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Can Disclosure Regulation Impede Innovation?

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Dedication

To Mark, Amy, and Sarah

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Abstract

Can Disclosure Regulation Impede Innovation?

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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, a 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 allocate fewer resources to R&D after the law change and that smaller firms reduce R&D intensity more than large firms. Furthermore, after adoption of the AIPA, 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. However, there is some evidence that firms adapt their patenting strategies in response. Specifically, the law increases foreign patent filings among smaller firms and increases the use of voluntary patent publication requests for all firms, perhaps to better take advantage of licensing opportunities. Results are robust to a variety of alternatives and do not appear to

be attributable to the dot com bubble. Taken together, my evidence corroborates concerns raised by critics of the AIPA even as it suggests some achievement of international harmonization goals. I also inform academics interested in the role of patent disclosure and the real effects of disclosure regulation.

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Chapter 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-eight 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 increased 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 benefit of innovating decreases and firms could devote fewer resources to R&D ex ante, my proxy for innovation incentives (Gilbert 2006). However, knowledge spill-outs can be beneficial to a firm if they serve to deter entrants or allow for greater licensing opportunities (Glaeser and Landsman 2018; 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 of these effects from more transparent patent disclosure is an empirical question.

A point of contention in the policy debate surrounding the adoption of the AIPA was whether small firms were at greater risk of losing their competitive advantage from more 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 for whom patents appear to be an important intellectual property protection, defined as firms

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

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 a function of delays at the patent office where a patent application is filed (Farre-Mensa, Hegde, and Ljungqvist 2017) and firm choice of patenting strategies. To address the effect of firm choice in the partitioning variable, I employ control, fixed effects and matching strategies and find results are robust. Furthermore, in later tests I also consider an alternative treatment and control sample that does not rely on the filing-to-publication lag to identify treatment status. 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 decrease R&D intensity between ten and thirteen percent of pre-event levels relative to control firms, depending on the specification. This effect is increasing in the extent of disclosure acceleration. Further, I

[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.

find either no change or a decrease in R&D efficiency, depending on the measure used. This suggests that R&D intensity decreases are more likely due to proprietary cost concerns and not due to 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. I also find the following additional results: 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 by forward citations received) is significantly lower after the AIPA compared to the largest firms. Fourth, the largest firms increase market share significantly while smaller firms' market share declines. Finally, I find no evidence that firms switch from making R&D investments in-house to acquiring R&D-intensive firms.

I also find some evidence that firms adapt their patenting strategies following the AIPA. First, I find that smaller firms increase foreign patent filings, suggesting some benefits from international harmonization. Second, consistent with the notion that in a post-AIPA environment, the costs of patent disclosure are lower, firms of all sizes elect to have a greater share of their patent filings published voluntarily ahead of the eighteen month disclosure rule, perhaps to take advantage of licensing opportunities. Smaller firms increase voluntary publication requests to a greater extent than the largest firms. Taken together, my results suggest that the largest firms benefit the most from patent transparency, while smaller firms incur some costs and adapt their strategies.

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 replicate using a pseudo-event date of 1991 that also coincided with an economic downturn. Fifth, further analyses indicate that my results are unlikely to be attributable to 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 (patent class 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 by 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 that 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 (Chambers, Jennings and Thompson 2002; Donelson and Resutek 2012; Lev and Sougiannis 1996; Lin and Wang 2016). A related stream of research finds that 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 role of patent disclosure 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 role of patent disclosure 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), while a smaller number investigate innovation-related consequences (Hedge, Herkenhoff, and Zhu 2018; Hussinger, Keusch and Moers 2018; Kim 2018). To my knowledge, I am the first to provide empirical evidence consistent with the concern that smaller entities are disadvantaged by transparent patent disclosure. These results are important given a recent call to further shorten the patent filing-to-publication lag (Ouellette 2012).

Chapter 2: Setting and Institutional Background

2.1. THE AMERICAN INVENTORS PROTECTION ACT

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-four months in my sample. Thus, this law change accelerated innovation disclosure for U.S. firms by an average of sixteen 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 by seven months from 2000 to 2001.[4]

[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

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 six firms whose pre-period 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 as was the case prior to the AIPA, provided the patent is ultimately granted.

2.2. POLICY DEBATE

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, 604). Large firms argued that the law change would

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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).

[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 six firms from my sample.

allow earlier access to foreign competitor patent filings in English (Wise 1997). While that argument may be politically expedient, it also stands to reason that large firms could access even domestic competitors' patent filings sooner as a result of the law. The head of an intellectual property trade organization composed primarily of large corporations argued that early patent publication reduces duplicative research and helps firms to avoid litigation, thereby increasing legal certainty (Duffy, Gregory, Rines, Wamsley, and Wyatt 1998, 619). Policymakers in turn were interested in harmonizing U.S. patent law with international jurisdictions. The director of the USPTO, Q. Todd Dickinson, said the AIPA "brings us one step closer to an international patent" (USPTO 2000).

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). A prominent patent attorney, Douglas Wyatt, contended that the AIPA is a "disincentive to the inventor to invent" if "the big corporations are going to walk away with it" (Duffy, Gregory, Rines, Wamsley, and Wyatt 1998, 631). Even though patent protection commences from the date of disclosure both before and after the AIPA (conditional on ultimately obtaining a patent), these arguments have merit to the extent that small firms are unwilling or unable to sue large corporations for infringement to enforce their patent rights.

Academic research supports the notion that small firms are less successful in enforcing patent protection than larger corporations. Bessen and Meurer (2013) find that firms with larger patent portfolios are more likely to win a lawsuit against prospective infringers, likely because having more patents increases the chances of finding an infringement somewhere in the portfolio. Furthermore, large firms are more likely to employ internal patent legal counsel, which is associated with lower legal costs, suggesting greater efficiency in pursuing legal remedies (Lanjouw and Lerner 2001).

2.3. Academic Research on the AIPA

Published work using the AIPA as a setting is scarce and examines the timing of licensing or disclosure choices of patent holders exempt from pre-grant disclosure, research questions distinct from the current study (Graham and Hegde 2015; Hegde and Luo 2017). Concurrent work also has a different focus, ranging from how the AIPA impacts institutional ownership (Blanco, Garcia, Wehrheim 2018) to the cost of debt (Saidi and Zaldokas 2017). Other working papers investigate the impact of the AIPA on forward patent citations (Baruffaldi and Simeth 2018; Hegde, Herkenhoff, and Zhu 2018). However, these studies are performed at the patent level; thus, they cannot speak to how the AIPA affects a firm's allocation of resources to R&D or how the combined patent portfolio effect influences R&D-related outcomes. Tellingly, fully seventy-eight percent of all patents in my sample are held by firms in the largest size quartile. Thus, patent-level analyses could over-weight patent holdings by large firms and fail to find important differences attributable to the patent holders' size.

There are three, currently unpublished studies that are more closely related to this study. First, Kim (2018) finds that the effect of the AIPA depends on how closely related a firm is to its competitors in the technology space vs. product market space, as proxied for by the similarity in patent holdings across technology classes and sales across industries, respectively. He finds that closeness in the technology space is positively associated with forward patent citations, other measures of patent importance and R&D intensity, while closeness in the product market space has a negative association with these measures. Importantly, the net magnitude of the effects he documents is a negative association between the AIPA and innovative outcomes, consistent with my results. His sample includes all firms with at least one patent in the pre and post period and the design implicitly assumes that all sample firms are equally impacted by the law change. In contrast, I explicitly measure a firm's exposure to the law change by using the filing-to-publication lag to identify firms most affected by the eighteen-month disclosure rule. Furthermore, Kim (2018) does not investigate the impact of firm size and thus cannot speak to size-related concerns voiced in the policy debate.

Second, Guo (2018) is primarily interested in how the AIPA affects a firm's disclosure policies. He finds that manufacturing firms in more affected industries redact technology information from material contract filings and provide fewer forward-looking disclosures after adoption of the AIPA, while the readability of 10-Ks improves. However, in order to document that the AIPA has potential to influence firms' disclosure policies, he also examines patent citations and R&D expenditures. He finds a decrease in patenting activity and forward citations and no change in R&D expenditures, with some evidence that affected firms use more trade secrecy after the AIPA. I differ from Guo (2018) in that I measure affected firms at the firm level, not the industry level, and that I include firms in a broad sample of industries, not just in manufacturing. Importantly, I also explicitly require my sample firms to have significant patenting activity in the pre-period in an effort to identify firms for whom patenting is their best intellectual property protection strategy. It is potentially for this reason I find different results for R&D and trade secrecy usage. Specifically, Guo (2018) finds that firms with more discretion in their intellectual property protection strategies substitute away from patenting into trade secrecy, while I find no reduction in patenting in a sample comprised of the significant producers of patented inventions.

Finally, Hussinger, Keusch and Moers (2018) find that public firms file fewer patents and receive fewer citations after the AIPA relative to private firms. They find no change in R&D investment and an increase in trade secrecy usage, similar to Guo (2018). They attribute these results to the loss of insider trading opportunities for management that incentivize risky investment. While they examine the effect of the AIPA on public firms relative to private firms, I explicitly measure firms' exposure to the disclosure acceleration in the AIPA. Also, by including only firms with significant patenting activity in my sample, I am focused on the behavior of the significant producers of patented innovations, not just any firm with a patent that may have more discretion in pursuing different intellectual property protection strategies.

Chapter 3: Background 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, 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 affects the real decisions of other firms, are one such externality. If disclosure by the firm allows *other* firms to make better decisions, disclosure regulation can be welfare increasing.

However, the literature on the real effects of disclosure regulation is relatively sparse 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 this type of disclosure. 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-differences 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 permits testing whether disclosure regulation can influence innovation.

A recent literature studies how the voluntary disclosures that contribute to a firm's general information environment influence innovation. Using international data, Zhong (2018) finds that transparency (as proxied 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 other firms' 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 result 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 research 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, this 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. Both before and after the AIPA, a firm can request that the USPTO publish a patent application in advance of the eighteen-month disclosure deadline. The AIPA could

[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.

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. Supporting this notion, Glaeser and Landsman (2018) find that firms in more competitive industries (as proxied for by HHI industry concentration) are more likely to have shorter publication delays, suggesting they make greater use of voluntary requests for patent publication.

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 they do not opt out 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.

[7] Graham and Hegde's (2015) evidence 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 argument, 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.

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[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).

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

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

These predictions 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 the evidence of reduced R&D intensity, I explore the possibility of efficiency improvements in Section 5.4.

3.2.3. Impact of Firm Size

Large firms may 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 relation 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.

Chapter 4: Sample and Research Design

4.1. Sample Selection and Data

My empirical analysis employs a generalized difference-in-differences design around the 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 whose best intellectual property protection is achieved through patenting, proxied by firms that file 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 both on processing time at the patenting office and a firm's patent filing choices. First, at the USPTO, a patent application is assigned to a technology group comprised of patent examiners who are specialists in the area (Farre-Mensa, Hegde, and Ljungqvist 2017). The time a patent is under review depends on the specialists' backlog and government resources devoted to hiring patent examiners. As processing delays cluster by technology type, a potential internal validity threat occurs if macroeconomic events interact with the type of technology a firm pursues to produce spurious results. I address this possibility by including both industry by year and patent technology class by year fixed effects in Table 15. I discuss these and additional tests to address the impact of macroeconomic events in Section 5.10.

Second, a firm's patent filing choices also influence the filing-to-publication lag. There are two relevant types of filing choices: 1) whether or not to file a patent application abroad and 2) whether or not to voluntarily request early publication. A firm chooses the jurisdictions in which it files a patent application, with the first order concern of obtaining patent protection for a given invention. However, if a firm chooses to pursue foreign patent protection, this choice shortens the filing-to-publication lag as foreign jurisdictions have long had the eighteen-month disclosure rule. A second firm choice is the option to request early publication for a patent filing. Both before and after the AIPA, a firm can request that the U.S. patent office publish a patent application early. If a firm requests early publication for some of its patents, this will also reduce the filing-to-publication lag and make a firm more likely to be in the control group. Untabulated analysis confirms that control firms have higher rates of foreign filings and voluntary publication requests. To address these potential selection effects, I include controls for determinants of these filing choices as well as employ fixed effects and matching strategies. I discuss these procedures in Sections 4.2, 5.7 and 5.8.

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 from twenty-six months in 2000 to seventeen months in 2001. 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 and a half months in 2001, which represents a decrease of only two and a half 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 5.9.

Table 1 Panel A summarizes 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 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 6,520 treatment firm-year observations and 1,970 control firm-year observations.[10] As I do not explicitly require data for all variables used in a specific regression, 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

[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 11,762 firm-year observations. I find the results are robust using this alternative sample.

[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 13 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 all firms in the Fama French 12 computer industry from the analysis. As discussed in Section 5.10, I also drop high tech firms (firms with SIC codes between 7370 and 7379) and my results are robust.

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.

4.2. RESEARCH DESIGN

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

$$R\&D\ Intensity_{i,t} = \alpha + \beta_1 Treat_i \times Post_t + \beta_2 Size_{i,t} + \beta_3 ROA_{i,t} + \beta_4 Loss_{i,t} + \beta_5 MTB_{i,t} + \beta_6 Foreigninc_{i,t} + \beta_7 Industry\ Concentration_{i,t} + \beta_8 Leverage_{i,t} + \beta_9 InstitOwn\%_{i,t} + \beta_{10} NoAnalyst_{i,t} + \beta_{11} R\&DMissing_{i,t} + \beta_{12} Post\ x\ MTB_{i,t} + \beta_{13} Post\ x\ Leverage_{i,t} + \beta_{14} Post\ x\ Instit.\ Own.\ \%_{i,t} + \beta_{15} Post\ x\ Analyst\ Following_{,t} + \sum_{i=1 to j} \delta_i Firm_i + \sum_{m=1 to k} \xi_m Year_m + \varepsilon_{i,t} \tag{1}$$

Post takes on the value of one for fiscal years 2001-2005 and zero for fiscal years 1996-2000. *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.

4.2.1. Dependent Variable Measurement

I operationalize 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 cause the results. 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). $\beta_1 > 0$ implies that treatment firms have a relatively greater incentive to innovate while $\beta_1 < 0$ implies a reduction in incentives to innovate.

I also consider several alternatives to my primary measure of R&D intensity. 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.

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 better proxy than sales 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 in R&D intensity for treatment firms relative to control firms. I attribute this null result to the noise introduced when using a flow instead of a stock variable as a scalar. The coefficient of variation is a useful statistic to compare variation in two variables even when the means are different from one another as is the case with *R&D Intensity* and the ratio of R&D expenditures to sales. The coefficient of variation is calculated as the ratio of the standard deviation to the mean. I find that the coefficient of variation for R&D expenditures to sales is almost twice that of *R&D Intensity* (2.21 vs. 1.27, respectively).This statistic corroborates that empirically, using assets as a scalar provides a more stable base.

Finally, while total assets is a superior proxy for firm resources than sales, accounting assets may be understated for firms in my sample that engage in significant R&D investments which accounting rules don't recognize. Therefore, I also consider an alternative scalar: total assets plus as-if capitalized R&D expenditures as of the beginning of the year. I compute as-if capitalized R&D expenditures following Hirshleifer, Hsu and Li (2013) as follows: $R\&D\ exp_{i,t} + 0.8 * R\&D\ exp_{i,t-1} + 0.6 * R\&D\ exp_{i,t-2} + 0.4 * R\&D$

$exp_{i,t-3} + 0.2 * R\&D\ exp_{i,t-4.}$ Using this alternative measure of *R&D Intensity*, my main results are robust.

4.2.2. Control Variables

I include a vector of time-varying controls to improve the precision of my model. Specifically, I control for size as proxied by the log of total assets, ROA and a loss indicator as proxies for profitability, MTB as a proxy for investment opportunities, and leverage as a measure of financial constraints. I include the share of income attributable to foreign operations to control for differences in treatment and control firms in foreign patent filing choices. Research has found a positive association between industry concentration and patent disclosure delay (Glaeser and Landsman 2018), which implies firms in more concentrated industries request voluntary patent publication less often than firms in less concentrated industries. Thus, I include *Industry Concentration* to control for a firm's choice to request voluntary patent publication. 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 (Cho 2015; Hope and Thomas 2008; Zhong 2018). An indicator for missing R&D values controls for changes in firms' reporting of R&D (Koh and Reeb 2015).

I also include the interaction of several of my control variables with an indicator for *Post*. Doing so allows me to control for changes in the relationship between *R&D Intensity* and the control variable around the time of the AIPA. Specifically, *Post x MTB* controls for the possibility that investment opportunities changed after the dot com bubble. Controlling for *Post x Leverage* accounts for the possibility that transparent patent disclosure impacts R&D intensity through reducing information asymmetry between the firm and providers of debt financing (Saidi and Zaldokas 2017). Finally, *Post x Instit. Own. %* and *Post x Analyst Following* control for the effect of the AIPA on institutional ownership and analyst forecasting shown in concurrent work (Blanco, Garcia, and Wehrheim 2018; Mohammadi, Beyhaghi and Khashabi 2018).

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.[12]

[12] 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.

Chapter 5: Empirical Results

5.1. Descriptive Statistics

Table 2 includes descriptive statistics for treatment and control firms, both before and after 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 differences in these changes are insignificant. The univariate difference-in-differences statistic is marginally positive for the number of patents even though the change from the pre- to the post-period is insignificant for both treatment and control firms. Treatment firms increase both the number of jurisdictions in which they file patent applications as well as request voluntary publication more compared to the changes in these outcomes for control firms, a point I return to in Section 5.8.

There are some statistically significant differences in observable characteristics between treatment and control firms in the pre-period (untabulated). Notably, control firms file for patent protection in more jurisdictions than treatment firms and also elect voluntary patent publication more often. This suggests that, empirically, both patent office filing delays and firm strategy determine the filing-to-publication lag. To address this, I control for these observable differences in my analysis, utilize firm and year fixed effects, and perform covariate balanced matching in Table 13 Panel B. Also, I note that identification in a difference-in-differences design relies on the key assumption of parallel trends for consistent estimation (Roberts and Whited 2013), a point I validate in my setting in the following section.

5.2. DOES TRANSPARENT PATENT DISCLOSURE ERODE INCENTIVES TO INNOVATE?

Table 3 presents the main results estimating equation (1) to test *H1*. I find that R&D intensity for treatment firms decreases between ten and thirteen percent of pre-period levels, depending on the specification.[13] This result suggests that transparent patent disclosure reduces 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

[13] 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 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 -0.016 from Table 3 Column 3 as the coefficient value.

consistent with prior research. *Size* is significantly negative while *Loss* is significantly positive, implying that small, less profitable firms invest more intensively in R&D. This result is consistent with firms in an introductory life cycle stage, who are small and unprofitable, and devote more resources to R&D (Dickinson 2011). At the same time, *ROA* before R&D expenditures is positively related to *R&D Intensity*. This could be the case if firms use profitability in other areas to make R&D investments. As expected, greater *MTB* is positively related to R&D intensity, suggesting firms with greater investment opportunities increase R&D intensity more, though this effect is attenuated in the post period (*Post x MTB*). The total effects of controls for capital market effects (*Leverage + Post x Leverage, Institutional Ownership % + Post x Instit. Own. %, No. Analyst Following + Post x Analyst Following*) are insignificant. As expected, *R&D Missing* is negatively related to R&D intensity.

I examine the validity of the parallel trend assumption by replacing *Post* in column 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.

5.3. 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-publication lag (fourteen 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. 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.[14]

[14] I find that the correlation between the filing-to-publication lag and firm size is not significant (0.0016, p-value 0.89). This suggests that the variation in patent disclosure acceleration is distinct from the effects of firm size that I document in Section 5.5.

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 as-if capitalized 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:

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

$\beta_1 > 0$ 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 relative to control 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 indicates 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 indicates that R&D profitability does not change. Taken together, these results are inconsistent with the decline in R&D intensity resulting from efficiency gains, on average. In fact, there is some evidence that the average firm becomes less efficient after the AIPA. This result can obtain if disclosure regulation changes the competitive landscape so 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. This does not appear to be the case. I specifically control for investment opportunities as proxied by the MTB ratio. I include the interaction of *Post x MTB* to further allow for the possibility that investment opportunities change after the AIPA. As shown in Table 3 columns 2 and 3, I continue to find a decrease in R&D intensity.

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.

The results 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 suggests there is no significant change in R&D intensity. I interpret this result as evidence the largest firms anticipate R&D to be 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, this evidence indicates that 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 the largest 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 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 suggests 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.[15]

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 account for the fact that patents filed in more jurisdictions are more highly cited. Column 1 suggests that there is no difference in forward citations between treatment and control firms following the AIPA, on average. Column 2 indicates 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 appear to bear

[15] 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 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 on average nor significant 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.

negative innovation consequences in terms of patent impact 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 repeat the analyses using *#Patents* as a dependent variable and include an additional control for *R&D Intensity* to control for efficiency effects (Zhong 2018). Table 8 Panel B suggests there is no significant change in patenting after the AIPA on average (Column 1), nor difference in patenting between the largest and smaller firms (Column 2). 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 disclosure transparency, I should find firms stop patenting to avoid disclosure altogether. Recall that my sample of firms have at least three patents in five years of the pre-period, 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.

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 do not find a 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.[16] Thus, the decrease in *Patent Impact* is interpretable as a decrease in innovation quality.

I next examine whether these outcomes ultimately translate into changes in market power, using a firm's market share as a proxy. Table 9 suggests that there is no change in market share on average (Column 1). The largest firms have a market share 3.6% higher than smaller firms, which represents a total effect of the law of 2.7% for larger firms (Column 2). Smaller firms experience a significant decrease 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, the results in Table 9 include a control for acquisition activity (Compustat AQC/AT_{t-1}) and its interaction with *Post* and the finding of increased market power for the largest firms persists.

[16] 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 and increase the use of trade secrecy as proxied for by mentions of trade secrecy in SEC filings. They attribute this effect to the loss of insider trading opportunities that incentivize managers to take on risky investment. Their findings suggest that the substitution out of patenting and into trade secrecy occurs in a sample including firms with only occasional patenting activity.

5.7. Does the AIPA Change Firms' R&D Investment Strategies?

It is possible that firms adapt their R&D investment strategy to the changing dynamics of innovation after the AIPA. Specifically, instead of pursuing R&D investments in-house, perhaps firms adjust to acquiring R&D from existing firms. To explore this possibility, I examine several variables intended to capture acquisition activity: 1) spending on any acquisition, 2) the number of total acquisitions announced in a year, 3) the R&D intensity of a firm's target, 4) the number of announced acquisitions where the target has non-zero R&D expenditures, 6) the share of foreign acquisitions and 7) the share of withdrawn acquisitions. Results for the main effect are presented in Table 10 Panel A and for the effect of firm size in Panel B.

I find that there is no change in acquisition activity on average and that neither the number nor amount of acquisitive activity changes for the largest or smaller firms, whether measured using all acquisitions or acquisitions of R&D. Thus, the results do not appear to support the notion that treatment firms have lower in-house R&D intensity because they increase acquisitions of R&D intensive firms.

However, there is some evidence that the AIPA changed firms' acquisition strategies. Specifically, Table 10 Panel B shows that the largest firms increase the share of foreign acquisitions. Proponents of the AIPA argued that early patent disclosure would reduce the processing costs of foreign patent filings (Duffy, Gregory, Rines, Wamsley, and Wyatt 1998, 620). For example, the Japanese patent office would publish a Japanese patent filing after eighteen months both before and after the AIPA, but the filing would be published in Japanese. After the AIPA, if a Japanese patent were also filed in the U.S., it would be published earlier in English under the eighteen months disclosure rule. If large treatment firms are best positioned to benefit from reduced information processing costs of foreign filings, it could manifest as an increasing share of foreign acquisitions as the results in Table 10 Panel B Column 5 suggest.

There is also weak evidence that a reduced share of acquisitions made by smaller treatment firms are withdrawn. Table 10 Panel B Column 6 shows a significant decrease in the share of withdrawn acquisitions only for smaller treatment firms (*Treat x Post*), however, the difference between the largest and smaller treatment firms is insignificant (*Large x Treat x Post*). If smaller treatment firms benefit from improved patent transparency of potential targets, this could present as a decreasing share of withdrawn acquisitions. Taken together, the evidence does not appear to support the idea that firms switch from investing in R&D in-house to acquiring R&D, although there may be some informational benefits that influenced treatment firms' acquisition strategies.

5.8. DOES THE AIPA CHANGE FIRMS' PATENTING STRATEGIES?

The evidence thus far suggests the AIPA has real effects on firms' innovation investments and outcomes. As firms adapt to the new regulation, it is also possible that companies altered their patenting strategies. One goal of the AIPA was to harmonize U.S. patent law with the international community, which historically required eighteen-month disclosure. Since after the AIPA, the U.S. also had pre-grant disclosure, firms no longer stand to benefit from additional secrecy time by only filing for patent protection in the U.S. That being the case, it is possible that the AIPA had the effect of increasing foreign patent filings.

To examine this possibility, I count the number of jurisdictions in which a firm files patent applications for a single invention. I then take the average number of jurisdictions over a firm's patent filings for the year and use this as an alternative dependent variable. Table 11 Panel A presents the results. I find that the number of jurisdictions in which a firm files for patent protection significantly increases on average (Column 1). Column 2 shows that smaller treatment firms drive this increase and that the largest treatment firms change the number of jurisdictions significantly less than smaller firms, with an overall effect of no change in the number of jurisdictions. Thus, while the AIPA appears to have imposed costs on smaller firms through loss of lead time, the law also had the effect of increasing the number of countries in which smaller firms seek patent protection. In this sense, the AIPA does appear to benefit smaller firms and perhaps achieve a goal of international harmonization.

A second way in which firms could change their patenting strategy is to request voluntary patent publication. As discussed previously, both before and after the AIPA, a company can request that the USPTO publish a patent application early and the USPTO will grant the request with some delay for processing time. While the results suggest smaller firms in particular may have preferred the longer secrecy time that existed prior to the AIPA, the fact remains that in a post-AIPA environment, the marginal cost of timely patent disclosure decreases. In other words, now that eighteen-month patent disclosure is required, firms lose less secrecy time by further accelerating patent disclosure and are thus more willing to request voluntary publication.

I use the share of voluntary publications in a firm's patent applications as a dependent variable and present results in Table 11 Panel B. I find that, on average, firms request voluntary publication more after the AIPA (Column 1). Column 2 reveals that this increase is present both for the largest and smaller treatment firms, although the largest firms increase voluntary publication significantly less than smaller firms. Hegde and Luo (2017) find firms are more willing to license inventions shortly after patent publication. Thus, perhaps the observed increase in voluntary publications is due to firms' adapting their strategy to license inventions earlier after the AIPA as opposed to preserving lead time.

In sum, the results presented suggest smaller firms reduce R&D intensity while the largest firms make no change. The largest firms experience an increase in R&D efficiency and market share, while smaller firms appear to have a decrease in efficiency and innovation quality following transparent patent disclosure. However, the AIPA also has the effect of increasing smaller firms' international patent filings and all firms' voluntary patent publication requests, perhaps to facilitate licensing arrangements. Therefore, while the largest firms appear to benefit from the AIPA by some measures, there is evidence that smaller firms adapt their patenting strategies in response.

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

To address the concern that selection effects or pre-existing differences cause my results, I employ three strategies: 1) an alternative formulation of treatment and control groups, 2) matched sample analyses 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.

5.9.1. European Control Sample

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, the self-selection effects of foreign patent filings and voluntary publication are mitigated in this setting.

However, the European control group comes with several costs as well. First, data availability does not allow me to control for analyst following, institutional ownership or the share of foreign income. Second, European control firms are less likely to meet the parallel trend assumption than U.S. control firms. 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, with the notable exception of a significantly negative coefficient for 1996. Furthermore, there is reason to believe that European patenting firms were not similarly impacted by the internet bubble burst in the U.S. Consequently, even if a statistical analysis showed the parallel trend assumption were valid in the pre-period, it stands to reason that the parallel trends would not have continued into the post period in the absence of treatment.

For these reasons, I use the U.S. control firm sample throughout my main tests and pursue a control and fixed effects strategy to address any selection effects. The strategy of using multiple treatment and control groups is in keeping with Roberts and Whited (2013) who note that different groups are “helpful in so far as those differences are likely to come with different biases.” To the extent that both control groups yield similar inferences, this corroborates my inferences.

Table 12 Panel A suggests that U.S. patenting firms have a significant decrease in R&D intensity and European firms have a marginal increase. Treatment firms also have a greater decrease in ROA, increases in investment opportunities as proxied for by MTB, and experience an increase in industry concentration (Difference-in-Differences column). Both treatment and control firms decrease missing R&D values, though the largest change is present for European control firms. These differences highlight the importance of controlling for these factors.

Table 12 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). These results 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.

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 12 results are robust to this alternative.

5.9.2. Matched Sample Analyses

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 13 Panel A presents results. These results 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 13 Panel B).

5.9.3. Pseudo-event Analysis

Third, I use a pseudo-event date and repeat the analysis. If differences between treatment and control firms cause my results, the same results should obtain using a different time period 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. I present the results in Table 14. 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 results are robust to an alternative treatment and control sample, matched samples and a pseudo-event test.

5.10. 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 results 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.

Second, 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. To address this possibility, I include firm and industry by year fixed effects in my design and present results in Table 15 Panel A. Industry by year fixed effects allow for the response to macroeconomic events to vary by industry. I find that while the main effect is no longer significant, smaller treatment firms significantly decrease R&D intensity while the largest firms make no change and that the difference between the largest and smaller firms is statistically significant. As an alternative to traditional industry groupings, I also use the specific patent class the patent office assigns to each patent. For each firm, I identify the modal patent class in which a firm files patent applications and include patent class by year fixed effects. Results are presented in Table 15 Panel B and inferences are unchanged from those using traditional industry groupings.

Third, in untabulated analysis, I explicitly remove high tech firms following Efendi, Files, Ouyang and Swanson (2012) and find my results still hold.[17] Fourth, I use 1991 as a pseudo-event year in the pseudo-event analysis (Table 14), which also corresponds with a U.S. economic recession, and results do not obtain. Fifth, the result 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).

Finally, 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

[17] 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.

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 do not find a change for treatment firms relative to control firms. This evidence is inconsistent with the decrease in R&D intensity merely reflecting treatment firms decrease in expenditures across the board. As a whole, the evidence is inconsistent with the notion that my results are solely attributable to macroeconomic events.

5.11. DO FIRMS ANTICIPATE THE EFFECT OF THE AIPA?

Congress passed the AIPA on November 29, 1999 but the implementation of the eighteen-month disclosure rule took effect for patents filed on or after November 29, 2000. Therefore, it is possible that firms changed R&D intensity in anticipation of the final rule becoming effective. To the extent firms did made changes in anticipation of the law, this should bias against my 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. I continue to find a significant difference between the largest and smaller firms. Specifically, smaller firms significantly decrease *R&D Intensity* while the largest firms make no change, consistent with my main result, although there is no longer a significant decrease in *R&D Intensity* on average. I conclude anticipatory effects were not significant enough to preclude my findings on the effect of firm size.

Chapter 6: Conclusion

I examine whether disclosure regulation can impede firms' incentive to innovate. After a patent law change that increased patent disclosure transparency, I find firms allocate fewer resources to R&D. This result suggests the costs associated with this change in required disclosure dominate the 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. My results also indicate 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. However, the law does appear to encourage international patent filing among smaller firms and reduces costs to requesting voluntary patent publication, which may allow firms to pursue greater licensing opportunities.

This paper is subject to various limitations. First, the results cannot speak to the total welfare implications of the AIPA as I focus on R&D incentives and outcomes for only the producers of patented innovations. It remains possible that other R&D-related benefits accrue to parties outside the sample. Second, though the pattern of results discussed in Section 5.10 is inconsistent with macroeconomic events being the sole cause of my results, the co-occurrence of the AIPA with the dot com bubble remains a limitation.

Taken as a whole, my results present a somewhat mixed view of transparent patent disclosure. On the one hand, transparency does not appear to confer innovation benefits to the significant producers of patents on average. Instead, smaller firms devote fewer resources to R&D when transparent patent disclosure is required, but do not patent less despite apparent efficiency losses. This tendency could result from 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. On the other hand, to the extent the law increases foreign patent filings or facilitates licensing opportunities there is an apparent bright side. These results should be of interest to researchers interested in the real effects of disclosure regulation and those involved in patent regulation.

Tables

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
Retain observations with a patent application in three out of five years of the pre-event period	13,558
Retain observations with ten consecutive years of data	8,490
Treatment firm-year observations	6,520
Control firm-year observations	1,970

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	261	3.07	219	3.36	42	2.13
Consumer Durables	396	4.66	257	3.94	139	7.06
Manufacturing	1,800	21.20	1,311	20.11	489	24.82
Oil, Gas, and Coal	119	1.40	79	1.21	40	2.03
Chemicals and Allied Products	452	5.32	231	3.54	221	11.22
Computers, Software, and Electronic Equipment	2,976	35.05	2,519	38.63	457	23.20
Telephone and Television Transmission	92	1.08	92	1.41	0	0.00
Wholesale, Retail, and Some Services	65	0.77	62	0.95	3	0.15
Healthcare, Medical Equip. & Drugs	2,018	23.77	1,490	22.85	528	26.80
Other	311	3.66	260	3.99	51	2.59
Total	8,490		6,520		1,970	

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 Differences**	
	Pre	*Post*	*Difference*		*Pre*	*Post*	*Difference*			
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	0.12	-0.05	***	-0.02	*
$Opinc_{t+1, t+5}$	0.65	0.56	-0.09	***	0.70	0.54	-0.16	**	0.07	
Patent Impact	0.73	0.69	-0.04	***	0.69	0.67	-0.02		-0.02	
Market Share	0.05	0.06	0.01	***	0.05	0.06	0.01	*	0.00	
Size	5.68	6.15	0.47	***	5.63	6.02	0.39	***	0.08	
ROA	0.06	0.00	-0.06	***	0.07	0.02	-0.05	***	-0.01	
Loss	0.36	0.44	0.08	***	0.32	0.39	0.07	***	0.01	
MTB	4.62	3.36	-1.26	***	3.88	3.07	-0.81	***	-0.45	
Foreign Income	0.13	0.16	0.03	**	0.18	0.24	0.06	**	-0.03	
Industry Concentration	0.19	0.21	0.02	***	0.19	0.20	0.01	**	0.01	
Leverage	0.17	0.20	0.03	***	0.20	0.24	0.04	***	-0.01	
Institutional Ownership %	0.36	0.47	0.11	***	0.37	0.47	0.10	***	0.01	
No. Analyst Following	5.24	6.05	0.81	***	4.47	5.09	0.62	**	0.19	
R&D Missing	0.04	0.03	-0.01	*	0.04	0.02	-0.02	*	0.01	
#Patents, untransformed	41.99	44.78	2.79		22.17	21.86	-0.31		3.10	
#Patents	2.13	2.16	0.03		1.85	1.75	-0.10		0.13	*
Trade Secrets	0.52	0.62	0.10	***	0.45	0.52	0.07	***	0.03	
Acquisition Spending	0.03	0.02	-0.01	***	0.03	0.03	0.00		-0.01	
Number of Acquisitions	0.86	0.65	-0.21	***	0.64	0.45	-0.19	***	-0.02	
Target R&D Intensity	0.00	0.00	0.00		0.00	0.00	0.00		0.00	
Number of R&D Acquisitions	0.07	0.05	-0.02	***	0.04	0.03	-0.01	**	-0.01	
Foreign Acquisitions	0.10	0.10	0.00		0.12	0.10	-0.02	*	0.02	
Withdrawn Acquisitions	0.01	0.00	-0.01	*	0.00	0.00	0.00		-0.01	
Number of Jurisdictions	2.35	2.32	-0.03		3.34	2.87	-0.47	***	0.44	***
Voluntary Publication	0.14	0.38	0.24	***	0.29	0.42	0.13	***	0.11	***
Firm-year Observations	3,260	3,260			985	985				

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***	-0.016**	-0.016**
	(-3.404)	(-2.212)	(-2.009)
Size		-0.032***	-0.031***
		(-5.667)	(-5.163)
ROA		0.052***	0.054***
		(5.453)	(6.067)
Loss		0.028***	0.027***
		(3.124)	(3.210)
MTB		0.001***	0.001***
		(4.711)	(4.653)
Foreign Income		0.003*	0.003*
		(1.845)	(1.847)
Industry Concentration		-0.039	-0.045
		(-1.287)	(-1.509)
Leverage			-0.008
			(-0.577)
Institutional Ownership %			-0.023***
			(-2.907)
No. Analyst Following			-0.001*
			(-1.899)
R&D Missing			-0.076**
			(-2.541)
Post x MTB		-0.001***	-0.001***
		(-2.757)	(-2.784)
Post x Leverage			0.026
			(1.023)
Post x Instit. Own. %			0.015**
			(2.262)
Post x Analyst Following			0.001*
			(1.915)
Observations	8,404	7,664	7,641
Adjusted R-squared	0.643	0.659	0.661
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.

Dependent Variable:	(1) R&D Intensity	(2) R&D Intensity	(3) R&D Intensity
High Accel. x Treat x Post	-0.025***	-0.012***	-0.011***
	(-3.968)	(-2.964)	(-2.661)
Treat x Post	-0.013**	-0.012	-0.012
	(-2.008)	(-1.568)	(-1.504)
Size		-0.032***	-0.030***
		(-5.632)	(-5.170)
ROA		0.052***	0.054***
		(5.398)	(6.042)
Loss		0.028***	0.027***
		(3.115)	(3.202)
MTB		0.001***	0.001***
		(4.517)	(4.536)
Foreign Income		0.003*	0.003*
		(1.859)	(1.860)
Industry Concentration		-0.040	-0.045
		(-1.318)	(-1.532)
Leverage			-0.006
			(-0.475)
Institutional Ownership %			-0.022***
			(-2.746)
No. Analyst Following			-0.001*
			(-1.944)
R&D Missing			-0.076**
			(-2.552)

Table 4: Extent of Acceleration, continued

	(1)	(2)	(3)
Dependent Variable:	R&D Intensity	R&D Intensity	R&D Intensity
Post x MTB		-0.001***	-0.001***
		(-2.654)	(-2.766)
Post x Leverage			0.025
			(0.953)
Post x Instit. Own. %			0.014**
			(2.049)
Post x Analyst Following			0.001**
			(2.066)
Observations	8,404	7,664	7,641
Adjusted R-squared	0.644	0.659	0.662
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	-0.032***	
	(-2.699)	
R&D x Treat x Post		0.632
		(0.854)
Observations	6,970	6,940
Adjusted R-squared	0.615	0.781
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	0.024**
	(2.403)
Treat x Post	-0.020**
	(-2.179)
Overall Effect for Large Treatment Firms	0.004
Significance Level	0.436
Observations	7,641
Adjusted R-squared	0.662
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	0.038*	
	(1.894)	
Treat x Post	-0.040***	
	(-2.723)	
Large x R&D x Treat x Post		1.798**
		(1.990)
R&D x Treat x Post		0.588
		(0.735)
Overall Effect for Large Treatment Firms	-0.002	2.386***
Significance Level	0.874	0.000
Observations	6,970	6,940
Adjusted R-squared	0.615	0.781
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

	(1)	(2)
Dependent Variable:	Patent Impact	Patent Impact
Large x Treat x Post		0.078***
		(2.870)
Treat x Post	-0.028	-0.049**
	(-1.451)	(-2.127)
Overall Effect for Large Treatment Firms		0.029
Significance Level		0.187
Observations	6,541	6,541
Adjusted R-squared	0.406	0.407
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 8: Patent Impact, Number of Patents and Trade Secrets, continued

Panel B: #Patents

Dependent Variable:	(1) #Patents	(2) #Patents
Large x Treat x Post		0.087
		(0.751)
Treat x Post	0.081	0.055
	(1.625)	(1.074)
Overall Effect for Large Treatment Firms		0.142
Significance Level		0.200
Observations	7,641	7,641
Adjusted R-squared	0.858	0.858
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 8: Patent Impact, Number of Patents and Trade Secrets, continued

Panel C: Trade Secrets

Dependent Variable:	(1) Trade Secrets	(2) Trade Secrets
Large x Treat x Post		0.019
		(0.345)
Treat x Post	0.027	0.022
	(1.188)	(0.813)
Overall Effect for Large Treatment Firms		0.041
Significance Level		0.369
Observations	6,616	6,616
Adjusted R-squared	0.801	0.801
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		0.036***
		(3.030)
Treat x Post	-0.002	-0.009*
	(-0.484)	(-1.934)
Overall Effect for Large Treatment Firms		0.027**
Significance Level		0.013
Observations	7,641	7,641
Adjusted R-squared	0.854	0.856
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 10: Acquisitions

This table presents DID regression results for acquisition activity. Panel A presents results comparing changes in the outcome for treatment firms relative to control firms (*Treat x Post*). Panel B 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.

Panel A: Main Effect

Dependent Variable:	(1) Acquisition Spending	(2) Number of Acquisitions	(3) Target R&D Intensity	(4) Number of R&D Acquisitions	(5) Foreign Acquisitions	(6) Withdrawn Acquisitions
Treat x Post	-0.005	-0.028	0.000	0.003	0.012	-0.000
	(-1.136)	(-0.390)	(0.022)	(0.192)	(0.791)	(-0.180)
Observations	7,641	7,647	7,647	7,647	7,647	7,647
Adjusted R-squared	0.125	0.500	0.156	0.218	0.205	0.055
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 10: Acquisitions, continued

Panel B: Effect of Firm Size

Dependent Variable:	(1) Acquisition Spending	(2) Number of Acquisitions	(3) Target R&D Intensity	(4) Number of R&D Acquisitions	(5) Foreign Acquisitions	(6) Withdrawn Acquisitions
Large x Treat x Post	-0.008	0.041	-0.003	-0.012	0.084**	0.008
	(-0.744)	(0.225)	(-0.870)	(-0.313)	(2.137)	(1.532)
Treat x Post	-0.003	-0.048	0.001	0.003	-0.009	-0.003*
	(-0.629)	(-0.764)	(0.452)	(0.236)	(-0.600)	(-1.790)
Overall Effect for Large Treatment Firms	-0.011	-0.007	-0.002	-0.009	0.075**	0.005
Significance Level	0.271	0.973	0.473	0.815	0.039	0.263
Observations	7,641	7,647	7,647	7,647	7,647	7,647
Adjusted R-squared	0.124	0.501	0.156	0.221	0.206	0.056
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 11: Changes in Patent Filing Choices

Panel A presents DID regression results for the average number of foreign jurisdictions in which a firm files for patent protection and Panel B presents results for the share of a firm's patent portfolio it chooses to publish early. 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.

Panel A: International Patent Filings

Dependent Variable:	(1) Number of Jurisdictions	(2) Number of Jurisdictions
Large x Treat x Post		-0.393*
		(-1.707)
Treat x Post	0.408***	0.511***
	(2.814)	(2.962)
Overall Effect for Large Treatment Firms		0.118
Significance Level		0.463
Observations	7,647	7,647
Adjusted R-squared	0.342	0.343
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 11: Changes in Patent Filing Choices, continued

Panel B: Voluntary Patent Publication

Dependent Variable:	(1) Voluntary Publication	(2) Voluntary Publication
Large x Treat x Post		-0.074**
		(-2.045)
Treat x Post	0.105***	0.123***
	(4.695)	(4.896)
Overall Effect for Large Treatment Firms		0.049*
Significance Level		0.088
Observations	7,647	7,647
Adjusted R-squared	0.307	0.308
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 12: 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 Differences**	
	Pre	*Post*	*Difference*		*Pre*	*Post*	*Difference*			
R&D Intensity	0.15	0.11	-0.04	***	0.04	0.05	0.01	*	-0.05	***
Size	5.67	6.12	0.45	***	7.28	7.65	0.37	***	0.08	
ROA	0.07	0.01	-0.06	***	0.07	0.06	-0.01		-0.05	***
Loss	0.35	0.43	0.08	***	0.14	0.22	0.08	***	0.00	
MTB	4.47	3.24	-1.23	***	4.94	2.45	-2.49	***	1.26	**
Industry Concentration	0.19	0.20	0.01	***	0.17	0.15	-0.02	***	0.03	***
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	4,245	4,245			820	820				

Table 12: Alternative Treatment and Control Groups, continued

Panel B: DID Regression Results

	(1)	(2)
Dependent Variable:	R&D Intensity	R&D Intensity
Large x Treat x Post		0.043***
		(3.086)
Treat x Post	-0.043***	-0.056***
	(-3.487)	(-4.044)
Overall Effect for Large Treatment Firms		-0.013*
Significance Level		0.035
Observations	8,132	8,132
Adjusted R-squared	0.671	0.672
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 13: 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		0.028**
		(2.029)
Treat x Post	-0.023*	-0.028**
	(-1.843)	(-2.031)
Overall Effect for Large Treatment Firms		0.000
Significance Level		0.967
Observations	3,115	3,115
Adjusted R-squared	0.693	0.694
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 13: Matched Sample DID Regression Results, continued

Panel B: Entropy Balanced Matching

Dependent Variable:	(1) R&D Intensity	(2) R&D Intensity
Large x Treat x Post		0.019*
		(1.960)
Treat x Post	-0.013*	-0.016**
	(-1.939)	(-1.996)
Overall Effect for Large Treatment Firms		0.003
Significance Level		0.681
Observations	7,641	7,641
Adjusted R-squared	0.670	0.671
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 14: 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		0.003
		(0.852)
Treat x Post	-0.003	-0.004
	(-1.505)	(-1.401)
Overall Effect for Large Treatment Firms		-0.001
Significance Level		0.428
Observations	5,419	5,419
Adjusted R-squared	0.800	0.800
Controls	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

Table 15: Alternative Fixed Effect Structure

Panel A presents DID regression results using industry (3-digit SIC) by year and firm fixed effects and Panel B employs patent class by year and firm fixed effects. Column 1 presents the DID regression results for R&D intensity 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.

Panel A: Industry by Year and Firm Fixed Effects

	(1)	(2)
Dependent Variable:	R&D Intensity	R&D Intensity
Large x Treat x Post		0.027**
		(2.472)
Treat x Post	-0.016	-0.021*
	(-1.630)	(-1.977)
Overall Effect for Large Treatment Firms		0.006
Significance Level		0.406
Observations	7,179	7,179
Adjusted R-squared	0.640	0.640
Controls	YES	YES
Industry by Year FE	YES	YES
Firm FE	YES	YES

Table 15: Alternative Fixed Effect Structure, continued

Panel B: Patent Class by Year and Firm Fixed Effects

Dependent Variable:	(1) R&D Intensity	(2) R&D Intensity
Large x Treat x Post		0.037***
		(2.701)
Treat x Post	-0.024	-0.033*
	(-1.513)	(-1.885)
Overall Effect for Large Treatment Firms		0.004
Significance Level		0.611
Observations	6,285	6,285
Adjusted R-squared	0.673	0.674
Controls	YES	YES
Industry by Year FE	YES	YES
Firm FE	YES	YES

Figures

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

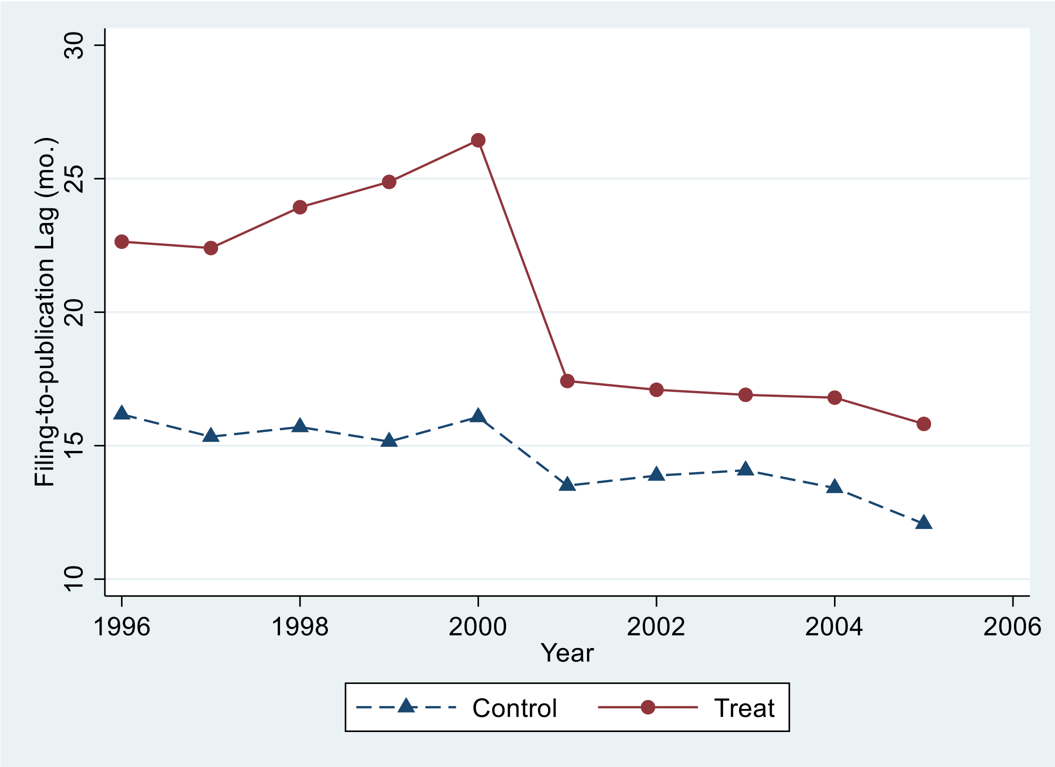
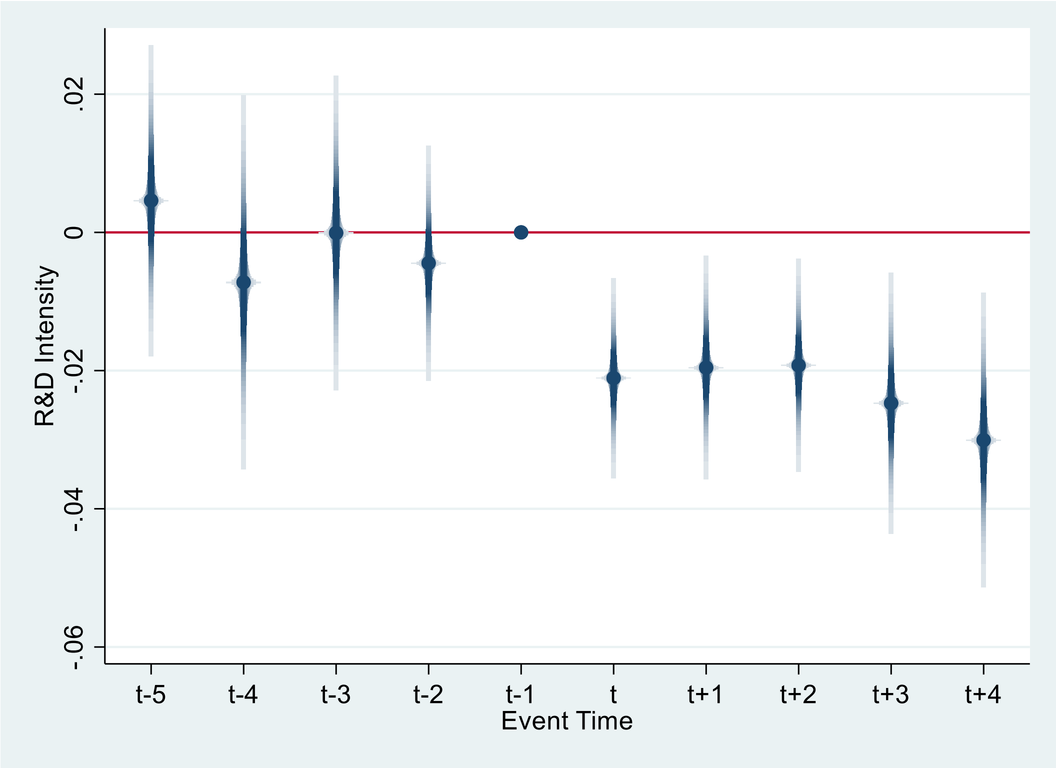


Figure 2: Parallel Trend Assumption



Appendices

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 ($\mathrm{XRD/AT_{t-1}}$). 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, scaled by total assets. (OIBDP+XRD+XAD)/AT.
Patent Impact	The log of one plus the average forward citations for a firm's patents filed in year *t*. Forward citations are calculated at the patent level as 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 logarithm 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.
Target R&D Intensity	The logarithm of one plus the ratio of all targets' R&D expense to all targets' total assets ($\mathrm{XRD/AT_{t-1}}$). Missing values are set to zero. Obtained from SDC.
Number of Acquisitions	The number of acquisitions a firm announces in a year. Obtained from SDC.
Number of R&D Acquisitions	The number of acquisitions a firm announces in a year where the target had non-zero R&D expenditures in their most recent financials. Obtained from SDC.
Foreign Acquisitions	The ratio of the number of foreign acquisitions to total acquisitions a firm announces during a year. Obtained from SDC.
Withdrawn Acquisitions	The ratio of the number of withdrawn acquisitions to total acquisitions a firm announces during a year. Obtained from SDC.

Number of Jurisdictions	The average across a firm's patents filed in year *t* of the number of jurisdictions in which a firm files for patent protection.
Voluntary Publication	The average across a firm's patents filed in year *t* of an indicator for voluntary publication. For both patents filed internationally and for patents only filed in the U.S. after 2000, voluntary publication takes on the value of one when the patent grant date is after the publication date and the time between filing a patent and its publication is less than eighteen months. For patents only filed in the U.S. in 2000 or earlier, voluntary publication takes on the value of one when the patent grant date is not equal to the publication date.
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 income before extraordinary items plus R&D expenditures divided by total assets (IB+XRD/AT). Obtained from Compustat.
MTB	The ratio of the market value of equity to the book value of equity. ((PRCC_F*CSHO)/(CEQ+TXDB)). Obtained from Compustat.
Foreign Income	The percent of total pre-tax income attributable to foreign operations. (PIFO/PI). Obtained from Compustat.
Industry Concentration	The natural log of the sum of the squared market share of each firm in a four-digit SIC code in a year. Market share is calculated as the sales of a particular company divided by the total sales of the SIC code.
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%

APPENDIX B. DATA COLLECTION PROCEDURES

This appendix details the procedures used to extract patent records and match them to corporate owners. First, I describe the patent data. Next, I specify the steps used in my data collection process.

B.1. Description of Patent Data

Patent applications must be filed with the appropriate patent office to receive patent protections in a given jurisdiction. Governments grant exclusivity rights for an invention in return for disclosure that allows others to replicate the invention and build on its innovations. Accordingly, patent offices make patent records publicly available. These records include patent applications and patent grants with information on the invention itself, as well as those seeking patent protection. Typical fields of interest to researchers are the original assignee (patent owner); application filing, publication and grant dates; technology class of the invention; and a list of citations to patents and other scientific sources on which an invention draws.

I use patent data made available through Google BigQuery.[18] BigQuery is an enterprise data warehouse for data scientists that stores information using Google's infrastructure. The data housed on BigQuery is accessed through SQL queries. I use a series of SQL queries to extract data from Google BigQuery, create a comprehensive

[18] Specifically, I use the "publications_201710" table whose underlying data is obtained from the Documentation Database (DOCDB) maintained by the European Patent Office. Data enrichments to the DOCDB are provided by IFI Claims, a leading provider of global patent data.

dataset of patent records, and match them to corporate owners. Google BigQuery contains published patent records from 17 patent offices around the world.[19] Thus, my dataset is unique because it captures information about the jurisdictions in which patent protection is sought for a single invention, includes citations received from patents all around the world, includes all patent applications even if there is no subsequent patent grant, and extends the time series of data through records published as of October 2017. Notably, the SQL queries and matching procedures I develop can be used to readily update the dataset with new patent records as they become available on BigQuery.

B.2. Data Collection

B.2.1. Overview

My data collection proceeds in the following steps:

1) Extract all pertinent patent records filed in or after 1980. Specifically, I collect non-design patent records that are filed in or after 1980 and available on BigQuery as of October 2017 for a given jurisdiction.

2) Create a file that links assignee names listed in BigQuery to a firm's *gvkey* in Compustat North America and Compustat Global.

3) Merge the firm's *gvkey* in to the dataset constructed in Step 1) above using the BigQuery assignee name.

[19] The patent offices are the United States, Europe, Japan, China, South Korea, WIPO, Russia, Germany, the United Kingdom, Canada, France, Spain, Belgium, Denmark, Finland, Luxembourg, and the Netherlands.

4) Calculate patent-based variables.

5) Aggregate patent variables to the firm-year level.

Through these procedures I obtain a dataset containing firm-year, patent-based measures that can be linked to financial data on Compustat using the gvkey variable. In the following sections I elaborate on several of these steps as necessary for transparency and replicability.

B.2.2. Link Assignee Names to Company Identifier

Patent records include the name of a patent's "assignee," the legal term for the patent's owner. Patent records also list the inventor, which can one or more individuals, but not a legal entity such as a corporation. For corporate owned patents, the inventor(s) is frequently listed as the assignee on a patent application and at some point in the patent granting process, ownership is transferred to the corporation. Assignee names are not standardized within or across patent offices. Given these complexities, matching patent records to individual firms is challenging, a fact discussed in prior research using patent-based measures (Balsmeier, Li, Chesebro, Zang, Fierro, Johnson, and Fleming 2016; Hall, Jaffe and Trajtenberg 2001; Kogan, Papanikolaou, Seru, and Stoffman 2017). The approach I adopt leverages the significant name cleaning and standardization performed by prior research teams and allows for the addition of new firms in years subsequent to existing databases' sample periods.

The output from Step 2) as outlined in Section 2.1 above is a list of assignee names included in BigQuery that are linked to Compustat's gvkey. To obtain this list, I first replicate the name match performed by prior research teams in their sample periods. Second, I extend that name match to all other instances of the same BigQuery assignee, including for years after those covered by existing databases and to other jurisdictions. Third, for any remaining records, I use a name matching algorithm to match the BigQuery assignee name to the company's legal name in Compustat North America and Compustat Global.

First, if a patent's record number exists in the data compiled by Kogan, Papanikolaou, Seru, and Stoffman 2017, I match that record to the corporation identified in their data. The Kogan et al. 2017 data goes through 2010 and matches U.S. patent records to CRSP's permno identifier. I use the CRSP/Compustat Merged Database to translate from CRSP permno to Compustat's gvkey. The Kogan et al. 2017 data builds upon, extends and corrects the NBER patent data compiled by Hall, Jaffe, and Trajtenberg 2001. Therefore, by replicating the name match used in Kogan et al. 2017, I ensure that my data takes advantage of the name matching performed by both Hall, Jaffe, and Trajtenberg 2001 as well as Kogan, Papanikolaou, Seru, and Stoffman 2017. Another advantage of using the Kogan et al. data is that it allows me to check the completeness of the BigQuery data. Kogan et al. 2017 match a total of 1.3 million patent records to CRSP for the time period from 1980-2010 (see their Table A.2 Assignee Matching by Decade). I verified that there are indeed 1.3 million patent records in BigQuery with a direct match to the Kogan et al. 2017 dataset (reconciled to within less than 1%).

Second, for each BigQuery assignee name that is present in the Kogan et al. data, I apply the same assignee-gvkey link for other instances of the same BigQuery assignee, even for patents not included in the Kogan et al. data. The implications of this procedure are that patent records filed after Kogan et al.'s sample period but with the same assignee name as a patent record in their dataset are linked to the same gvkey. Also, assignee names present during Kogan et al's sample period that occur in other jurisdictions in any time period are linked to the same gvkey; this occurs when domestic corporations apply for patent protection in foreign jurisdictions. Finally, because Kogan et al. only use U.S. patent records that are ultimately granted, my extension of their match may also apply to U.S. applications during the Kogan et al. sample period where there is no patent grant. This can occur if the application is subsequently abandoned by the firm or if the application is filed late in my sample period and has yet to be granted. Thus, this step expands the scope of coverage beyond Kogan et al.'s data to include records later in time, in other jurisdictions and for applications not granted.

Third, for records not linked to a gvkey in the preceding steps, I use a name matching algorithm to generate a similarity score between a BigQuery assignee name and Compustat's company legal name. The algorithm uses inverse word frequency as weights in assigning matches, so words that occur frequently in the data (e.g. "American") are given less weight than more unusual names ("Bausch"). This procedure is available in STATA as the package called "matchit".[20]

To perform the name match, I require a list of BigQuery assignee names and corporate legal names from Compustat. First, I create a list of unique BigQuery assignee names that represent potential corporate assignees. Because corporations may not be inventors, I identify patent records where the list of assignees is not included in the list of inventors and remove duplicate assignee names from the results. Before applying the name matching algorithm, I also clean and standardize the BigQuery assignee names using the STATA .do files made available by the Hall, Jaffe, and Trajtenberg 2001 team.[21] This name cleaning and standardization removes punctuation and designations of corporate form (such as "Inc." or "Corp."). The purpose of selecting only potentially corporate assignee names and standardizing names is to improve the accuracy and efficiency of the name match.

In performing the name match, I use the Compustat legal names from both Compustat North America and Compustat Global. This data step allows me to identify patent holdings for firms added to Compustat in recent time periods as well as expanding the scope of prior name matches that only used Compustat North America (e.g. the NBER database documented in Hall, Jaffe, and Trajtenberg 2001).

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[20] The specific options I use are weights(simple) and similmethod(token), which weight words based on their inverse frequency and compare each individual word in two strings when making a match, respectively.

[21] Programs available at https://sites.google.com/site/patentdataproject/Home/posts/namestandardizationroutinesuploaded.

After applying the above three steps, I check that each unique BigQuery assignee is matched to only one gvkey. In the infrequent instances where an assignee name is linked to multiple gvkeys, I repeat the “matchit” routine and choose the link with the highest similarity score. The culmination of these steps generates a cleaned file linking BigQuery assignee names to Compustat’s gvkey. I then merge the firm’s gvkey in to the BigQuery dataset of all patent records filed in or after 1980. As a final check on the name matching procedures, I identify and correct instances where patent records within the same family were matched to multiple gvkeys (only 3% of patent records). I default to choosing a Kogan et al. match or extension and use STATA’s “matchit” routine to break any remaining ties.

B.2.3. Calculate Patent-based Variables

Though a detailed definition of variables is included in Appendix A, the calculation of forward citations received (Patent Impact) merits further discussion. An individual patent record (e.g. an application or grant) belongs to a patent family, which is a collection of patent records that all pertain to the same underlying invention. As my dataset contains complete information about an invention’s patent family comprised of records from around the world, I am able to take a broader view of citation-based measures than prior researchers. Specifically, in counting citations received, I identify unique citations received by any patent record in the invention’s family. If multiple documents in a patent family cite the same patent, I count that citation only once. The implication of this measurement decision is that I count all worldwide citations a patent receives, not just those citations received from U.S. patent documents, as is the case in much of prior research.

B.2.4. Aggregate Patent Variables to the Firm-year Level

The number of citations received is calculated at the patent record level and then aggregated to the firm-year level. Complicating this aggregation process is the fact that information about a single invention is captured in multiple patent documents all considered part of the same patent family. I reduce the individual patent-level dataset down to one patent record per patent family, retaining the filing date of the earliest filing in a given jurisdiction (e.g. the earliest U.S. filing date for firms incorporated in the U.S.). The implication of this choice is that I only count one patent per unique invention, regardless of the number of patent documents that exist in the patent family. I then average patent-level measures within a firm-year based on the filing date.

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