Can Disclosure Regulation Impede Innovation?

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Abstract: I investigate whether mandating transparent patent disclosure fosters or harms incentives to innovate. While transparent patent disclosure reveals proprietary information to competitors and reduces a firm's lead time and competitive advantage, the firm stands to benefit from knowledge spill-ins from competitors either through reduced uncertainty or improved efficiency. I exploit the implementation of the American Inventors Protection Act ("AIPA") in 2001, which accelerates the dissemination of patent information, as a shock to the transparency of patent disclosure. The results suggest the AIPA reduces firm incentives to innovate. I find that firms devote fewer resources to R&D after the law change and that smaller firms reduce R&D intensity more than large firms. Furthermore, smaller firms produce fewer patents per dollar of R&D stock and receive fewer forward patent citations than large firms even as large firms experience an increase in R&D profitability and market share. These findings imply that the largest firms benefit from transparency while smaller firms are harmed. Results are robust to a variety of alternatives and do not appear to be driven by the dot com bubble. Taken together, my evidence supports concerns raised by critics of the AIPA and informs academics interested in the role of patent disclosure and the real effects of disclosure regulation.

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1. Introduction

Disclosure regulation can be justified when a firm's disclosure impacts other firms' operational choices, potentially allowing all firms to make better decisions and thus improve social welfare (Beyer, Cohen, Lys, and Walther 2010, 315-316). However, when managers know disclosure of proprietary information is required, that could change incentives to engage in the disclosed activity in the first place (Leuz and Wysocki 2016). I investigate whether transparent disclosure regulation fosters or stifles incentives to innovate, using patent disclosure and patented inventions as a setting.

How disclosure impacts innovation is fundamental both to economic growth and the purpose of the U.S. patent system. Firms in industries with significant intellectual property rights are a powerful force in the economy, supporting 30% of employment and accounting for 38% of U.S. GDP in 2014 (USPTO 2016). Fundamentally, a patent grants its owner monopoly rights for a period of time and the payment is public disclosure of the protected invention. Despite the economic importance of patents and the crucial role of patent disclosure, there is a dearth of empirical evidence on how patent disclosure relates to innovation (Williams 2017).

I exploit the enactment of the U.S. American Inventors Protection Act of 1999 ("AIPA") to address my research question. Prior to the AIPA, patent applications and their detailed technical information were published by the U.S. Patent and Trademark Office ("USPTO") at the time a patent was granted, with an average lag between filing a patent application and patent grant of thirty-three months. The AIPA changed patent law to require patent applications filed after November 29, 2000 to publish eighteen months after the filing date, independent of whether a patent is ultimately granted. The AIPA thereby improved patent disclosure transparency along two dimensions: 1) made a greater number of patent filings publicly available by publishing patent applications filed but not granted and 2) accelerated the timing of patent publication in the U.S. by fifteen months on average. The law change therefore allows me to identify the impact of transparent patent disclosure on firm incentives to innovate.

Transparent patent disclosure can increase or decrease incentives to innovate depending on the effects of information flowing from a firm to its rivals ("spill-out") or flowing from rivals to a firm ("spill-in"). Knowledge spill-outs can decrease incentives to innovate if transparency allows rivals to use disclosed knowledge to erode a firm's competitive advantage (Levin, Klevorick, Nelson, and Winter 1987). Although the specific invention disclosed in a patent is protected, transparent disclosure reduces a firm's lead time in developing follow-on inventions. Thus, the cost of innovating increases and firms could devote fewer resources to R&D, my proxy for innovation incentives, *ex ante* (Gilbert 2006). However, knowledge spill-outs can be beneficial to a firm if they serve to deter entrants or allow for greater licensing opportunities (Hegde and Luo 2018). Knowledge spill-ins can increase innovation incentives if rival information facilitates new inventions, firms make better project selection and continuation decisions, or firms experience increase certainty (Czarnitzki and Toole 2011; Hegde, Herkenhoff, and Zhu 2018). The net impact is an empirical question.

A point of contention in the policy debate is whether small firms are at greater risk of losing their competitive advantage due to transparent patent disclosure than large firms. Twenty-five Nobel Laureates in science and economics opposed the AIPA, arguing it would "discourage the flow of new inventions…by curtailing the protection [small inventors] obtain through patents relative to the large multi-national corporations" (Modigliani 1999). Large firms' R&D is more productive than small firms (Ciftci and Cready 2011) and large firms arguably have more developed "downstream R&D" processes necessary to make R&D investments profitable (Cohen 2010; Rosenberg 1994).[1] Therefore, large firms could have the advantage over small firms in capitalizing on knowledge spill-ins. Furthermore, large, diversified firms could be more willing to invest in R&D made riskier by patent transparency (Cohen 2010). Alternatively, small firms could use knowledge spill-ins better than large firms due to a culture that incentivizes innovation (Holmstrom 1989) or differences in the marginal costs to innovate (Cohen 2010). Due to these competing explanations, the impact of firm size is unclear *ex ante.*

I employ a generalized difference-in-differences design using five years before and after the AIPA to address my research question. I identify a sample of firms filing at least one patent application in three years of the pre-period. I use SQL queries to extract novel patent data from Google's big data platform, BigQuery, which identifies the first patent publication date for an invention in the world. I define treatment firms as those whose pre-period average filing-to-publication lag is greater than eighteen months and control firms as those whose filing-to-publication lag is less than or equal to eighteen months.[2] The filing-to-publication lag is largely a function of delays at the patent office where a patent application is filed and thus unlikely to be a firm choice variable (Farre-Mensa, Hegde, and Ljungqvist 2017), though in later tests I also consider an alternative treatment and control sample that does not rely on the filing-to-

[1] Downstream R&D processes includes activities such as marketing and financing required to take an idea from development to diffusion in the marketplace.

[2] While AIPA increased transparency both by publishing patent applications not granted ("abandoned patents") and accelerating the timing of patent publications, I only use the filing-to-publication lag as a means of identifying affected firms. Conceptually, the impact on firms' lead time due to accelerating disclosure is likely a more significant effect than the publication of abandoned patents, as firms abandon less important patents where the expected future costs of patenting do not exceed its benefits. Empirically, prior to the AIPA, patent documents were only published when granted, making an analysis of patent abandonments intractable in my difference-in-differences design. Just using the available post-period data on patent abandonments, I find approximately 4% of patents are abandoned in my sample of firms and that there is no significant difference in the abandonment rate between treatment and control firms. This corroborates the understanding that using the filing-to-publication lag to identify treatment firms likely captures the most significant of the two effects.

publication lag. I proxy for a firm's incentive to innovate using R&D intensity (Koh and Reeb 2015; Zhong 2018).

The evidence suggests that transparent patent disclosure reduces firms' incentives to innovate. I find that after the AIPA, treatment firms devote fewer resources to R&D efforts compared to control firms. Specifically, treatment firms decrease R&D intensity between eleven and thirteen percent of pre-event levels, depending on the specification. This effect is increasing in the extent of disclosure acceleration. I find either no change or a decrease in R&D efficiency, depending on the measure used, suggesting that R&D intensity decreases are more likely due to proprietary cost concerns and not firms making more efficient decisions.

Regarding the impact of firm size, I find that firms in the top size quartile do not change R&D intensity while smaller firms significantly decrease R&D intensity, suggesting that smaller firms anticipate greater costs from transparent patent disclosure. In terms of R&D outcomes, I find the following: first, R&D efficiency, measured as the ratio of the number of patents to the past five years' R&D expenditures, declines more for smaller firms relative to the largest firms. Second, large firms' R&D investments are more profitable after the law change as evidenced by a higher predictability of R&D for future earnings. Third, smaller firms' patent impact (as proxied for by forward citations received) is significantly lower after the AIPA compared to the largest firms. Finally, I find that the largest firms increase market share significantly more than smaller firms following transparent patent disclosure. Taken together, my findings suggest that smaller firms are harmed by transparent patent disclosure while the largest firms benefit, supporting the contention of AIPA critics.

In robustness checks, I find that my results are unlikely due to selection effects or concurrent economic events. First, evidence is consistent with the parallel trend assumption being met in my setting. Second, inferences are robust to using U.S. patenting firms as a treatment sample and European patenting firms as a control. This design abstracts away from the filing-to-publication lag as a potential selection mechanism. Third, results are consistent using two different matched samples. Fourth, results do not present using a pseudo-event date of 1991 that also coincided with an economic downturn. Fifth, further analyses show findings are unlikely to be driven by the internet bubble. Specifically, my conclusions hold after excluding high tech firms that were likely hardest hit by the dot com crash. Also, inferences hold when I explicitly allow for industries to respond differently to macroeconomic events by including industry by year fixed effects. Finally, if treatment firms pursue different technologies from control firms and consequently were harder hit by the internet bubble, I would expect treatment firms to also decrease spending unrelated to R&D. Contrary to this alternative explanation, I find treatment firms do not change rent expense relative to control firms.

This research makes several contributions. First, I contribute to the relatively sparse literature on the real effects of disclosure regulation. We have some evidence on how market participants use regulated disclosure, but less is known about how the disclosing entity responds. My research answers the recent call in Leuz and Wysocki (2016) for "more empirical research on the prevalence and magnitude of real effects with respect to corporate investment and other real economy actions." I find significant and economically meaningful reductions in R&D intensity after patent disclosure regulation.

Second, I contribute to the literature in accounting on R&D investment. Research suggests capitalized R&D is value-relevant to investors (Lev and Sougiannis 1996; Oswald, Simpson and Zarowin 2017) and R&D intensive firms earn excess future returns (Donelson and Resutek 2012; Lev and Sougiannis 1996; Lin and Wang 2016). A related stream of research finds managers provide R&D-related disclosures in response to investor demand and this information is useful (Chen, Gavious, and Lev 2017; Jones 2007; Merkley 2014). Given this evidence, it is understandable that in a recent survey of financial statement users conducted by the FASB's advisory council, one of the top three suggested FASB agenda items was intangible assets. Users felt better information is needed and a feasible solution could be conformity with IFRS on capitalizing development costs (FASB 2015; Lev 2018). An implication of my study is if further financial statement recognition or disclosure of proprietary R&D investment is required, the FASB should consider the potential R&D-incentive effects on affected firms.

Finally, I contribute to the literature on the disclosure role of patents and the policy debate surrounding the AIPA. In an invited review of the economics literature on patent research, Williams (2017) notes that economists have examined the impact of patent *protection* on R&D investment with mixed evidence, but scant evidence exists on how the *disclosure* role of patents affects R&D investment (Williams 2017). From a policy perspective, one goal of the patent system is "to foster and reward invention" (Aronson v. Quick Point Pencil Co. 1979) and recent empirical research argues that there is societal under-investment in R&D (Bloom, Schankerman and Van Reenen 2013; Lucking, Bloom and Van Reenen 2018). And yet, I find that "one of the most fundamentally significant changes to the U.S. patent system this century" (USPTO 2000) had the effect of reducing the share of resources patenting firms devote to R&D. Concurrent working papers have identified capital market benefits of the AIPA (Blanco, Garcia, Wehrheim 2018; Lev and Zhu 2018; Mohammadi, Beyhaghi and Khashabi 2018; Saidi and Zaldokas 2017). To my knowledge, I am the first to provide empirical support for the concern that smaller entities are disadvantaged by transparent patent disclosure. These findings are important given a recent call to further shorten the patent filing-to-publication lag (Ouellette 2012).

2. Setting and Institutional Background

Congress passed the AIPA to harmonize U.S. patent law with other countries, which had long published patents after eighteen months.[3] The AIPA accelerated the diffusion of patent knowledge by requiring publication of patent applications eighteen months after the filing date, whether or not the patent is ultimately granted. In the U.S., patent applications were historically confidential until patent grant, at which point the patent application was made public. Congress passed the AIPA in 1999, requiring the USPTO to publish patent applications eighteen months from their filing date for patent applications filed on or after November 29, 2000. In 2000, the average lag between filing a patent application and its publication in the U.S. was approximately thirty-three months in my sample. Thus, this law change accelerated innovation disclosure for U.S. firms by an average of fifteen months. Many U.S. firms also file for patent protection internationally, where patent applications have historically been published eighteen months after filing. Foreign patent filings notwithstanding, empirically I find that the worldwide filing-to-publication lag in my sample decreased seven months from 2000 to 2001.[4]

Congress created an exception to the eighteen month publication rule for inventions with a patent application filed only in the U.S. If a firm does not seek foreign patent protection for the same invention, it may make a non-publication request at the time of filing. In my sample of public firms with significant patenting activity, there are only five firms whose pre-period

[3] There were other less significant reforms included in the AIPA, including disclosure requirements for invention promotion firms, adjustments to patent fees, and patent term extensions in the event of USPTO delays. It is perhaps for these reasons that the act was named "American Inventors Protection Act."

[4] There are institutional reasons why the AIPA accelerated patent disclosure even for U.S. firms filing for foreign patent protection. Prior to the AIPA, U.S. firms could file for patent protection in the U.S. and wait up to twelve months before filing a foreign patent application and still (retroactively) receive foreign patent protection from the date of the U.S. filing. The foreign jurisdiction published after eighteen months, thus U.S. applications filed abroad could be published a maximum of thirty months after filing in the U.S. (Johnson and Popp 2003, page 98).

patents were filed exclusively in the U.S.[5] Thus, the AIPA required accelerating patent disclosure for at least part of my sample firms' patent portfolio.

The AIPA also allowed patent holders to retroactively collect royalties beginning from the patent publication date. Previously, patents provided a right to exclude other parties from the sale, use or manufacture of a patented invention beginning at the time a patent was granted. After the AIPA, when a patent is granted, the owner can collect royalties from any party that infringed on the patent starting when the patent application was published. This provision thus provides patent protection from the time of public disclosure, provided the patent is ultimately granted.

3. Literature Review and Hypotheses Development

3.1. Literature Review

Theoretical accounting literature highlights the potential for competitors to use firm disclosures to the disclosing firm's harm, as a result of disclosing proprietary information (Admati and Pfleiderer 2000; Darrough 1993; Verrecchia 2001). A large body of empirical disclosure research focuses on proprietary costs as a determinant of managers' voluntary disclosure choices, with the finding that firms voluntarily disclose less when proprietary costs are high (see e.g. Cao, Ma, Tucker, and Wan 2018; Verrecchia and Weber 2006), though there exists some mixed evidence (Beyer et al. 2010, page 306). However, even if disclosure is net costly to an individual firm, disclosure regulation could be justified on the basis of positive externalities. Beyer et al. (2010) posit that "real externalities", whereby a firm's disclosure impacts the real decisions of other firms, are one such externality. If disclosure allows firms to make better decisions, disclosure regulation can be welfare increasing.

However, the literature on the real effects of disclosure regulation is relatively sparse

[5] Given the small sample size, this exception does not provide an opportunity to identify a control group. Practically speaking, my results hold if I exclude those five firms from my sample.

and has largely focused on capital investment efficiency. Several papers find that firms improve capital investment efficiency after implementation of regulations that improve transparency, using IFRS adoption, internal control weakness disclosures and segment disclosures as settings (Chen, Young, and Zhuang 2013; Cheng, Dhaliwal, and Zhang 2013; Cho 2015). There is also evidence that competitors use mandatory disclosure to the detriment of the disclosing firm. Collins, Kim, and Ohn (2018) compare acquirers in M&A transactions that are required to disclose revenue information to acquirers who do not make such disclosures. They find disclosing firms experience an increase in competition as measured by the similarity between firms' product descriptions in the 10-K. Further, rivals are more likely to increase investment or engage in M&A transactions. Gipper (2016) performs a difference-in-difference analysis around the required expansion of executive compensation disclosures. He finds an increase in compensation levels, consistent with disclosure affecting managers' outside employment opportunities when competitors have improved information. However, neither of these settings permit testing whether disclosure regulation can influence innovation.

A recent literature studies how the information environment impacts innovation. Using international data, Zhong (2018) finds that transparency (as proxied for by six firm-level measures such as earnings smoothing and the use of global accounting standards) is positively associated with R&D intensity, the number of patents and innovative efficiency measured using the ratio of the number of patents to R&D stock. These results do not obtain in countries with high proprietary costs (i.e. where intellectual property rights are weak). Park (2018) finds a positive association between financial reporting quality and innovation, as proxied for by accruals quality and the number of patents and forward patent citations, respectively. Fogel-Yaari (2016) similarly finds a positive association between disclosure quality (measured using the principal components of 10-K readability, discretionary accruals and management guidance) and patent counts and citations. These papers focus on voluntary reporting transparency and are thus unable to detect positive real externalities of mandatory disclosure transparency.

3.2. Hypothesis Development

3.2.1. Necessary Conditions for the AIPA to Influence Innovation Incentives

In order to influence firms' R&D incentives 1) patent filings must contain decision useful information and 2) the AIPA must accelerate the spread of knowledge contained in patents. First, patent filings must contain useful information. In a survey of national U.S. R&D labs, Cohen, Goto, Nagata, Nelson, and Walsh (2002) find patents are a moderately or very important source of information about rivals' R&D in 49.1% of their U.S. sample, the third most importance source of information after publications and informal exchange. Studies find a stronger association between R&D expense and equity valuation for firms with higher-quality patents (Hirschey and Richardson 2004; Hirschey, Richardson, and Sholz 2001). Empirically, Lev and Zhu (2018) find the AIPA negatively affects the positive relation between idiosyncratic return volatility and R&D intensity. They interpret this as evidence the AIPA reduces investors' uncertainty about R&D due to the information revealed in patent applications. Similarly, Mohammadi, Beyhaghi and Khashabi (2018) find that analyst forecast errors decrease following the AIPA. The evidence suggests industry practitioners and investors find patent filings useful.

Second, the AIPA must increase the speed at which patent information is disseminated. Concurrent work uses micro evidence at the patent level to investigate the impact of the AIPA on forward citations received and the time it takes for a patent to be subsequently cited. Hegde, Herkenhoff, and Zhu (2018) find patents take between 25% and 29% less time to be subsequently cited after the AIPA. Baruffaldi and Simeth (2018) find that a one year increase in publication time decreases forward citations by between 9% and 13%, suggesting that decreases in publication time should increase forward citations. Thus, evidence suggests the AIPA has the effect of increasing patents' dissemination and the pace of knowledge diffusion.

3.2.2. Incentives to Innovate

A firm's incentive to innovate depends on the difference between earnings from investing in research and development versus earnings if a firm does not invest in R&D (Gilbert 2006). If a firm anticipates transparent patent disclosure to be a net cost, it will invest less in R&D *ex ante*. Conversely, if a firm expects returns to R&D to increase, it will allocate more resources to R&D. The net effect of transparent patent disclosure on the incentive to innovate depends on the impact of 1) a firm's own disclosure and 2) the disclosure of other firms. I term the former a knowledge spill-out effect and the latter a knowledge spill-in effect.

Knowledge spill-outs have at least three potential effects on the incentive to innovate: transparent disclosure of a firm's own patents 1) represents a proprietary cost, 2) has the potential to deter entry, and 3) presents an opportunity to earn royalties. First, patent disclosure has the potential to reveal proprietary information and reduce a firm's competitive advantage in R&D. Levin, Klevorick, Nelson, and Winter (1987) survey public firms with R&D activity and find lead time and moving quickly down the learning curve are two of the top three most effective methods of protecting a firm's competitive advantage. Before the AIPA, a firm had from the time of a breakthrough to the date a patent was granted (two to three years on average) to develop an invention in secrecy. Firms could use the time to not only develop the patented invention, but also progress to the next series of related inventions in secrecy. In this sense, the AIPA reduces a firm's competitive advantage by giving rivals the opportunity to appropriate benefits a disclosing firm would have had in the absence of transparent patent disclosure. These proprietary costs reduce incentives for firms to allocate resources to R&D investment *ex ante*.[6]

Second, a disclosing firm may benefit from transparent patent disclosure if it deters future entry, either by new companies or existing rivals entering the same product space. Publication of a firm's patent application signals to potential entrants that there are barriers to entry: entrants will have to pay royalties to the firm in order to operate in the market. The AIPA could improve the efficacy of disclosure to deter entry by providing a timelier, more credible disclosure mechanism than a firm's own voluntary disclosures. As a result, firms could increase R&D intensity if they expect higher returns after the AIPA through reduced competition.

Third, a disclosing firm could benefit from knowledge spill-outs by licensing inventions to receive royalty payments. Hegde and Luo (2018) find that licensing delays in the biomedical industry decrease by an average of ten months after the AIPA and that licensing is more likely to take place shortly after a patent application is published. If a firm licenses technologies sooner after the AIPA, it could extend the period over which a firm collects royalties. Graham and Hegde (2015) use patent level data and find that the majority of patents eligible for exemption from the eighteen month publication rule do not opt-out of early disclosure.[7] One possible reason for this is that firms want to take advantage of early licensing. If firms expect net benefits from licensing after the AIPA, they will devote more resources to R&D *ex ante*.

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[6] Specific ways a rival can use a disclosing firm's patent disclosure include obtaining services such as "patent invalidity searches," where an attorney performs a search to identify prior inventions with the aim of invalidating a competitor's patent. A rival can also execute a "patent fence" strategy, where the rival patents improvements to a disclosing firm's patent to prevent them from doing so. Also, competitors may "design around" existing patents by redesigning their own products to avoid patent infringement.

[7] This finding from Graham and Hegde (2015) does not negate the importance of proprietary costs to patent holders. A firm has a portfolio of intellectual property to protect and the cost benefit tradeoff of early disclosure can be different depending on the type of invention. For example, IBM states in its 2017 annual report that it licenses technologies when they are in more mature markets. In that case, the benefits from licensing apparently outweigh proprietary cost concerns. However, firms likely prefer secrecy for their most important, cutting-edge technologies. Corroborating this, Graham and Hegde (2015) also find that measures of an invention's importance (number of claims and patent renewal rates) are highest for patents filed in foreign jurisdictions or patents that opt-out of eighteen month disclosure, not for patents that are voluntarily disclosed early.

Knowledge spill-ins potentially influence the incentive to innovate in three ways: 1) help firms develop new inventions, 2) improve project selection and continuation decisions, and 3) reduce uncertainty about R&D investment. First, the patent system is designed to publicly disclose inventions in the hope that other inventors will benefit from the knowledge.[8] Ouellette (2012) finds in her survey of scientific researchers that 70% of respondents who read patents do so to look for technical information, including how to solve a technical problem, or to browse information on cutting-edge technologies. If knowledge spill-ins allow a firm to progress its own research agenda in a more cost-effective way, I expect R&D intensity to increase.

Second, firms may make more efficient project decisions by reducing wasteful, duplicative R&D efforts. Timely access to competitor patents allows firms to identify technologies that rivals have already developed and provides management the opportunity to make more efficient R&D investment choices. Hegde, Herkenhoff, and Zhu (2018) find that after the AIPA, there is less overlap between technologically similar patents, consistent with a decrease in duplicative R&D efforts. If a firm invests R&D more efficiently after the AIPA, it could respond by allocating more resources to R&D as returns to R&D increase. Alternatively, a firm could decrease R&D intensity if it determines the current level of R&D output is optimal and the same level of output can be achieved using less R&D investment.

Third, transparent disclosure of competitor projects can reduce uncertainty about the competitive landscape and thereby incentivize firms to invest more in R&D. Czarnitzki and Toole (2011) find a negative association between R&D and uncertainty as proxied for by volatility of revenue from new products, suggesting that uncertainty reduces R&D investment.

[8] The U.S. Supreme Court highlights the importance of patent disclosure stating "additions to the general store of knowledge are of such importance to the public wealth that the Federal Government is willing to pay the high price of 17 years of exclusive use for its disclosure" (Kewanee Oil Co. v. Bicron Corp. 1974).

Therefore, by reducing uncertainty, patent disclosure could increase R&D incentives. Given the competing arguments outlined above, I state my hypothesis in the null:

H1: Firms do not change their R&D intensity following the AIPA.

The predictions above imply that if I observe an R&D intensity decrease it could either be due to proprietary cost concerns or improved efficiency. Alternatively, if I observe that R&D intensity increases, it could be due to the impact of deterring entry, licensing benefits or knowledge spill-in benefits. Given my finding of reduced R&D intensity, I explore the possibility of efficiency improvements in Section 5.4.

3.2.3. Impact of Firm Size

The policy debate created a "fault line" in the patenting community between large corporations in support of the AIPA and small entities in opposition (Duffy, Gregory, Rines, Wamsley, and Wyatt 1998). Large firms supported the law change, arguing it would allow earlier access to foreign competitor patent filings in English (Wise 1997). In contrast, small businesses and individual inventors opposed the law. In the Congressional debate, it was argued that transparent patent disclosure "places a much greater burden on [an] inventor, especially when they are small, to protect their invention" (Kaptur 1997). Large firms could anticipate greater benefits than small firms from transparent patent disclosure for various reasons.

First, Ciftci and Cready (2011) find that large firms have higher future operating income per dollar of R&D investment than small firms, suggesting large firms have greater R&D productivity. Relatedly, large firms may have more developed "downstream R&D" processes required to turn investments in innovation into a commercial success, such as distribution and advertising (Cohen 2010; Rosenberg 1994). If large firms are better at converting R&D knowledge spill-ins into profitable products and services, they stand to gain more from R&D

investment after the AIPA. Second, large firms operate in a greater breadth of technologies than small firms (Bloom, Schankerman, and Van Reenen 2013). Consequently, large firms can apply the knowledge gained from competitors to more inventions than smaller firms operating in niche technologies (Cohen and Klepper 1996). Third, larger and diversified firms are better able to diversify the additional risk that could follow R&D investments when proprietary information is more transparent (Cohen 2010). Ciftci and Cready (2011) find that the positive relationship between R&D intensity and the volatility of future earnings is decreasing in firm size, consistent with this argument.

However, these arguments are not without tension. Large firms could be less likely to capture returns from transparent innovation disclosure than smaller firms. Small firms operate with less bureaucracy, thus allowing them to focus on scientific and technological advancement. Small firms have a culture more conducive to fostering innovation (Holmstrom 1989). With this singular task, small firms could speed up the process of bringing innovations to market and have an advantage in using knowledge spill-ins relative to large firms required to manage a heterogeneous mix of tasks. Also, large firms have a lower marginal cost of investing in R&D than smaller firms due to economies of scale (Cohen 2010). If so, knowledge spill-ins could reduce the marginal cost of R&D disproportionately more for the small firm as it leverages the technological developments of competitors. I therefore state my second hypothesis in the null.

H2: The change in R&D intensity following the AIPA does not depend on firm size.

4. Sample and Research Design

4.1. Sample Selection and Data

My empirical analysis employs a generalized difference-in-differences design around implementation of the AIPA. I examine the within-firm change from five years before to five years after the enactment of the AIPA in 2001 for treatment firms relative to control firms. My sample includes U.S. firms with significant patent activity in the pre-period, defined as filing at least one patent application in three of the five years. This restriction ensures patenting is important to these firms and thus a change in patent disclosure timing has the potential to influence behavior.

I partition my sample firms into treatment and control groups based on the average filing-to-publication lag in the pre-period. Firms with publication lags greater than eighteen months are classified as treatment firms and those with publication lags less than or equal to eighteen months are classified as control firms. I use novel patent data to identify the first patent publication date worldwide for a given invention. This feature is important because prior to the AIPA, competitors could access a firm's patent filings published with an eighteen-month lag in foreign jurisdictions, even if publication in the U.S. was delayed until patent grant. Using only U.S. publication dates would incorrectly classify firms as being treated when they were not.

The filing-to-publication lag depends on processing time at the patenting office and the specific processes in the jurisdiction in which a patent in filed (Farre-Mensa, Hegde, and Ljungqvist 2017). At the USPTO, a patent application is assigned to a technology group comprised of patent examiners who are specialists in the area. The time a patent is under review depends on the specialists' backlog and government resources devoted to hiring patent examiners. Furthermore, the worldwide filing-to-publication lag depends on the patenting processes in each jurisdiction where a patent application is filed. Thus, if a firm files a patent application in the U.S. and Europe, the filing-to-publication lag depends on the processing time and rules governing patent publication in both the U.S. and Europe. Patent processing delays are largely out of a firm's control, though to the extent they vary by technology type, there is a potential selection issue. I explore potential selection issues and how they could interact with macroeconomic events in Sections 5.7 and 5.8, respectively.

Figure 1 graphs the worldwide filing-to-publication lag for treatment vs. control firms over the sample period. The publication lag for treatment firms dropped sharply to eighteen months in 2001 from twenty-six months in 2000. This discontinuity validates that treatment firms experienced a significant acceleration of patent disclosure. Control firms had an average publication lag of sixteen months in 2000 that decreased to thirteen months in 2001, which represents a decrease of only three months, though the difference is statistically significant (p-value <0.01). This change in publication lag for control firms is due to some patents in the control firms' pre-period portfolio having a greater than eighteen month lag, even though the pre-period average is sixteen months. After the AIPA, the absence of these longer lags brings down the firm-level average, even for control firms. In this sense, control firms were partially treated by the AIPA. However, I continue to find similar results using alternative methods to identify treatment and control groups as discussed in Section 5.7.

Table 1 Panel A documents the sample selection criteria. I begin with non-financial and non-insurance U.S. firm-years available on Compustat from 1996-2005 that have non-zero R&D intensity or a patent application filing. I then require observations to have non-missing SIC code and data necessary to calculate control variables. I retain only firms with patenting activity in three out of five pre-period years and require firms to be in the sample the entire ten year period.[9] My final sample includes 6,210 treatment firm-year observations and 1,930 control firm-year

[9] I require firms to be present throughout the sample period to ensure that a changing sample composition does not unduly influence my results. In untabulated analysis, I follow the same sample selection criteria as in Table 1 Panel A, but remove the requirement that firms have ten consecutive years of data. This procedure leaves a sample size of 12,745 firm-year observations. I find the results are robust using this alternative sample.

observations.[10] As I do not explicitly require data for all dependent variables used, the number of firm-year observations in a given test differs depending on data availability.

Table 1 Panel B includes the sample composition by Fama French 12 industries for the entire sample, treatment firms and control firms. Eighty percent of observations are in the manufacturing, computer or healthcare industries. The breakout by industry for treatment and control firms is similar, though treatment (control) firms include a larger proportion of companies in the computer (chemical) industry.[11] Overall, approximately eighty percent of both treatment and control observations are in the same three industries.

For patent-based measures, I collect patent data from Google BigQuery. Google BigQuery covers public patent applications and grants from seventeen patent offices around the world, including the United States Patent and Trademark office. I identify all patent documents with a filing date of 1996 to 2005. I then match these records to corporate assignees in Compustat by first leveraging the name matching procedures performed by Hall, Jaffe and Trajtenberg (2001) and Kogan, Papanikolaou, Seru and Stoffman (2017). For remaining records, I use a name matching algorithm to identify patents assigned to corporations. For a detailed description of data collection procedures, please see Appendix B. In my final sample of patents, I retain only those patents ultimately granted, consistent with prior patent datasets (Hall, Jaffe and Trajtenberg 2001; Kogan, Papanikolaou, Seru and Stoffman 2017). I obtain financial statement data from Compustat North America and Compustat Global.

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[10] Although there are a fewer number of control firm observations than treatment firm observations, this disparity does not appear to be driving my results. In Table 11 Panel A, in a sample matched on Fama French 12 industry and size, I randomly drop treatment observations until there are equal numbers of treatment and control observations; my results continue to hold.

[11] My results are robust to excluding firms all firms in the Fama French 12 computer industry from the analysis. As discussed in Section 5.8, I also drop high tech firms (firms with SIC codes between 7370 and 7379) and my results are robust.

4.2. Research Design

I use a generalized difference-in-differences design to assess the impact of transparent innovation disclosure on incentives to innovate. The general model I use is as follows:

$$R\&D\ Intensity_{i,t} = \alpha + \beta_1 Treat_i \times Post_t + \beta_2 Size_{i,t} + \beta_3 ROA_{i,t} + \beta_4 Loss_{i,t} + \beta_5 Leverage_{i,t} + \beta_6 InstitOwn\%_{i,t} + \beta_7 NoAnalyst_{i,t} + \beta_8 R\&DMissing_{i,t} + \sum_{i=1 to j} \delta_i Firm_i + \sum_{m=1 to k} \xi_m Year_m + \varepsilon_{i,t} \tag{1}$$

Post takes on the value of one for fiscal years 2001-2005 and zero for fiscal years 1996-2000.[12] *Treat* takes on the value of one for U.S. firms whose average filing-to-publication lag is greater than eighteen months in the pre period and zero otherwise. Note that the main effects of *Treat* and *Post* are subsumed by firm and year fixed effects, respectively.

I proxy for the incentive to innovate using R&D intensity (Koh and Reeb 2015; Zhong 2018). An ideal case would be to observe how managers plan to allocate their existing resources to various investment opportunities as a way of revealing a firm's incentive to innovate. However, I only observe actual R&D expenditures for the year, which I use as a proxy for planned R&D spending. I proxy for existing firm resources using lagged total assets. I calculate R&D intensity as the natural log of one plus the ratio of R&D expenditures to lagged total assets to ensure outliers do not drive the results.[13, 14] $\beta_1 > 0$ implies that firms have a greater incentive

[12] As the AIPA was passed on November 29, 1999 but the implementation of the eighteen month disclosure rule took effect for patents filed on or after November 29, 2000, it is possible that firms changed R&D intensity in anticipation of the final rule becoming effective. To the extent firms did so, this should bias against me finding results as I include fiscal year 2000 in my pre-period. However, I also explore the robustness of my results to anticipatory effects by removing fiscal year 2000 observations from my sample and rerun equation (1). I find that inferences are robust.

[13] I replace missing R&D values with zero and include an indicator variable for whether R&D was missing as a control variable (Koh and Reeb 2015). Main results are robust to several alternatives. First, I replace missing values of R&D with the industry average. Second, I drop observations with missing R&D. These two alternatives are suggested by Koh and Reeb (2015). Koh and Reeb (2015) further suggest including a pseudo-blank indicator (a patent exists, but R&D is missing) as a control in addition to an indicator for missing R&D, but given my sample selection criteria, the indicator variable for missing R&D is perfectly collinear with a pseudo-blank indicator. Third, I calculate R&D intensity as the ratio of R&D expense to lagged total assets (without the log transformation) and my inferences are unchanged. Thus, the results from various alternatives corroborate my conclusions.

[14] I do not use the ratio of R&D expenditures to sales as a proxy for the incentive to innovate for both conceptual and empirical reasons. Conceptually, I am interested in how firms choose to allocate their resources and assets are a

to innovate while $\beta_1 < 0$ implies a reduction in incentives to innovate.

I include a vector of time-varying controls to improve the precision of my model. Specifically, I control for size as proxied for by the log of total assets, ROA and a loss indicator as proxies of profitability, and leverage as a measure of financial constraints.[15] Controlling for financial constraints also accounts for the possibility that transparent patent disclosure could impact R&D intensity through reducing information asymmetry between the firm and providers of debt financing (Saidi and Zaldokas 2017). I also include the percentage of institutional ownership and analyst following to control for the possibility that disclosure improves these parties' ability to discipline managers (Blanco, Garcia, and Wehrheim 2018; Cho 2015; Hope and Thomas 2008; Mohammadi, Beyhaghi and Khashabi 2018; Zhong 2018). An indicator for missing R&D values controls for changes in firms' reporting of R&D (Koh and Reeb 2015). I include firm fixed effects and year fixed effects in all models. Firm fixed effects control for time-invariant factors, such as managerial risk preferences in investing, that can affect firms' investment in innovation. Time fixed effects control for macroeconomic events impacting all firms in a given year, such as the business cycle. I cluster all standard errors by industry.[16]

5. Empirical Results

5.1. Descriptive Statistics and Parallel Trends

Table 2 includes descriptive statistics for treatment and control firms, before and after

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better proxy for firm resources. Empirically, R&D expenditures to sales is volatile over my sample period, while using assets as a scalar provides a more stable base. When I use R&D expenditures to sales as an alternative dependent variable, I find no change for treatment firms relative to control firms. I attribute this to the noise introduced when using a flow instead of a stock variable as a scalar.

[15] As defined in Appendix A, *ROA* also includes R&D expense. In untabulated analysis, I recalculate *ROA* after adding back R&D expense and find the results continue to hold. Thus, the findings do not appear to be explained by some mechanical relation between *ROA* and *R&D Intensity*.

[16] I use three-digit SIC industries in clustering to ensure there is no small sample bias introduced by using too few clusters (Cameron, Gelbach, and Miller 2011; Kezdi 2004). All else equal, it is more rigorous to use the highest level of aggregation on which to cluster standard errors. However, I alternatively cluster standard errors at the firm level and my results continue to hold.

the AIPA. Both treatment and control firms have a significant decrease in R&D intensity after transparent patent disclosure, but the decrease for treatment firms is significantly larger than for control firms. Both treatment and control firms have significant changes in the control variables around the law change, however, the difference in these changes is not significant. There are some statistically significant differences in observable characteristics between treatment and control firms in the pre-period (untabulated). I control for these observable differences in my analysis, perform covariate balanced matching in Table 11 Panel B, and note that identification in a difference-in-differences design relies on the key assumption of parallel trends for consistent estimation (Roberts and Whited 2013).

I examine the validity of the parallel trend assumption by replacing *Post* in equation (1) with an event-time indicator. I omit year *t-1* as the benchmark group as including all event-year indicators in the same regression results in perfect collinearity. This design can be interpreted as mapping out the treatment effect over time. Figure 2 plots the regression coefficients and confidence intervals of interest. Prior to AIPA implementation in year *t*, the coefficients are not significantly different from zero. The decrease in R&D intensity becomes significant in year *t*, with significantly negative coefficients persisting through year *t+4*. The evidence from this analysis is consistent with the parallel trend assumption being valid in my setting.

5.2. Does Transparent Patent Disclosure Erode Incentives to Innovate?

Table 3 presents the main results using equation (1) to test *H1*. I find that R&D intensity for treatment firms decreases between eleven and thirteen percent of pre-period levels, depending on the specification.[17] This result suggests that transparent patent disclosure reduces

[17] Because I take the natural log of one plus R&D intensity, coefficient estimates cannot be directly interpreted as a percentage change in R&D intensity. I back transform each value before calculating the percentage change. The lower bound change in R&D intensity using the Table 3 Column (1) coefficient of -0.021 divided by the treatment

incentives to innovate. In column (1), I include only firm and year fixed effects without additional control variables to address any potential concern about the "bad controls" problem. If control variables are also changing in response to the treatment, then including them in a regression to identify the treatment effect introduces an econometric bias similar to a selection problem (Angrist and Pischke 2008). As my conclusions are identical using a model both with and without control variables, the bad controls problem does not appear to be a concern.

Columns (2) and (3) present results using basic controls and adding controls for potential capital market effects, respectively. I continue to find that R&D intensity decreases after the AIPA using these specifications. The direction of control variables is consistent with prior research. *Size* and *ROA* are significantly negative while *Loss* is significantly positive, implying that small, less profitable firms invest more intensely in R&D. This is consistent with firms in an introductory life cycle stage, who are characterized as small and unprofitable, devoting more resources to R&D (Dickinson 2011). The controls for capital market effects (*Leverage, Institutional Ownership %, No. Analyst Following*) are generally insignificant. As expected, *R&D Missing* is negatively related to R&D intensity.

5.3. Is the Decrease in R&D Intensity Attributable to Disclosure Changes?

To corroborate that the channel through which I observe a decrease in R&D intensity is due to an acceleration of patent disclosure, I examine whether treatment firms with the greatest acceleration of disclosure decrease R&D intensity more than other treatment firms. I do so by creating a variable, *High Accel*. that takes on the value of one for firms in the highest quartile of average pre-period filing-to-publication lag and zero otherwise. In untabulated results, I confirm that *High Accel* firms have a larger decrease from 2000 to 2001 in worldwide filing-to-

firm pre-period value from Table 2 of 0.15. The exact calculation is as follows: $(e^{-0.021}-1)/(e^{0.15}-1)$= -0.11. The upper bound is calculated analogously using -0.018 from Table 3 Column (3) as the coefficient value.

publication lag (thirteen months) compared to non-*High Accel* firms (five months). I include all possible interactions between *High Accel.*, *Treat* and *Post* that are not perfectly collinear with firm and year fixed effects, but do not present them for parsimony.

Table 4 includes the results. The coefficient on *High Accel. x Treat x Post* represents the change in R&D intensity attributable to treatment firms experiencing the greatest decrease in filing-to-publication lag compared to other treatment firms. I find that *High Accel.* firms decrease R&D intensity more than other treatment firms and that this difference is statistically significant. However, other treatment firms still significantly reduce R&D intensity relative to control firms (*Treat x Post* coefficient). The results are consistent with the interpretation that the reduction in incentives to innovate I observe in Table 3 is due to the acceleration of patent disclosure.

5.4. Are Changes in R&D Intensity Due to Efficiency Improvements?

As discussed in Section 3.2.2., the observed decrease in R&D intensity could be due to either proprietary cost concerns or improved efficiency. To help distinguish between these two channels, I use two proxies for R&D efficiency as dependent variables. First, following Hirshleifer, Hsu and Li (2013) and Zhong (2018), I define #Patents/R&D Stock as the natural log of one plus the ratio of the number of patents filed in year t divided by the R&D stock from the prior five years, depreciated using a twenty percent rate. Conceptually, this measure captures the number of patentable inventions produced per dollar of recent R&D investment.

Second, I measure R&D efficiency based on R&D profitability. Similar to Curtis, McVay and Toynbee (2018), I model R&D profitability based on the following equation:

$$Opinc_{it+1,\,t+5} = \alpha + \beta_1 R\&D_{i,t} + \beta_2 Capex_{i,t} + \beta_3 Acquis_{i,t} + \beta_4 SG\&A_{i,t} + \beta_5 BTM_{i,t} + \beta_6 Opinc_{i,t} + \beta_7 Loss_{i,t} + \beta_8 Size_{i,t} + \beta_9 Leverage_{i,t} + \sum_{i=1toj} \delta_i Firm_i + \sum_{m=1tok} \xi_m Year_m + \varepsilon_{i,t} \quad (2)$$

$\beta_1 > 0$ in equation (2) implies that R&D positively predicts future operating income. I then interact *R&D* with *Treat x Post* to examine whether R&D becomes more or less predictive of future earnings for treatment firms following the AIPA. I also include all possible interactions of *R&D*, *Treat* and *Post* that are not perfectly collinear with firm and year fixed effects in my model, though do not tabulate them for parsimony.

Results are presented in Table 5. Column (1) shows that after the AIPA, treatment firms produce fewer patents per dollar of R&D stock on average and that this difference is statistically significant. Column (2) demonstrates that R&D profitability does not change. Taken together, these findings are inconsistent with the decline in R&D intensity resulting from efficiency gains. In fact, there is some evidence that the average firm becomes *less* efficient after the AIPA. This can be the case if disclosure regulation changes the competitive landscape such that firms have to invest more R&D to find sufficiently novel innovations that pass the patentability hurdle.

A related interpretation is that treatment firms experience a decrease in investment opportunities coincident with the AIPA that results in a decrease in R&D intensity. In untabulated analysis, I find the decrease in R&D intensity persists after controlling for a firm's market-to-book ratio. Also, if I include the market-to-book ratio as the dependent variable in equation (1), I find no evidence of changes after the AIPA for treatment firms relative to control firms. Thus, the findings do not appear to be driven by changing investment opportunities.

5.5. Does the Impact of Transparent Patent Disclosure Depend on Firm Size?

To test H2, I create an indicator variable, *Large*, that takes on the value of one for firms in the top quartile of average pre-period *Size* and zero otherwise. I modify equation (1) to include all possible interactions between *Large*, *Treat* and *Post* that are not perfectly collinear with firm and year fixed effects as well as the full set of control variables included in Table 3 Column (3). Results are included in Table 6.

Findings indicate that the impact of transparent patent disclosure on the incentive to innovate depends on firm size. Specifically, the largest firms allocate significantly more resources to R&D relative to smaller firms after the law change (Table 6 *Large x Treat x Post*), although the overall effect for large treatment firms shows no significant change in R&D intensity. I interpret this as evidence the largest firms anticipate R&D to be at least as profitable after the AIPA compared to before the law change. The coefficient on *Treat x Post* indicates smaller treatment firms significantly decrease R&D intensity. Taken together, the evidence shows smaller firms expect R&D investment to be less profitable following the AIPA and the largest firms anticipate no change in profitability.

5.6. Do the Largest vs. Smaller Firms Realize Different Outcomes?

The results presented thus far suggest large firms do not decrease R&D intensity while smaller firms do. As R&D intensity is an input-based measure of innovation, a natural question is whether R&D output also differs by firm size. To explore this possibility, I examine three output-based measures of innovation: 1) *#Patents/R&D Stock*, 2) R&D profitability, and 3) *Patent Impact* as proxied for by the average number of forward patent citations received. Table 7 presents results for *#Patents/R&D Stock* and R&D profitability by firm size. I find that the largest firms are significantly more efficient than smaller firms using *#Patents/R&D Stock* as a proxy, (Table 7 Column (1) *Large x Treat x Post*), though the overall effect for large firms is no significant change in efficiency. Smaller firms produce fewer patents per dollar of R&D stock invested (Table 7 Column (1) *Treat x Post*). Column (2) shows that R&D investment becomes incrementally more profitable for the largest firms, and that the overall effect for large firms is an increase in R&D profitability while smaller firms experience no change.[18]

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[18] Curtis, McVay and Toynbee (2018) use adjusted future net income as a primary specification. I use adjusted future operating income as a dependent variable, consistent with the intent to measure operating benefits of R&D

Table 8 Panel A presents results for *Patent Impact*. In addition to the control variables included in equation (1), I also include the average number of jurisdictions in which a patent is filed as a control to address the possibility that patents filed in more jurisdictions are simply highly cited. Column (1) documents that treatment firms receive marginally fewer forward citations following the AIPA, on average. Column (2) shows that the largest firms have significantly greater *Patent Impact* than smaller firms (*Large x Treat x Post*), with the overall impact on large firms being no change in forward citations. Smaller firms have a significant decrease in the number of forward citations received (*Treat x Post*). Again, I find that smaller firms bear negative innovation consequences while the largest firms do not.

Firms' patents could be less highly cited after the AIPA if they fail to patent their most important inventions due to proprietary cost concerns. I do not find that is the case in my setting. I rerun results using *#Patents* as a dependent variable and include an additional control for *R&D Intensity* to control for efficiency changes (Zhong 2018). Table 8 Panel B shows a statistically weak, one percent increase in patenting after the AIPA on average (Column (1)), and no difference in patenting between the largest and smaller firms (Column (2)).[19] Thus, the evidence is consistent with a decline in patent quality following the law change, perhaps because firms rush the innovation process given an increasingly competitive environment (Hopenhayn and Squintani 2015). One might argue that if the AIPA provided a costly shock to innovation

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investments as opposed to the impact R&D intensity might have on below the line items, such as special items or discontinued operations. Ciftci and Cready (2011) also use operating income in their model. If I use adjusted net income as a dependent variable, I find no change in R&D profitability nor difference between the largest and smaller firms. The difference between adjusted and operating net income does not change for large vs. smaller firms after the AIPA, suggesting that including below the line items adds noise to the analysis.

[19] I back transform each value before calculating the percentage change as follows: $(e^{0.097}-1)/(e^{2.14}-1)$= 0.01. However, the lack of significance on the univariate DID statistic for the number of patents (Table 2) suggests the increase in Table 8 Panel B Column (1) is driven by the inclusion of control variables in the model. In terms of the increase in the total number of patents, substituting the untransformed number of patents as a dependent variable in Table 8 Panel B suggests an on average increase of 1.5 patents for treatment firms in the post period.

disclosure transparency, I should find firms stop patenting to avoid disclosure altogether. Recall that my sample of firms have significant patenting activity, likely because patenting is the best method to obtain protection for their inventions given the nature of the technology they pursue or for the legal protection it provides from infringement lawsuits. Thus, while it is possible that some firms stop patenting after the law change, that does not appear to be the average effect for my sample.[20]

To further corroborate this interpretation, I examine the use of trade secrets as an alternative to patenting. Following Glaeser (2018), I proxy for the use of trade secrets by identifying firm-year observations that mention trade secrecy in the 10-K filing. Specifically, I use Python to download and parse 10-K filings and define *Trade Secrets* equal to one if the filing mentions “trade secrecy”, “trade secret” or “trade secrets” and zero otherwise. Results are included in Table 8 Panel C. I find no significant difference in trade secret mentions for treatment firms after the AIPA relative to control firms (Column 1) or for large versus smaller treatment firms (Column 2). The results suggest that firms do not pursue trade secrecy as a substitute to patenting following the AIPA. Thus, the decrease in *Patent Impact* is interpretable as a decrease in innovation quality.

Taken together, my results show that smaller firms have worse R&D outcomes post-AIPA while the largest firms have no change or even evidence of improvement. I next examine whether these R&D outcomes ultimately translate into changes in market power, using a firm’s market share as a proxy. Table 9 shows that there is no change in market share on average (Column 1). The largest firms have a market share 3.5% higher than smaller firms, which

[20] Using a sample of firms with any patent filing, not just firms with significant patenting activity, Hussinger, Keusch, and Moers (2018) find that public firms reduce the number of patents relative to private firms. They attribute this effect to the loss of insider trading opportunities that incentivize managers to take on risky investment.

represents a total effect of the law of 2.6% for larger firms (Column 2). Smaller firms have no significant change in market share. It is possible that the largest firms obtain this increase in market power by acquiring troubled firms after the 2001 recession and not through transparent patent disclosure. To address this possibility, in untabulated analysis I 1) control for acquisition activity and find my results continue to hold and 2) do not find a difference in acquisition activity for large vs. smaller treatment firms around the AIPA. In sum, the evidence suggests smaller firms are harmed by transparent disclosure, while the largest firms benefit.

5.7. Are the Results Due to Selection Effects or Pre-existing Differences?

To address the concern that selection effects or pre-existing differences drive my results, I employ three strategies: 1) an alternative formulation of treatment and control groups, 2) matched sample analysis and 3) a pseudo-event test. It is possible for selection effects into treatment and control conditions to cause spurious results if the average filing-to-publication lag is a firm choice, such as differences in the jurisdictions in which firms file for patent protection. Note that this selection effect would have to interact with the treatment to produce my results, as a constant difference would be eliminated in my DID design.

I form an alternative set of treatment and control firms to test the robustness of my results. Specifically, I include all firms used in my main analysis as U.S. treatment firms and compare these companies to European firms with significant patenting activity. Using this control group, treatment and control status is determined by the firm's country of incorporation. As firms are unlikely to change country of incorporation in anticipation of a patent law change, self-selection is mitigated in this setting.[21]

[21] The parallel trend assumption appears to be met using this control group. Untabulated analysis analogous to Figure 1 shows that the effect of being treated on R&D intensity in the pre-period is insignificant in the pre-period and shifts to being significantly negative in the post-period. However, data availability does not allow me to control for institutional ownership or analyst following using European firms.

Table 10 Panel A shows that U.S. patenting firms have a significant decrease in R&D intensity and European firms have a marginal increase. While control variables change for both treatment and control firms, they are mostly insignificantly different from each other (Difference-in-Differences column). Table 10 Panel B presents the DID regression results for the main effect of transparent patent disclosure on R&D intensity (Column 1), as well as differences by size (Column 2). The findings are consistent with those previously reported: on average, treatment firms decrease R&D intensity following the AIPA and smaller firms decrease R&D intensity significantly more than the largest firms.[22]

Second, to address the concern of treatment firms having different characteristics than control firms, I use two matched sample analyses. First, I match firms on Fama French 12 industries and size using coarsened exact matching and randomly drop observations so that there is an equal number of treatment and control firms remaining in the sample (Iacus, King and Porro 2012). Table 11 Panel A presents results. The findings are consistent with my main analysis: firms reduce R&D intensity on average and smaller firms to a greater extent than the largest firms. Thus, differences in industry composition or disparity in the number of treatment and control observations do not appear to drive my results. Second, I use entropy balanced sampling, which applies a weight to each observation in order to balance treatment and control firms on both the first and second moments of control variables (Hainmueller 2012). Again, my main results hold (Table 11 Panel B).

Third, I use a pseudo-event date and rerun the analysis. If differences between treatment and control firms cause my results, the same results should obtain using a different time period

[22] IFRS allows for capitalization of development costs (the “D” in “R&D”) under certain conditions. As an alternative, I calculate R&D intensity for European control firms using the sum of both R&D expense and gross deferred charges. Gross deferred charges (pneumonics DC + AMDC in Compustat Global) includes capitalized development costs in addition to other long-term prepayments. Table 10 results are robust to this alternative.

absent a treatment. I use a sample period from 1986 to 1995, with 1991 as the event year. I employ the same sample selection criteria as in Table 1, but remove the requirement that firms are present all ten years in order to have a sufficient sample of firms. The results are shown in Table 12. I find that there are no significant differences in R&D intensity either on average or for firms of different sizes. This evidence is inconsistent with systematic differences between treatment and control firms leading to my results. Taken together, my findings are robust to an alternative treatment and control sample, matched samples and a pseudo-event test.

5.8. Are the Results Due to Concurrent Macroeconomic Events?

The AIPA was implemented in 2001 and coincides with the so-called "dot com" bubble and ensuing recession. Thus, it is natural to ask whether my results merely reflect this macroeconomic phenomenon. Several considerations and findings suggest that is not the case. First, by construction, my design employs a group of control firms that are also subject to the same macroeconomic conditions as treatment firms as well as year fixed effects and my results obtain. There is still the possibility that treatment and control firms have different industry composition and react systematically differently to the internet bubble in a way that causes my results. Second, to address this possibility, I include firm and industry by year fixed effects in my design and present results in Table 13. Industry by year fixed effects allow for the response to macroeconomic events to vary by industry. I find that my inferences are unchanged.

Third, in untabulated analysis, I explicitly remove high tech firms following Efendi, Files, Ouyang and Swanson (2012) and find my results still hold.[23] Fourth, I use 1991 as a pseudo-event year in the pseudo-event analysis (Table 12), which also corresponds with a U.S.

[23] High-tech firms are defined as firms with SIC codes between 7370 and 7379. Furthermore, if I remove all firms in the Fama French 12 industry "Computers, Software, and Electronic Equipment" from Table 1 Panel B, my results continue to hold.

economic recession, and results do not obtain. Fifth, the finding that the decrease in R&D intensity is increasing in the extent of disclosure acceleration is inconsistent with the dot com bubble driving results (Table 4). However, it is still possible that treatment firms, perhaps because they pursue more complex technologies, are both hardest hit by the 2001 recession and also have the longest pre-period filing-to-publication lags. If that is the case, I expect treatment firms to reduce spending unrelated to R&D intensity decreases. Substituting rent expense for the dependent variable in equation (1), I find no change for treatment firms relative to control firms. This finding is inconsistent with the decrease in R&D intensity merely reflecting treatment firms decreasing expenditures across the board. As a whole, the evidence is inconsistent with the notion that macroeconomic events drive my results.

6. Conclusion

I examine whether disclosure regulation can impede firms' incentive to innovate. Using a patent law change that increased patent disclosure transparency, I find firms allocate fewer resources to R&D. This suggests the costs dominate other potential benefits. Additionally, smaller firms decrease their R&D intensity whereas the largest firms do not, consistent with smaller firms perceiving greater costs to investing in R&D. Results further show that smaller firms require more R&D dollars to produce the same number of patents and that their patents are of lower impact following the AIPA, while the largest firms increase R&D profitability and market share after the law change.

This paper is subject to at least two limitations. First, the results cannot speak to the total welfare implications of the AIPA as I focus on R&D incentives and outcomes for firms in my sample. Given the survivorship bias inherent in my sample, it remains possible that other R&D-related benefits accrue to parties outside the sample. Second, though the pattern of results discussed in Section 5.8 is inconsistent with macroeconomic events being the sole driver of my findings, the co-occurrence of the AIPA with the dot com bubble remains a limitation.

Taken as a whole, my results present a somewhat cynical view of transparent patent disclosure. Transparency does not appear to confer innovation benefits to the significant producers of patents on average. Instead, firms devote fewer resources to R&D when transparent patent disclosure is required, but do not patent less despite apparent efficiency losses. This could be due to the perceived need to hold patents as a defensive mechanism in the event of an infringement lawsuit or because ultimately patenting remains the best method firms have to protect inventions that are easy to reverse engineer once on the market. These finding should be of interest to researchers interested in the real effects of disclosure regulation and those involved in patent regulation.

References

Admati, A. R. and P. Pfleiderer. 2000. Forcing firms to talk: financial disclosure regulation and externalities. *Review of Financial Studies* 13 (3): 479–519.

Angrist, J. D., and J. S. Pischke. 2008. Mostly harmless econometrics: An empiricist's companion. Princeton University Press.

Aronson v. Quick Point Pencil Co., 440 U.S. 257, 262 (1979).

Baruffaldi, S., and Simeth, M. 2018. *Patents and Knowledge Diffusion: The Effect of Early Disclosure*. Available at: http://dx.doi.org/10.2139/ssrn.3160533

Beyer, A., Cohen, D. A., Lys, T. Z., and Walther, B. R. 2010. The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics* 50 (2): 296-343.

Blanco, I. and García, S. and Wehrheim, D. 2018. *Looking for Transparency: Institutional Ownership and Innovation Disclosure*. Available at: http://dx.doi.org/10.2139/ssrn.3132494

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

Cameron, A. C.; J. B. Gelbach; and D. L. Miller. 2011. Robust inferences with multiway clustering. *Journal of Business and Economic Statistics* 29: 238-249.

Cao, S., Ma, G., Tucker, J. W., and Wan, C. 2018. Technological peer pressure and product disclosure. *The Accounting Review* (forthcoming).

Chen, C., D. Young, and Z. Zhuang. 2013. Externalities of mandatory IFRS adoption: Evidence from cross-border spillover effects of financial information on investment efficiency. *The Accounting Review* 88: 881–914.

Chen, E., Gavious, I. and Lev, B., 2017. The positive externalities of IFRS R&D capitalization: enhanced voluntary disclosure. *Review of Accounting Studies* 22(2): 677-714.

Cheng, M., Dhaliwal, D., and Zhang, Y. 2013. Does investment efficiency improve after the disclosure of material weaknesses in internal control over financial reporting?. *Journal of Accounting and Economics* 56 (1): 1-18.

Cho, Y. J. 2015. Segment disclosure transparency and internal capital market efficiency: Evidence from SFAS No. 131. *Journal of Accounting Research* 53 (4): 669-723.

Ciftci, M. and Cready, W.M., 2011. Scale effects of R&D as reflected in earnings and returns. *Journal of Accounting and Economics* 52(1): 62-80.

Cohen, W. M. 2010. "Fifty Years of Empirical Studies of Innovative Activity and Performance." Handbook of the Economics of Innovation. Editors Hall, B. H., and Rosenberg, N. (Vol. 1). Elsevier.

Cohen, W. M., Goto, A., Nagata, A., Nelson, R. R., and Walsh, J. P. 2002. R&D spillovers, patents and the incentives to innovate in Japan and the United States. *Research policy* 31 (8-9): 1349-1367.

Cohen, W. M., and Klepper, S. 1996. A reprise of size and R&D. *The Economic Journal*, 925-951.

Collins, D. and Kim, J. and Ohn, H. 2018. *Do Mandatory Accounting Disclosures Impair Disclosing Firms' Competitiveness? Evidence from Mergers and Acquisitions.* Available at: http://dx.doi.org/10.2139/ssrn.3138584

Curtis, A. and McVay, S. and Toynbee, S., 2018. *The Changing Implications of Research and Development Expenditures for Future Profitability*. Available at: https://ssrn.com/abstract=2402886.

Czarnitzki, D., and Toole, A. A. 2011. Patent protection, market uncertainty, and R&D investment. *The Review of Economics and Statistics* 93 (1): 147-159.

Darrough, M. N. 1993. Disclosure policy and competition: Cournot vs. Bertrand. *The Accounting Review*, 534-561.

Dickinson, V. 2011. Cash flow patterns as a proxy for firm life cycle. *The Accounting Review* 86 (6): 1969-1994.

Donelson, D.C. and Resutek, R.J., 2012. The effect of R&D on future returns and earnings forecasts. *Review of Accounting Studies* 17(4): 848-876.

Duffy, J. F., Gregory, H., Rines, R., Wamsley, H. and D. Wyatt. 1998. Early Patent Publication: A Boon or Bane-A Discussion on the Legal and Economic Effects of Publishing Patent Applications after Eighteen Months of Filing. *Cardozo Arts and Entertainment Law Journal* 16: 601.

Efendi, J., Files, R., Ouyang, B., and Swanson, E. P. 2012. Executive turnover following option backdating allegations. *The Accounting Review* 88 (1): 75-105.

Farre-Mensa, J., Hegde, D., and Ljungqvist, A. 2017. *What is a patent worth? Evidence from the US patent "lottery".* Working paper, National Bureau of Economic Research.

FASB, 2015. Financial Accounting Standards Advisory Council September 29, 2015 meeting minutes. Obtained from https://www.fasb.org/cs/ContentServer?c=Document_C&cid=1176166425393&d=&pagename=FASB%2FDocument_C%2FDocumentPage.

Fogel-Yaari, H. 2016. CEO characteristics, disclosure quality, and innvotion. Working paper.

Gipper, B. 2016. Assessing the effects of mandated compensation disclosures. Working paper, The University of Chicago.

Gilbert, R. 2006. Looking for Mr. Schumpeter: Where Are We in the Competition-Innovation Debate?. *Innovation Policy and the Economy* 6: 159-215.

Glaeser, S. 2018. The effects of proprietary information on corporate disclosure and transparency: Evidence from trade secrets. *Journal of Accounting and Economics* (forthcoming).

Graham, S. and Hegde, D., 2015. Disclosing patents' secrets. *Science*, 347(6219): 236-237.

Hainmueller, J. 2012,"Entropy Balancing: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. *Political Analysis* 20 (1): 25-46.

Hall, B. H., Jaffe, A. B., and Trajtenberg, M. 2001. *The NBER patent citation data file: Lessons, insights and methodological tools*. Working paper, National Bureau of Economic Research.

Hegde, D. and Herkenhoff, K. and Zhu, C. 2018. *Patent Disclosure*. Available at: http://dx.doi.org/10.2139/ssrn.3158031.

Hegde, D. and Luo, H., 2018. Patent publication and the market for ideas. *Management Science*, 64(2): 652-672.

Hirschey, M., and Richardson, V.J., 2004. Are scientific indicators of patent quality useful to investors? *Journal of Empirical Finance* 11(1): 91-107.

Hirschey, M., Richardson, V.J. and Scholz, S., 2001. Value relevance of nonfinancial information: The case of patent data. *Review of Quantitative Finance and Accounting* 17(3): 223-235.

Hirshleifer, D., Hsu, P. H., and Li, D. 2013. Innovative efficiency and stock returns. *Journal of Financial Economics* 107 (3): 632-654.

Holmstrom, B. 1989. Agency costs and innovation. *Journal of Economic Behavior & Organization* 12 (3): 305-327.

Hope, O. K., and Thomas, W. B. 2008. Managerial empire building and firm disclosure. *Journal of Accounting Research* 46 (3): 591-626.

Hopenhayn, H., and Squintani, F. 2015. Patent rights and innovation disclosure. *The Review of Economic Studies* 83 (1): 199-230.

Hussinger, K., Keusch, T. and Moers, F. 2018. *Insider Trading and Corporate Innovation: The Real Effects of Disclosure.* Available at: http://dx.doi.org/10.2139/ssrn.3164596.

Iacus, S. M., King, G., and Porro, G. 2012. Causal inference without balance checking: Coarsened exact matching. *Political analysis* 20 (1): 1-24.

Johnson, D.K.N. and Popp, D. 2003. Forced out of the closet: The impact of the American Inventors Protection Act on the timing of patent disclosure. *Rand Journal of Economics* 34 (1): 96–112.

Jones, D.A., 2007. Voluntary disclosure in R&D-intensive industries. *Contemporary Accounting Research* 24(2): 489-522.

Kaptur 1997. 143 Congressional Record 6136, 6150-51 (daily ed. Apr. 23, 1997).

Kewanee Oil Co. v. Bicron Corp., 416 U.S. 470, 481 (1974).

Kezdi, G. 2004. Robust standard error estimation in fixed-effects panel models. *Hungarian Statistical Review Special* 9: 96-116.

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

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

Leuz, C., and Wysocki, P. D. 2016. The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of Accounting Research* 54 (2): 525-622.

Lev, B. 2018. *Intangibles*. Working paper available at SSRN: http://dx.doi.org/10.2139/ssrn.3218586

Lev, B. and Sougiannis, T., 1996. The capitalization, amortization, and value-relevance of R&D. *Journal of Accounting and Economics* 21(1): 107-138.

Lev, B. and Zhu. 2018. Patent disclosures reduce investors' R&D uncertainty and firm's cost of capital. Working paper, New York University.

Levin, R.C., Klevorick, A.K., Nelson, R.R., and Winter, S.G. 1987. Appropriating the returns from industrial research and development. *Brookings Papers on Economic Activity* 1987 (3): 783–831.

Lin, J.C. and Wang, Y., 2016. The R&D premium and takeover risk. *The Accounting Review* 91(3): 955-971.

Lucking, B., Bloom, N., and Van Reenen, J. 2018. Have R&D Spillovers Changed? Working paper, National Bureau of Economic Research.

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

Modigliani, F. 1999. *An open letter to the U.S. Senate*. Available at: http://eagleforum-org.eagleforum.info/patent/nobel_letter.html.

Mohammadi, A., Beyhaghi, M., and Khashabi, P. 2018. *Technology Disclosure and Capital Market Uncertainty: The Role of Patents.* Available at: http://dx.doi.org/10.2139/ssrn.3181936

Oswald, D., Simpson, A. and Zarowin, P. 2017. *The Information Benefits of R&D Capitalization*. Working paper available at SSRN: http://dx.doi.org/10.2139/ssrn.2952388

Ouellette, L. L. 2012. Do patents disclose useful information? *Harvard Journal of Law and Technology* 25 (2) 532-587.

Park, K., 2018. Financial reporting quality and corporate innovation. *Journal of Business Finance & Accounting* 45(7-8): 871-894.

Roberts, M. R., and Whited, T. M. 2013. Endogeneity in empirical corporate finance. *Handbook of the Economics of Finance* (Vol. 2, pp. 493-572). Elsevier.

Rosenberg, N. 1994. *Exploring the black box: Technology, economics, and history*. Cambridge University Press.

Saidi, F. and Zaldokas, A., 2017. *How Does Firms' Innovation Disclosure Affect Their Banking Relationships?* Available at SSRN: https://ssrn.com/abstract=2715925

U.S. Patent and Trademark Office (USPTO). 2000. *USPTO Will Begin Publishing Patent Applications* (November 27). Available at: https://www.uspto.gov/about-us/news-updates/uspto-will-begin-publishing-patent-applications.

U.S. Patent and Trademark Office (USPTO). 2016. *Intellectual Property and the U.S. Economy: 2016 Update.* Available at: https://www.uspto.gov/sites/default/files/documents /IPandtheUSEconomySept2016.pdf

Verrecchia, R.E., 2001. Essays on disclosure. Journal of Accounting and Economics 32, 97–180.

Verrecchia, R.E., Weber, J. 2006. Redacted disclosure. *Journal of Accounting Research* 44: 791–814.

Williams, H. L. (2017). How do patents affect research investments? *Annual Review of Economics*, 9, 441-469.

Wise, A. 1997. *Patent measure would enhance U.S. competitiveness*. Available at: https://www.bizjournals.com/dallas/stories/1997/12/29/editorial2.html.

Zhong, R. I. 2018. Transparency and firm innovation. *Journal of Accounting and Economics* (forthcoming).

Appendix A - Variable Definitions

Variable	Definition
Dependent Variables	
R&D Intensity	The logarithm of one plus the ratio of R&D expense to total assets (XRD/AT_{t-1}). Missing values are set to zero. Obtained from Compustat.
#Patents/R&D Stock	The log of one plus the number of patents a firm files in year *t* divided by R&D stock. Following Zhong (2018), R&D stock is the sum of five years' cumulative R&D expenditures assuming a 20% depreciation rate, calculated as follows: $R\&D\ Stock_t = XRD_t + 0.8 * XRD_{t-1} + 0.6 * XRD_{t-2} + 0.4 * XRD_{t-3} + 0.2 * XRD_{t-4}$.
Opinc	The sum of operating income plus R&D expenditures plus advertising expense plus depreciation expense, scaled by total assets. (OIBDP +XRD+XAD+DP)/AT.
Patent Impact	The log of one plus the median value of a firm's patents filed in year t of the number of times a patent was cited by another patent, scaled by the total number of citations received for patents filed by public companies in the same technology class-year-jurisdiction. Technology class is the first three digits of a patent's primary cooperative patent classification.
Market Share	The ratio of firm *i*'s sales (SALE) to the sum of sales for all firms in the same 3-digit SIC industry-year.
#Patents	The natural log of one plus the number of patents applied for in year *t*.
Trade Secrets	Takes on the value of one for firm-years that mention the phrase "trade secrecy", "trade secret" or "trade secrets" in the 10-K filing and zero otherwise.
Independent Variables	
Treat	Takes on the value of one if a firm has at least one patent application in three out of five years of the pre-event period and whose average filing-to-publication lag is greater than eighteen months in the pre-period. Takes on the value of zero for firms with at least one patent application in three out of five years of the pre-event period and whose average filing-to-publication lag is less than or equal to eighteen months in the pre-period.
Post	Takes on the value of one for fiscal years 2001-2005 and zero for fiscal years 1996-2000.
Control Variables	
Size	The log of total assets (AT), obtained from Compustat.
Leverage	The leverage ratio calculated as total liabilities divided by total assets (DLTT+DLC)/AT. Obtained from Compustat.
ROA	Return on assets computed as operating income before depreciation divided by total assets OIBDP/AT. Obtained from Compustat.
Loss	Takes on the value of one if income before extraordinary items (IB) is negative and zero otherwise.
Institutional Ownership %	The percentage of institutional ownership.
No. Analyst Following	The number of analysts following the firm.
R&D Missing	Takes on the value of one for firm-year observations where R&D expenditures are

	coded missing in Compustat and zero otherwise.
Additional Variables for Equation (2)	
R&D	The ratio of R&D expenditures to total assets (XRD/AT_{t-1}). Missing values are set to zero. Obtained from Compustat.
Capex	The ratio of capital expenditures less cash received from the sale of equipment to total assets ((CAPEX – SPPE)/ AT_{t-1}). Obtained from Compustat.
Acquis	The ratio of acquisition expenditures to total assets (ACQ/AT_{t-1}). Missing values are set to zero. Obtained from Compustat.
SG&A	The ratio of selling, general and administrative expense plus R&D expenditures to total assets ((XSGA + XRD)/AT_{t-1}). Missing values are set to zero. Obtained from Compustat.
BTM	The ratio of the book value of equity to market value of equity ((CEQ+TXDB)/(PRCC_F*CSHO)). Obtained from Compustat.

All continuous variables are winsorized at 1%

Figure 1 – Filing-to-publication Lag by Treatment Status

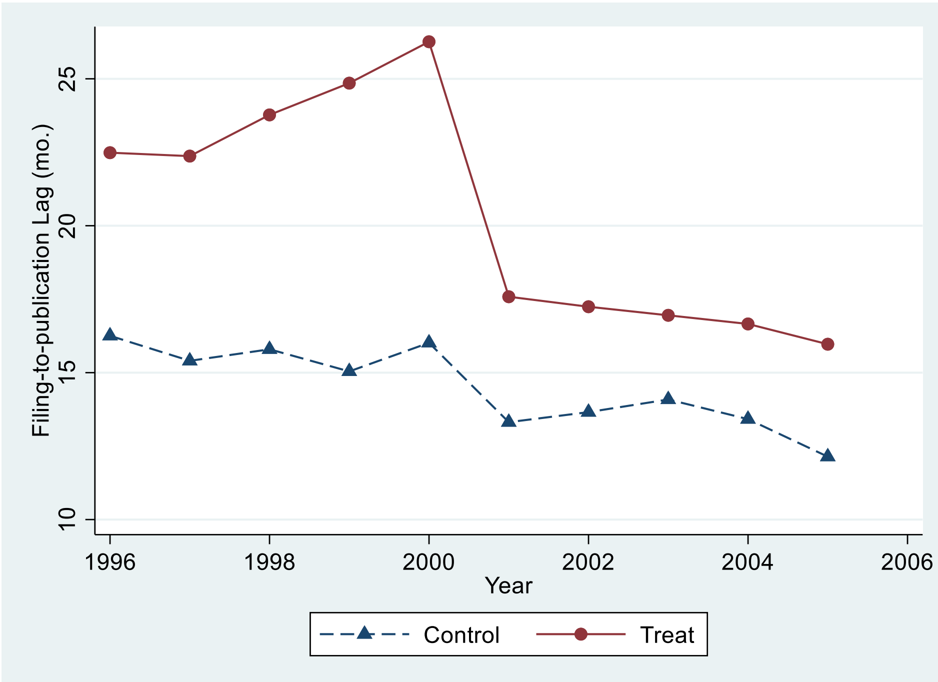

Figure 2 – Parallel Trend Assumption

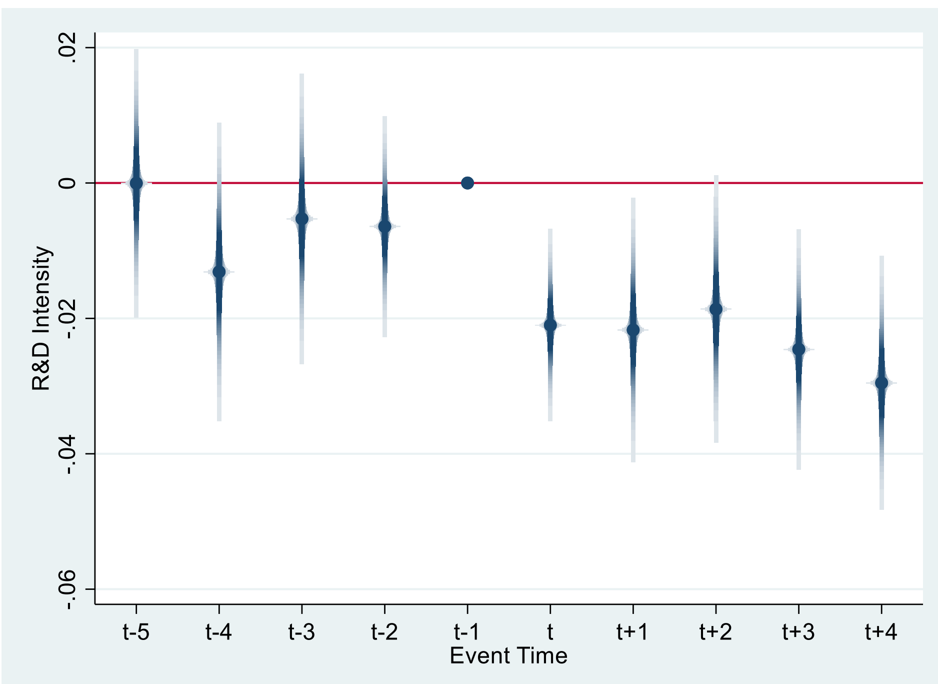

Table 1 - Sample Selection and Composition

Panel A

Criteria	Number of firm-year observations
Non-regulated, U.S. firms-years on Compustat from 1996-2005 with either: 1) R&D intensity greater than zero or 2) number of patent filings greater than zero	33,667
Observations with non-missing SIC and data necessary for the calculation of the control variables	32,421
Retain observations with a patent application in three out of five years of the pre-event period	12,962
Retain observations with ten consecutive years of data	8,140
Treatment firm-year observations	6,210
Control firm-year observations	1,930

Note: The above sample size represent the maximum sample used in a given test; actual sample sizes used in the regression analysis may be smaller if data is not available for the specific variables employed.

Panel B

	Combined Sample		Treatment		Control	
Fama French 12 Industry	*Frequency*	*Percent*	*Frequency*	*Percent*	*Frequency*	*Percent*
Consumer Non-durables	251	3.08	209	3.37	42	2.18
Consumer Durables	396	4.86	257	4.14	139	7.20
Manufacturing	1,765	21.68	1,286	20.71	479	24.82
Oil, Gas, and Coal	119	1.46	79	1.27	40	2.07
Chemicals and Allied Products	452	5.55	231	3.72	221	11.45
Computers, Software, and Electronic Equipment	2,783	34.19	2,344	37.75	439	22.75
Telephone and Television Transmission	83	1.02	83	1.34	0	0.00
Wholesale, Retail, and Some Services	65	0.80	62	1.00	3	0.16
Healthcare, Medical Equip. & Drugs	1,960	24.08	1,435	23.11	525	27.20
Other	266	3.27	224	3.61	42	2.18
Total	8,140		6,210		1,930	

Note: Utilities and Financial firms are excluded for the sample, so there are only ten of the Fama French twelve industries represented.

Table 2 - Descriptive Statistics

This table presents the means and differences in means of the variables of interest and control variables for treatment and control firms. The sample period is 1996-2005 with 1996-2000 comprising the pre-period and 2001-2005 comprising the post-period. ***, ***, * indicates statistical significance at 1%, 5%, and 10%, respectively. Detailed definitions of variables are provided in Appendix A.

	Treatment				**Control**				**Difference-in**	
	Pre	*Post*	*Difference*		*Pre*	*Post*	*Difference*		**Differences**	
R&D Intensity	0.15	0.11	-0.04	***	0.12	0.10	-0.02	***	-0.02	***
#Patents/R&D Stock	0.21	0.14	-0.07	***	0.17	0.13	-0.04	***	-0.03	*
$Opinc_{t+1, t+5}$	0.66	0.55	-0.10	***	0.69	0.53	-0.16	**	0.06	
Patent Impact	0.73	0.69	-0.04	***	0.69	0.66	-0.03	*	-0.01	
Market Share	0.05	0.06	0.01	***	0.05	0.06	0.01	*	0.00	
Size	5.71	6.18	0.47	***	5.63	6.01	0.38	***	0.09	
ROA	-0.08	-0.13	-0.05	***	-0.05	-0.10	-0.05	***	0.00	
Loss	0.35	0.43	0.08	***	0.31	0.38	0.07	***	0.01	
Leverage	0.18	0.21	0.03	***	0.20	0.23	0.03	***	0.00	
Institutional Ownership %	0.37	0.47	0.10	***	0.37	0.47	0.10	***	0.00	
No. Analyst Following	5.28	6.09	0.81	***	4.55	5.07	0.52	*	0.29	
R&D Missing	0.04	0.04	0.00		0.04	0.02	-0.02		0.02	
#Patents, untransformed	42.59	44.86	2.27		22.47	22.25	-0.22		2.49	
#Patents	2.14	2.18	0.04		1.85	1.77	-0.08		0.12	
Trade Secrets	0.52	0.62	0.10	***	0.45	0.52	0.07	***	0.03	
Firm-year Observations	3,105	3,105			965	965				

Table 3 – DID Regression Results

This table presents DID regression results. Industry-clustered t-statistics are reported in parenthesis. ***, ***, * indicates statistical significance at 1%, 5%, and 10%, respectively (two-tailed). All other variables are as described in Appendix A.

Dependent Variable:	(1) R&D Intensity	(2) R&D Intensity	(3) R&D Intensity
Treat x Post	-0.021***	-0.019***	-0.018***
	(-3.290)	(-3.007)	(-2.897)
Size		-0.032***	-0.029***
		(-6.161)	(-5.610)
ROA		-0.035**	-0.043**
		(-2.037)	(-2.002)
Loss		0.010**	0.009**
		(2.249)	(2.244)
Leverage			-0.036
			(-1.509)
Institutional Ownership %			-0.011
			(-1.294)
No. Analyst Following			-0.001*
			(-1.792)
R&D Missing			-0.065***
			(-2.775)
Observations	8,108	8,108	8,108
Adjusted R-squared	0.641	0.661	0.662
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 4 – Extent of Acceleration

This table presents DID regression results comparing treatment firms with the highest disclosure acceleration to other treatment firms (*High Accel. x Treat x Post*). *High Accel.* takes on the value of one for firms in the top quartile of the firm-level average number of months between filing a patent application and its publication anywhere in the world during the pre-period. Industry-clustered t-statistics are reported in parenthesis. ***, ***, * indicates statistical significance at 1%, 5%, and 10%, respectively (two-tailed). All other variables are as described in Appendix A.

	(1)	(2)	(3)
Dependent Variable:	R&D Intensity	R&D Intensity	R&D Intensity
High Accel. x Treat x Post	-0.020***	-0.016***	-0.015***
	(-3.074)	(-3.032)	(-2.918)
Treat x Post	-0.015**	-0.014*	-0.013*
	(-2.110)	(-1.950)	(-1.866)
Size		-0.032***	-0.029***
		(-6.196)	(-5.706)
ROA		-0.035**	-0.043**
		(-2.081)	(-2.033)
Loss		0.010**	0.009**
		(2.249)	(2.239)
Leverage			-0.036
			(-1.496)
Institutional Ownership %			-0.011
			(-1.301)
No. Analyst Following			-0.001*
			(-1.763)
R&D Missing			-0.065***
			(-2.742)
Observations	8,108	8,108	8,108
Adjusted R-squared	0.642	0.661	0.663
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table 5 – R&D Efficiency

This table presents DID regression results for measures of R&D Efficiency comparing treatment to control firms. Industry-clustered t-statistics are reported in parenthesis. ***, ***, * indicates statistical significance at 1%, 5%, and 10%, respectively (two-tailed). All other variables are as described in Appendix A.

	(1)	(2)
Dependent Variable:	#Patents/R&D Stock	$Opinc_{t+1, t+5}$
Treat x Post	-0.023**	
	(-2.242)	
R&D x Treat x Post		0.686
		(0.894)
Observations	7,352	6,770
Adjusted R-squared	0.616	0.779
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 6 – Effect of Firm Size on R&D Intensity

This table presents DID regression results comparing the largest treatment firms to smaller treatment firms and the largest control firms (*Large x Treat x Post*) and comparing smaller treatment firms to smaller control firms (*Treat x Post*). *Large* takes on the value of one for firms in the top quartile of average pre-period size and zero otherwise. The overall effect of the AIPA on *Large* treatment firms is the sum of the coefficients *Large x Treat x Post* and *Treat x Post*. The significance level is based on a Wald test that the sum of the coefficients is equal to zero. Industry-clustered t-statistics are reported in parenthesis. ***, ***, * indicates statistical significance at 1%, 5%, and 10%, respectively (two-tailed). All other variables are as described in Appendix A.

	(1)
Dependent Variable:	R&D Intensity
Large x Treat x Post	0.022**
	(2.372)
Treat x Post	-0.023***
	(-2.903)
Overall Effect for Large Treatment Firms	-0.001
Significance Level	0.809
Observations	8,108
Adjusted R-squared	0.665
Controls	YES
Year FE	YES
Firm FE	YES

Table 7 – Effect of Firm Size on R&D Efficiency

This table presents DID regression results comparing changes in efficiency for the largest treatment firms to smaller treatment firms and the largest control firms (*Large x Treat x Post*) and comparing changes in efficiency for smaller treatment firms to smaller control firms (*Treat x Post*). *Large* takes on the value of one for firms in the top quartile of average pre-period size and zero otherwise. The overall effect of the AIPA on *Large* treatment firms is the sum of the coefficients *Large x Treat x Post* and *Treat x Post*. The significance level is based on a Wald test that the sum of the coefficients is equal to zero. Industry-clustered t-statistics are reported in parenthesis. ***, ***, * indicates statistical significance at 1%, 5%, and 10%, respectively (two-tailed). All other variables are as described in Appendix A.

	(1)	(2)
Dependent Variable:	#Patents/R&D Stock	$Opinc_{t+1,\, t+5}$
Large x Treat x Post	0.033*	
	(1.674)	
Treat x Post	-0.030**	
	(-2.323)	
Large x R&D x Treat x Post		1.767*
		(1.777)
R&D x Treat x Post		0.648
		(0.786)
Overall Effect for Large Treatment Firms	0.002	2.415***
Significance Level	0.861	0.000
Observations	7,352	6,770
Adjusted R-squared	0.619	0.779
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 8 – Patent Impact, Number of Patents and Trade Secrets

Panels A - C present regression results for *Patent Impact*, *#Patents*, and *Trade Secrets*, respectively. Columns (1) present results comparing changes in the outcome for treatment firms relative to control firms (*Treat x Post*). Columns (2) present results comparing changes in the outcome for the largest treatment firms to smaller treatment firms and the largest control firms (*Large x Treat x Post*) and comparing changes in the outcome for smaller treatment firms to smaller control firms (*Treat x Post*). *Large* takes on the value of one for firms in the top quartile of average pre-period size and zero otherwise. The overall effect of the AIPA on *Large* treatment firms is the sum of the coefficients *Large x Treat x Post* and *Treat x Post*. The significance level is based on a Wald test that the sum of the coefficients is equal to zero. Industry-clustered t-statistics are reported in parenthesis. ***, ***, * indicates statistical significance at 1%, 5%, and 10%, respectively (two-tailed). All other variables are as described in Appendix A.

Panel A: Patent Impact

Dependent Variable:	(1) Patent Impact	(2) Patent Impact
Large x Treat x Post		0.055*
		(1.911)
Treat x Post	-0.035*	-0.051**
	(-1.814)	(-2.097)
Overall Effect for Large Treatment Firms		0.004
Significance Level		0.826
Observations	7,019	7,019
Adjusted R-squared	0.418	0.419
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Panel B: #Patents

Dependent Variable:	(1) #Patents	(2) #Patents
Large x Treat x Post		0.048
		(0.466)
Treat x Post	0.097*	0.083
	(1.905)	(1.618)
Overall Effect for Large Treatment Firms		0.131
Significance Level		0.195
Observations	8,108	8,108
Adjusted R-squared	0.859	0.859
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 8 – Patent Impact, Number of Patents and Trade Secrets, cont.

Panel C: Trade Secrets

Dependent Variable:	(1) Trade Secrets	(2) Trade Secrets
Large x Treat x Post		0.015
		(0.286)
Treat x Post	0.026	0.023
	(1.229)	(0.844)
Overall Effect for Large Treatment Firms		0.038
Significance Level		0.371
Observations	7,222	7,222
Adjusted R-squared	0.796	0.796
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 9 – Market Share

This table presents DID regression results for market share. Column (1) presents results comparing changes in the outcome for treatment firms relative to control firms (*Treat x Post*). Column (2) presents results for the largest treatment firms to smaller treatment firms and the largest control firms (*Large x Treat x Post*) and comparing changes in market share for smaller treatment firms to smaller control firms (*Treat x Post*). *Large* takes on the value of one for firms in the top quartile of average pre-period size and zero otherwise. The overall effect of the AIPA on *Large* treatment firms is the sum of the coefficients *Large x Treat x Post* and *Treat x Post*. The significance level is based on a Wald test that the sum of the coefficients is equal to zero. Industry-clustered t-statistics are reported in parenthesis. ***, ***, * indicates statistical significance at 1%, 5%, and 10%, respectively (two-tailed). All other variables are as described in Appendix A.

Dependent Variable:	(1) Market Share	(2) Market Share
Large x Treat x Post		0.035***
		(2.688)
Treat x Post	-0.001	-0.009
	(-0.168)	(-1.605)
Overall Effect for Large Treatment Firms		0.026**
Significance Level		0.023
Observations	8,140	8,140
Adjusted R-squared	0.835	0.837
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 10 – Alternative Treatment and Control Groups

All U.S. Firms with Significant Patenting Activity vs. European Firms with Significant Patenting Activity

This table includes descriptive statistics (Panel A) and DID regression results (Panel B) for R&D intensity using all U.S. firms with significant patenting activity compared to European firms with significant patenting activity. In Panel B, Column (1) presents results comparing treatment to control firms (*Treat x Post*). Column (2) presents regression results comparing changes in R&D intensity for the largest treatment firms to smaller treatment firms and the largest control firms (*Large x Treat x Post*) and comparing changes in R&D intensity for smaller treatment firms to smaller control firms (*Treat x Post*). *Large* takes on the value of one for firms in the top quartile of average pre-period size and zero otherwise. The overall effect of the AIPA on *Large* treatment firms is the sum of the coefficients *Large x Treat x Post* and *Treat x Post*. The significance level is based on a Wald test that the sum of the coefficients is equal to zero. Industry-clustered t-statistics are reported in parenthesis. ***, ***, * indicates statistical significance at 1%, 5%, and 10%, respectively (two-tailed). Remaining variables are described in Appendix A.

Panel A: Descriptive Statistics

	Treatment				Control				Difference-in	
	Pre	*Post*	*Difference*		*Pre*	*Post*	*Difference*		**Differences**	
R&D Intensity	0.14	0.11	-0.03	***	0.04	0.05	0.01	*	-0.04	***
Size	5.70	6.15	0.45	***	7.28	7.65	0.37	***	0.08	
ROA	-0.07	-0.12	-0.05	***	0.03	0.02	-0.01	**	-0.04	***
Loss	0.34	0.42	0.08	***	0.14	0.22	0.08	***	0.00	
Leverage	0.18	0.21	0.03	***	0.20	0.22	0.02	**	0.01	
R&D Missing	0.04	0.03	-0.01		0.38	0.27	-0.11	***	0.10	***
Observations	4,070	4,070			820	820				

Panel B: DID Regression Results

Dependent Variable:	(1) R&D Intensity	(2) R&D Intensity
Large x Treat x Post		0.042***
		(3.836)
Treat x Post	-0.038***	-0.050***
	(-3.966)	(-4.561)
Overall Effect for Large Treatment Firms		-0.008*
Significance Level		0.058
Observations	9,649	9,649
Adjusted R-squared	0.685	0.687
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 11 – Matched Sample DID Regression Results

Panel A presents DID regression results using coarsened exact matching and Panel B employs entropy balanced matching. Columns (1) presents the regression results for R&D intensity comparing treatment to control firms (*Treat x Post*). Columns (2) present results comparing changes in R&D intensity for the largest treatment firms to smaller treatment firms and the largest control firms (*Large x Treat x Post*) and comparing changes in R&D intensity for smaller treatment firms to smaller control firms (*Treat x Post*). *Large* takes on the value of one for firms in the top quartile of average pre-period size and zero otherwise. The overall effect of the AIPA on *Large* treatment firms is the sum of the coefficients *Large x Treat x Post* and *Treat x Post*. The significance level is based on a Wald test that the sum of the coefficients is equal to zero. Industry-clustered t-statistics are reported in parenthesis. ***, ***, * indicates statistical significance at 1%, 5%, and 10%, respectively (two-tailed). All other variables are as described in Appendix A.

Panel A: Coarsened Exact Matching

Dependent Variable:	(1) R&D Intensity	(2) R&D Intensity
Large x Treat x Post		0.031***
		(2.910)
Treat x Post	-0.021**	-0.028***
	(-2.176)	(-2.634)
Overall Effect for Large Treatment Firms		0.003
Significance Level		0.593
Observations	3,407	3,407
Adjusted R-squared	0.683	0.685
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 11 – Matched Sample DID Regression Results, cont.

Panel B: Entropy Balanced Matching

Dependent Variable:	(1) R&D Intensity	(2) R&D Intensity
Large x Treat x Post		0.015*
		(1.665)
Treat x Post	-0.015***	-0.018**
	(-2.698)	(-2.428)
Overall Effect for Large Treatment Firms		-0.003
Significance Level		0.560
Observations	8,108	8,108
Adjusted R-squared	0.667	0.669
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 12 – Pseudo-event DID Regression Results

Column (1) presents the DID regression results for R&D intensity using 1991 as a pseudo-event date comparing treatment to control firms (*Treat x Post*). Column (2) presents DID regression results comparing changes in R&D intensity for the largest treatment firms to smaller treatment firms and the largest control firms (*Large x Treat x Post*) and comparing changes in R&D intensity for smaller treatment firms to smaller control firms (*Treat x Post*). *Large* takes on the value of one for firms in the top quartile of average pre-period size and zero otherwise. The overall effect of the AIPA on *Large* treatment firms is the sum of the coefficients *Large x Treat x Post* and *Treat x Post*. The significance level is based on a Wald test that the sum of the coefficients is equal to zero. Industry-clustered t-statistics are reported in parenthesis. ***, ***, * indicates statistical significance at 1%, 5%, and 10%, respectively (two-tailed). All other variables are as described in Appendix A.

Dependent Variable:	(1) R&D Intensity	(2) R&D Intensity
Large x Treat x Post		0.002
		(0.913)
Treat x Post	-0.003	-0.004
	(-1.394)	(-1.454)
Overall Effect for Large Treatment Firms		-0.002
Significance Level		0.349
Observations	6,765	6,765
Adjusted R-squared	0.803	0.803
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 13 – Industry by Year and Firm Fixed Effects

Column (1) presents the DID regression results for R&D intensity using industry by year and firm fixed effects comparing treatment to control firms (*Treat x Post*). Column (2) presents DID regression results comparing changes in R&D intensity for the largest treatment firms to smaller treatment firms and the largest control firms (*Large x Treat x Post*) and comparing changes in R&D intensity for smaller treatment firms to smaller control firms (*Treat x Post*). *Large* takes on the value of one for firms in the top quartile of average pre-period size and zero otherwise. The overall effect of the AIPA on *Large* treatment firms is the sum of the coefficients *Large x Treat x Post* and *Treat x Post*. The significance level is based on a Wald test that the sum of the coefficients is equal to zero. Industry-clustered t-statistics are reported in parenthesis. ***, ***, * indicates statistical significance at 1%, 5%, and 10%, respectively (two-tailed). All other variables are as described in Appendix A.

Dependent Variable:	(1) R&D Intensity	(2) R&D Intensity
Large x Treat x Post		0.029***
		(3.094)
Treat x Post	-0.016**	-0.023***
	(-2.172)	(-2.768)
Overall Effect for Large Treatment Firms		0.006
Significance Level		0.216
Observations	8,108	8,108
Adjusted R-squared	0.674	0.675
Controls	YES	YES
Industry by Year FE	YES	YES
Firm FE	YES	YES