.053**
	(-3.780)	(-2.196)
MTB_t	0.195***	0.190***
	(24.443)	(23.130)
$Loss_t$	-0.145***	-0.134***
	(-6.538)	(-6.029)
$Constant$	0.076	-0.014
	(0.585)	(-0.105)
Firm fixed effects	Y	Y
Year fixed effects	Y	Y
N	10315	9986
R^2	0.355	0.367

This table reports the results of the value-relevance test. The dependent variable is the abnormal buy-and-hold return during the 12-month period ended on the earnings announcement month. $Ln\_n(eco)\_discl_{i,t}$ is the natural algorithm of one plus the scaled number (economic value) of disclosed pending patents measured at the earnings announcement date. $SUE_{i,t}$ is the earnings surprise measured by the distance between the actual EPS and the consensus EPS forecast of the analysts scaled by the price at the end of the year. Detailed variable definitions are in the Appendix. The t-statistics are reported in parentheses and are computed based on standard errors clustered by firm. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels (two-tail), respectively.

Table 8 Investment-q sensitivity test

	(1)	(2)	(3)	(4)
	RD_inv_t		Ab_RD_t	
$totalq_{t-1} * Ln\_n\_discl_t$	0.003**		0.001***	
	(2.294)		(4.697)	
$Ln\_n\_discl_t$	0.001		0.001	
	(0.668)		(0.837)	
$Ln\_n\_pend_t$	0.007***		0.004***	
	(2.705)		(3.109)	
$Ln\_n\_grant_t$	-0.023***		-0.004***	
	(-8.620)		(-3.151)	
$totalq_{t-1} * Ln\_eco\_discl_t$		0.002**		0.000***
		(2.019)		(3.237)
$Ln\_eco\_discl_t$		0.000		0.002***
		(0.232)		(2.821)
$Ln\_\text{eco}\_pend_t$		0.014***		0.005***
		(5.281)		(4.294)
$Ln\_\text{eco}\_grant_t$		-0.014***		-0.002
		(-4.905)		(-1.426)
$totalq_{t-1}$	0.004***	0.004***	0.000*	0.000*
	(2.897)	(2.964)	(1.805)	(1.789)
Controls	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y
N	14779	14223	14086	13561
R^2	0.595	0.598	0.382	0.389

This table reports the results of the investment-q sensitivity test. In Column (1) and (2), the dependent variable is $RD\_inv_{i,t}$, defined as R&D expenditure in year *t* divided by the sum of tangible and intangible capital in year *t-1*. In Column (3) and (4), the dependent variable is abnormal R&D. $Totalq_{i,t-1}$ is firm value divided by the sum of tangible and intangible capital (Peters and Taylor, 2017). $Ln\_n(eco)\_discl_{i,t}$ is the natural algorithm of one plus the scaled number (economic value) of disclosed pending patents. Detailed variable definitions are in the Appendix. The t-statistics are reported in parentheses and are computed based on standard errors clustered by firm. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels (two-tail), respectively.

Table 9 Additional tests

Panel A: Sample partitioned by financial constraint

	(1)	(2)	(3)	(4)
		Ab_RD_t		
	Low Constraint	*High Constraint*	*Low Constraint*	*High Constraint*
$Ln\_n\_discl_t$	0.003**	0.000		
	(2.524)	(0.145)		
$Ln\_n\_pend_t$	0.001	0.007***		
	(0.855)	(2.772)		
$Ln\_n\_grant_t$	-0.001	-0.005**		
	(-0.328)	(-2.103)		
$Ln\_eco\_discl_t$			0.003***	0.001
			(3.386)	(0.993)
$Ln\_\mathrm{eco}\_pend_t$			0.003	0.008***
			(1.397)	(2.975)
$Ln\_\mathrm{eco}\_grant_t$			0.000	-0.004
			(0.196)	(-1.550)
Controls	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y
N	6184	5159	5926	4994
R^2	0.402	0.419	0.419	0.418
	-0.003		-0.002	
Coefficient diff -Chow Test	(-1.31)		(-1.04)	

Panel B: Sample partitioned by market competition

	(1)	(2)	(3)	(4)
		Ab_RD_t		
	Low Competition	*High Competition*	*Low Competition*	*High Competition*
$Ln\_n\_discl_t$	0.000	0.005***		
	(0.061)	(3.518)		
$Ln\_n\_pend_t$	0.005***	0.004		
	(2.826)	(1.587)		
$Ln\_n\_grant_t$	-0.004**	-0.003		
	(-2.113)	(-1.500)		
$Ln\_eco\_discl_t$			0.002**	0.005***
			(2.246)	(3.803)
$Ln\_\mathrm{eco}\_pend_t$			0.005***	0.004*
			(2.902)	(1.906)
$Ln\_\mathrm{eco}\_grant_t$			-0.002	-0.001
			(-1.224)	(-0.603)
Controls	Y	Y	Y	Y

Firm fixed effects	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y
N	6288	6106	6026	5897
R^2	0.413	0.398	0.416	0.404
	-0.005 ***		-0.003 **	
Coefficient diff -Chow Test	(-3.00)		(1.97)	

Panel A reports the effect of disclosed pending patents on abnormal R&D in subsamples with high and low financial constraint in the pre-AIPA period. Panel A partitions the sample by the median of the average financial constraint in each 2-digit SIC industry in the pre-AIPA period. Financial constraint is measured by the 10-K text-based financial constraint measure developed by Hoberg and Maksimovic (2015). Panel B reports the effect of disclosed pending patents on abnormal R&D in subsamples with high and low market competition in the pre-AIPA period. Panel B partitions the sample by the median of the average market competition faced by firms in each 2-digit SIC industry in the pre-AIPA period. The market competition is measured by Herfindahl-Hirschmann Index (HHI) using the 10-K text-based industry classification developed by Hoberg and Phillips (2016). The tests of the coefficient difference on $Ln\_n(eco)\_discl_{i,t}$ between the subsamples are displayed at the bottom of each panel. Detailed variable definitions are in the Appendix. The t-statistics are reported in parentheses and are computed based on standard errors clustered by firm. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels (two-tail), respectively.

Table 10 Robustness tests

Panel A: Additional controls

	(1)	(2)	(3)	(4)
		Ab_RD_t		
$Ln\_n\_discl_t$	0.003***		0.002***	
	(3.524)		(3.652)	
$Ln\_n\_pend_t$	0.003**		0.002*	
	(2.440)		(1.891)	
$Ln\_n\_grant_t$	-0.004***		-0.004***	
	(-3.045)		(-3.503)	
$Ln\_eco\_discl_t$		0.003***		0.002***
		(4.858)		(3.700)
$Ln\_\text{eco}\_pend_t$		0.004***		0.002**
		(2.811)		(2.404)
$Ln\_\text{eco}\_grant_t$		-0.002*		-0.002**
		(-1.654)		(-2.319)
$Spillover\_naics4 * post$	0.004	0.005*		
	(1.471)	(1.658)		
$ln\ \_spilltec_{t-1}$			0.026**	0.026**
			(2.277)	(2.313)
$ln\ \_spillsic_{t-1}$			0.000	-0.000
			(0.045)	(-0.055)
Controls	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y
N	12010	11633	7271	7068
R^2	0.402	0.405	0.398	0.401

Panel B: Alternative samples

	(1)	(2)	(3)	(4)
		Ab_RD_t		
$Ln\_n\_discl_t$	0.003***		0.003***	
	(2.717)		(4.036)	
$Ln\_n\_pend_t$	0.003**		0.004***	
	(2.050)		(2.882)	
$Ln\_n\_grant_t$	-0.002		-0.003***	
	(-1.608)		(-2.621)	
$Ln\_eco\_discl_t$		0.003***		0.004***
		(3.579)		(5.722)
$Ln\_\text{eco}\_pend_t$		0.005***		0.004***
		(2.858)		(2.989)
$Ln\_\text{eco}\_grant_t$		-0.001		-0.001
		(-0.983)		(-0.984)
Controls	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Industry-year fixed effects	Y	Y	Y	Y

N	8535	8239	11379	10950
R^2	0.434	0.436	0.406	0.410

This table reports the results of robustness tests. Column (1) and (2) of Panel A control for the interaction between the firm's relative spillover position and the post-AIPA indicator, the main variable of interest in Kim and Valentine (2021). Column (3) and (4) of Panel A control for the lagged technology or product market closeness-weighted R&D of peer firms, defined in Bloom et al. (2013) and Lucking et al. (2017). Column (1) and (2) of Panel B exclude high-tech firms, following Ljungqvist and Wilhelm (2003). Column (3) and (4) of Panel B exclude firm-year observations before 1998. Detailed variable definitions are in the Appendix. The t-statistics are reported in parentheses and are computed based on standard errors clustered by firm. *, **, *** indicate the statistical significance at the 10%, 5%, 1% levels (two-tail), respectively.