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Pre-Grant Patent Disclosure and Analyst Forecast Accuracy

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Pre-Grant Patent Disclosure and Analyst Forecast Accuracy

Abstract. We examine the relationship between pre-grant patent disclosure and analyst forecast accuracy. We take advantage of the passage of the American Inventor's Protection Act (1999), which mandates the pre-grant public disclosure of all information in patent application documents within 18 months of the initial filings. We find that on average, the pre-grant patent disclosure of corporate inventions significantly improves the accuracy of analyst forecasts about the patenting firm and that this improvement is greater for firms with higher research and development intensity. Nevertheless, improvements in the accuracy of analysts' forecasts are smaller when firms issue more original and scientifically broader patents. Also, this effect is weaker for firms in states without legal protection for trade secrets.

Keywords: disclosure • analyst forecast • patent • information asymmetry • American Inventor's Protection Act

JEL classifications: G14, G30, M41, O30

1. Introduction

Although sell-side financial analysts require thorough information to evaluate research and development (R&D) projects, details on the progress and outcomes of such projects are often kept secret and are usually disclosed only after the patent rights are granted. This makes R&D projects a key source of information asymmetry between firms and capital markets (Lev 2000, Brown and Martinsson 2018) and consequently a driver of analyst forecast error (Lang and Lundholm 1996, Barron et al. 2002, Amir et al. 2003). R&D-intensive firms therefore suffer from a higher cost of capital, underinvestment, and undervaluation (Hong et al. 2000, Lui et al. 2012, Gurun et al. 2015). In this study, we investigate the extent to which the pre-grant disclosure of patent application documents can alleviate the information asymmetry described above. Specifically, we ask to what extent, and under what conditions, pre-grant patent disclosure helps financial analysts improve the accuracy of their earnings forecasts about the applicant firm.

Patent application documents are rich and credible sources of information about corporate inventions. Yet, it is unclear to what extent the information conveyed through this channel is digested by financial analysts. Although these technical documents are originally written for an audience "skilled in the art"— namely, fellow inventors and scientists—the financial sector is increasingly opening up to science-oriented analysts capable of analyzing corporate R&D (Swarup 2008). In this study, we want to understand if disclosure through patent applications can mitigate the information asymmetry caused by corporate R&D. This question is especially relevant considering that prior works have highlighted the ineffectiveness of traditional accounting measures in providing information on R&D-intensive firms (see Cañibano et al. 2000, Merkley 2014, Gu and Lev 2017).

Any empirical attempt to investigate the effect of patent disclosure on analyst forecast accuracy faces two immediate identification challenges: The decision to disclose information is an endogenous managerial choice. Moreover, besides their disclosure function, patents have a protection function—that is, to safeguard the exclusive right of the patentee to practice inventions upon the granting of the patent. Thus, to measure the disclosure effect of patents we have to disentangle it from their protection effect. We take a step toward overcoming these challenges by taking advantage of a quasi-natural experiment that resulted from the passage of the American Inventor's Protection Act (AIPA) of 1999. This act was originally designed to disclose inventions in new patent applications to avoid duplicative or parallel inventive efforts. Prior to the passage of AIPA, a firm that applied for a patent in the United States was not required to disclose any information about the application before the patent grant date. As of November 29, 2000, AIPA requires the United States Patent and Trademark Office (USPTO) to publish all U.S. patent applications 18 months after the first filing date, regardless of whether the patent is eventually rejected, accepted, or abandoned by the patentee.[1] This was a significant and plausibly exogenous change to the disclosure of corporate innovations, and hence, it addresses

[1] Filing-to-grant lags were on average more than 30 months before AIPA (Graham and Hegde 2015).

the first identification challenge. Since the AIPA separated the timing of the disclosure from the timing of patent protection, it also addresses the second identification challenge.

We address our research question by taking advantage of the exogenous variations in the disclosure effect of AIPA, driven by firm-specific heterogeneity in the pre-AIPA filing-to-grant time lags (Hegde and Luo 2018, Saidi and Zaldokas 2020). In some technological fields, the average time lag between patent filing and patent granting is much shorter than in others. Thus, the disclosure effect of AIPA is smaller for firms in these fields, and the effect on analyst forecast accuracy should be less pronounced relative to firms in other fields. Using historical filing-to-grant lags lets us conduct a difference-in-differences analysis to investigate the causal effect of patent information disclosure on analyst forecast accuracy.

Our analysis yields several important findings. First, a pre-grant patent disclosure through AIPA significantly improves the forecast accuracy of financial analysts. A one-standard-deviation increase in the treatment variable (pre-AIPA firm-specific filing-to-grant time lags) is associated with a reduction of about 23.66% in the mean analyst forecast error. This improvement in forecast accuracy is observed across both short- and long-horizon forecasts. Second, we find that the pre-grant disclosure effect of AIPA in improving forecast accuracy is significantly larger for firms with higher R&D intensity. Third, pre-grant disclosure is less effective in improving forecast accuracy for firms issuing more original patents or patents that are scientifically broader in scope. This finding implies that financial analysts assess less broad and more familiar patents more accurately, whereas their assessments of broader and less familiar patents are often noisy and less accurate, and therefore disclosures are not as helpful in these cases. This finding is also consistent with work showing that more novel and complex technologies are less favored by capital markets because they are costlier to assess by financial analysts (Benner 2010). Finally, our results also show that the information disclosed in pre-grant patent applications is more positively associated with analyst forecast accuracy for firms in states supporting legal protection for trade secrets.

To check the validity of our difference-in-differences analysis and refute possible alternative explanations, we analyze the potential indirect and contaminating effects of AIPA on the behavior and innovativeness of firms (e.g., patenting quantity or quality). Additionally, we assess the potential effect of other confounding trends, such as the internet bubble, on our results. Overall, these analyses provide evidence in support of our methodology and the use of AIPA as a plausibly exogenous shock to disclosure. Also, as an alternative approach, we conduct a set of event-study analyses, measuring the changes in analyst forecast accuracy after pre-grant disclosure. The results are consistent with the results from our difference-in-differences methodology and strongly support our theoretical arguments.

This study contributes to the disclosure literature, particularly to studies addressing the challenges of R&D-intensive firms in capital markets and the limitations of the current accounting measures used for them (Bhattacharya and Ritter 1983, Lang and Lundholm 1996, Cañibano et al. 2000, Lev 2000, Barron et al. 2002, Amir et al. 2003, Gu and Lev 2017, Brown and Martinsson 2018). We provide evidence on how pre-grant patent information is digested by financial analysts. By doing so, we highlight a credible disclosure channel that can mitigate some of the informational challenges resulting from R&D projects as discussed in this literature. Our work also contributes to ongoing research on the effects of AIPA on various markets. This literature emphasizes the role of innovation disclosure through AIPA in reducing information asymmetry between market participants. AIPA is found to lower information costs in markets for technology and to accelerate patent licensing (Hegde and Luo 2018). For the credit market, Saidi and Zaldokas (2020) show that innovation disclosure facilitates firms' access to lenders, resulting in a lower cost of debt. Mohammadi and Khashabi (2020) focus on venture financing and document that AIPA reduces information asymmetry regarding patenting start-ups and increases the likelihood of their funding. Similarly, Chondrakis et al. (2021) find that AIPA intensifies merger and acquisition activities, yet reduces acquirer returns. Finally, Hegde et al. (2018) highlight the role of AIPA in improving the efficiency of stock price discovery. Our work adds to this growing body of literature by underscoring another important effect of patent disclosure through AIPA on capital markets—that is, reducing information constraints regarding R&D-intensive firms and facilitating their earnings forecasts by financial analysts.

2. Institutional Background (AIPA)

2.1. An Exogenous Shock to Innovation Disclosure

Before 2000, there was a key feature in the U.S. patent system that made it quite exceptional compared to those in the rest of the world. Unlike other major patent systems (e.g., in Japan or Europe), patent application details were publicly disclosed in the United States only *after* the patent had been granted (Gallini 2002, Harhoff and Wagner 2009). This feature effectively postponed the disclosure function of patenting to the grant date, which was typically a few years after the application date. AIPA, enacted by the U.S. Congress on November 29, 1999, changed this feature by requiring patent applications filed in the United States to be publicly disclosed by the USPTO exactly 18 months after the application date, regardless of whether the patent was granted. Patent applicants who do not apply for foreign patents on the same invention can opt out of pre-grant publication. However, Graham and Hegde (2015) show that very few patent applicants opt out of the pre-grant publication. As a result, AIPA mandated that firms disclose key information about their R&D output in a standardized and credible way as required by patenting guidelines (Graham and Hegde 2015), even though the protection afforded by a patent does not start until the actual granting of the patent. For these reasons, Williams (2017) argues that AIPA as a policy change provides a suitable and natural setting for analyzing the effect of innovation disclosure. Accordingly, AIPA is used as an exogenous shock to patent disclosure in a number of recent studies (see, e.g., Hegde et al. 2018, Hegde and Luo 2018, Barrufaldi and Simeth 2020, Mohammadi and Khashabi 2020, Saidi and Zaldokas 2020, Chondrakis et al. 2021).

2.2. Variations in the Disclosure Effect of AIPA

The disclosure effect of AIPA is not uniform across all firms and industries and depends on their average (pre-AIPA) filing-to-grant time lags. In some technological fields in which firms are active and for which they file patents, there are longer time lags between patent application (filing) and grant dates; in other fields, this lag is shorter. For firms with longer pre-AIPA average time lags between patent application and grant dates, the impact of AIPA on disclosing corporate inventions is more significant. On the contrary, for firms for which patent grants often happen soon after patent applications, AIPA's impact is less significant. To illustrate, suppose that we compare a firm for which the average (pre-AIPA) time lag between its patent application and grant is 12 months with another firm for which the average time lag between its patent application and grant is 36 months. For the former firm, prior to AIPA's enactment, financial analysts already had access to the content of patent documents filed in the preceding year and earlier. However, for the latter firm, prior to AIPA, analysts had access only to the content of patent documents that were filed three years before or earlier, not to the more recently developed inventions. Hence, an analyst had more information on the former firm compared to the latter. As such, the effect of AIPA is larger for firms with longer filing-to-grant time lags. We use the heterogeneity in pre-AIPA time lags, at both the firm level and the industry level, as a basis for our empirical methodology.

2.3. Significance of the Disclosure Effect of AIPA

The AIPA disclosure channel has a significant effect on the information environment around affected firms as it provides novel and credible information at a significantly lower search cost. Regarding information novelty, one should note that before AIPA, voluntary disclosures of inventions—through alternative channels such as conference calls, web pages, or media postings—were quite rare for two main reasons: (1) A condition for granting patent rights is that an application should be filed at the patent office before the invention has been disclosed to the public. Disclosing an invention before patent filing makes it count as "prior art," and it thus becomes ineligible to receive patent protection.[2] (2) Besides the fear of leaking information on unprotected inventions to competitors, any disclosure outside of the USPTO would exclude the alternative protection option of secrecy in the event the patent application was rejected. Thus, in the majority of pre-AIPA cases, public disclosure and patent grants happened at the same time, and pre-grant disclosure was very rare.

Although other international patent systems—such as those of the EU and Japan—already enforced the 18-month disclosure mandate before AIPA, there is little evidence about whether international patent filings pre-AIPA would have provided access to patent application details and, as a result, reduced the novelty and significance of disclosure by AIPA. In reality, disclosures by international filings are not effective or comparable to AIPA in reducing information asymmetries (see Hegde and Luo 2018). One reason for this is

[2] The U.S. patent system allows for a short "general grace period," which is typically 12 months. Any technology that is publicly disclosed beyond this period is not eligible to be patented, as it is regarded as "prior art" (Franzoni and Scellato 2010). The Worldwide International Patent Office (WIPO) and the European Patent Office (EPO) do not consider a grace period.

that patents filed in other intellectual property jurisdictions were mostly filed in foreign languages; thus, using them were not very convenient for analysts. Another reason is that these international applications were typically not cataloged and searchable for financial analysts. In most cases, this information was not digitized and not available online. Last, foreign filings constituted a very small part of firms' patents.[3]

Disclosure through AIPA is more credible and less subjective than the information conveyed via other disclosure channels. This is because the technology holders may risk delay or denial of their patent applications by making imprecise claims. As Hegde and Luo (2018, p. 654) argue, "Disclosure through an official, standardized, and centralized repository may affect market transactions in ways that cannot be achieved through [other] voluntary disclosure."

Finally, AIPA also systematically reduces the information search cost for financial market players. The USPTO catalogs patent publications and makes them more accessible and searchable through its centralized repositories. Therefore, discovering the disclosed technological information has become considerably easier than in the pre-AIPA period.

3. Theoretical Background and Hypothesis Development

3.1. Research and Development Disclosure and Financial Analysts

R&D projects are inherently uncertain (Arrow 1962, Lev 2000, Kothari et al. 2002). There are some aspects of R&D projects that are unknown to both corporate insiders and outsiders—for example, uncertainty regarding new scientific discoveries. There are, however, other aspects of R&D projects that insiders possess and develop knowledge of but are not typically diffused to externals—for example, details on a recently developed technology or an R&D project failure. These aspects are kept secret to mitigate the costs associated with information leakage to competitors (Brown and Martinsson 2018). This is how R&D projects generate information asymmetry between managers and financial markets (Aboody and Lev 2000, Coff and Lee 2003), which, in turn, leads to lower analyst forecast accuracy (Gu and Wang 2005). The information asymmetry generated by R&D has adverse effects on public firms, ranging from a higher cost of capital to underinvestment and undervaluation (Brennan et al. 1993, Womack 1996, Hong et al. 2000, Piotroski and Roulstone 2004, Ertimur et al. 2007, Litov et al. 2012, Lui et al. 2012, Gurun et al. 2015).

Brown and Martinsson (2018) argue that a richer information environment reduces information asymmetry between markets and corporate insiders and generates broader capital market benefits.[4] Financial analysts are key players in this context through their role in gathering, validating, and analyzing the information

[3] In our sample, on average (median) 7.6% (1.2%) of firms' patents had foreign priority in the pre-AIPA period.

[4] Bushee and Friedman (2015) show that higher-quality disclosure standards are associated with stock returns that are less sensitive to noise driven by investors' short-term moods. They argue that by having access to informative corporate disclosures, investors are more likely to base investment decisions on such disclosures and less likely to rely on misattributed feelings like moods.

disclosed by firms. Financial analysts generate earnings forecasts and make buy or sell recommendations to market participants (Healy and Palepu 2001, Merkley 2014). This institutional function of analysts is central in making firms' disclosures effective in the capital market as well as in reducing the adverse effects of information asymmetry. Consistent with the above, Lang and Lundholm (1996) show that the ratings that an analyst assigns to the quality of a firm's disclosure are negatively related to the analyst's earnings forecast error on that firm. Similarly, Hope (2003) highlights that the amount and quality of disclosure are positively associated with the accuracy of analyst forecasts.

The literature thus far, has studied traditional disclosure channels as sources of information for financial analysts. In addition to these channels, one can consider patent documents as a special source of a firm's R&D disclosure to markets. The prospect of legal protection offered by patents encourages the disclosure of inventions (Long 2002) and facilitates the functioning of markets for technologies and ideas (Anton and Yao 2002, Gans et al. 2008, Arora and Gambardella 2010, Williams 2017). In line with this argument, Hegde and Luo (2018) provide evidence on the positive effect of the pre-grant disclosure on innovation licensing transactions. Their study finds that inventions are significantly more likely to be licensed after their disclosure and between publication and grant, which supports the facilitative role of disclosure. Consistent with this, Mohammadi and Khashabi (2020) show that pre-grant disclosure facilitates investment tie formation between start-ups and corporate venture capitals. A recent and emerging stream of literature also documents capital market reactions to (pre-grant) patent disclosures (Kogan et al. 2017, Hedge et al. 2018). Nevertheless, the degree to which an analyst can correctly digest this information—and consequently its precise effect on analyst forecast accuracy—is as yet unknown.

3.2. Pre-Grant Patent Disclosure and Analyst Forecast Accuracy

As discussed in the previous sections, the pre-grant disclosure of patent documents provides a reliable source of information about a firm's innovative processes and products. Besides technical and innovative details, the pre-grant disclosure of patent documents reveals other relevant information of value for a financial analyst. For instance, it highlights the scope and potential of the R&D activities conducted by a firm, which were previously unknown. Public companies typically announce their innovation targets and agendas in conference calls, and thus pre-grant disclosures reveal whether these goals are being met, are close to being met, or are far from being met. This information has important implications for the forecasting of R&D expenditures. The patent application document also reveals the research outcome, and it therefore helps analysts to estimate the magnitude of expenses for the development phase of the corresponding invention. Such estimates facilitate forecasting of a patent applicant's future spending (Amir and Lev 1996, Merkley 2014). Moreover, pre-grant disclosure also facilitates forecasting of the applicant's future earnings through licensing and royalty revenues in technology markets. In some cases, firms already start to commercialize innovative products before the patent grant (marked as "patent pending" products on the market). Pre-grant disclosure assists analysts in evaluating the potential for such future earnings, which may be realized before patent grants. Finally, since pre-grant disclosures are cataloged and standardized, they facilitate a better comparison between a firm's invention and the inventions of its competitors. Therefore, analysts are able to predict R&D responses, races, and their effects more efficiently.

To summarize, we hypothesize that information disclosed in patent documents reduces information asymmetry between firms and capital markets and consequently reduces forecast error about them:

H1. The pre-grant disclosure of patent documents reduces analyst forecast error about the applicant firm.

In our theoretical arguments, focus is placed on the component of forecast error that stems from information asymmetry caused by R&D projects. Gu and Wang (2005) argue that accessing information and accurately evaluating the future performance of R&D-intensive firms are increasingly difficult. On the contrary, firms with low R&D intensity are more predictable, and further information does not convey significant forecast benefits about them. As firms with higher R&D intensity suffer more from information asymmetry, we hypothesize that the pre-grant disclosure of patent information for these firms will have a larger impact on financial analysts' forecast accuracy relative to firms with lower R&D intensity:

H2. The pre-grant disclosure effect of patents in reducing analyst forecast error is larger for firms with higher R&D intensity.

H2 practically serves as a test of the mechanism through which our theoretical arguments in H1 materialize: if a key source of analysts' forecast error about a firm is its R&D projects, we should expect pre-grant disclosure to reduce the forecast error more for firms with higher R&D intensity.

Next, we turn to the characteristics of firms' patent portfolio as a boundary condition for the effectiveness of this disclosure mechanism. It is important to note that firms' technologies and patent portfolios differ significantly in their characteristics (Hall et al. 2005, Gambardella et al. 2008). For instance, whereas one firm might generally patent narrow and less original technologies, another firm might often file very broad or more original technologies. We argue that the scientific breadth and originality of a firm's patents can affect the advantage that patent disclosure conveys to financial analysts.

More original and broader patents are usually related to wider technical fields (Lerner 1994, Harhoff and Wagner 2009) or are built on relatively broader sets of scientific areas (Trajtenberg et al. 1997). For financial analysts who specialize in certain fields, understanding the precise prospects of a broad patent is challenging and costly. Also, original patents are likely to entail more novel and complex knowledge in scientific frontiers for which analysts could lack the expertise to analyze or would need to exert costlier effort to understand (Benner 2010). These factors distort the disclosure function of patents, especially for nonscientist audience. Thus, analysts are likely to make both upward and downward errors when evaluating public firms that are filing more original and scientifically broader patents. As a result, we hypothesize that pre-grant patent disclosure would be less effective in reducing analysts' forecast error in such cases.

H3. The pre-grant disclosure effect of patents in reducing analyst forecast error is smaller for firms issuing more original and scientifically broader patent applications.

Besides its technological portfolio, a firm's legal protection landscape also influences the effectiveness of pre-grant patent disclosure. One of the most relevant legal protections for R&D-intensive firms is provided through laws on trade secrets (Cohen et al. 2000).[5] Trade secrets laws have direct implications for corporate policy on transparency and consequently on the information asymmetry between firms and capital markets (Glaeser 2018). Trade secrets are information items that derive future economic value from not being appropriable by competitors. It is estimated that U.S. public firms own $5 trillion in trade secrets, which is approximately 20% of their total market capitalization (U.S. Chamber of Commerce 2016). Given this level of economic significance, the legal protection regime concerning trade secrets would significantly shape the information environment of firms.

Firms naturally withhold their valuable information from the public for fear of misappropriation by competitors. However, in some circumstances, managers may find benefits in publicly revealing some of this information—for example, to signal their firm's performance and prospects to investors and capital markets (Bhattacharya and Ritter 1983, Houston et al. 2010, Chen et al. 2011, Balakrishnan et al. 2014). However, the presence of stronger trade secrets protection—such as the Uniform Trade Secrets Act in the United States–discourages such public disclosures and leads firms toward more secrecy. For a piece of valuable information to be legally considered and protected as a trade secret, it should be completely withheld from the public by the owner (Png 2017). Accounting reports also do not easily communicate the value of these trade secrets (Dechow et al. 2010). As a result, the presence of trade secrets protection increases the information asymmetry between firms and capital markets (Glaeser 2018). Thus, pre-grant patent disclosure in these environments is expected to have a more significant effect.

In summary, we argue that in environments with stronger trade secrets protection, information asymmetry regarding R&D is aggravated. Therefore, we hypothesize that pre-grant patent disclosure in such environments has a bigger impact on reducing analysts' forecast error.

[5] It is important to highlight that firms may choose alternative protection means (e.g., complementary assets, alliances, and lead timing) and disclosure strategies (e.g., open science and patent-publication disclosure); see Gans et al. (2017) for an overview. Our theoretical arguments regarding the interplay of disclosure and trade secrets is based on a *ceteris paribus* assumption: we argue that all else being equal, the effect of pre-grant disclosure in reducing analyst forecast error is larger on firms with stronger trade secrets protection.

H4. The pre-grant disclosure effect of patents in reducing analyst forecast error is larger for firms with stronger trade secrets protection.

4. Data and Sample Construction

4.1. Data

We build our sample by merging three sources of data: (1) Standard and Poor's Compustat data on publicly traded firms in the United States, (2) the Institutional Brokers Estimate System (I/B/E/S) data on financial analysts, and (3) the Kogan et al. (2017) patent database, which contains information on patent applications and grants, the identity of patent assignees, and citations. This data set consists of all U.S. patents granted during the period 1926–2010 (7.8 million patents). We complemented the patent data by using Patentsview (https://patentsview.org/, version May 2018) for all analyses of patent characteristics (i.e., originality, scope, and forward citations). Following Hall et al. (2005), we extract information for all publicly traded manufacturing companies in the United States (Standard Industrial Classification [SIC] 2000–3999). Also, following the patent literature, we apply the following general selection criteria for sample firms: (1) total assets of more than $10 million, (2) R&D expenses amounting to no more than sales, and (3) belonging to an industry, defined as four-digit SIC codes, with at least five firms.

We match firm-level data with patent data using the PERMNO identifier. Further, we match the outcome data with analysts' earnings forecasts provided by I/B/E/S. We limit the sample to firms with at least one patent before and one patent after AIPA. Our final sample includes 5,659 firm-year observations (837 firms) between 1995 and 2005. We limit the sample to this period because AIPA was implemented in 2000, which is the midpoint of our analysis window. Online Appendix 1, Panel A shows the distribution of observations across different years.

4.2. Measure of Analysts' Forecast Error

Following Dhaliwal et al. (2012), we measure analysts' forecast error as the average of the absolute value of the difference between the forecasts provided by the analysts and actual earnings, normalized by the stock price at the beginning of the year:

$$Analyst\ error_{it} = \left(\frac{1}{N_{it}}\sum\left|\left(EPS\ forecast_{jit} - \ actual\ EPS_{it}\right)\right|/P_{it}\right). \tag{1}$$

In Equation (1), *EPS* stands for the earnings per share, subscript *i* refers to firm *i*, subscript *j* refers to analyst *j*, and subscript *t* refers to time (fiscal year). *N* refers to the number of analysts following firm *i* at time *t*. In the main analysis, we limit the forecast horizon to the current-year forecasts (*Analyst error*). The average forecast error in our sample is 2.8%. We also perform analyses using the forecast for the next year (*Analyst* *error (t+1)*) and the year after (*Analyst error (t+2)*). The average forecast error of the next year and the year after in our sample is 3.9% and 4.6%, respectively. Online Appendix 1, Panel B reports the number of observations as well as the mean, and the standard deviation of *Analyst error* across all industries (two-digit SIC).

4.3. Measures of Disclosure Shock and Treatment

The first independent variable for our difference-in-differences strategy is the shock dummy (*Post-AIPA*), which takes a value of one for years after the United States enacted AIPA (after 2000) and zero for years before. We define the continuous treatment measure, *Treatment*, as the average time lag between patent applications and patent grants for each firm during 1996–1999. In a robustness check, we also measure this variable at the level of industry (four- and two-digit SIC). To calculate the treatment, we first measure the time lag between patent applications and grants for each patent class during 1996–1999. Then, for each firm, we calculate the weighted average of the time lag between patent applications and grants based on patenting activities in 1996–1999. We calculate the measure in months and transform it into years by dividing it by 12. The treatment variable is on average 2.56 years (30.7 months). Online Appendix 1, Panel B reports the mean and the standard deviation of the treatment variable across all industries (two-digit SIC). The firms in the Electronic and other Electrical Equipment and Components, except Computer Equipment (two-digit SIC 36), have on average the highest treatment value, followed by firms in Measuring, Analyzing, and Controlling Instruments (two-digit SIC: 38).

4.4. Measure of R&D Intensity

To capture within-industry heterogeneity of R&D intensity (H2), we divide the sample into two subsamples, including firms with higher than and firms with lower than industry-median (two-digit SIC) R&D intensity. A firm's pre-AIPA R&D intensity is calculated as the average of the firm's R&D intensity as observed during 1996–1999. R&D intensity is defined as R&D expenditures divided by sales. Following prior research, we replace the missing values for R&D with zero (e.g., Glaeser 2018). We also include the continuous measure of R&D intensity in all models as a control variable. In our sample, firms invest on average $243.6 million in R&D. This is equivalent to 6.2% of their sales.

4.5. Measures of Patent Originality and Breadth

To test H3, we measure the originality and breadth of patents by using the originality index as developed by Trajtenberg et al. (1997) and the scope index as introduced by Lerner (1994).[6] The originality index indicates

[6] Most measures used in the innovation literature were developed at the patent level (e.g., forward citation, originality, generality, and scope). However, researchers have also used these measures at the firm level to assess firm-level innovation (e.g., Lerner 1994, Hall et al. 2005).

the diversity of patents cited for a given patent. The originality index is computed as the Herfindahl index of technical classes of cited patents (Trajtenberg et al. 1997). For each firm, we compute the average originality for the pre-AIPA (1996–1999) patent portfolio. Then we classify firms with originality higher than the industry (two-digit SIC) median as the high-originality sample, while the rest are categorized as the low-originality sample.

Patent breadth refers to the scope of technological fields that it covers. Broader patents are usually related to a larger number of technological fields. Similar to Lerner (1994), we compute firm-level average patent scope, indicated by the number of different International Patent Classification codes of pre-AIPA (1996–1999) patents portfolios. We next classify firms with higher than the industry (two-digit SIC) median scope as the high-breadth sample and categorize the rest as the low-breadth sample.

4.6. Measure of Heterogeneity in Trade Secrets Protection

Glaeser (2018) shows that firms headquartered in states that adopted the Uniform Trade Secrets Act (UTSA) are more likely to pursue trade secrecy. Our measure of trade secrets protection is a dummy variable that is assigned a value of one for firms headquartered in a state that adopted UTSA and zero otherwise—for a detailed description of UTSA, see Png (2017) and Glaeser (2018). Online Appendix 1, Panel C shows the states where sample firms are headquartered and their effective year of UTSA. The enactment date of UTSA for the adopting states (except Pennsylvania, 2004, and Tennessee, 2000) was prior to AIPA (1999). As a robustness check, we exclude firms headquartered in Pennsylvania and Tennessee. The results remain similar.

4.7. Control Variables

Following the literature, we control for a host of variables that affect disclosure and forecast accuracy. All control variables are measured based on values at the end of the prior year (*t-1*). These variables include (1) the stock of patents, measured as the number of patent applications over the preceding three years (natural logarithm+1),[7] (2) institutional ownership, which measures the share of ownership by institutional investors, (3) a loss indicator, which is a dummy variable that equals one if the firm's net income is negative and zero otherwise, (4) earnings volatility, which is measured as the time-series standard deviation of earnings per share (EPS) of the last 10 years, (5) a leverage ratio, defined as the ratio of debt to assets, (5) the size of the firm, measured as the natural logarithm of total assets, (6) the natural logarithm of firm age, (7) the natural logarithm of stock turnover, and (8) the firm's market-to-book ratio. Also, following the analyst forecast literature, we control for analyst coverage in our model, which measures the number of security analysts tracking and issuing earnings forecasts for a firm during a specific year. On average (median), 10.98 (8) analysts cover a given firm

[7] As alternatives, we also use the number of patents in the previous year and previous two years and the number of patent applications in the current year. The results are very similar and are available upon request.

in our sample. Further, following Tan et al. (2011), we control for the natural logarithm of the average amount of time between the forecast date and actual earnings. On average, the time between the forecast and the actual earnings in our sample is 163 days. We also control for time-varying characteristic of industry (four-digit SIC) to capture other time-varying heterogeneities in a firm's industry—namely, the industry analyst error.[8] Furthermore, we control for industry concentration using the Herfindahl-Hirschman index (HHI) of revenue of industry. The HHI in our sample is on average 4.9%. In order to take into account macroeconomic changes that may affect the earnings forecast, we include year fixed effects.

We winsorize all continuous variables at the 1st and 99th percentiles to ensure that our results are not driven by outliers. Online Appendix 2 reports all variables and their definitions. Table 1 reports the descriptive statistics of all variables used in the main analyses, including the mean, standard deviation, p25, median, and p75.

5. Empirical Model

5.1. The Difference-in-Differences Model

To examine the relation between pre-grant patent disclosure and analyst forecast accuracy, we use a difference-in-differences strategy. This method allows us to estimate the effect of treatment on the analysts' forecast error as the outcome by comparing what happens to the outcome before and after the treatment, depending on the intensity of the treatment. Despite the continuous nature of the treatment variable in our model, the interpretation remains similar to that in a simple binary treatment model (Acemoglu et al. 2004, Angrist and Pischke 2009). We estimate the following specification for firm *i* and year *t*:

$$Analyst\ error_{it} = \beta_1\ Post\ AIPA_t + \beta_2 Treatment_i + \beta_3 Treatment_i \times Post\ AIPA_t + \beta_4\ Z_{i(t-1)} + \varepsilon_{it}. \quad (2)$$

In Equation (2), the forecast $error_{it}$ is the forecast error associated with firm i at time t. $Treatment_i$ is defined at the firm level and measures the intensity of the effect of AIPA. $Post\ AIPA_t$ is a dummy variable that equals one for the post-AIPA period, from 2001 to 2005. $Z_{i(t-1)}$ is a vector of time-varying controls, as discussed in the previous section. To control for a firm's invariant fixed effect and for time-variant macroeconomic conditions affecting all firms, we add firm and year fixed effects to the model. Due to the inclusion of these fixed effects in the analysis, the main model used in this study is reduced to the following:

$$Analyst\ error_{it} = \gamma_1 Treatment_i \times Post\ AIPA_t + \gamma_2\ Z_{i(t-1)} + Y_t + u_i + \varepsilon_{it}, \quad (3)$$

where u_i and Y_t denote firm and year fixed effects, respectively. The coefficient of interest in Equation (3) is γ_1. Given the continuous nature of our treatment variable, the difference-in-differences estimate should be interpreted as the average treatment effect on the treated (ATT); γ_1 indicates the effect on the outcome that

[8] Our results are robust to the exclusion of this control variable.

results from an increase in the treatment intensity. Further, since we are using panel data, error terms can be serially correlated for a given firm. Therefore, we cluster robust errors at the firm level. Alternatively, we also cluster standard errors at the year, industry, and industry-year levels. The results are very similar.

6. Results

6.1. Main Results (H1–H4)

Our main analysis focuses on the effect of disclosure due to AIPA on analyst forecast accuracy. Table 2 reports the results of our difference-in-differences analysis to test H1 (pre-grant patent disclosure improves analyst forecast accuracy) and H2 (pre-grant patent disclosure has a larger impact on analyst forecast accuracy for firms with higher R&D intensity). Model 1 reports the effect of AIPA on the forecast error within the full sample. The estimate shows that after the passage of AIPA, on average, analyst forecast errors decreased more for firms with a higher pre-AIPA time lag between patent application and grant (larger treatment intensity) relative to other firms. The coefficient of interest for *Post AIPA* × *treatment* is negative and statistically significant (a coefficient of –0.025, with a *p*-value = 0.014). This implies that for a one-standard-deviation increase in the treatment variable, the average analyst forecast error is reduced by around 23.75% of the mean value of analyst forecast error (0.028). These findings support H1.

To test H2, we divide our sample according to whether firms have higher pre-AIPA R&D intensity than the median of the industry (Model 2) or lower pre-AIPA R&D intensity than the median of the industry (Model 3). The empirical evidence is consistent with H2, confirming that the effect of treatment is larger for firms with higher R&D intensity (a coefficient of –0.028, with a *p*-value = 0.023) relative to firms with lower R&D intensity (a coefficient of –0.010, with a *p*-value = 0.484). The *p*-value for the test of differences between coefficients is equal to 0.453.[9]

Table 3 reports the results of our analysis to test H3 (pre-grant patent disclosure has a smaller effect on reducing analyst forecast error for firms issuing more original and broader patent applications) and H4 (the effect of pre-grant patent disclosure in reducing analyst forecast error is larger for firms with stronger trade secrets protection). We classify firms with pre-AIPA originality levels higher than the industry median as the high-originality sample (Model 1), while the rest are categorized as the low-originality sample (Model 2). We also classify firms with pre-AIPA scope levels higher than the industry median as the high-breadth sample (Model 3), while the rest are categorized as the low-breadth sample (Model 4).[10] The split sample analysis shows that the disclosure effect is most evident in firms with lower patent originality (Model 2: a coefficient of –0.031, with a *p*-value = 0.062) and lower patent breadth (Model 4: a coefficient of –0.032, with a *p*-value

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[9] We also used the annual R&D intensity relative industry. Result shows that higher R&D intensity is associated with more reduction in error.

[10] The sample is reduced in these analyses since for some firms we were not able to calculate originality and breadth in the pre-AIPA period.

= 0.026), whereas no similar effect is found in firms with higher patent originality (Model 1: a coefficient of –0.008, with a *p*-value = 0.427) and breadth (Model 3: a coefficient of –0.010, with a *p*-value = 0.520). The results show that the disclosure effect of patents in reducing analyst forecast error is less effective for firms issuing more original and broader patents, thereby supporting H3.[11] The coefficients are different from each other (Model 1 vs. Model 2: *p*-value = 0.007; Model 3 vs. Model 4: *p*-value = 0.042).

To test H4, we divide firms into two groups based on whether they are headquartered in states that have adopted UTSA. The results are provided under Models 5 and 6 in Table 3. The results support H4, confirming that the effect of the treatment is larger for firms headquartered in UTSA states (Model 5: a coefficient of –0.049, with a *p*-value = 0.002) versus firms headquartered in states that did not pass UTSA (Model 6: a coefficient of 0.006, with a *p*-value = 0.753).[12] The coefficients in Models 5 and 6 are statistically different from each other (*p*-value = 0.012).

6.2. Additional Analysis

6.2.1. The Impact of Pre-Grant Patent Disclosure Over Time. In the main analysis, we focus on current-year forecasts; in this section, we investigate the impact of disclosure for longer-term predictions. This is relevant because the technological information disclosed in patents may have some lag before their full effect on a firm's earnings is observed. In Table 4, similar to Dhaliwal et al. (2012), we illustrate the impact of disclosure on analyst forecast errors with a horizon of zero (Model 1, similar to the main analysis), one (Model 2), and two (Model 3) years. The results show that disclosure has a negative and statistically significant effect on all three forecast horizons (Model 1: a coefficient of –0.025, with a *p*-value = 0.014; Model 2: a coefficient of –0.029, with a *p*-value = 0.078; Model 3: a coefficient of –0.030, with a *p*-value = 0.007). The coefficients in Models 1–3 imply that a one-standard-deviation increase in the treatment is associated with 23.75%, 22.04%, and 19.46% better analyst forecast accuracy (relative to the mean of error), respectively. These results suggest that pre-grant disclosure is positively associated with analyst forecast accuracy in both short- and long-horizon forecasts.

6.2.2. Alternative Treatment Definitions. In this section, we investigate whether the main results are robust to alternative definitions of the treatment variable (Online Appendix 4). The main treatment variable (Model 1 in Online Appendix 4) is measured based on the weighted average time lag between patent applications and grants for each firm during 1996–1999. To calculate this treatment, we first measure the time lag between patent applications and grants for each patent class at the section level during 1996–1999. Then, for each firm, we calculate the weighted average of the time lag between patent applications and grants based on patenting

[11] As an alternative we divided sample based on being high on both originality and breadth. Results are similar and effect is smaller when firm have both higher originality and breadth than industry.

[12] As an alternative to using UTSA, we also use the data provided by Glaeser (2018) and divide the sample based on whether firms used trade secrets prior to AIPA. The results are consistent with our findings in Table 3. These results are reported in Online Appendix 3.

activities in 1996–1999. In Model 2, we calculate the treatment (*treatment 1*) based on the median of the time lag between patent applications and grants (instead of the weighted average) for each firm during 1996–1999. In Model 3 (4), we use the subsection of patent class instead of section (subsection and median instead of section and weighted average) to calculate the *treatment 2* (*treatment 3*) variable. The results show that the effect remains negative and statistically significant across all models (Model 1: a coefficient of –0.025, with a p-value = 0.014; Model 2: a coefficient of –0.031, with a p-value = 0.014; Model 3: a coefficient of –0.018, with a p-value = 0.002; Model 4: a coefficient of –0.017, with a p-value = 0.004).

In the main analysis, we calculate the treatment at the firm level. As a robustness test, we repeat the analysis using industry-level treatment definition. In Model 5 and 6, following Saidi and Zaldokas (2020), we use the average time lag between patent applications and grants for each firm's industry at four-digit (*treatment industry*) as well as two-digit SIC codes (*treatment industry2*). These treatment variables have the advantage of being less related to firm characteristics. The results are consistent with the main model and show that the industry-level treatments are negatively related to analyst forecast error (Model 5: a coefficient of –0.011, with a p-value = 0.004; Model 6: a coefficient of –0.053, with a p-value = 0.043).

6.2.3. Internal Validity of Difference-in-Differences Analysis. Our use of the difference-in-differences method is based on a few assumptions. In this subsection, we discuss how we verify the validity of the difference-in-differences approach by conducting several relevant analyses.

First, in our theoretical arguments, we assume that AIPA does not have a major effect on the firm's innovativeness or patenting, and only increases information disclosure through the publication of patent documents. In our setting, this assumption implies that an increase in the treatment variable after AIPA is not correlated with the frequency of patenting and the quality of innovations. To examine the validity of this assumption, we examine whether firm-level patenting and patent quality are significantly different pre- and post-AIPA. We measure firm-level patenting by calculating a firm's total annual number of patents (*Patent*) and total annual weighted number of patents (*Scaled patent*) in which each patent is weighted by the number of patents filed in the same year and technology class. Also, based on the total number of citations received by patents in the next five years from their application date, we proxy firm-level quality of innovation using two variables: the total number of forward citations for all patents (*Scaled citation*[13]) and the average number of forward citations per patent (*Average citation*). We also use the annual total value of patents (log) measured by Kogan et al. (2017). The results show that there are no statistically significant differences (p-values are, respectively, 0.126, 0.468, 0.301, 0.378, and 0.967) across the quantity and quality of patenting before and after AIPA (Table 5, Models 1–5). Similarly, we test whether AIPA changed firms' use of alternative protection

[13] Each citation is scaled by average citations to patents filed in the same year and in the same technology class.

mechanisms for their innovations (*Trade secrets*). Reassuringly, we find no significant relation between the treatment variable and the use of trade secrets (Table 5, Model 6).

Apart from innovativeness, firms might change their behavior and become more predictable because of the passage of AIPA. In that case, the observed effect may be due to changes in firm behavior and not because of patent disclosure. To alleviate this concern, we conduct a placebo test in which the dependent variable is the analyst forecast error from a time-series model of earnings. We use the random walk (RW) model because it is simple yet accurate (Bradshaw et al. 2012). Accordingly, we build the dependent variable in Table 5, Model 7 as the absolute value of differences between lagged EPS (EPS_{t-1}) and actual EPS (EPS_t) divided by lagged EPS (*RW EPS error)*. Model 7 shows that there is no statistically significant relation between the treatment level and the analyst forecast error from a time-series model of earnings (*p*-value = 0.261).

Second, the difference-in-differences analysis also relies on the parallel trends assumption in the pre-treatment period: if there was no shock, then we should not have observed any different trends between the treatment sample and the control sample. We verify this assumption by conducting two sets of analyses, following Roberts and Whited (2013). In doing so, we repeat our analysis on a 10-year period prior to AIPA (1990–1999) with a placebo shock. We assume that in the middle of this 10-year period (1995), a fake AIPA occurred (*fake-AIPA*). We would thus expect *not* to observe similar effects to the real AIPA in this analysis. Repeating our analysis using this new time window shows (Online Appendix 5, Model 4) that the coefficient (*Treatment* × *fake AIPA*) is positive (*p*-value = 0.793). Then we repeat our analysis by including pre-AIPA dummies (t-1 and t-2) and their interactions with the treatment. We do this first separately (model 1 and model 2) and then include them together (model 3). The results show that the effects of pre-AIPA dummies are are positive (*p*-values = 0.384 and 0.163, respectively), confirming the validity of the empirical strategy (Online Appendix 5, Model 3).

Another potential concern is that some industry characteristics might be correlated with our treatment variable[14] such that the results are not necessarily driven by the treatment. To address this concern, we analyze the correlations between several pre-AIPA industry-level characteristics (at four-digit SIC[15]) and the treatment variable at the industry level. These industry-level characteristics include average R&D expenditure (R&D), capital expenditure (*CAPX*), sales growth, number of patents, and average citations per patent. The results (Online Appendix 6) does not show a specific pattern between the treatment variable and these industry-level characteristics (*p*-values = 0.141, 0.414, 0.554, 0.116, and 0.613, respectively).

6.2.4. Internet Bubble and Alternative Forecast Error Definitions. In this section, we discuss several additional analyses performed to test the robustness of our difference-in-differences methodology. First, AIPA

[14] This concern is more serious when we use the treatment at the industry level instead of the firm level. Hence analyses uses industry level treatment.
[15] If we use two-digit SIC, the results are similar.

coincided with the internet (dot-com) bubble and the stock market crash that followed. One concern is that the potential concurrent effect of the dot-com bubble might have impacted our results. Our sample includes only manufacturing firms, whereas the dot-com bubble was mainly a shock to firms in the information technology industry, which are classified as part of the service, not the manufacturing sector. Therefore, this concern should be less severe in our setting. Nevertheless and following Ljungqvist and Wilhelm (2003), we exclude those industries that were most affected by the dot-com bubble.[16] The results (reported in Online Appendix 7, Model 1) remain similar to our results in the main analysis.

Second, in our analysis, as the main dependent variable, we use the standard measure of analyst forecast error, which is the average of the absolute value of the difference between the forecast provided by the analysts and the actual earnings, normalized by the stock price at the beginning of the year. To alleviate the concern that our results are driven by outliers, we take a number of steps. First, we winsorize analyst forecast error in the main analysis. Second, we create an alternative variable (*Error norm*), which is calculated as the difference between the analyst forecast error of a firm and the average analyst forecast error of the industry divided by the average forecast error of the industry (Online Appendix 7, Model 2). We find the results to be very similar to the results of our main analyses.

Analysts could issue more than one forecast for a firm in a given year (Bartov et al. 2002). As a robustness check (Online Appendix 7, Model 3), we consider only the last forecast of the year (*Error last*) and find similar results as in our main analysis. Finally, to ensure that the denominator of analyst forecast error does not drive our results (i.e., the stock price at the beginning of the year), we alternatively normalize the variable by the absolute actual EPS (*Error 2*). The results (Online Appendix 7, Model 4) remain similar to those in our main analysis, thereby providing additional support for H1.

6.2.5 Event-Study Analysis. The difference-in-differences approach used thus far has the advantage of exploiting an *exogenous* policy change (AIPA) to establish causality. The treatment in this approach is based on the filing-to-grant time lags of firms' pre-AIPA patent portfolios. Thus, it does not directly test whether new patent disclosure drives the increase in analyst accuracy. An alternative and more direct test of this mechanism is the event-study approach. This approach examines the impact of a patent disclosure on the accuracy of subsequent analysts' forecasts of the patenting firm. While this empirical approach is not based on an exogenous shock, it has the advantage of testing the assumption that published patents are a source of new information for analysts. In this section, we explain this empirical strategy and its results.[17]

[16] The excluded industries correspond to SIC codes 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), and 4899 (communication services).

[17] In Online Appendix 8, we discuss the challenges of an event study in the context of analyst forecasts and present alternative approaches that we use to address these challenges. In this section due to brevity, we present only one of these approaches.

Following an event-study approach, we examine whether the forecast accuracy of an analyst about a firm improves within a short time window after a patent disclosure by that firm. Since forecast accuracy generally improves over time, it is also important to consider counterfactual increases in accuracy in the empirical design. We therefore build a control group to account for this time trend and to ensure that the estimated effect is driven by the patent disclosure.

Accordingly, we focus on an event-study specification in which the unit of analysis is the analyst-firm-*revision round* level. The term "revision round" refers to the period between a given analyst's two consecutive forecasts. The dependent variable in our event-study approach is the absolute analyst forecast error at the end of a revision round. This variable is defined as the absolute value of differences between forecasted EPS and actual EPS divided by actual EPS. We also use a relative analyst forecast error as an alternative dependent variable, defined as the absolute value of differences between forecasted EPS and actual EPS divided by stock price at the beginning of the year. As mentioned above, the main explanatory variable—i.e., the event—is a dummy variable that takes a value of one if a patent disclosure has taken place during the *revision round* and zero otherwise. We define an analyst-firm-revision round as a treatment round if it contains at least one patent disclosure. We define an analyst-firm-revision round as a control round if it contains no patent disclosure. Also, given that long revision rounds might be noisy and less informative about the effect of a disclosure, we limit the length of revision rounds to a maximum of 120 days in the main specifications. We also report analyses using 60 and 90 days limit as robustness checks. In all specifications, we control for firm, analyst, and year fixed effects in addition to the control variables included in Table 2. We also control for the length of the revision round and the time to actual earnings announcement.

The results of the event-study analyses are presented in Table 6. The results show that a forecast revision after a patent disclosure has on average a smaller error relative to an otherwise similar forecast revision without a patent disclosure. More specifically, Models 1–3 show that patent disclosure reduces an analyst's forecast error by 0.6–1.5 percentage points. These are equivalent to a reduction of 4%–11% in the mean of forecast error. In Models 4–6, where we use relative forecast error as the dependent variable, the results are similar and significant at the 1% level.[18]

Table 7 reports the results from the test of H2–H4. Column 1 replicates the main effect of disclosure from Table 6. In Column 2, we include the treatment dummy and its interaction with R&D intensity. We note that the interaction term conveys an additional negative effect on the analyst forecast error when there is a patent disclosure (p-value = 0.002). This result supports H2. In Columns 3 and 4, we include the treatment

[18] In addition, we perform a "dose-response" analysis, checking if multiple patent disclosures within a revision round are associated with larger accuracy gains. To that end, we repeat the event study, restricting the sample to revision rounds with at least one patent disclosure, and use the logged number of patent disclosures during the round as the explanatory variable. The results (Online Appendix 9) show that the larger the number of patent disclosures during a revision round, the bigger the increase in analyst forecast accuracy.

dummy and its interactions, respectively, with patent originality and patent breadth.[19] In both models, the coefficient of the interaction term is positive and statistically significant (Model 3: a coefficient of 0.020, with a *p*-value = 0.058; Model 4: a coefficient of 0.002, with a *p*-value = 0.057). These results thus support H3. Lastly, Column 5 reports the result from the test of H4. We include an interaction term between the UTSA dummy and the treatment dummy. UTSA is associated with an extra reduction in error by 1.9 percentage points (equivalent to a 13.8% reduction when compared to the mean error) when a patent disclosure occurs. Thus, the result supports H4. Overall, the event-study analysis demonstrates that our findings using difference-in differences approach are robust.

7. Conclusion

This study measures the extent to which innovation disclosure (through pre-grant patent documents) improves analyst forecasts of R&D-intensive firms. Taking advantage of a legislative shock to the U.S. patent system (AIPA), we find that pre-grant patent disclosure significantly improves analyst forecast accuracy. This improvement is observed across both short- and long-horizon forecasts. The disclosure effect of AIPA is significantly larger for firms with higher R&D intensity. Yet, firms disclosing scientifically broader and more original patents experience less improvement in analyst forecast accuracy. Finally, we find that AIPA's disclosure effect is larger for firms in states with better legal protection of trade secrets. These results are consistent and robust across alternative empirical approaches and robustness checks.

Our results indicate that financial analysts process and benefit from the information disclosed in patent documents even before the patent grant. The findings also highlight that, aside from the advantages created from the legal protection function, patenting creates value for R&D-intensive firms through the disclosure function. Therefore, our findings also have implications for the trade-off between patenting and secrecy for R&D-intensive firms.

AIPA is a specific disclosure channel that requires inventions to be published through a credible, standardized, and centralized repository. The specificity of this setting implies that generalizing our results to settings in which other types of innovation disclosure might take place should be done cautiously. Our results mainly highlight the *positive* effects of pre-grant patent disclosure on capital market players. Future research could consider potential *negative* impacts of pre-grant patent disclosure through AIPA. For instance, a valid concern, also raised during the AIPA debates in the U.S. Congress, is that requiring firms to disclose their technology through patent application before a patent is granted may discourage firms from seeking patents for their inventions. Also, our findings show that firms issuing more original and novel patents do not benefit from disclosure in terms of improved forecast accuracy. This may lead managers with strong career concerns to

[19] If there is more than one patent in a revision round, we consider the maximum value of originality and breadth for patents in that revision round. If there is no patent, we replace the value with zero.

chiefly focus on less risky, narrower, and more incremental R&D projects. These potential mechanisms represent a fruitful avenue for future research.

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Table 1. Summary Statistics of Variables Included in the Main Regressions (*N* = 5,659)

	Mean	Std. dev.	p25	Median	p75
Analyst error	.028	.104	.001	.004	.014
Analyst error(t+1)	.035	.110	.003	.008	.026
Analyst error(t+2)	.041	.097	.004	.013	.037
Treatment	2.56	.266	2.354	2.482	2.865
Post AIPA	.439	.496	0	1	1
High R&D	.515	.5	0	1	1
High originality	.571	.495	0	1	1
High breadth	.502	.5	0	1	1
UTSA	.632	.482	0	1	1
R&D intensity	.062	.073	.01	.032	.094
Patent stock (log)	3.215	1.861	1.792	2.996	4.466
Institutional ownership	.524	.249	.36	.572	.716
Loss	.179	.383	0	0	0
Earnings volatility	.015	.016	.005	.01	.017
Debt to assets	.494	.21	.329	.504	.638
Assets (log)	6.913	1.805	5.521	6.763	8.184
Age (log)	2.646	.636	2.197	2.89	3.178
Stock turnover (log)	2.438	.871	1.865	2.429	3.014
Market-to-book ratio	2.038	1.206	1.248	1.629	2.36
Analyst coverage	10.98	9.362	4	8	15
Time to forecast (log)	5.078	.421	5.008	5.142	5.249
Industry analyst error	.054	.153	.007	.016	.044
Industry concentration	.049	.025	.033	.044	.054

Note. This table summarizes the variables used in regression analysis. Variable definitions are provided in Online Appendix 2.

Table 2. Impact of AIPA on Analyst Earnings Forecast Error

	(1)	(2)	(3)
Sample	Full sample	High R&D	Low R&D
Post AIPA × Treatment	-0.025**	-0.028**	-0.010
	(0.010)	(0.012)	(0.014)
R&D intensity	0.292***	0.291***	-0.004
	(0.062)	(0.067)	(0.112)
Patent stock (log)	-0.005*	-0.005**	-0.004
	(0.003)	(0.002)	(0.005)
Institutional ownership	-0.021*	-0.026**	-0.039*
	(0.012)	(0.012)	(0.020)
Loss	0.010*	0.005	0.012
	(0.005)	(0.007)	(0.010)
Earnings volatility	-0.071	-0.141	-0.132
	(0.218)	(0.289)	(0.294)
Debt to assets	0.035**	0.036*	0.067***
	(0.017)	(0.019)	(0.025)
Assets (log)	0.012**	0.006	0.008
	(0.005)	(0.005)	(0.009)
Age (log)	0.022**	0.033***	0.028*
	(0.010)	(0.010)	(0.016)
Stock turnover (log)	-0.002	-0.008	0.003
	(0.004)	(0.005)	(0.005)
Market-to-book ratio	-0.008***	-0.008***	-0.010***
	(0.001)	(0.002)	(0.003)
Analyst coverage	-0.001**	-0.000	-0.001*
	(0.000)	(0.000)	(0.001)
Time to forecast (log)	0.008**	0.018***	-0.001
	(0.004)	(0.005)	(0.005)
Industry analyst error	0.135***	0.101**	0.175***
	(0.030)	(0.041)	(0.047)
Industry concentration	0.224	0.304*	0.105
	(0.155)	(0.161)	(0.289)
Year FE	YES	YES	YES
Firm FE	YES	YES	YES
N	5,659	2,717	2,560
Adjusted R^2	0.538	0.613	0.436

Notes. This table provides the results of our main regression analysis. The dependent variable in all models is analyst forecast error (*Analyst error*), measured as average of the absolute difference between the actual EPS and the forecasts of analysts scaled by the stock price at the beginning of the year. Model 1 includes all firms in the sample. Model 2 (3) includes firms with lower (higher) pre-AIPA R&D intensity than median of industry. Clustered robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. Heterogeneous Effect of Public Disclosure of Patents

	(1)	(2)	(3)	(4)	(5)	(6)
	High originality	Low originality	High breadth	Low breadth	UTSA = 1	UTSA = 0
Post AIPA × Treatment	-0.008	-0.031*	-0.010	-0.032**	-0.049***	0.006
	(0.011)	(0.017)	(0.015)	(0.014)	(0.016)	(0.019)
Control	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	3011	2266	2650	2627	3551	2063
Adjusted R^2	0.599	0.461	0.631	0.399	0.506	0.642

Notes. The dependent variable in all models is analyst forecast error (*Analyst error*), measured as average of the absolute difference between the actual EPS and the forecasts of analysts scaled by the stock price at the beginning of the year. Model 1 includes firms with higher than industry median patent originality. Model 2 includes firms with lower than industry median patent originality. Model 3 includes firms with higher than industry median patent scope. Model 4 includes firms with lower than industry median patent scope. Model 5 includes firms headquartered in states that passed UTSA, and Model 6 includes firms headquartered in states that did not pass UTSA. All models include all control variables: R&D intensity, patent stock, institutional ownership, loss, earnings volatility, debt to assets, assets (log), age (log), stock turnover (log), market-to-book ratio, analyst coverage, time to forecast, industry analyst error and industry concentration in addition to firm and year fixed effects. Clustered robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Impact of AIPA on Analyst Earnings Forecast Error with Different Time Horizons

	(1)	(2)	(3)
Dep. var.	Analyst error	Analyst error(t+1)	Analyst error(t+2)
Post AIPA × Treatment	–0.025**	–0.029*	–0.030***
	(0.010)	(0.016)	(0.011)
Controls	YES	YES	YES
Year FE	YES	YES	YES
Firm FE	YES	YES	YES
N	5,659	5,192	2,897
Adjusted R^2	0.538	0.653	0.747

Notes. The dependent variable in Model 1 is current-year analyst forecast error (*Analyst error*), measured as average of the absolute difference between the actual EPS and the forecasts of analysts scaled by the stock price at the beginning of the year. Dependent variables in Models 2 and 3 are analyst forecast error for the next year (*Analyst error (t+1)*) and the year after (*Analyst error (t+2)*), respectively. All models include all control variables: R&D intensity, patent stock, institutional ownership, loss, earnings volatility, debt to assets, assets (log), age (log), stock turnover (log), market-to-book ratio, analyst coverage, time to forecast, industry analyst error, and industry concentration in addition to firm and year fixed effects. In model 2 we control for Analyst coverage (t+1) and industry analyst error (t+1). In model 2 we control for Analyst coverage (t+2) and industry analyst error (t+2). Clustered robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Effect of AIPA on Firms' Patenting Frequency, Quality of Patents, and Predictability of Earnings per Share

Dep. var.	(1) Patent	(2) Scaled patent	(3) Scaled citation	(4) Average citation	(5) Patent value (log)	(6) Trade secret	(7) RW EPS error
Post AIPA × Treatment	45.615 (29.807)	0.011 (0.016)	22.947 (22.193)	–0.089 (0.101)	0.006 (0.138)	–0.007 (0.060)	–0.212 (0.188)
Controls	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
N	5,659	5,659	5,659	5,659	5,659	5,659	5,632
Number of firms	837	837	837	837	837	837	835
Adjusted R^2	0.873	0.884	0.883	0.434	0.925	0.571	0.146

Notes. In Model 1, the dependent variable is yearly total number of patents. In Model 2, the dependent variable is yearly total number of weighted patents in which each patent is weighted by the number of patents filed in the same year and same technology class. In Model 3, the dependent variable is annual total number of citations scaled by average citation to patents filed in the same year and same technology class. In Model 4, the dependent variable is the average number of forward citations per patents. In Model 5, the dependent variable is yearly value of all patents measured by Kogan et al. (2016). In Model 6, the dependent variable is an indicator equal to one if the firm's 10-K filing mentions "trade secret" or "trade secrecy" (Glaeser 2018). In Model 7, the dependent variable (Random Walk (RW) EPS error) is absolute value of differences between lagged EPS (EPS_{t-1}) and actual EPS (EPS_t) divided by lagged EPS. All models include all control variables: R&D intensity, patent stock, institutional ownership, loss, earnings volatility, debt to assets, assets (log), age (log), stock turnover (log), market-to-book ratio, analyst coverage, time to forecast, industry analyst error, and industry concentration in addition to firm and year fixed effects. Clustered robust standard errors are reported in parentheses.

Table 6. Event-study Analyses at Analyst-Firm-Revision Level Using Revision Length of 120, 90, and 60 days

	(1)	(2)	(3)	(4)	(5)	(6)
Revision length	120 days	90 days	60 days	120 days	90 days	60 days
Dep. var.	Absolute forecast error			Relative forecast error		
Treatment	–0.015***	–0.006***	–0.007***	–0.004***	–0.003***	–0.004***
	(0.002)	(0.002)	(0.003)	(0.000)	(0.001)	(0.001)
Control	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES	YES	YES
N	78,434	57,609	37,342	77,547	56,950	36,949
Adjusted R^2	0.254	0.255	0.259	0.321	0.335	0.336

Notes. The unit of observation is an analyst-firm-revision round. A revision round is the period between two consecutive analyst forecasts about a given year's annual EPS. The dependent variable in Models 1–3 (4–6) is absolute (relative) error of the analyst forecast at the end of the revision round. The treatment observations are revision rounds during which a patent publication has occurred. All models include all control variables in Table 2 (R&D intensity, patent stock, institutional ownership, loss, earnings volatility, debt to assets, assets (log), age (log), stock turnover (log), market-to-book ratio, analyst coverage, time to forecast, industry analyst error, and industry concentration, in addition to length of revision (log), time to earnings announcement (log), firm, analyst, and year fixed effects. Clustered robust standard errors are reported in parentheses. *** indicates statistical significance at the 1% level.

Table 7. Event-study Analyses at Analyst-Firm-Revision Level Testing Hypotheses H1–H4

	(1) H1	(2) H2	(3) H3	(4) H3	(5) H4
Treatment	–0.015***	–0.008***	–0.030***	–0.021***	–0.002
	(0.002)	(0.002)	(0.008)	(0.004)	(0.003)
Treatment × R&D intensity		–0.069***			
		(0.022)			
Originality			0.008		
			(0.011)		
Treatment × Originality			0.020**		
			(0.010)		
Breadth				0.001	
				(0.001)	
Treatment × Breadth				0.002**	
				(0.001)	
UTSA					0.030**
					(0.010)
Treatment × UTSA					–0.019***
					(0.003)
R&D intensity	0.291***	0.222***	0.191***	0.191***	0.189***
	(0.055)	(0.056)	(0.055)	(0.055)	(0.055)
Control	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES	YES
N	78,434	78,434	78,434	78,434	78,434
Adjusted R^2	0.254	0.254	0.254	0.254	0.254

Notes. The unit of observation is an analyst-firm-revision round. A revision round is the period between two consecutive analyst forecasts about a given year's annual EPS. The dependent variable in Models 1–3 (4–6) is absolute (relative) error of the analyst forecast at the end of the revision round. The treatment observations are revision rounds during which a patent publication has occurred. All models include all control variables in Table 2 (R&D intensity, patent stock, institutional ownership, loss, earnings volatility, debt to assets, assets (log), age (log), stock turnover (log), market-to-book ratio, analyst coverage, time to forecast, industry analyst error, and industry concentration), in addition to length of revision (log), time to earnings announcement (log), firm, analyst, and year fixed effects. The length of revision round in all models is 120 days. Robust standard errors are reported in parentheses. ** and *** indicate statistical significance at the 5%, and 1% levels, respectively.