Mandatory Corporate Patent Disclosures and Innovation

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Abstract

I investigate the effect of corporate patent disclosures on innovation. Using the American Inventor's Protection Act (AIPA) as a plausibly exogenous shock to corporate patent disclosures, I find evidence of the AIPA shaping innovation through two simultaneous channels. First, the AIPA encourages a firm to innovate by facilitating access to the scientific information contained in other firms' patent disclosures. Second, the AIPA discourages a firm from innovating by increasing the risk of leaking business-related strategies through its own patent disclosures. These findings are consistent with the view that corporate patents contain information useful for both science and business, and highlight their respective roles in generating both spillover benefits and proprietary costs of mandating patent disclosures. Finally, using textual analysis, I find that firms with high proprietary costs respond to the AIPA by strategically changing their patent disclosures to obfuscate exploitable business-related signals.

Key words: Corporate disclosure, patent disclosure, innovation, spillovers, proprietary costs

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1 Introduction

[The information in patents] adds to the general store of knowledge [and is] of such importance to the public weal that the Federal Government is willing to pay the high price of 17 years of exclusive use for its disclosure, which disclosure, it is assumed, will stimulate ideas and the eventual development of further significant advances in the art.

– The U.S. Supreme Court (Kewanee Oil Co. v. Bicron Corp., 416 U.S. 470).

The patent system requires patenting firms to disclose the details of their inventions publicly in exchange for short-term monopoly rights.[1] As the Supreme Court quote above suggests, the disclosure requirement aims to promote the dissemination of knowledge and stimulate innovation. To date, however, evidence on whether or how patent disclosures affect innovation is scarce (Williams (2017)).[2] This study examines the effects of patent disclosures on corporate innovation.

The enactment of the American Inventor's Protection Act (AIPA) on Nov 29, 2000, represents a plausibly exogenous expansion of firms' patent disclosure requirements, as it increased the timeliness and scope of patent disclosures (Hegde and Luo (2018)). Before the AIPA, only US *granted* patents were disclosed at the time of grant, which happened, on average, 38 months after filing. Since the enactment of the AIPA, firms must disclose US patent applications within 18 months after filing, regardless of whether the application is eventually granted patent rights. Thus the AIPA accelerated disclosure by about 20 months and required the disclosure of granted as well as pending applications.

The AIPA likely affects corporate innovation through two countervailing forces. On the one hand, similar to the literature on knowledge spillovers (e.g., Foster (1981); Furman and Stern (2011); Badertscher, Shroff, and White (2013)), greater availability of knowledge from the disclosure of *others'* patents is likely to facilitate a firm's innovation. On the other hand, similar to

[1] Specifically, the disclosure provision in patent law (35 U.S.C. section 112) requires the patent applicant to describe the invention to promote information diffusion and enable improvements of the original invention.
[2] Williams (2017) suggests that there is no systematic study that investigates the relation between patent disclosures and innovation. This is in stark contrast to the numerous studies that examine the effect of patent rights on innovation.

the literature on proprietary costs (e.g., Verrecchia (1983); Anton and Yao (1994); Verrecchia and Weber (2006) Berger and Hann (2007)), the costs of having to disclose proprietary patent information *to others* likely reduce a firm's incentive to pursue patented innovations. Thus the effect of the mandate depends on which side of the informational "exchange" – knowledge spillovers vs. proprietary costs – dominates (Minnis and Shroff (2017)).

The informational exchange induced by the AIPA likely occurs along two distinct types of information embedded in patent disclosures. First, patent disclosures can trigger the exchange of novel *scientific* information between firms (Ouellette (2017)). For example, a patent filed by an automobile manufacturer can provide scientific knowledge that a lawn mower maker finds useful in building better mower engines. Second, patent disclosures can trigger the exchange of *business-related* signals between firms (Horstmann, MacDonald, and Slivinski (1985); Boulakia (2001)). For example, a firm's filing of a patent related to virtual reality technology can inform its product market competitors. The patent can reinforce competitors' beliefs that VR technology has strong market potential or perhaps suggest a company is lagging the market, prompting it to make strategic acquisitions.

Taken together, my hypothesis is that the AIPA will trigger the exchange of both scientific and business-related information, and these exchanges will increase a firm's innovation if the spillover benefits dominate and decrease a firm's innovation if the proprietary costs dominate.

To estimate the exchange of science and business information, I rely on firm exposure measures developed by Bloom, Schankerman, and Van Reenen (2013) that distinguish a firm's position in the technology and product-market spaces. This approach uses information on the distribution of the firm's patenting across technology fields and its sales across different industries. These measures capture the likelihood that a firm exchanges useful scientific information or business-related information with other firms, conditional on a disclosure shock. In my context, I use the measures of Bloom et al. (2013) to separately identify the AIPA's impact of increased exchange of scientific and business-related information on a firm's innovation.

I use a sample of 259,368 patents owned by 525 unique firms over the period 1996–2005. My main tests compare a firm's innovation before vs. after the AIPA, conditional on a firm's likelihood of exchanging scientific and business information with other firms. I use patent citations as my main proxy for innovation following prior research, but verify my findings with other proxies of innovation in further tests described below.[3] I include firm and year fixed effects to control for time-invariant factors (e.g., some firms are intrinsically more innovative) and trends (e.g., introduction of high-speed internet). Following Lerner and Seru (2017), I also include patent-technology-class fixed effects in some specifications to account for heterogeneity across patent classes (e.g., patents in certain sectors tend to be more innovative).

My tests show that early patent disclosures mandated by the AIPA *foster* a firm's innovation, through the greater exchange of scientific information, but *impede* a firm's innovation when the law triggers an exchange of business signals. Specifically, the portfolio of patents filed over the five years after the AIPA held by firms with the highest likelihood of exchanging scientific (business) information receive about 575 additional (525 fewer) patent portfolio citations, relative to pre-AIPA averages. Kogan, Papanikolaou, Seru, and Stoffman (2017) estimate that one additional patent citation is roughly worth \$15,000 to \$500,000, suggesting the effect is material.

I corroborate and extend my results by examining firms' real decisions – R&D spending and hiring decisions – as input-based proxies for innovation. Specifically, after the AIPA, firms that are more likely to exchange scientific (business) information invest more (less) in R&D, hire more

[3] A patent that receives more citations over its lifetime is assumed to be more innovative (Lerner and Seru (2017)).

(fewer) educated scientists, and incumbent scientists become more (less) productive. In addition, I show that these effects begin only among patents filed after two years following the AIPA and gradually rise in magnitude over time, consistent with the slow moving nature of innovation. These results collectively corroborate the inference that the documented change in patent citations is driven by fundamental shifts in firms' innovative effort.

A plausible interpretation for the positive innovation effect of exchanging scientific information is that the knowledge spillover benefits of other firms' disclosures of scientific information dominate the proprietary costs of having to disclose scientific information to others. Similarly, the negative innovation effect of exchanging business information is likely a reflection that the proprietary costs of revealing exploitable business signals to others dominate the benefits of receiving business signals from others' disclosures.

I perform two tests to investigate the plausibility of this interpretation. First, I estimate information "spill-ins" by weighting the Bloom et al. (2013) measures by the number of pre-AIPA patents of other firms. The idea is that, when other firms hold more patents, the disclosure shock of the AIPA is likely to generate more patent information "spilling in" from other firms to a focal firm. Similarly, I measure information "spill-outs" by weighting the Bloom et al. (2013) measures by the pre-AIPA patents of the focal firm. I find that the positive innovation effect of exchanging scientific information is primarily driven by greater information spill-ins induced by the AIPA, consistent with knowledge spillovers from others' disclosures driving the firm's increase in innovation. By contrast, I find that the negative innovation effect of exchanging business information is driven by greater information spill-outs, consistent with proprietary costs of having to disclose to others, discouraging the firm to innovate.

Second, prior research in accounting suggests that a firm can strategically obfuscate the linguistic content of its disclosures to conceal information from rivals (Li (2010); Loughran and McDonald (2016); Bushee, Gow, and Taylor (2018)). Relatedly, research in law and linguistics argue that using "vague expressions" in legal documents like patents can be an effective way to achieve strategic obfuscation (Myers (1996); Choi and Triantis (2010); Hall and Harhoff (2012)).[4,5] Consistent with these arguments, I find that firms are more likely to include vague expressions in their patents when forced to exchange business information after the AIPA, corroborating the inference that the law induces proprietary costs by forcing firms to exchange business information. By contrast, I find no evidence of firms increasing the use of vague expressions when forced to exchange scientific information after the AIPA. This suggests that the proprietary costs of revealing scientific information is likely not as high, perhaps because of strong US patent laws that prevent scientific knowledge from being expropriated (Galasso and Schankerman (2015)).

The results discussed so far provide evidence that the effects of early patent disclosures have strong heterogeneity across firms – the AIPA increases innovation by inducing the exchange of scientific information, but decreases it by inducing the exchange of business information. An important follow-up question is whether the AIPA, on net, helps or hurts innovation when aggregated across firms.[6]

To answer this question, I assess the aggregate impact of the AIPA. To do so, in addition to examining the effects on the regulated firms (i.e., patent holding firms in my main sample), it is important to gauge potential externalities to all firms in the industry/economy. I thus augment my main sample to include Compustat/CRSP firms that do not hold patents. In particular, for each industry I compute the proportion of firms that hold patents, relative to those that don't, during the

[4] Of course, too much vagueness is costly, since patent examiners can reject patents for incoherent writing (Ouellette (2012)).
[5] To estimate the amount of vague expressions in my sample, I use Arinas (2012)'s list of vague expressions found in US patents.
[6] The question is important because market-wide effects are a central justification for disclosure mandates (Dye (1990), Leuz (2010), Berger (2011), Badertscher et al. (2013), Shroff (2016), Leuz and Wysocki (2016), Breuer (2017)).

pre-AIPA period to capture the extent of a given industry's treatment intensity of the AIPA. The idea is that, if the spillover benefits (proprietary costs) dominate at the industry level, I should observe an industry's treatment intensity to be positively (negatively) linked to industry-wide innovation. I find that the AIPA boosts industry-wide R&D and market value, providing initial evidence that the spillover benefits dominate proprietary costs at the industry level, on average.

This paper contributes to the literature in several ways. First, it extends the broad and growing literature on the real effects of disclosure that is central to accounting research.[7] In particular, my study's focus on corporate innovation (a real outcome), corporate patent disclosures (a form of disclosure), and the proprietary costs and spillover benefits associated with mandatory disclosure arrangements (a channel) are three important features of this study that expand our understanding on the real effects of disclosure. By doing so I contribute, (i) to a call for research by Leuz and Wysocki (2016) who suggest that investigating the impact of disclosure on innovation and exploring nontraditional forms of disclosure more generally to be fruitful areas of accounting research (e.g., Sutherland (2018)); and (ii) to the lack of evidence on whether/how spillovers and proprietary costs of disclosure have real effects (Roychowdhury, Shroff, and Verdi (2018)). This paper also extends prior studies that typically investigate spillovers and proprietary costs of disclosure in isolation. My findings illustrate that the two effects are two sides of the same coin: forcing firms to share proprietary patent information can be privately costly but socially beneficial.

My paper also relates to recent studies by Zhong (2018), Hussinger, Keusch, and Moers (2018), and Hegde, Herkenhoff, and Zhu (2018). Zhong (2018) shows that firm-level measures of financial

[7] See for example, Kanodia (2006), Biddle and Gilles (2006), McNichols and Stubben (2008), Biddle, Hilary, and Verdi (2009), Francis, Huang, Khurana, and Pereira (2009), Bushman, Piotroski, and Smith (2011), Chen, Hope, Li, and Wang (2011), Badertscher et al. (2013), Balakrishnan, Core, and Verdi (2014), Cheng, Dhaliwal, and Zhang (2013), Shroff, Verdi, and Yu (2014), Cho (2015), Dyreng, Lindsey, Markle, and Shackelford (2015), Kanodia and Sapra (2016), Breuer (2017), Christensen, Floyd, Liu, and Maffett (2017), Shroff (2017), Granja (2018).

reporting quality boost innovation by reducing managerial career concerns. Hussinger, Keusch, and Moers (2018) show that patent disclosures reduce innovation, due to managers' reduced ability to conduct insider trading. And Hegde et al. (2018), on the other hand, provide evidence that the AIPA spurs innovation by promoting knowledge diffusion and reducing the risk of duplicate R&D efforts. Unlike these studies, mine examines the impact of patent disclosures on innovation, shaped by knowledge spillovers and proprietary costs, documents both benefits and costs, examines labor market effects for scientists, demonstrates via textual analysis the pratice of strategic patent disclosure using vague expressions, and provides exploratory analyses on aggregate effects.

Second, this paper contributes to the literature studying the patent system (e.g., Williams (2013); Galasso and Schankerman (2015); Cockburn, Lanjouw, and Schankerman (2016)). In her recent survey, Williams (2017) argues that estimating the economic impact of patent disclosures is central to specifying an optimal design for the patent system. Despite the importance of patent disclosures, very little empirical evidence is available on whether or how patent disclosures affect innovation. This paper fills this void by providing some of the first empirical evidence on how and to what extent disclosures required by the patent system affect corporate innovation. Specifically, I show that the AIPA triggers the exchange of scientific and business-related information and these exchanges increase (decrease) a firm's innovation because the spillover benefits of other firms' disclosures (the proprietary costs of own firm's disclosures) dominate.

2 Background and Hypotheses Development

2.1 Patents and its Disclosure Function

In the theoretical model of Nordhaus (1969), patents create stronger incentives for innovation, *ex-ante*, by promising inventors the right to extract monopoly profits from the invention *ex-post* (i.e., by granting patent protection). In this sense, the patent system poses a tradeoff between the social gains from increased incentives to innovate and the social deadweight losses from monopolistic patent protection.[8]

As a way to combat the social losses, the US Patent and Trademark Office (USPTO) requires applicants to disclose their inventions publicly in exchange for receiving a US patent. This arrangement promotes the dissemination of knowledge through patent disclosures and stimulates the creation of new innovations by other inventors (Ouellette (2012), Fromer (2016)). Consistent with the motive to efficiently disseminate knowledge, patentees in the United States must satisfy the following disclosure requirements: 1) *written description*, 2) *enablement*, and 3) *best mode.* These collectively promote the efficient use of patent information by other inventors. Specifically, the first paragraph of 35 U.S.C. section 112 says:

> *The specification shall contain a <u>written description</u> of the invention, and of the manner and process of making and using it, in such full, clear, concise, and exact terms as to <u>enable</u> any person skilled in the art to which it pertains, or with which it is most nearly connected, to make and use the same, and shall set forth the <u>best mode</u> contemplated by the inventor of carrying out his invention.* [emphasis added][9]

In essence, patentees must communicate their discoveries not only in a clear fashion (written description) but also in a way that someone "skilled in the art" can replicate and use the knowledge

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[8] Nordhaus (1969) model is part of an extensive literature that examines *patent protection* and innovation (Hall and Harhoff (2012), Moser (2013), Williams (2017) provide excellent reviews). The theoretical relation, however, between patent protection and innovation is more nuanced. For example, Edmund (1977) argues that monopoly rights are needed to encourage innovation *after* the patent is granted. Others have theorized that patents may actually hinder innovation (Heller and Eisenberg (1998)). However, given my paper's focus on patent *disclosures*, I abstract away from these nuanced relations and assume that patents are ex post costly, which is consistent with recent empirical evidence of, for example, Galasso and Schankerman (2015).

[9] See https://www.uspto.gov/web/offices/pac/mpep/s2161.html and Ouellette (2012) for a more details.

to innovate further (enablement). Moreover, patentees must provide the details, if possible, on the most efficient way to carry out the invention (best mode). The institutional motive of patent disclosures is consistent with prior research that views knowledge as a vital input for technological progress (Scotchmer (1991); Furman and Stern (2011)).

2.2 American Inventor's Protection Act (AIPA)

The AIPA required all patent applications filed on or after November 29, 2000, to be disclosed 18 months after the application date. Prior to the law's enactment, patent applications were disclosed only upon grant, which happened on average 38 months after the application date. Thus the AIPA not only significantly accelerated public access to patent information (from 38 to 18 months, on average), it also increased the scope of publicly available patent information, as it gave access to pending applications.[10] The policy change is summarized in Figure 1. Among policymakers, the AIPA has been argued to be one of the most significant changes in patent law history, especially in the context of the disclosure function of patents (Ergenzinger (2007)). Hence the AIPA's effect on corporate innovation is likely to be significant.

In addition to its economic significance, the AIPA's passage was difficult to anticipate by firms, due to strong disagreement among policymakers leading up to the final signing of the bill in November 1999.[11] For example, 26 Nobel laureates, including economist Franco Modigliani, believed that the disclosure rule would impose significant proprietary costs and called for the law not be enacted.[12] This opposition led to many rounds of debate and amendments, which caused considerable uncertainty as to whether the mandate would eventually pass. Hence firms were

[10] While the AIPA accelerated the public access to patent disclosures, it is, in theory, unclear whether it necessarily increased the scope of publicly available patent information. If a sufficient number of firms responded by filing fewer patent applications, we might actually observe a decline in the scope of publicly available patent information. However, if anything, the number of patent applications appears to have increased over time: source.
[11] See Ergenzinger (2007) for a details on the political dynamics leading up to the passage of the AIPA.
[12] Source: Franco Modigliani, An Open Letter to the U.S. Senate, Eagle Forum.

unlikely to take significant actions to adjust their innovation decisions, which often requires high adjustment costs (e.g., hiring a new team of scientists), prior to the confirmed enactment. Instead, I expect firms to alter their innovation decisions after the enactment of the AIPA.

2.3 Mandatory Patent Disclosures and Corporate Innovation

Mandatory disclosure arrangements, such as the AIPA, can be characterized as inducing a forced exchange of information among regulated firms, beyond what these firms would be willing to disclose voluntarily. A firm receives more information from the disclosure of others while simultaneously revealing more about itself. This framework is at the core of the theoretical work on the relation between innovation and disclosures, such as patent applications.

Specifically, mandating patent disclosures can stimulate a firm to innovate by facilitating knowledge spillovers from other firms' disclosures (e.g., Scotchmer (1991); Aghion, Dewatripont, and Stein (2008)). Or it can discourage the firm from innovating due to the proprietary costs of having to disclose its patented innovations to other firms (e.g., Arrow (1962); Bhattacharya and Ritter (1983); Anton and Yao (1994); Bessen (2005); Aoki and Spiegel (2009)).[13] This tension is perhaps best described by Scotchmer (1991): "patent law requires disclosure for the same reason that innovators dislike it: it is the vehicle by which technical knowledge is passed from the patenting firm to its competitors." Thus the AIPA may increase a firm's innovation if the spillover benefits dominate proprietary costs but decrease innovation if proprietary costs dominate the spillover benefits. The impact of the AIPA on a firm's innovation therefore is an empirical question.

Moreover, research suggests that patent disclosures can induce the exchange of two types of information between firms. First, they can trigger the exchange of useful *scientific* information

[13] More precisely, the proprietary cost argument is about patenting becoming a less effective way to protect innovations, and as such discouraging firms from innovating. This assumes that other methods of protection, like trade secrets, are not perfect substitutes.

that other sources, such as the academic literature, do not provide for corporate scientists (Ouellette (2017)). To the extent that patent disclosures abide by the original intent of the mandate (35 U.S.C. section 112), patents can provide detailed scientific knowledge directly relevant for future inventors. Second, patent disclosures can also trigger the exchange of signals that enable product market rivals to make more competitive *business* decisions (Horstmann et al. (1985); Boulakia (2001)). Patents contain highly disaggregated information on what, how, and to what extent a firm has invested in innovation. Thus, unlike summary metrics like R&D figures in financial statements, patents can provide product market signals on the profitability of a certain market, potential M&A targets, and demand trajectories (Lerner and Seru (2017)).[14] Motivated by these discussions, I hypothesize the following.

H$_a$: The AIPA triggers the exchange of *scientific* information between firms, and this exchange increases (decreases) a firm's innovation if knowledge spillovers (proprietary costs) dominate.

H$_b$: The AIPA triggers the exchange of *business* information between firms, and this exchange increases (decreases) a firm's innovation if knowledge spillovers (proprietary costs) dominate.

3 Data, Key Variables, and Summary Statistics

3.1 Data and Sample Selection

Using Google Patents, I obtain 632,104 US patents granted by 2012 that were filed between 1996-2005 by publicly traded US firms. This data provides key patent characteristics, such as the number of citations (received as of 2012), number of review months (i.e., the number of months between the application and grant dates), the number of claims that a patent legally received, a patent's technology class, and the textual content of the patent, among others.

I intersect this data with two "firm position" measures provided by Bloom et al. (2013). These

[14] I provide more discussion on the scientific and business information contained in patents, as well as examples in Appendix B.

measures distinguish a firm's position in technology and product market spaces, using patenting patterns across technology fields and its sales activity across different industries, respectively. The motivation for using these measures is to estimate a firm's likelihood of exchanging scientific and business information with other firms, which I discuss in more detail in Section 3.3. I require firms to have relevant CRSP/Compustat variables, such as market cap, book assets, and returns. Last, I require firms to have filed at least one patent prior to AIPA and after. This yields a final sample of 259,368 firm-patent observations comprised of 525 unique firms over the period 1996–2005.

My sample represents a significant portion of patented innovations by publicly traded firms over my sample period. Specifically, my sample represents 41.3% (= 259,368/632,104) of all corporate patents and 51.9% (= 2,992,241/5,769,499) of all corporate patent citations realized by 2012. The solid bars in Figure 2 illustrate that electronics, business services, computer equipment, and chemicals are the top four industries in my sample. The dotted bars show that the observations that were excluded due to data restrictions mentioned above have similar industry composition. I incorporate the excluded observations when I examine aggregate industry-wide innovation effects of the AIPA, discussed in Section 4.5.

3.2 Key Dependent Variables: Measuring Innovative Activity

Patenting reflects both the quality and quantity of the innovative output of firms (Hall, Jaffe, and Trajtenberg (2001); Lerner and Seru (2017)). In particular, the number of citations a firm's portfolio of patents receives over the patents' lifetime can proxy for the firm's innovation quality, whereas the number of patents held by a firm can proxy for innovation quantity (e.g., Aghion, Van Reenen, and Zingales (2013); Fang, Tian, and Tice (2014); Bernstein (2015); Zhong (2018)).

Both citation patterns and patent counts vary over time and across technologies. Variation may stem from the complexity of technologies or from changes in patent law (Lerner and Seru (2017)). Therefore, a simple comparison of raw patent citations or counts is only partially informative. To mitigate these issues, I follow Hall et al. (2001) and construct *Scaled Citations* by scaling the citation count by the average number of citations among patents in the same tech class and in the same filing year. Similarly, to construct a scaled measure of patent counts, I weight each patent by the average number of patents granted by firms in the same tech class and year, such that patents granted in tech-years with many patents receive less weight. *Scaled Count* is the sum of these scaled values over a firm's quarter and indicates a firm's innovative quantity for a given quarter.

Patent data also provides an opportunity to uncover the underlying nature of innovation along various dimensions. First, following Trajtenberg, Henderson, and Jaffe (1997), I construct measures of *Originality* and *Generality*, which use the distribution of citations.[15] In particular, a patent that *cites* a wider array of technology classes is viewed as more original. On the other hand, a patent *cited by* a wider array of technology classes is viewed as being more general. Similar to patent citations and counts, I adjust these measures by the average values of originality and generality by technology class and year to create the variables *Scaled Originality* and *Scaled Generality*. Moreover, Kogan et al. (2017) provide estimates of a patent's worth to a firm's shareholders, *KPSS Value*. This measure is based on the stock price responses around the date of patent grant and captures the private value, more so than the scientific contribution, of a patent.

The measures discussed so far relate to innovative output. To understand the drivers behind these innovations, I also measure innovative input or effort made by firms. Specifically, I use R&D expenditure and labor market decisions, such as hiring patterns of scientists from Harvard Business School (HBS)'s inventor-level patenting database. I discuss the HBS database in Section 4.3.

[15] *Originality* (*Generality)* are the Herfindahl index of the cited (citing) patents that capture dispersion across technology classes.

3.3 Key Independent Variables: Firm Proximity Measures

I construct proxies that measure the extent to which firms exchange scientific and business-related information, conditional on a disclosure shock such as the AIPA. To this end, I follow Jaffe (1986) and Bloom et al. (2013) to compute two proximity measures that estimate the scientific and product market closeness of any firm-pair i and j:

$$TECH_{i,j} = \frac{(T_i T_j')}{(T_i T_i)^{\frac{1}{2}} (T_j T_j')^{\frac{1}{2}}} \tag{1}$$

$$PROD_{i,j} = \frac{(P_i P_j')}{(P_i P_i)^{\frac{1}{2}} (P_j P_j')^{\frac{1}{2}}} \tag{2}$$

where vector $T_i = (T_{i,1}, T_{i,2}, \dots, T_{i,426})$, such that $T_{i,\tau}$ is the average share of patents of firm i in technology class τ, based on 426 different technology classes defined by USPTO. Similarly, vector $P_i = (P_{i,1}, P_{i,2}, \dots, P_{i,597})$, such that $P_{i,\rho}$ is the average share of sales of firm i in the four-digit industry ρ, based on 597 different industries defined by the Compustat Segment Dataset. Mathematically, $TECH_{i,j}$ and $PROD_{i,j}$ range between 0 and 1, where higher values indicate greater overlap in technology and sales activity, respectively. Bloom et al. (2013) use patent data from 1970 to 1999 to construct $TECH_{i,j}$ and accounting data from 1980 to 2001 to construct $PROD_{i,j}$, both of which are made publicly available by the authors.[16]

The basic idea of $TECH_{i,j}$ is that firm-pairs that tend to patent in similar technological areas (i.e., have higher values of $TECH_{i,j}$) are more likely to be scientific peers and thus exchange

[16] $TECH_{i,j}$ and $PROD_{i,j}$ were first developed by Jaffe (1986), and these measures assume firms exchange information only along the same technology classes and sales segments and rule out exchanges that may occur across different but related technology classes and sales segments. Bloom et al. (2013) develop extensions that account for cross-class/segment information exchanges using the Mahalanobis norm. While the intuition for this extension is straightforward, the calculation is notationally involved, and thus I refer interested readers to Bloom et al. (2013) for a more detailed discussion. The main results for my study are based on the Mahalanobis extensions that allow for cross-class/segment information exchanges. But as shown in Table IA2, my results are robust to using the more basic Jaffe-based measures that assume firms exchange information only along the same technology classes and sales segments.

scientific information with one another, conditional on a disclosure shock. Similarly, the idea of $PROD_{i,j}$ is that firm-pairs that tend to generate sales in similar product markets (i.e., have higher values of $PROD_{i,j}$) are more likely to be product market peers and thus exchange business-related signals, conditional on a disclosure shock.[17]

Panel A of Figure 3 plots the distribution of $TECH_{\mathrm{i,j}}$ and $PROD_{i,j}$. The plot reveals that the two are positively correlated with a Pearson correlation of 0.35, meaning that, on average, a firm's product market peer is also likely its technology peer. Nonetheless, the correlation is still well below 1, indicating substantial independent variation between the two distance measures, which allows me to distinguish empirically the intensity of scientific and business-information exchanges between firms. For example, IBM, Apple, Motorola, and Intel are all close in technology space, but only IBM and Apple compete in the PC market and only Motorola and Intel compete in the semiconductor market, with little product market interaction across the two pairs.[18]

To assess the impact of the AIPA on a *firm's* innovation, I aggregate the firm-pair estimates $TECH_{\mathrm{i,j}}$ and $PROD_{i,j}$ at the firm level to measure a firm's overall "exposure" to scientific and business information exchange with all other firms in my sample:

$$TECHExchange_i = \sum_{j \neq i} TECH_{i,j} \tag{3}$$

$$PRODExchange_i = \sum_{j \neq i} PROD_{i,j} \tag{4}$$

Intuitively, conditional on a disclosure shock, $TECHExchange_i$ ($PRODExchange_i$) estimates a firm's intensity of exchanging scientific (business) information with all other sample firms. Panel

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[17] The mathematical expression for both $TECH_{i,j}$ and $PROD_{i,j}$ is known as the "cosine similarity" that is generically used to assess the similarity of any two vectors of data. For example, applications in accounting research include the work of Brown and Tucker (2011) and Merkley (2014), who study the textual similarity of MD&A disclosures using cosine similarity.

[18] For example, IBM and Intel have $TECH_{i,j}$ = 0.76 but $PROD_{i,j}$ = 0.01. The sample average for $TECH_{i,j}$ ($PROD_{i,j}$) is 0.04 (0.01).

B of Figure 3 plots the distribution of (3) and (4). The figure reveals that GE has the highest $TECHExchange_i$, whereas Motorola has the highest $PRODExchange_i$. Therefore, in my context, GE is likely to experience the strongest intensity of scientific information exchange with other firms while Motorola is likely to experience the strongest intensity of business information exchange with other firms, as a result of the AIPA.[19] To facilitate interpretation, I standardize (3) and (4) to have mean 0 and standard deviation of 1 for all of my analyses.

3.4 Controls

Knowledge spillovers and proprietary costs (i.e., the forced exchange of information) may not be the only channels through which patent disclosures affect corporate innovation. Patent disclosures also can reduce information asymmetry between firms and capital providers. For example, Saidi and Zaldokas (2017) show that patent disclosures can help firms switch lenders, thereby reducing the cost of debt. Moreover, a recent study by Hussinger et al. (2018) shows that patent disclosures can curb managers' insider trading, reducing their incentive to take on risky, innovative projects. Accordingly, I include in my model a host of control variables that represent a firm's level of financing frictions, agency conflict, and investment opportunity: *Firm Age*, *R&D*, *Size*, *Profitability*, *Book-to-Market*, *Cash Holdings*, and *Filing-Month-Returns*.

My inferences may also be biased by firms' unobservable relation to the patenting process. For instance, firms may have the strategic insights to apply for patents precisely when a lenient patent examiner is more likely to be drawn or when patent examiners are less busy. Whichever the case, my inferences may be confounded by omitted patent characteristics correlated with patent citations. Thus I include three observable patent characteristics—*Review Months*, *Number of Claims*

[19] In additional tests in Section 4.5, I test various alternative model specifications. My results remain robust. For example, my results are robust to using Hoberg and Phillips (2016) product market similarity index, instead of $PRODExchange_i$.

Granted, and *Patent Word Count*—as controls.

Finally, my main regression model, discussed in more detail below, includes firm, year, and patent tech-class fixed effects to account for unobserved heterogeneity that persists over time and is constant in the cross-section. (Appendix A provides the definitions of all variables in this study.)

3.5 Summary Statistics

Panel A of Table 1 tabulates summary statistics for patent and firm characteristics. The average patent received about 10.35 citations by 2012, spent about 37.83 months in review, and contains 6,619 words. Moreover, the average sample firm that owns these patents is quite mature (about 31 years since IPO) and large ($820 million in market capitalization). Panel B of Table 1 shows the differences in these characteristics across the highest and lowest terciles of $TECHExchange_i$ and $PRODExchange_i$. All of the differences are statistically significant at the 10% level or lower, except for the filing month returns.

4 Empirical Model and Results

The central prediction of this paper is that the AIPA induced both the exchange of scientific and business information, which increases (decreases) innovation if the knowledge spillover benefits (proprietary costs) dominate. To test this prediction, I estimate the following model:

$$\begin{aligned} Y_{i,p,t} = \beta_1 TECHExchange_i \times PostAIPA_{i,p,t} + \beta_2 PRODExchange_i \times PostAIPA_{i,p,t} \\ + \gamma_1 X_{i,t} + \gamma_2 Z_{p,t} + \delta_i + \pi_t + \phi_p + u_{i,t} \end{aligned} \tag{5}$$

The unit of observation is patent p, patent filing date t, filed by firm i. The dependent variable, $Y_{i,p,t}$ represents the set of innovation proxies discussed in Section 3.2, that is, *Scaled Citations* for innovative quality, and *KPSS Value*, *Originality*, and *Generality* for the underlying nature of innovation. $PostAIPA_{i,p,t}$ is a dummy variable, indicating whether a patent is filed on or after

November 29, 2000. $X_{i,t}$ represents a vector of time-varying firm-level controls; $Z_{p,t}$ is a vector of time-varying patent-level controls; δ_i, π_t, ϕ_p are firm, year, and patents' technology-class fixed effects, respectively. I cluster standard errors at the firm and year-month level, allowing the error term to have an idiosyncratic component with full cross-period and cross-sectional dependence. Last, to test the innovation quantity effects, I use *Scaled Patent Count.* For this test, I collapse the patent data at the firm-quarter level to measure the number of patents filed in a given quarter by a firm. The firm-quarter framework is also used for testing changes in *R&D* investment.

The model compares the innovative activities of firms that are more likely to exchange information with other firms ("treatment firms"), relative to those that are less likely to exchange information ("comparison firms") before and after the AIPA. Specifically, β_1 represents the AIPA's effect on a firm's innovation through the increased exchange of scientific information, whereas β_2 represents the law's effect on a firm's innovation through the increased exchange of business information.

4.1 Evidence of the AIPA's effect on Innovative Activity

Column (1) of Panel A of Table 2 shows that β_1 is significantly positive (= 0.032, *t*-stat = 3.19), while β_2 is significantly negative (-0.050, *t*-stat = -2.35) with respect to *Scaled Citations*. This implies that a one standard deviation increase in $TECHExchange_i$ and $PRODExchange_i$ induces a 3.17% and -4.95% change in average *Scaled Citations* as a result of AIPA.[20] In terms of raw citations, this translates into 12.78% and -11.72%, respectively.[21] Given that an average firm in my sample received about 900 raw citations per year for its portfolio of patents prior to the AIPA,

[20] 3.17% = 0.032/1.01 and -4.95% = -0.05/1.01, where 1.01 is the average number of scaled citations in the pre-AIPA period
[21] See Panel B column (6) of Table IA2 in the Internet Appendix for details.

the effect translates into about 575 additional (525 fewer) raw citations for a one standard deviation increase in $TECHExchange_i$ ($PRODExchange_i$) over the five years after the AIPA. Kogan et al. (2017) estimate that one additional patent citation around the median number of citations is approximately worth $15,000 to $500,000, suggesting the effect is material. Assuming a patent citation is worth $275,000, a five-year 550 citation effect is about $142 million—or about 18% of the average sample market capitalization, which is about $820 million. Column (2) shows these relations are robust to the inclusion of patent technology-class fixed effects, alleviating concerns that my estimates are affected by heterogeneity across technology classes (Lerner and Seru (2017)). Moreover, column (3) shows that the findings are robust to a Poisson specification.

A key identifying assumption for my main tests is parallel trends. The differences in *Scaled Citations* should be constant, leading up to the passage of the AIPA across variations in $TECHExchange_i$ and $PRODExchange_i$. To test this assumption, Figure 4 plots the coefficient estimates of $TECHExchange_i$ an $PRODExchange_i$ for the years leading up to AIPA, leaving out the two years prior to AIPA (i.e., years "-1 and -2") as benchmarks for comparison.[22] The figure shows the patent citation effects of both $TECHExchange_i$ and $PRODExchange_i$ are absent in the pre-AIPA years, whereas significant effects begin to appear in the years after the law.

Figure 4 also illustrates that the patent citation effects are gradual and begin only two years after AIPA. This is consistent with firms altering their research investments and the corresponding innovative output changing slowly. The pattern, however, is inconsistent with an "endogenous patenting" story, in which the AIPA simply affects firms' decisions on which innovations to patent, which would likely yield a more immediate change in citations (Galasso and Schankerman (2015)).

[22] The figure's estimates and confidence intervals are taken from a regression that runs *Scaled Citations* on a series of year dummy variables based on a patent's filing year, relative to the AIPA's passage on November 29, 2000.

To further explore whether the patent citation effects are mechanically driven by the changes in firms' patenting choices, I examine firms' patenting behavior. The concern is that higher (lower) values in *Scaled Citations* may be mechanically driven by firms' higher (lower) patenting threshold. This may lead to the addition of high- (low-) quality patents and hence higher (lower) average patent citations, without firms actually becoming more (less) innovative. Column (1) of Panel B of Table 2 shows that *Scaled Patent Count* actually increases with $TECHExchange_i \times PostAIPA_{i,p,t}$, which loses its significance in the Poisson model, as shown in column (2). On the other hand, I do not find a statistically reliable relation between *Scaled Patent Count* and $PRODExchange_i \times PostAIPA_{i,p,t}$. Taken together, it seems unlikely that the change in patent citations is mechanically driven by the changes in firms' patenting decisions.

There are two possible reasons for the weak relation between AIPA and *Scaled Patent Count*. First, patent count-based proxies may be noisy proxies for innovation. Research argues that patent counts cannot distinguish between breakthroughs from marginal innovations and are less correlated with indicators of economic importance, such as firm's market value, compared to citations-based proxies (Griliches (1990); Hall, Jaffe, and Trajtenberg (2005); Kogan et al. (2017)). Second, to the extent that patent counts represent the number of projects undertaken, firms may prefer to innovate by investing more (or less) on existing projects, rather than initiating (or terminating) projects.

In Figure 5, I plot the distribution of the estimated coefficients and *t*-statistics of *Scaled Citations* on $TECHExchange_i \times PostAIPA_{i,p,t}$and $PRODExchange_i \times PostAIPA_{i,p,t}$, based on 500 placebo regressions using randomized "placebo dates". The distributions for the coefficients and *t*-statistics, based on the placebo regressions, are centered around zero, which contrasts starkly with the estimated effects of Table 2, shown by the red lines in Figure 5. I conclude that the documented effects of the AIPA on corporate innovation are unlikely to be spurious.

4.2 Underlying Nature of Innovation

In Panel A of Table 3, I explore whether the changes in patent citations are associated with changes in the nature of projects undertaken. Columns (1), (2), and (3) show results with respect to *KPSS value*, *Scaled Generality*, and *Scaled Originality*. I find that an increased exchange of scientific (business) information, due to the AIPA, results in an increase (decrease) along all three of these dimensions of innovation. Hence the changes in innovation quality measured by patent citations seem to be accompanied by firms producing innovations that have significant changes in their stock-market-based value (*KPSS Value)*, their relevance to a broader set of technologies (*Scaled Generality)*, and their reliance on a broader set of technologies (*Scaled Originality)*.

In Panel B of Table 3, I examine whether an increased exchange of scientific (business) information, due to AIPA, is linked to firms' propensity to renew their patents. In the United States, patentees must pay maintenance fees 3.5, 7.5, and 11.5 years after the grant date to maintain their patent rights. These payments escalate over time, and the decision to pay them is solely at the inventor's discretion. Hence eventual renewal rates likely capture the value of a patent, which is privately observable to the firm.[23] Based on data provided by Graham and Hegde (2015), I can observe renewal rates at 3.5 and 7.5 years. Based on a dummy variable of whether a patent is renewed for a given horizon, I find patents filed after the AIPA are significantly more (less) likely to be renewed at both 3.5 and 7.5 years, with higher values of $TECHExchange_i \times PostAIPA_{i,p,t}$ ($PRODExchange_i \times PostAIPA_{i,p,t}$), relative to patents filed beforehand. Although, I lose statistical significance for the OLS specification for 3.5 years in column (1).

[23] The payment schedules are $1,600, $3,600, $7,400 per patent at 3.5, 7.5, 11.5 years. See the following link for more details.

Taken together, AIPA's effect on corporate innovation appears to be multifaceted. By inducing the exchange of scientific (business) information, firms engage in innovation that has higher (lower) *KPSS value*, *Scaled Generality*, *Scaled Originality*, and renewal rates of innovation.

4.3 Real Decisions of Firms: R&D and Labor Market Decisions

To further corroborate that the patent citation results in Table 2 reflect changes in innovation, I examine whether firms alter their real decisions in a fashion consistent with the citation results.

4.3.1 R&D

Following the literature, I first investigate changes in R&D expenditures as a proxy for firms' innovation effort. Column (1) of Table 4 shows that $TECHExchange_i \times PostAIPA_{i,p,t}$ ($PRODExchange_i \times PostAIPA_{i,p,t}$) has a significant positive (negative) relation to R&D, consistent with the patent citation results being driven by firms investment in intangibles. On the other hand, column (2) shows that firms do not change their capital expenditures. The muted effect on capex alleviates concerns related to unobserved macroeconomic trends or investment opportunity shocks driving my R&D result, as these factors likely would affect capital expenditures as well. Collectively, the AIPA increases (decreases) R&D by inducing the exchange of scientific (business) information, consistent with the patent-based innovation results.

4.3.2 Labor Market Decisions

Inventor Level Data

In practice, 50% or more of R&D spending is the wages and salaries of engineers and scientists (Hall and Lerner (2010)). Hence labor market decisions are an integral part of corporate innovation. The patent database provides an interesting opportunity to conduct inventor-level analyses, since patents identify the name of the inventor and its assignee (most often the inventor's employing firm). Inventor-level analyses, however, are challenging for two reasons. First, the inventors' names are often unreliable, because the same inventor may use different abbreviations of his or her first name across different patents or different inventors may have identical names. Second, while it is possible to infer whether an inventor switched firms (for example, an inventor filing a patent with Intel in 1998 and with IBM in 2004), it is unobservable when exactly the inventor moved. Moreover, if an inventor does not file a patent at the new firm, I cannot observe the move.

To circumvent the name matching issue, I use Harvard Business School's patenting database, which provides unique inventor identifiers. The unique identifiers are based on disambiguation techniques that mitigate the name matching problem (Ronald, Alexander, and Lee (2013)). When a patent has multiple inventors, I divide the number of patent citations by the number of inventors to construct inventor-level citations, although my inferences are not sensitive to this requirement.

To reliably measure inventor mobility, I restrict my attention to the subsample of inventors who file a patent at least once before the AIPA and at least once afterward. Therefore, the analysis is likely to be about inventors that are more inventive and frequent patent filers. Following Bernstein (2015), I classify inventors into three types.

1. *Stayer*: An inventor with at least one patent prior to and at least one patent after the AIPA at the same sample firm.

2. *Leaver*: An inventor with at least one patent prior to the AIPA at a sample firm and at least one patent afterward at a different firm.

3. *New Hire*: An inventor with at least one patent after the AIPA at a sample firm, but no patents before, and at least one patent prior to the AIPA at a different firm.

These restrictions yield a total of 40,437 inventors composed of 33,219 stayers, 4,143 leavers, and 3,075 new hires. Moreover, for each of these inventors, I compute *% Change in Citations*, defined as the percentage change in an inventor's average patent citations before and after AIPA.

Inventor-Level Analysis

Based on the constructs above, I examine the inventor-level effects around the AIPA. The analysis is conducted at the inventor level and does not have a time dimension. Accordingly, I modify model (5) by dropping the *PostAIPA* dummy. Also, because $TECHExchange_i$ and $PRODExchange_i$ are time-invariant, I include industry fixed effects, instead of firm fixed effects.

Columns (1) and (2) of Table 5 show that $TECHExchange_i$ ($PRODExchange_i$) is associated with a higher (lower) likelihood of retaining their inventors as well as a higher (lower) likelihood of hiring new inventors. These findings demonstrate the change in innovation around AIPA documented before is backed by corresponding changes to firms' inventor mobility decisions.

To understand whether the changes in corporate innovation are also linked to productivity changes at the inventor-level, I investigate the changes in innovation productivity among *Stayers* in column (3). Again, consistent with firms' real decisions driving the innovation results, column (3) shows that *% Change in Citations* increases (decreases) with $TECHExchange_i$ ($PRODExchange_i$). Columns (4) and (5) show these productivity shocks are concentrated among the most productive *Stayers*, defined as *Stayers* in the top tercile of pre-AIPA citations.

4.4 Mechanism: Knowledge Spillovers versus Proprietary Costs

A plausible interpretation for the positive innovation effect of exchanging scientific information is that the knowledge spillover benefits of other firms' disclosures of scientific information dominate the proprietary costs of having to disclose this sort of information to others. Similarly, the negative innovation effect of exchanging business information is likely to reflect that the proprietary costs of revealing business signals to others dominate the benefits of receiving these signals from others' disclosures. I perform two additional tests to investigate the plausibility of this interpretation.

4.4.1 Direction of Information Spillovers (Spill-in versus Spill-out)

First, I decompose both $TECHExchange_i$ and $PRODExchange_i$ into two components that represent the likelihood of being on the receiving end of the information exchange and the likelihood of being on its revealing end: the suffix "$\_Spillin$" and "$\_Spillout$" denote the likelihood of being on the receiving and revealing end, respectively. I estimate spill-ins by weighting $TECHExchange_i$ and $PRODExchange_i$ by the number of pre-AIPA patents of other firms. Similarly, I measure information spill-outs by weighting these measures by the number of pre-AIPA patents of the focal firm. The idea is that, when other firms (the focal firm) hold more patents, the disclosure shock of the AIPA is likely to generate more information spilling in from other firms to the focal firm (spilling out from the focal firm to other firms). As an alternative approach, I weight $TECHExchange_i$ and $PRODExchange_i$ by the average pre-AIPA R&D expenditures, instead of patents. The suffix "$\_pat$" and "$\_R\&D$" denote the proxies used for information spill-ins and -outs.

Table 6 shows the positive innovation effect of exchanging scientific information is driven by the higher information spill-ins from others' disclosures, consistent with knowledge spillovers driving the focal firm's increase in innovation, as shown by the positive coefficients on *TECHExchange_Spillin_#pat*PostAIPA* and *TECHExchange_Spillout_R&D*PostAIPA* (first and fifth rows). By contrast, I find the negative innovation effect of exchanging business information is driven by the higher information spill-outs, consistent with proprietary costs discouraging the firm to innovate, shown by the negative coefficients on *PRODExchange_Outflow_#pat*PostAIPA* and *PRODExchange_Outflow_R&D*PostAIPA* (fourth and eighth rows). The muted effects in all the other rows indicate the forced disclosure of scientific information to others and the disclosure of business information from others do not materially impact a firm's innovation.

4.4.2 Strategic Patent Disclosures

Second, research in accounting suggests that a firm can strategically obfuscate the linguistic content of its disclosures to conceal information from rivals (Li (2010); Loughran and McDonald (2016); Bushee et al. (2018)). In the context of patents, for example, Hall and Harhoff (2012) argue that the "benefits of [patent disclosures] may be limited by careful drafting of the patent or by the omission of essential (tacit) know-how." But using too much vagueness can be costly since examiners can reject patents on grounds of incoherent writing (Ouellette (2012)).

Thus firms with the highest level of proprietary costs likely have the strongest incentive to engage in the strategic use of vague expressions when drafting their patents after the AIPA. To the extent that the AIPA's negative innovation effect of exchanging business information is driven by proprietary costs concerns, I expect to observe $PRODExchange_i \times PostAIPA_{i,p,t}$ to be positively linked to the use of vague expressions. To identify vague expressions, I rely on Arinas (2012), who studies a sample of 350 randomly selected US patents and compiles a list of vague expressions most prevalent in his sample. Using textual analysis, I then count the number of vague expressions in each of my sample patents and divide it by the total number of words to create *% of Vague Expressions* (I provide the definitions and list of vague expressions in Appendix C and Appendix D). Further, I include *Scaled Citation* as control to account for the possibility that the use of vague expressions is correlated with the nature of the invention, similar in spirit to Bushee et al. (2018).

Column (1) of Panel A of Table 7 shows that *% of Vague Expressions* is positively linked to $PRODExchange_i \times PostAIPA_{i,p,t}$, indicating firms with the higher likelihood of exchanging business information draft their patents with more vagueness after AIPA. On the other hand, there is no significant relation between *% of Vague Expressions* and $TECHExchange_i \times PostAIPA_{i,p,t}$. This suggests the proprietary costs of revealing scientific information is likely not as high, perhaps because of the strong US patent laws that prevent scientific knowledge from being expropriated.

Breaking down the text in patents by sections, columns (2) through (6) show that $PRODExchange_i \times PostAIPA_{i,p,t}$ has a statistically significant positive relation with *% of Vague Expressions* in the abstract, background/summary, description of drawings sections but an insignificant relation in the detailed description and a weakly positive relation with claims/conclusions sections. One possible explanation for the absence of an effect in the detailed description and weaker relation in claims/conclusions is that these sections are the most scrutinized by patent examiners, providing less opportunity for manipulation.

Last, similar in spirit to Bird and Karolyi (2016) and Abramova, Core, and Sutherland (2018), I investigate whether firms strategically change the number of figures that they include in their patents. To the extent that figures effectively communicate information in patents, firms that are exposed to high proprietary costs may choose to exclude them from their patents after the AIPA. Consistent with firms with the higher likelihood of exchanging business information being exposed to proprietary costs, Panel B of Table 7 shows that *Number of Figures* has a statistically significant negative relation with $PRODExchange_i \times PostAIPA_{i,p,t}$ but an insignificant relation with $TECHExchange_i \times PostAIPA_{i,p,t}$. The results here, however, should be interpreted with caution, given the significant positive relation between *Number of Figures* and *Scaled Citations.*

4.5 Extensions and Robustness

4.5.1 Estimates of Aggregate Effects

The results discussed so far collectively provide evidence that the effects of early patent disclosures have strong heterogeneity across firms—the AIPA induces firms to exchange scientific information, which increases innovation, but also induces the exchange of business information, which decreases innovation. An important follow-up question is whether the AIPA, on net, helps or hurts innovation when aggregating across firms given these offsetting forces.

To offer evidence on the aggregate impact of AIPA, I examine aggregate effects. To do so, in addition to the effects on the regulated firms (i.e., patent holding firms in my main sample), it is important to gauge potential externalities to all firms in the industry/economy. As a result, I augment my main sample to include Compustat/CRSP firms that do not hold patents. This yields a sample of 1,739 industry-year observations using the four-digit SIC industry codes.[24] For each industry, I compute the proportion of firms that hold patents, relative to those that don't, during the pre-AIPA period to capture the extent of a given industry's treatment intensity of the AIPA. The idea is that, if the spillover benefits (proprietary costs) dominate at the industry level, I should observe an industry's treatment intensity to be positively (negatively) linked to industry-wide innovation. In particular, I create two industry-wide indices that measure the extent to which a given industry is affected by the AIPA, similar in the spirit to Breuer (2017) for industry *s*:

$$Share\_of\_Regulated\_Firms_s = \frac{n_s}{N_s} \tag{6}$$

$$Net\_Benefit\_Index_s = \frac{n_s}{N_s} \times \frac{\sum_{i \in s} TECHExchange_i}{\sum_{i \in s} PRODExchange_i} \tag{7}$$

The first index shown in (6), $Share\_of\_Regulated\_Firms_s$, is defined as the time-series average of patent filing firms in the five year pre-AIPA period for industry s (n_s), divided by the time-series average of the total number of firms over the same period for industry s (N_s). This measure estimates the *ex-ante* percentage of AIPA-regulated firms for each industry.

In light of my firm-level results that the AIPA boosts innovation through the exchange of scientific information ($TECHExchange_i$) and hurts it through the exchange of business

[24] I require industries to have at least five firms to reduce noise for the analyses.

information ($PRODExchange_i$), in (7) I consider a second index by multiplying $\frac{n_s}{N_s}$ with $\frac{\sum_{i \in s} TECHExchange_i}{\sum_{i \in s} PRODExchange_i}$. The latter expression represents an industry's likelihood of exchanging scientific information (the benefit), relative to exchanging business information (the cost).[25]

I rely on *R&D* expenditures to measure aggregate innovation as opposed to patent citations because some firms never patent over my sample period (i.e., the unregulated firms). I also examine other outcome variables commonly used in the literature—*Tobin's Q*, *Sales on Assets*, *Return on Assets*, *and Z-Score*, all of which are aggregated at the industry-year level.[26] Industry and year fixed effects are included to account for unobserved heterogeneity.

Column (1) of Panel A of Table 8 shows that $Share\_of\_Regulated\_Firms_s \times PostAIPA$ is positively linked to aggregate *R&D.* Consistent with AIPA stimulating more innovation at the industry level, on average. I document corresponding increases in *Tobin's Q* and *Z-Score,* as shown in columns (2) and (5), but fail to find significant effects on *Sales on Assets* and *Return on Assets.* I find qualitatively similar results using my second index, $Net\_Benefit\_Index_s$, as shown in Panel B of Table 8. The stronger magnitudes in Panel B suggests the positive aggregate innovation effects are greater among industries where exchanging scientific information is more likely, relative to exchanging business information, consistent with my firm-level findings. Figure 6 plots the percentage change in aggregate R&D around the AIPA against my two indices. This figure visually demonstrates the positive correlation between my indices and change in aggregate R&D.

4.5.2 Sensitivity Tests and Other Analyses

I conduct a series of robustness tests and other supplementary tests in the Internet Appendix.

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[25] For ease of interpretation, both indices are normalized to vary from 0 to 1.
[26] By aggregating, I'm computing the industry averages. Using industry sums does not impact the inferences of my results.

Panel A of Table IA2 shows that the main results of this paper based on *Scaled Citations* are robust to using different innovation proxies, such as *Raw Citations* and *ln(1+Citations)*, and different model specifications, such as negative binomial, zero-inflated negative binomial, zero-inflated Poisson model, and collapsing the data at the firm-quarter level. Panel B of Table IA2 demonstrates that my results are also robust to using different versions of the Bloom et al. (2013) measures—logged (first two rows), the *Jaffe* (third and fourth row), and decile portfolio (last two rows). Similarly, Panel C of Table IA2 shows that my results are robust to using alternative exchange measures. Specifically, I use one for science—$TECHExchange\_BioChemElec_i$, defined as the proportion of patents a firm files in chemistry, biology, and electronics during the pre-AIPA period. This measure is motivated by Ouellette (2017) finding that these technology sectors tend to produce patents with the most useful technical information. I use a second measure for business—$PRODExchange\_HobergPhillips_i$, which is the firm's pre-AIPA "total product market similarity," based on Hoberg and Phillips (2016). Panel D of Table IA2 shows that my results are robust to using *Raw Citations* as my main dependent variable and including technology class by year fixed effects, as opposed to *Scaled Citations*, which scales away effects of tech class by year, with firm and year fixed effects.

Table IA3 investigates an important implied relation of innovation and firm performance. Increases (decreases) in corporate innovation should have a positive (negative) effect on firm performance. The evidence presented in Table IA3 shows that this is indeed true. Specifically, I find that $TECHExchange_i \times PostAIPA_{i,p,t}$ ($PRODExchange_i \times PostAIPA_{i,p,t}$) has a positive (negative) link to four performance metrics—*Tobin's Q*, *Sales on Assets*, *ROA*, and *Altman Z Score*.

Firms with US patents that do not file foreign patent protection can opt out of the 18-month disclosure rule of the AIPA. This is another way in which firms can reduce proprietary cost concerns. Consistent with my findings of strategic disclosure behavior in Table 7, I find in Table IA4 that firms are more likely to exercise the secrecy option for higher values of $PRODExchange_i$. Finally, I conduct two subsample analyses in Table IA5 to address concerns about confounding events driving my main results. Specifically, I find that the effects in Table 2 are intuitively concentrated in industries where the effect of AIPA is likely to be strongest, that is, i) industries where patents are an important source of information and ii) those where seeking foreign patent protection is not common (and hence firms are unlikely to be able to opt out of the mandate). These subsample analyses raise the bar for confounding events to fully explain my main results. The confounding event would have to be correlated with the two industry characteristics—importance of patents as a source of information and the tendency to seek foreign protection—that are arguably specific to patent disclosure.

5 Conclusion

The AIPA induces firms to exchange scientific information, which increases innovation, but also induces the exchange of business information, which decreases innovation. I use patent citations as my main proxy for innovation. I find evidence that the positive innovation effect is driven by the knowledge spillover benefits of other firms' disclosures of scientific information, whereas the negative innovation effect of exchanging business information is driven by the proprietary costs of revealing exploitable business signals to others.

I also examine firms' real decisions—R&D and labor market decisions—as input-based proxies for innovation. Specifically, after the AIPA, firms that are more likely to exchange scientific (business) information invest more (less) in R&D and hire more (fewer) scientists. I also find that incumbent scientists become more (less) productive. In addition, I show that both the increase (decrease) in patent citations, due to greater exchange of scientific (business) information, begins only after two years after the AIPA, consistent with the slow moving nature of innovation. These results corroborate the inference that the documented change in patent citations is driven by fundamental shifts in firms' innovative effort.

The paper makes some inroads into estimating the economic consequences of patent disclosures, but much more could be done. Future research might examine the full interactive effects of patent disclosures with other more traditionally studied forms of corporate disclosure, such as financial statements, press releases, and analyst reports (e.g., Koh and Reeb (2015)). For example, Kanodia, Sapra, and Venugopalan (2004) show that intangible investments should be separated from operating expenses only when intangibles can be measured with sufficient precision. To the extent that patent disclosures of other firms provide relevant scientific information that helps a focal firm reliably measure intangibles, these disclosures may facilitate policies that aim to allow intangibles to be measured separately.

Future research might also delve further into the market-wide effects of the AIPA. This paper provides initial evidence that the law boosted industry-wide innovation. But to fully assess its welfare implications, future research might extend my findings to other related outcomes, such as economic growth, consumer welfare, and innovations by noncorporate entities.

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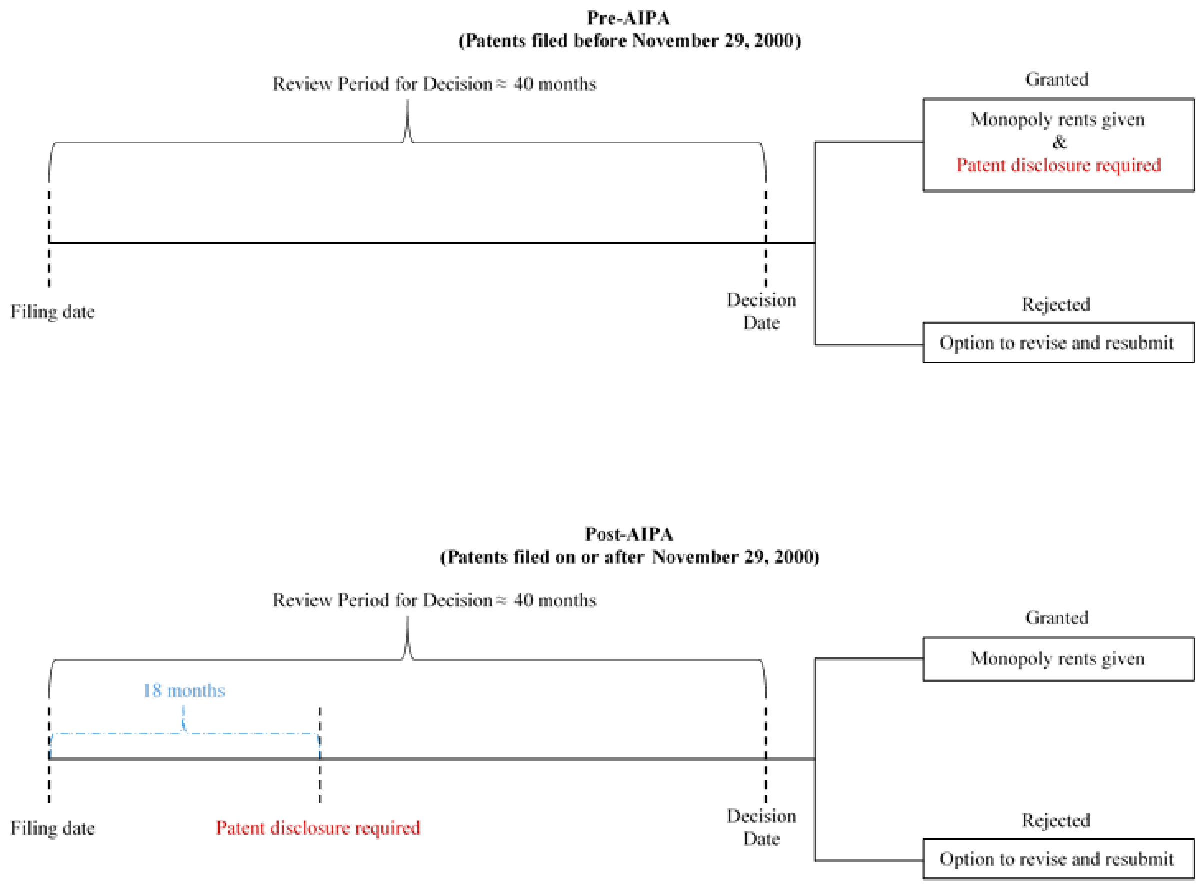
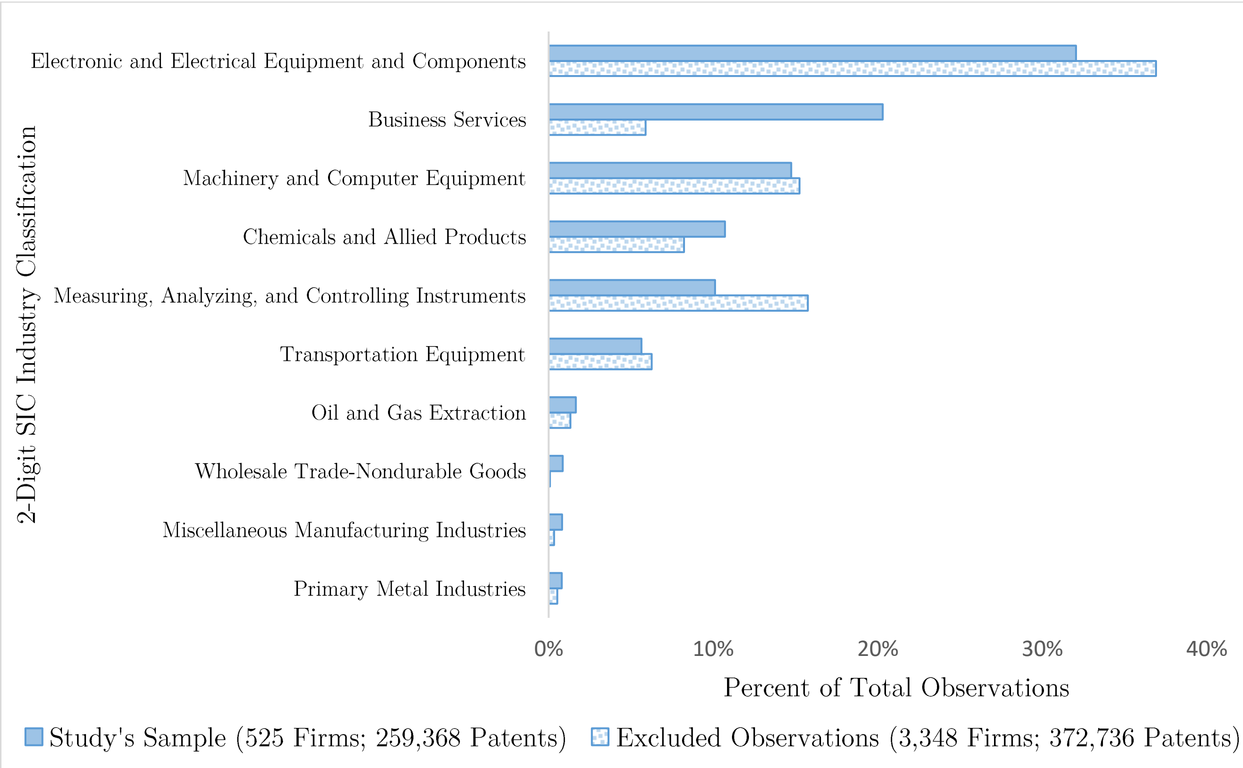
Figure 1. AIPA 18-month Disclosure Rule



Notes: The figure compares the patent disclosure rule before and after the AIPA. Before the AIPA, patents were disclosed when granted patent rights, which on average happened 40 months after the filing date. Afterward, all patent applications—including those that are rejected—are required to be disclosed 18 months after the filing date.

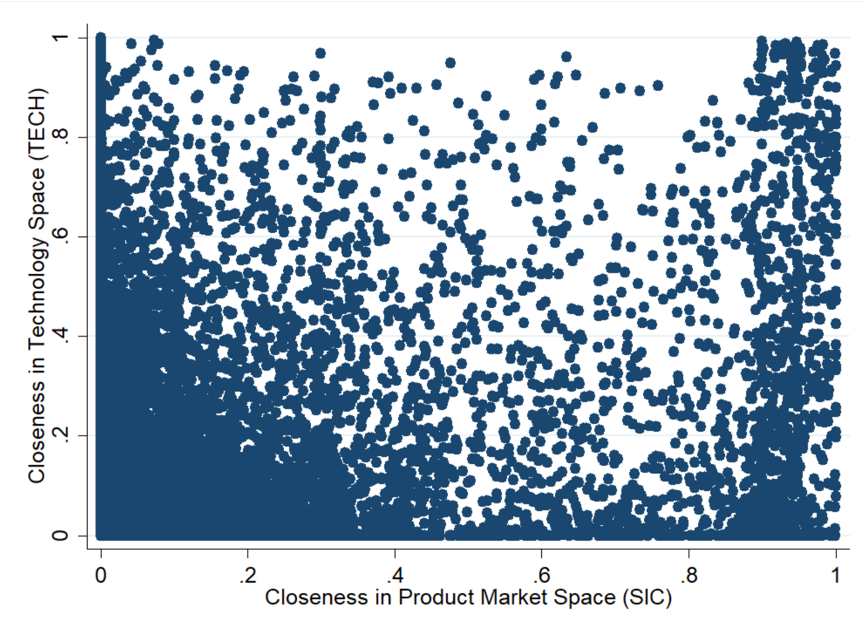
Figure 2. Observations by Industry



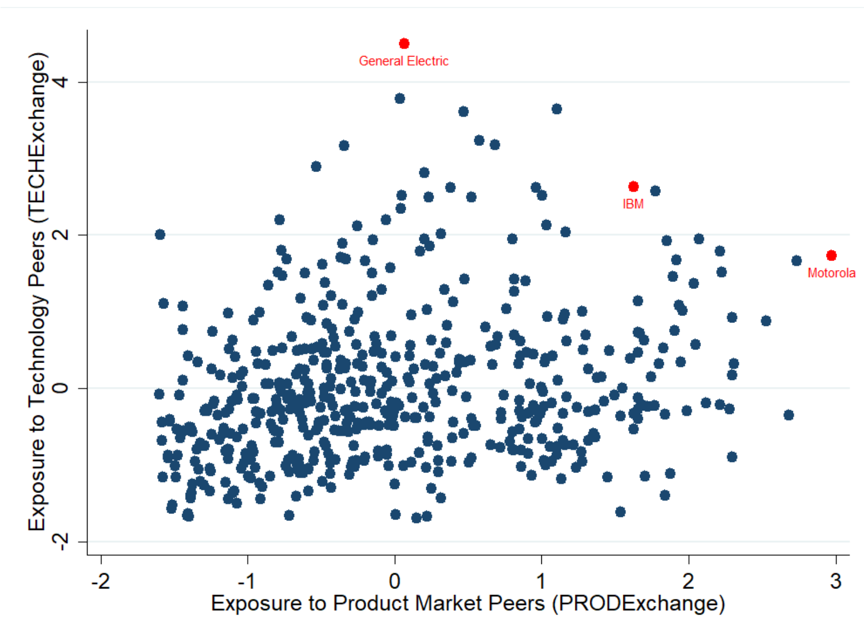
Notes: This figure plots the distribution of observations across two-digit SIC industries for the sample used in this study versus the observations censored out due to data restrictions discussed in section 3.1.

Figure 3. Firm Position Measures: Technology and Product Market

Panel A. Distribution of $TECH_{\text{i,j}}$ and $PROD_{i,j}$ (Firm-Pair level)

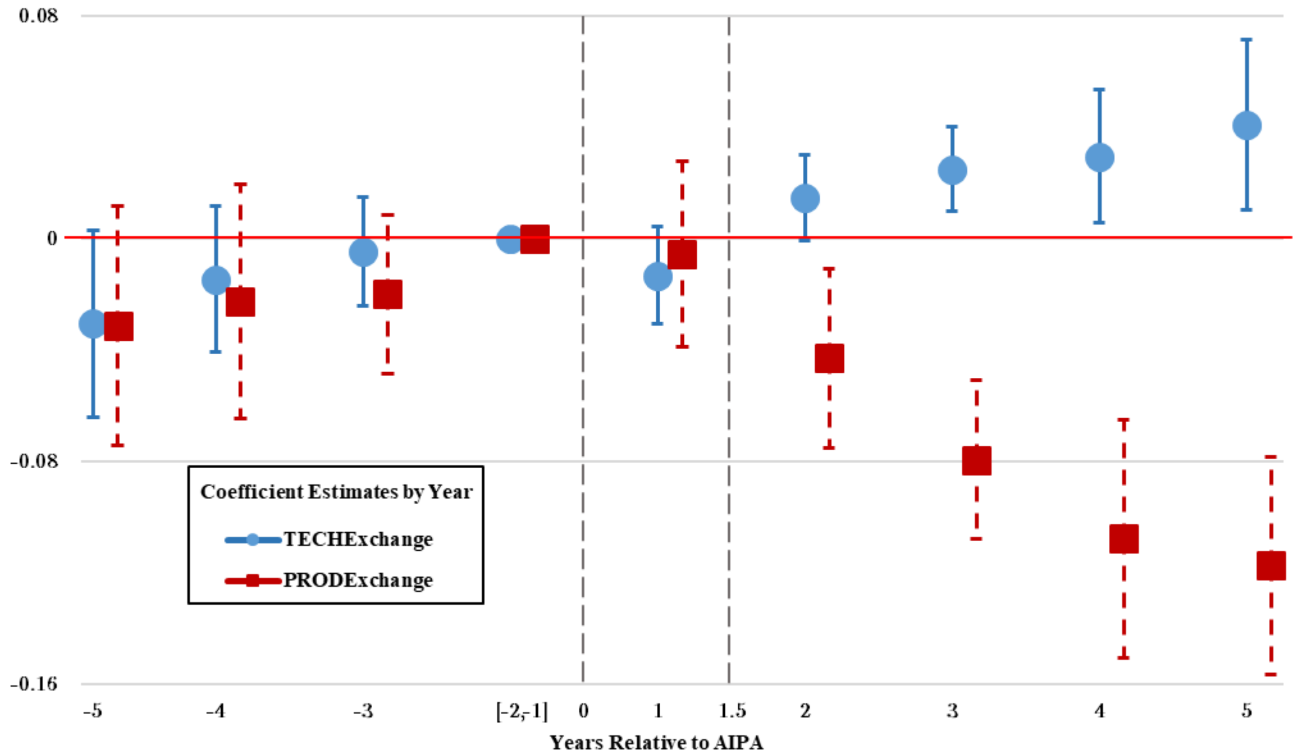


Panel B. Distribution of $TECHExchange_i$ and $PRODExchange_i$ (Firm level)



Notes: Panel A plots $TECH_{\text{i,j}}$ on $PROD_{i,j}$, which are proxies for the likelihood of firms i and j exchanging scientific and business-related information with each other, respectively, conditional on a disclosure shock. Panel B plots $TECH_{\text{i,j}}$ on $PROD_{i,j}$ for IBM. Panel C plots $TECHExchange_i$ on $PRODExchange_i$, which are proxies for the likelihood of firm i collectively exchanging scientific and business-related information with all other firms, conditional on a disclosure shock. Variables definitions are in Appendix A.

Figure 4. Parallel Trends in Scaled Patent Citations



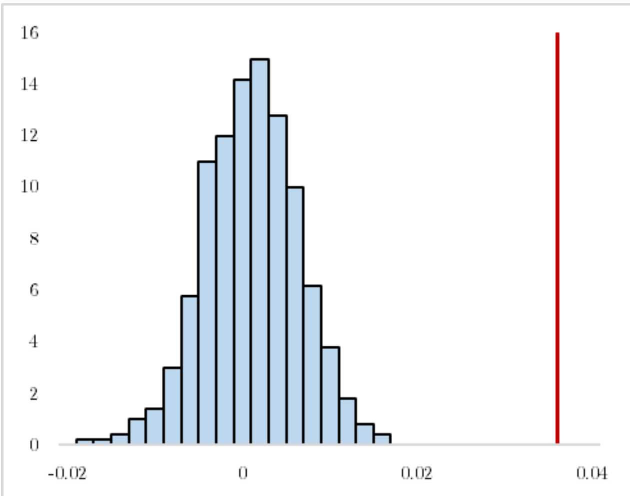
Notes: This figure shows changes in innovation quality, as measured by *Scaled Citations*, in the years around the AIPA. The estimates β_k (blue circles) and γ_k (red squares) and their 90% confidence intervals are from the following model:

$$Y_{i,p,t} = \sum_{\substack{k=-5 \\ k\neq -2,-1}}^{k=5} [\beta_k TECHExchange_i \times RelYear_{i,p,t} + \gamma_k PRODExchange_i \times RelYear_{i,p,t}] + \gamma_1 X_{i,t} + \gamma_2 Z_{p,t} + \delta_i + \pi_t + u_{i,t}.$$

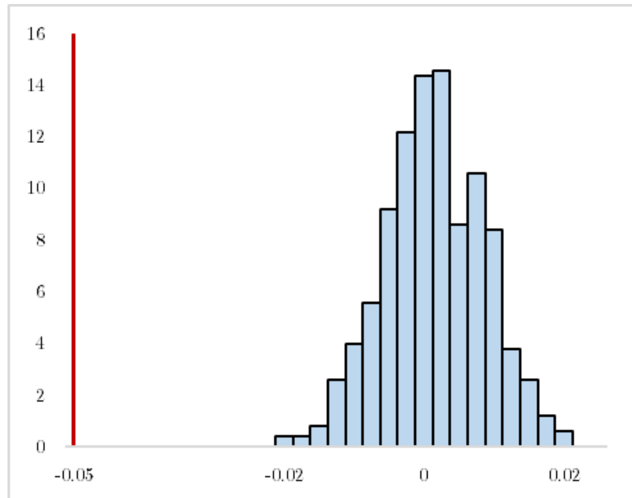
The unit of observation is at the patent level p, and the dependent variable is *Scaled Citations*. $RelYear_{i,p,t}$ is a dummy variable, indicating the relative year around AIPA (Nov. 29, 2000) in which a patent application was submitted (years -2 and -1 of the AIPA is the omitted category for comparison). For example, patents submitted in year "-1" are those submitted between Nov. 29, 1999 to Nov. 28, 2000; in year "1" are those submitted between Nov. 29, 2000 to Nov. 28, 2001, and so on. $X_{i,t}$ represents a vector of time-varying firm-level controls. $Z_{p,t}$ is a vector of time-varying patent-level controls. δ_i, π_t are firm and year fixed effects, respectively. Standard errors are clustered at the firm and year-month level. Variables definitions are in Appendix A.

Figure 5. Coefficient Estimates from Placebo Regressions

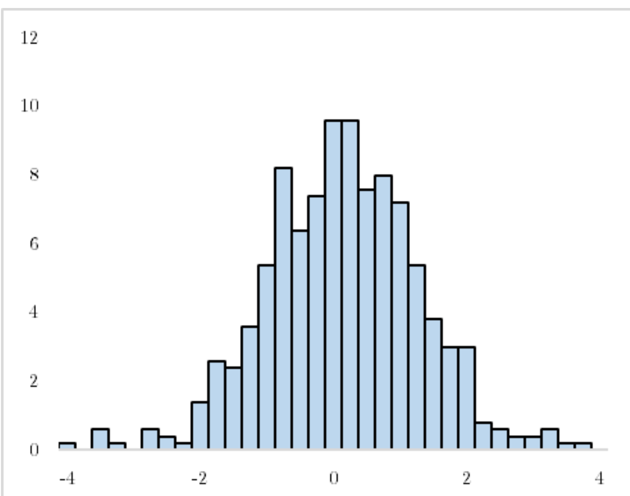
Panel A. TECHExchange*PostAIPA Coefficient (%)



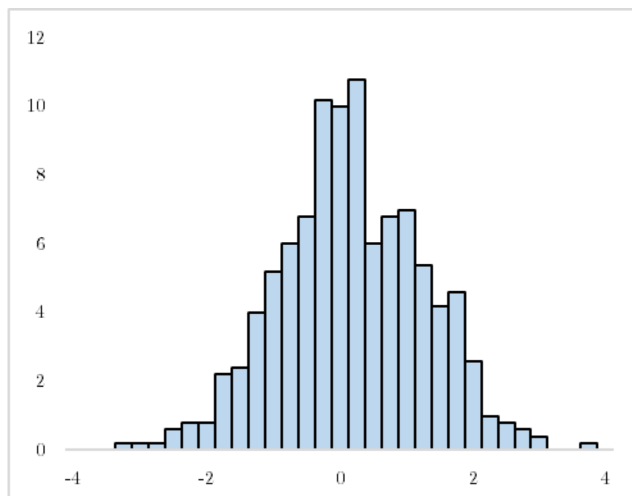
Panel B. PRODExchange*PostAIPA Coefficient (%)



Panel C. TECHExchange*PostAIPA t-statistic (%)



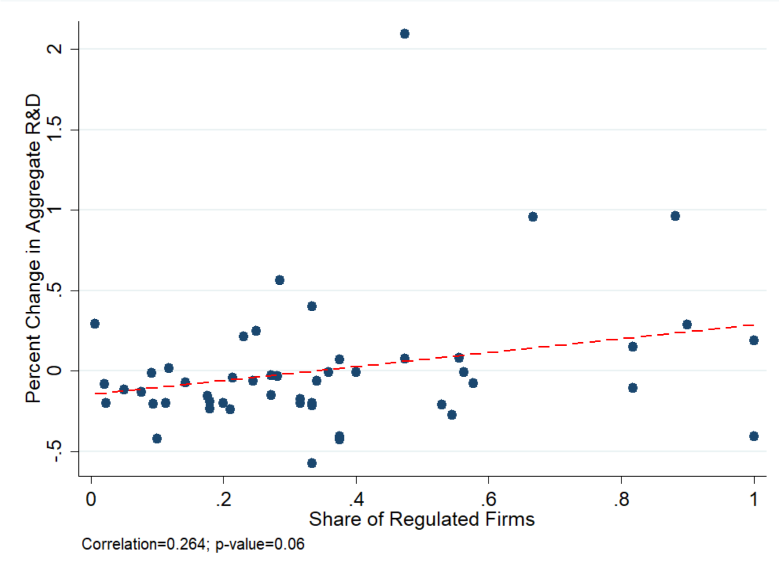
Panel D. PRODExchange*PostAIPA t-statistic (%)



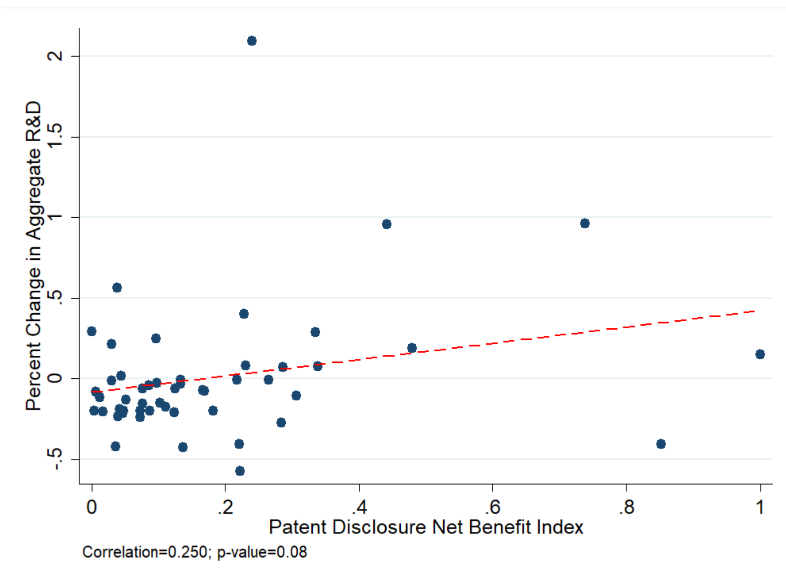
Notes: Panels A and B plot β_1 and β_2 from estimating equation (5)— corresponding to the specification of column (1) of Panel A of Table 2—across 500 placebo experiments. In each experiment, I randomly generate a different patent application date within my sample period, which spans from 1996–2005. I then re-estimate equation (5) based on these placebo application dates. The red solid lines represent the estimated values of β_1 and β_2, using the real data—column (1) of Panel A of Table 2. Panels C and D plot the *t*-statistics of the 500 placebo experiments.

Figure 6. Mandatory Patent Disclosure and Industry-Wide Innovation

Panel A. Share of Regulated Firms



Panel B. Net Benefit Index



Notes: Panel A plots *Aggregate R&D* on $Share\_of\_Regulated\_Firms_s$ as in equation (6). Panel B plots *Aggregate R&D* on $Net\_Benefit\_Index_s$ as in equation (7). *Aggregate R&D* is defined as firm-level R&D expenditures averaged across all firms in a given industry-year, using the four-digit SIC code to define industries. The red dotted lines are the linear lines-of-best-fit. Variable definitions are in Appendix A.

Table 1. Descriptive Statistics

Panel A. Patent and Firm Characteristics

Patent Characteristics	25th Percentile	Mean	Median	75th Percentile	SD
Raw Citations	1.00	10.35	4.00	11.00	20.46
Scaled Citations	0.17	1.06	0.56	1.29	1.71
Scaled Generality	0.00	1.02	1.06	1.47	0.84
Scaled Originality	0.59	1.02	1.08	1.40	0.68
Review Months	23.00	37.83	34.00	46.00	17.36
Allowed Claims	11.00	20.11	18.00	25.00	15.97
Patent Market Value (KPSS Value)	3.85	22.32	8.77	20.90	54.79
Number of Figures in Patent	4.00	9.43	7.00	12.00	9.39
Total Word Count	3748.00	6619.33	5316.00	7808.00	4751.11
Word Count by Patent Sections					
ABSTRACT	79.00	117.25	113.00	148.00	51.51
BACKGROUND & SUMMARY	662.00	1384.68	1030.00	1611.00	1284.77
DESCRIPTION OF DRAWINGS	85.00	190.26	148.00	239.00	175.34
DETAILED DESCRIPTION	1960.00	4396.52	3183.00	5218.00	4174.48
CLAIMS & CONCLUSION	50.00	530.61	351.00	769.00	597.86
Total Vague Expressions	62.00	124.53	97.00	153.00	99.36
Vague Expressions by Patent Sections					
ABSTRACT	1.00	2.34	2.00	3.00	2.32
BACKGROUND & SUMMARY	10.00	26.79	18.00	31.00	30.81
DESCRIPTION OF DRAWINGS	0.00	2.61	1.00	4.00	3.67
DETAILED DESCRIPTION	33.00	84.54	59.00	104.00	86.02
CLAIMS & CONCLUSION	0.00	8.25	3.00	10.00	12.97
Total %VagueExpressions	1.40	1.89	1.80	2.24	0.72
Firm Characteristics	25th Percentile	Mean	Median	75th Percentile	SD
TECHExchange (standardized)	-0.69	0.00	-0.19	0.48	1.00
PRODExchange (standardized)	-0.81	0.00	-0.13	0.81	1.00
Firm Age (in months)	211.00	371.07	321.00	451.00	225.33
R&D	0.00	1.39	0.78	2.19	1.80
Firm Size	12.10	13.62	13.56	15.07	2.19
Cash Holdings	2.02	12.90	6.40	17.93	15.72
ROA	0.28	0.84	1.34	2.40	3.41
Book-to-Market	0.25	0.53	0.42	0.68	0.47
Filing Month Returns	-0.07	0.02	0.01	0.09	0.17
Number of Patents	0.00	13.80	1.00	6.00	44.25
Scaled Number of Patents	0.18	0.29	0.26	0.37	0.15
Capital Expenditure	1.10	3.21	2.24	4.17	3.25

Table 1 [Continued]

Panel B. Patent and Firm Characteristics by Terciles of TECHExchange and PRODExchange

	By TECHExchange Terciles			By PRODExchange Terciles		
Patent Characteristics	Low	High	Difference	Low	High	Difference
Raw Citations	11.24	9.24	-2.00	9.00	10.75	1.74
Scaled Citations	1.20	0.98	-0.22	1.05	1.07	0.02
Scaled Generality	1.04	0.99	-0.05	1.01	1.05	0.04
Scaled Originality	1.06	0.99	-0.07	1.01	1.06	0.05
Review Months	36.47	34.30	-2.16	31.11	34.36	3.26
Allowed Claims	22.36	18.52	-3.83	20.02	20.59	0.57
Patent Market Value (KPSS Value)	27.72	16.27	-11.45	19.66	18.62	-1.04
Number of Figures in Patent	11.06	8.25	-2.81	8.72	9.80	1.08
Total Word Count	7652.75	5865.51	-1787.25	6701.92	5712.55	-989.37
Total Vague Expressions	142.44	110.16	-32.28	124.72	109.79	-14.93
Total %VagueExpressions	1.88	1.87	0.00	1.84	1.96	0.12
Firm Characteristics						
TECHExchange (standardized)	-0.94	1.12	2.06	-0.24	0.18	0.42
PRODExchange (standardized)	-0.24	0.29	0.54	-1.06	1.20	2.26
Firm Age (in months)	296.02	485.26	189.24	400.60	358.10	-42.49
R&D/Total Assets	1.37	1.26	-0.11	0.68	1.95	1.27
Firm Size	12.74	14.52	1.78	13.39	14.31	0.92
Cash Holdings	12.90	10.41	-2.49	7.88	18.66	10.78
ROA	0.74	0.93	0.19	1.13	0.92	-0.21
Book-to-Market	0.62	0.48	-0.13	0.59	0.45	-0.14
Application Month Returns	0.02	0.02	0.00	0.02	0.02	0.01
Number of patents	3.71	25.04	21.33	6.16	27.03	20.87
Scaled Number of Patents	0.29	0.29	-0.01	0.35	0.24	-0.11

Notes: Panel A presents the distribution of various patent (per patent) and firm (per quarter) characteristics at the 25th percentile mean, median, 75th percentile, and standard deviations. The patent characteristics are from Google Patents, whereas firm characteristics are from Compustat and CRSP. Panel B displays the patent and firm characteristics across the highest and lowest terciles of $TECHExchange_i$ on $PRODExchange_i$, where "Difference" is the difference across the highest and lowest of these terciles. Variable definitions are in Appendix A.

Table 2. Innovative Activity

Panel A. Innovation Quality

		(1) Scaled Citations (OLS)	(2) Scaled Citations (OLS)	(3) Scaled Citations (Poisson)
TECHExchange*PostAIPA (β1)		0.032***	0.035***	0.028***
		(3.19)	(3.46)	(2.97)
PRODExchange*PostAIPA (β2)		-0.050**	-0.051**	-0.049**
		(-2.35)	(-2.57)	(-2.32)
Magnitude	(β1)	3.17%	3.47%	2.77%
	(β2)	-4.95%	-5.05%	-4.85%
Controls		Yes	Yes	Yes
Firm FE		Yes	Yes	Yes
Year FE		Yes	Yes	Yes
Patent Class FE		No	Yes	No
Obs. (Firm-Patent)		259,368	259,368	259,368
Adjusted R-Sq./Pseudo R-Sq.		0.04715	0.05587	0.0398

Panel B. Innovation Quantity

		(1) Scaled Patent Count (OLS)	(2) Scaled Patent Count (Poisson)
TECHExchange*PostAIPA (β1)		0.0089*	0.0085
		(1.83)	(1.29)
PRODExchange*PostAIPA (β2)		0.0032	0.0067
		(0.83)	(1.18)
Magnitude	(β1)	0.31%	0.29%
	(β2)	0.11%	0.23%
Controls		Yes	Yes
Firm FE		Yes	Yes
Year FE		Yes	Yes
Obs. (Firm-Quarter)		17,271	17,271
Adjusted R-Sq./Pseudo R-Sq.		0.8611	0.1274

Notes: Panel A (B) reports the effect of the AIPA on innovation quality (quantity) using *Scaled Citations* (*Scaled Patent Count*) as the dependent variable. *PostAIPA* is a dummy variable equal to one if a patent is filed on or after the enactment of the AIPA and zero otherwise. $TECHExchange_i$ and $PRODExchange_i$ are proxies for the likelihood of firm i collectively exchanging scientific and business-related information with all other firms, respectively, conditional on a disclosure shock (Bloom et al. (2013)). Control variables included in the regressions are *Firm Age*, *R&D*, *Size*, *Profitability*, *Book-to-Market*, *Cash Holdings*, *Filing-Month-Returns*, *Review Months*, *Number of Claims Granted*, and *Patent Word Count*. The unit of observation for Panel B is at the firm-quarter level, and the firm-patent filing-date-level observations have been averaged at the firm-quarter level. All variable definitions are in Appendix A. *(OLS)* and *(Poisson)* indicate that the model is estimated using OLS and Poisson, respectively. *Magnitude* is the ratio of the estimated coefficient to the pre-AIPA average of *Scaled Citations* (*Scaled Patent Count)* in Panel A (B). The *t*-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm and year-month for Panel A and firm and quarter for Panel B. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels, respectively.

Table 3. Underlying Nature of Innovation

Panel A. Private Value, Generality, and Originality

	(1) KPSS Value	(2) Scaled Generality	(3) Scaled Originality
TECHExchange*PostAIPA (β1)	6.6415***	0.0167***	0.0109*
	(3.35)	(3.59)	(1.66)
PRODExchange*PostAIPA (β2)	-3.6933***	-0.0236***	-0.0301***
	(-3.24)	(-3.24)	(-3.04)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs. (Firm-Patent)	259,368	259,368	259,368
Adjusted R-squared	0.30858	0.23453	0.21594

Panel B. Patent Renewal Rates

	(1) Renewal 3.5 Years (OLS)	(2) Renewal 3.5 Years (Logit)	(3) Renewal 7.5 Years (OLS)	(4) Renewal 7.5 Years (Logit)
TECHExposure*PostAIPA (β1)	-0.004	0.1403*	0.041***	0.2919***
	(-0.35)	(1.88)	(3.64)	(3.20)
PRODExposure*PostAIPA (β2)	-0.014	-0.2268**	-0.053***	-0.3303***
	(-1.06)	(-2.20)	(-5.77)	(-3.80)
TECHExposure	-	-0.0441	-	-0.0907
	-	(-0.40)	-	(-0.89)
PRODExposure	-	0.2482**	-	0.2615**
	-	(2.21)	-	(2.36)
PostAIPA	-	-0.5173***	-	-1.1162***
	-	(-3.02)	-	(-8.88)
Constant	-	6.1908***	-	3.3607***
	-	(5.71)	-	(5.32)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
Obs. (Firm-Patent)	233,421	233,421	167,312	167,312
Pseudo R-squared	0.11135	0.0821	0.21989	0.0881

Notes: Panel A (B) reports the effect of the AIPA on the underlying nature of innovation using *KPSS Value*, *Scaled Generality*, and *Scaled Originality* (*Renewal Rates)* as the dependent variables. Discussion is provided in section 4.2. *PostAIPA* is a dummy variable equal to one if a patent is filed on or after the enactment of AIPA and zero otherwise. $TECHExchange_i$ and $PRODExchange_i$ are proxies for the likelihood of firm i collectively exchanging scientific and business-related information with all other firms, respectively, conditional on a disclosure shock (Bloom et al. (2013)). Control variables included in the regressions are *Firm Age*, *R&D*, *Size*, *Profitability*, *Book-to-Market*, *Cash Holdings*, *Filing-Month-Returns*, *Review Months*, *Number of Claims Granted*, and *Patent Word Count*. All variable definitions are in Appendix A. *(OLS)* and *(Logit)* indicate that the model is estimated using OLS and Logit, respectively. The *t*-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm and year-month. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels, respectively.

Table 4. Real Decisions of Firms: Investment Decisions

	(1)	(2)
	R&D	Capex
TECHExchange*PostAIPA (β1)	0.0557**	-0.0006
	(2.40)	(-0.91)
PRODExchange*PostAIPA (β2)	-0.1158***	-0.0006
	(-5.14)	(-0.59)
Magnitude (β1)	3.72%	-0.20%
(β2)	-8.01%	-0.20%
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Obs. (Firm-Quarter)	17,271	17,271
Adjusted R-Sq./Pseudo R-Sq.	0.09891	0.37858

Notes: This table presents the effect of AIPA on firms' investment decisions. In column (1), the dependent variable is *R&D*, whereas, in column (2), the dependent variable is *Capex*. The coefficient estimates are based on OLS. $TECHExchange_i$ and $PRODExchange_i$ are proxies for the likelihood of firm i collectively exchanging scientific and business-related information with all other firms, respectively, conditional on a disclosure shock (Bloom et al. (2013)). Control variables included in the regressions are *Firm Age*, *R&D*, *Size*, *Profitability*, *Book-to-Market*, *Cash Holdings*, *Filing-Month-Returns*, *Review Months*, *Number of Claims Granted*, and *Patent Word Count*. All variable definitions are in Appendix A. The unit of observation is at the firm-quarter level, and the firm-patent filing-date-level observations have been averaged at the firm-quarter level. *Magnitude* is the ratio of the estimated coefficient to the pre-AIPA average of the dependent variable. The *t*-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm and quarter. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels, respectively.

Table 5. Real Decisions of Firms: Labor Market Decisions

		(1) likelihood of Scientists Staying	(2) likelihood of Hiring Scientists	(3) % Change in Citations of Stayers	(4) % Change in Citations of Most Productive Stayers	(5) % Change in Citations of Least Productive Stayers
TECHExchange	(β1)	0.010**	0.026**	0.019**	0.041**	-0.015
		(2.21)	(2.11)	(2.11)	(2.35)	(-1.28)
PRODExchange	(β2)	-0.050***	-0.032***	-0.045***	-0.088***	-0.006
		(-3.58)	(-3.53)	(-4.67)	(-4.25)	(-0.52)
Controls		Yes	Yes	Yes	Yes	Yes
2-digit SIC Industry FE		Yes	Yes	Yes	Yes	Yes
Obs. (Inventor)		37,362	7,218	33,219	11,413	10,729
Adjusted R-Sq./Pseudo R-Sq.		0.0373	0.0833	0.0076	0.0218	0.0123

Notes: This table presents the effect of the AIPA on inventors' mobility and innovation productivity. Inventors are classified into three categories: *Stayer*, *Leaver*, and *New Hire*, as defined in section 4.3, following Bernstein (2015). The coefficient estimates are based on OLS. $TECHExchange_i$ and $PRODExchange_i$ are proxies for the likelihood of firm i collectively exchanging scientific and business-related information with all other firms, respectively, conditional on a disclosure shock (Bloom et al. (2013)). Control variables included in the regressions are *Firm Age*, *R&D*, *Size*, *Profitability*, *Book-to-Market*, *Cash Holdings*, *Filing-Month-Returns*, *Review Months*, *Number of Claims Granted*, and *Patent Word Count*. All variable definitions are in Appendix A. The unit of observation is at the inventor level, whereby both the firm and patent characteristics have been averaged at the inventor level, based on pre-AIPA averages. In column (1), the sample includes stayers and leavers, and the dependent variable equals one if the inventor stays at the firm. In column (2), the sample includes new hires and leavers, and the dependent variable equals one if the inventor is a new hire of the firm. In column (3), the sample is restricted to stayers, where *%Change in Citations* is defined as the percentage change in an inventor's average patent citation count before and after the AIPA. In column (4), the sample is restricted to stayers whose average pre-AIPA patent citations are in the top tercile, when compared to other inventors' average citations in the same two-digit SIC industry. In column (5), the sample is restricted to stayers whose average pre-AIPA patent citations are in the bottom tercile, when compared to other inventors' average citations in the same two-digit SIC industry. The *t*-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels, respectively.

Table 6. Direction of Information Spillovers (Disclosure from others vs. Disclosing to others)

	(1) Scaled Citations (OLS)	(2) Scaled Citations (OLS)	(3) Scaled Citations (Poisson)	(4) Scaled Citations (OLS)	(5) Scaled Citations (OLS)	(6) Scaled Citations (Poisson)
Proxy for "Spillover Direction": pre-AIPA #of Patents held						
TECHExchange_Spillin_#pat*PostAIPA	0.032***	0.031**	0.030***	-	-	-
	(2.70)	(2.28)	(3.04)	-	-	-
TECHExchange_Spillout_#pat*PostAIPA	0.010	0.016	0.006	-	-	-
	(0.56)	(0.94)	(0.34)	-	-	-
PRODExchange_Spillin_#pat*PostAIPA	-0.004	-0.003	-0.007	-	-	-
	(-0.66)	(-0.46)	(-1.15)	-	-	-
PRODExchange_Spillout_#pat*PostAIPA	-0.052***	-0.058***	-0.041**	-	-	-
	(-2.73)	(-3.21)	(-2.18)	-	-	-
Proxy for " Spillover Direction": pre-AIPA R&D expenditure						
TECHExchange_Spillin_R&D*PostAIPA	-	-	-	0.031***	0.031**	0.028***
	-	-	-	(2.66)	(2.24)	(2.97)
TECHExchange_Spillout_R&D*PostAIPA	-	-	-	0.012	0.017	0.007
	-	-	-	(0.61)	(1.00)	(0.39)
PRODExchange_Spillin_R&D*PostAIPA	-	-	-	-0.004	-0.003	-0.007
	-	-	-	(-0.61)	(-0.41)	(-1.11)
PRODExchange_Spillout_R&D*PostAIPA	-	-	-	-0.053***	-0.059***	-0.042**
	-	-	-	(-2.76)	(-3.25)	(-2.21)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Patent Class FE	No	Yes	No	No	Yes	No
Obs. (Firm-Patent)	259,368	259,368	259,368	259,368	259,368	259,368
Adjusted R-squared	0.04721	0.05559	0.00401	0.04721	0.05559	0.00401

Notes: This table reports the role of the direction of information spillovers (i.e., knowledge spillovers vs. proprietary costs) in dictating the relation between AIPA, $TECHExchange_i$, $PRODExchange_i$, and innovation. The suffixes "_Spillin" and "_Spillout" denote the likelihood of being on the receiving and revealing end, respectively. Specifically, I estimate information spill-in by weighting $TECHExchange_i$ and $PRODExchange_i$ by the number of pre-AIPA patents of other firms. Similarly, I measure information spill-out by weighting these measures by the number of pre-AIPA patents of the focal firm. As an alternative approach, I weight $TECHExchange_i$ and $PRODExchange_i$ by the average pre-AIPA R&D expenditures instead of patents. The suffixes "_pat" and "_R&D" denote the proxies used for information spill in and out. All variable definitions are in Appendix A. Further details are in section 4.4. The *t*-statistics reported in parentheses are computed based on standard errors clustered by firm and quarter. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels, respectively.

Table 7. Strategic Patent Disclosure

Panel A. Textual Analysis of the Sample Patents

	(1) % of Vague Expressions (Entire Patent)	(2) % of Vague Expressions (ABSTRACT)	(3) % of Vague Expressions (BACKGROUND & SUMMARY)	(4) % of Vague Expressions (DESCRIPTION OF DRAWINGS)	(5) % of Vague Expressions (DETAILED DESCRIPTION)	(6) % of Vague Expressions (CLAIMS & CONCLUSION)
TECHExchange*PostAIPA	-0.009	-0.017	-0.015	-0.023	0.011	-0.008
	(-1.07)	(-1.19)	(-1.07)	(-1.49)	(0.88)	(-0.51)
PRODExchange*PostAIPA	0.035*	0.041*	0.035**	0.088***	0.000	0.023
	(1.76)	(1.84)	(2.11)	(2.84)	(0.00)	(1.35)
Scaled Citations	0.003	0.009	-0.002	-0.003	0.004*	0.008*
	(1.61)	(1.58)	(-0.84)	(-0.68)	(1.71)	(1.95)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs. (Firm-Patent)	259,368	259,368	259,368	259,368	259,368	259,368
Adjusted R-squared	0.07577	0.02271	0.04199	0.07049	0.09065	0.01691

Table 7 [Continued]

Panel B. Number of Figures		
	(1) Number of Figures (OLS)	(2) Number of Figures (Poisson)
TECHExchange*PostAIPA (β1)	0.092	0.020
	(0.72)	(1.20)
PRODExchange*PostAIPA (β2)	-0.297*	-0.040**
	(-1.88)	(-2.03)
Scaled Citations	0.463***	0.040***
	(11.64)	(13.32)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Obs. (Firm-Patent)	259,368	259,368
Adjusted/Pseudo R-squared	0.16982	0.1246

Notes: This table reports the effect of firms' endogenous patent-disclosure quality responses to the AIPA. Panel A's dependent variable *%Vague Expressions* is an indication of lower disclosure quality, computed using textual analysis to identify the frequency of vague expressions used. Discussion of the use and definition of vague expressions in US patents is provided in section 4.4, Appendix C, and Appendix D. Column (1) computes *%Vague Expressions*, based on the entire patent application, whereas columns (2) through (6) compute *%Vague Expressions* for each of the patent subsection, as indicated in the parentheses below *%Vague Expressions*. Panel B's dependent variable *Number of Figures* is an indication of higher disclosure quality, computed using textual analysis of my sample patents to count the number of figures in patents. *PostAIPA* is a dummy variable equal to one if a patent is filed on or after the enactment of the AIPA and zero otherwise. $TECHExchange_i$ and $PRODExchange_i$ are proxies for the likelihood of firm i collectively exchanging scientific and business-related information with all other firms, respectively, conditional on a disclosure shock (Bloom et al. (2013)). Control variables included in the regressions are *Firm Age*, *R&D*, *Size*, *Profitability*, *Book-to-Market*, *Cash Holdings*, *Filing-Month-Returns*, *Review Months*, *Number of Claims Granted*, *Patent Word Count*, and *Scaled Citations*. All variable definitions are in Appendix A. *(OLS)* and *(Poisson)* indicate that the model is estimated using OLS and Poisson, respectively. The *t*-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm and year-month. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels, respectively.

Table 8. Aggregate, Industry-Wide Effects

Panel A. Share of Regulated Firms

	(1) Aggregate R&D	(2) Aggregate Tobin's Q	(3) Aggregate Sales on Assets	(4) Aggregate Return on Assets	(5) Aggregate Z-Score
Share_of_Regulated_Firms*PostAIPA	0.003**	0.289**	-0.007	0.001	10.352**
	(2.06)	(3.13)	(-0.59)	(0.26)	(2.00)
Controls	Yes	Yes	Yes	Yes	Yes
4-digit SIC Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs. (Industry-Year)	1,739	1,739	1,739	1,739	1,739
Adjusted R-squared	0.83696	0.82230	0.88614	0.56044	0.39781

Panel B. Net Benefit Index

	(1) Aggregate R&D	(2) Aggregate Tobin's Q	(3) Aggregate Sales on Assets	(4) Aggregate Return on Assets	(5) Aggregate Z-Score
Net_Benefit_Index*PostAIPA	0.005**	0.403***	0.001	0.008	13.321**
	(1.97)	(3.42)	(0.09)	(1.02)	(2.16)
Controls	Yes	Yes	Yes	Yes	Yes
4-digit SIC Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs. (Industry-Year)	1,739	1,739	1,739	1,739	1,739
Adjusted R-squared	0.83692	0.82201	0.88599	0.56085	0.39493

Notes: This table presents the industry-wide aggregate innovation effects of the AIPA. I augment my sample to include all Compustat/CRSP firms that do not hold patents. This yields a sample of 1,739 industry-year observations, using the four-digit SIC industry codes and requiring each four-digit SIC industry to have at least five firms in each of the sample years (1996–2005). Accordingly, all of the dependent variables (*R&D*, *Tobin's Q*, *Sales on Assets*, *Return on Assets*, and *Z-Score*) as well as the control variables are aggregated at the industry-year level by taking their industry-year averages. Panel A (B) uses $Share\_of\_Regulated\_Firms_s$ ($Net\_Benefit\_Index_s$) to measure an industry's treatment intensity, defined and discussed in section 4.5. *PostAIPA* is a dummy variable equal to one if a patent is filed on or after the enactment of the AIPA. All variable definitions are in Appendix A. The *t*-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by industry and year. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels, respectively.

Appendix A. Variables Definitions

Variables	Definitions	Source and Reference
Patent Characteristics		
$Raw\ Citations_{i,p,t}$	Number of citations a patent receives up until 2012.	-Google Patents/USPTO
$Scaled\ Citation_{i,p,t}$	*Raw Citations* divided by the average number of citations among patents in the same technology class and in the same filing year.	-Google Patents/USPTO
$Generality_{i,p,t}$	One minus the Herfindahl index for the technological classes of other patents that cite the focal patent.	-Google Patents/USPTO -Trajtenberg et al. (1997)
$Originality_{i,p,t}$	One minus the Herfindahl index for the technological classes of other patents that the focal patent cites.	-Google Patents/USPTO -Trajtenberg et al. (1997)
$Scaled\ Generality_{i,p,t}$	*Generality* divided by the average *Generality* among patents in the same technology class and in the same filing year.	-Google Patents/USPTO
$Scaled\ Originality_{i,p,t}$	*Originality* divided by the average *Originality* among patents in the same technology class and in the same filing year.	-Google Patents/USPTO
$KPSS\ Value_{i,p,t}$	A patent's economic value estimated based on the patent's grant day announcement returns. Specifics are provided by Kogan et al. (2017)	-Kogan et al. (2017)
$Allowed\ Claims_{i,p,t}$	The number of claims that the patent examiner allowed.	-Google Patents/USPTO
$Review\ Months_{i,p,t}$	The number of months between application date and grant date of a patent.	-Google Patents/USPTO
$Number\ of\ Figures_{i,p,t}$	The number of figures, charts, and diagrams included in the patent.	-Google Patents/USPTO
$Total\ Word\ Count_{i,p,t}$	The total number of words in the patent, excluding table captions and mathematical equations.	-Google Patents/USPTO
$\%Vague\ Expressions_{i,p,t}$	The total number of *Vague Expressions* (as defined in equation (5)) divided by *Total Word Count*	-Google Patents/USPTO -Appendix C
$Renewal\ 3.5\ Years_{i,p,t}$	Equal to one for patents that renew 3.5 years after grant and zero otherwise.	-Google Patents/USPTO
$Renewal\ 7.5\ Years_{i,p,t}$	Equal to one for patents that renew 7.5 years after grant and zero otherwise.	-Google Patents/USPTO
$PostAIPA_{i,p,t}$	Equal to one for patent applications filed after November 28, 2000, and zero otherwise.	-Google Patents/USPTO
Firm Characteristics		
$TECH^{Jaffe}_{i,j}$	The Jaffe technological distance between any given two firms *i* and *j* based on the uncentered correlations of patenting activity as described in equation (5).	-Google Patents/USPTO -Jaffe (1986)
$PROD^{Jaffe}_{i,j}$	The product market distance between any given two firms *i* and *j* based on the uncentered correlations of disaggregated sales activity as described in equation (5).	-Compustat -Jaffe (1986) -Bloom et al. (2013)
$TECH_{i,j}$	The Mahalanobis extension of $TECH^{Jaffe}$ that accounts for cross-technology-class knowledge spillovers. Developed and discussed by Bloom et al. (2013). Standardized with mean 0 and standard deviation 1.	- Bloom et al. (2013)
$PROD_{i,j}$	The Mahalanobis extension of $PROD^{Jaffe}$ that accounts for cross-product market interactions. Developed and discussed by Bloom et al. (2013) Standardized with mean 0 and standard deviation 1.	- Bloom et al. (2013)
$TECHExchange_i$	The average value of $TECH^{Jaffe}$ for firm *i* across all peer firms j as defined in equation (5).	- Bloom et al. (2013)
$PRODExchange_i$	The average value of $PROD^{Jaffe}$ for firm *i* across all peer firms j as defined in equation (5).	- Bloom et al. (2013)
$TECHExchange\_BioChemElec_i$	The proportion of patents a firm files in either chemistry, biology, or electronics technology. classes during the pre-AIPA period.	-Google Patents/USPTO -Ouellette (2017)

$PRODExchange\_HobergPhillips_i$	The firm's average pre-AIPA product market "similarities" measure developed by Hoberg and Phillips (2016).	-Hoberg and Phillips (2016)
$Firm\ Age_{i,q}$	The number of months since IPO.	CRSP
$R\&D_{i,q}$	R&D Expenditure divided by total assets.	Compustat
$Firm\ Size_{i,q}$	Log(1+Market Capitalization).	CRSP
$Cash\ Holdings_{i,q}$	Cash holdings divided by total assets.	Compustat
$ROA_{i,q}$	Return on assets is defined as operating income before extraordinary items divided by total assets.	Compustat
$BooktoMarket_{i,q}$	Book value of equity divided by total assets.	CRSP/Compustat
$Filing\ Month\ Returns_{i,q}$	Raw patent filing monthly returns minus the CRSP value-weighted index, averaged over quarter q.	CRSP
$Number\ of\ Patents_{i,q}$	Number of patents filed to a firm in quarter q.	-Google Patents/USPTO
$Scaled\ Number\ of\ Patents_{i,q}$	*Number of Patents* divided by the average number of patents filed in the same technology class and in the same filing year.	-Google Patents/USPTO
$High\ Patent\ Information_i$	Equal to one for firms in three-digit SIC industries that have an above median pre-AIPA fraction of patents filed in the chemistry, biology, and electronics sectors and otherwise zero.	-Google Patents/USPTO -Ouellette (2017)
$Low\ Opt\ Out\ Option_i$	Equal to one for firms in three-digit SIC industries that have an above median pre-AIPA fraction of patents that file for foreign protection and otherwise zero.	-Google Patents/USPTO -Ouellette (2017)
	Inventor Characteristics	
$Stayer_e$	An inventor with at least one patent prior to and at least one patent after the AIPA at the same sample firm.	-HBS Patenting Database
$Leaver_e$	An inventor with at least one patent prior to the AIPA at a sample firm and at least one patent after the AIPA at a different firm.	-HBS Patenting Database
$New\ Hire_e$	An inventor with at least one patent after the AIPA at a sample firm but no patents before and at least one patent prior to the AIPA at a different firm.	-HBS Patenting Database
$\%Change\ in\ Citations_e$	The percentage change in an inventor's average patent citations, relative to the AIPA.	-Google Patents/USPTO -HBS Patenting Database
$Most\ Productive_e$	Inventors in the top tercile of average citations prior to AIPA.	-Google Patents/USPTO -HBS Patenting Database
$Least\ Productive_e$	Inventors in the bottom tercile of average citations prior to AIPA.	-Google Patents/USPTO -HBS Patenting Database
	Industry Characteristics	
$Share\_of\_Regulated\_Firms_s$	The number of sample firms divided by the total number of firms in a given four-digit SIC industry.	-Bloom et al. (2013) -Compustat
$Net\_Benefit\_Index_s$	*Share* multiplied by $\sum_{i\in s} TECHExposure_i / (1+\sum_{i\in s} PRODExposure_i)$ as described in equation (7).	-Bloom et al. (2013) -Compustat

Notes: *i* denotes firm, *p* denotes patent, *t* denotes patent filing date, *j* denotes peer firms, *q* denotes quarter, *e* denotes inventor, *s* denotes four-digit SIC industry, *y* denotes year.

Appendix B. Scientific and Business-related Signals in Patents: Discussion and Example

B-1) Discussion[27]

Scientific Information in Patents

In practice, there is considerable debate about how much useful technical information patents contain (Williams (2017)). On the one hand, critics argue they contain little valuable scientific information because patentees may deliberately obfuscate the technical content to disclose as little as possible to potential competitors. Moreover, other technical literature (e.g., academic journals) may subsume patents' usefulness as a source for scientific information (Roin (2005); Devlin (2010)). On the other hand, recent survey evidence suggests that about 60% of all patent readers and 72% of those reading for scientific reasons found useful technical information in patents (Ouellette (2017)). Ouellette (2017) concludes that the usefulness of patents as a source of technical information, while heterogeneous, holds across a wide range of research fields and disciplines. For example, scientists responded that "patents can be useful in providing technical details that are often omitted from research publications" and that "most of the information in the journal literature is deliberately not published in a timely manner so it is absolutely essential to follow the patent literature." While the survey responses provide important anecdotal evidence that patents contain useful scientific information, systematic/archival evidence, especially in the context of whether patent disclosures foster innovation is scarce (Williams (2017)). Hence my paper contributes to this discussion by examining whether patent disclosures influence firms' innovation decisions.

Business Information in Patents

In addition to technical information, corporate patents, in particular, can reveal information about the disclosing firm's strategic *business decisions* (Horstmann et al. (1985); Oppenheim (1998)). For example, if a firm files an abnormally high rate of patents related to virtual reality technology, the patenting pattern can provide useful insights to its product market rivals (e.g., whether to enter or exit the market, whether to cut prices to better compete, etc.). Consistent with this view, a *Science* article by Boulakia (2001) provides an anecdotal account of AT&T, IBM, and Lucent allocating considerable amounts of resources to parse through, organize, and extract valuable information from the millions of publicly disclosed patents of their product market competitors. This business practice, known as "patent mapping" or "patent landscaping," allows firms to examine the overall landscape of competitors' patents without having to understand all of the intricate scientific details behind each one. By doing so, corporations can identify business entry points, litigation risk, potential customers, future competitive threats, and acquisition targets (see Entis (2014) for a more recent discussion). Consistent with these arguments, economists at the European Commission also argue that "the best predictor of what [firms] will be doing 10 years into the future is the current portfolio of the patents they have now," citing that Dow Chemical and DuPont as prominent examples that track competitors' patents for these reasons (Schechter (2017)). Whether these practices are part of a broader empirical regularity is again an empirical question.

[27] My own interviews with industry researchers suggest that tracking other firms' patents for both scientific and business-related information is common. For example, one of my interviewees, who works in the chemical industry, says that the technical information in other firms' patents helped with their firm's development of chemical mechanical planarization pads. He also says that tracking rivals' patents can affect business decisions, such as market entry and M&A.

Appendix B [Continued]

B-2) Example

I discuss IBM's patent, titled "Drone Delivery of Coffee Based on A Cognitive State of an Individual" ("The IBM Patent", US 10,040,551) to demonstrate i) how a patent can contain information relevant for both science and business and ii) what a typical patent looks like.

Summary of the IBM patent and its scientific versus business-related information

The IBM patent is about a drone that not only delivers coffee to consumers but uses artificial intelligence and biometrical data, such as pupil dilation, blood pressure, and facial expression, to predict consumer demand for coffee. The patent contains detailed scientific information on how to combine these technologies to create drones relevant in the coffee industry, as discussed below. Scientific peers of IBM, such as Amazon and Google, may find the details useful for their own innovations.

The same patent can also provide useful business information. For example, the patent may signal good market potential for creating delivery drones to Amazon and encourage Amazon to invest more in delivery drones. Even firms not in the drone industry, like Starbucks, may find useful business signals from the patent. For example, Starbucks may curb its expansion in response to higher projected demands for drone-delivered coffee.

Inside the IBM patent

A typical patent starts with a "cover page," which contains key patent information, such as the owner, application date, disclosure date, grant date, inventors, number of claims, the examiner, technology field, and an abstract. **Exhibit 1** below shows the cover page of the IBM patent.

Exhibit 1. Cover Page

(12) **United States Patent**
Erickson et al.

(10) **Patent No.: US 10,040,551 B2**
(45) **Date of Patent: Aug. 7, 2018**

(54) **DRONE DELIVERY OF COFFEE BASED ON A COGNITIVE STATE OF AN INDIVIDUAL**

(71) Applicant: **International Business Machines Corporation**, Armonk, NY (US)

(72) Inventors: **Thomas David Erickson**, Minneapolis, MN (US); **Rogerio S. Feris**, Hartford, CT (US); **Clifford A. Pickover**, Yorktown Heights, NY (US); **Maja Vukovic**, New York, NY (US)

(73) Assignee: **International Business Machines Corporation**, Armonk, NY (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 101 days.

(21) Appl. No.: **14/978,620**

(22) Filed: **Dec. 22, 2015**

(65) **Prior Publication Data**

US 2017/0174343 A1 Jun. 22, 2017

(51) **Int. Cl.**
E04H 3/04 (2006.01)
B64C 39/02 (2006.01)
(Continued)

(52) **U.S. Cl.**
CPC ***B64C 39/024*** (2013.01); ***A61B 5/01*** (2013.01); ***A61B 5/02055*** (2013.01); ***A61B 5/11*** (2013.01);
(Continued)

(58) **Field of Classification Search**
CPC A61B 5/1176; A61B 2034/2057; A61B 2034/2065; A61B 5/165; A61B 5/02055;
(Continued)

(56) **References Cited**

U.S. PATENT DOCUMENTS

5,094,153 A 3/1992 Helbling
6,419,629 B1 7/2002 Balkin et al.
(Continued)

FOREIGN PATENT DOCUMENTS

WO 0117362 3/2001
WO 2005000385 1/2005

OTHER PUBLICATIONS

Disclosed Anonymously, "Use of Flavors with Modifying Properties (FMP) in Flavor Compositions and Applications of FMP in Food and Beverage Products", IP.com No. 000240463, Jan. 30, 2015, pp. 1-43.
(Continued)

Primary Examiner — Jeffrey A Shapiro
(74) *Attorney, Agent, or Firm* — Fleit Gibbons Gutman Bongini Bianco PL; Gary Winer

(57) **ABSTRACT**

Coffee or other drink, for example a caffeine containing drink, is delivered to individuals that would like the drink, or who have a predetermined cognitive state, using an unmanned aerial vehicle (UAV)/drone. The drink is connected to the UAV, and the UAV flies to an area including people, and uses sensors to scan the people for an individual who has gestured that they would like the drink, or for whom an electronic analysis of sensor data indicates to be in a predetermined cognitive state. The UAV then flies to the individual to deliver the drink. The analysis can include profile data of people, including electronic calendar data, which can be used to determine a potentially predetermined cognitive state.

17 Claims, 4 Drawing Sheets

The body of the patent following the cover page generally consists of five sections, comprised of four sections with textual content—the background and summary, description of drawings, detailed description, and claims and conclusion—and a section that contains figures, drawings, and charts. The IBM patent has a total of about 12,000 words with four sheets of drawings (or eight figures). To illustrate, **Exhibit 2** shows the background and summary section of the IBM patent. This section provides a summary of what the innovation does. The detailed description section, shown in **Exhibit 3**, gives a more detailed account of how to practically implement the invention. For example, on page 13 of the patent, the inventors provide the technical details on how to analyze sleep data to predict human cognitive performance and predict consumer demand for coffee.

Exhibit 2. Background & Summary

FIELD OF THE DISCLOSURE

The disclosure relates to a system and method for using drones to deliver a drink to an individual, and more particularly, sensing a predetermined cognitive state of an individual to identify a candidate for delivery of a drink.

BACKGROUND OF THE DISCLOSURE

Quick and easy delivery of drinks is a new way of service around the world. Drone technology has increased to support delivery of packages around the world. Drone technology can also assist in customer service areas. Drones that are functioned to deliver products have yet to deliver beverages based on the person(s) being served to.

SUMMARY OF THE DISCLOSURE

In an embodiment of the disclosure, a method for delivering a drink to an individual comprises connecting the drink to an unmanned aerial vehicle (UAV); flying the UAV to an area including a plurality of people; scanning the people, using one or more sensors connected to the UAV, the one or more sensors connected to an electronic processing circuit which identifies an individual among the people that may have a predetermined cognitive state, based on sensor data; and flying the UAV to the individual that may have a predetermined cognitive state to deliver the drink to the individual.

In another embodiment of the disclosure, a method for delivering a drink to an individual comprises connecting at least one coffee drink to a fully autonomous unmanned aerial vehicle (UAV); the UAV autonomously flying to an area including a plurality of people; scanning the people, using one or more sensors connected to the UAV, the one or more sensors connected to an electronic processing circuit which identifies an individual among the people that may have a predetermined cognitive state, or that has indicated by a gesture that a drink is wanted, based upon sensor data; processing by the electronic processing circuit to determine that the individual is eligible for delivery of the drink; and the UAV autonomously flying to the individual that may have a predetermined cognitive state or who has gestured, to deliver the drink to the individual.

In a further embodiment of the disclosure, a system for delivering a drink to an individual, comprises at least one fully autonomous unmanned aerial vehicle (UAV); a drink holder connected to each of the at least one UAV; at least one sensor including at least a camera connected to the UAV; and at least one electronic processing circuit connected to obtain data from the at least one sensor, the circuit configured to use data from the sensors, including scanning images from the camera, to identify an individual that may have a predetermined cognitive state, or that has indicated by a gesture that a drink is wanted, based upon the sensor data, and to thereby cause the UAV to fly to the individual to deliver a drink to the individual from the drink holder.

Exhibit 3. Page 13 of Detailed Description

DETAILED DESCRIPTION OF THE DISCLOSURE

. . .

Sleep data can be analyzed in accordance with U.S. Pat. No. 6,419,629, for example, and the formula M=m(t) or $M_1=F+A_1*\cos(2Pi(t-V_1)/P_1)+A_2*\cos(2Pi(t-V_2)/P_2)$, as described therein can be used to enable the creation of predictive cognitive performance curves for a user. If the prediction is for poor performance due to sleep quality issues, L is increased. For this method, it may be necessary to first obtain data for the user relating to cognitive ability under controlled conditions, although if such data is unavailable, data from other individuals can be used to enable an estimated predictive cognitive capacity for a particular user herein.

Once sleep data has been obtained, it may be determined if user **400** has had sleep quality problems recently, and if cognitive capability is likely to be impaired, and if so, this can increase the value of L sufficiently to warrant an offer of coffee relative to other users. Other parameters can be probed as described herein, including biometric parameters. For example, drone **200** can be provided with sensors that can determine any or all of a heart rate, blood pressure, blood oxygen saturation, pupil dilation, breathing rate, skin temperature, a chemical composition of breath of user **400**, an extent of movement of user **400**, or any other physical parameters which can be analyzed for tiredness, sleepiness, or grogginess, and which can further increase a value of L, until a threshold parameter is reached for an offer of coffee. It can be advantageous to use at least two of the physiological parameters to increase an accuracy of a determination of L. Advantageously, the biometric parameters can be evaluated without contact with, or interruption to, the user. Sensors, a microphone, and a speaker are depicted as attached to drone **200** in FIG. **5**, in this example located upon a pod **264**. A display **266** is also illustrated.

. . .

Finally, **Exhibits 4 and 5** show Figures 5 and 8 in the IBM patent, respectively. Figure 5 depicts the idea of drones delivering drinks when a potential consumer waves at the drone. Figure 8 of the patent depicts a mobile computing system that can be used as part of the drone.

Exhibit 4. "Fig. 5" of the IBM patent

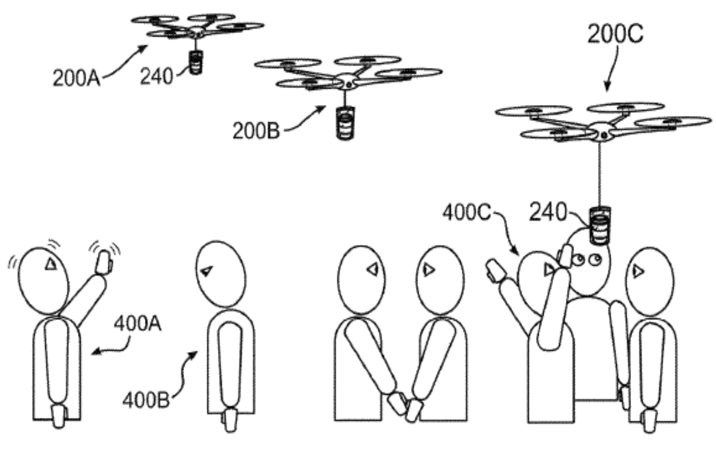


FIG. 5

Exhibit 5. "Fig. 8" of the IBM patent

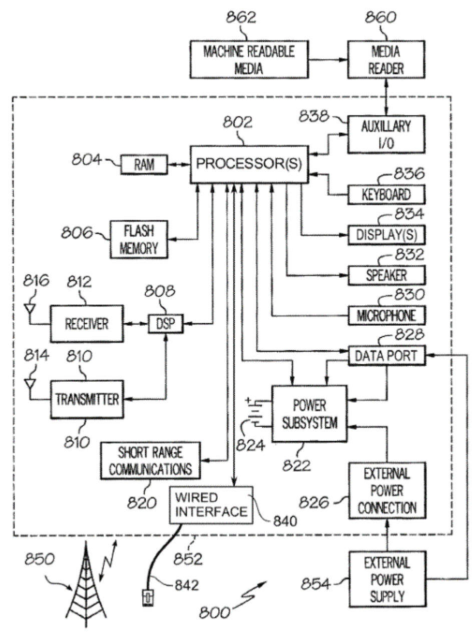


FIG. 8

Appendix C. Vague Expressions as a Metric for Patent Disclosure Quality

I discuss the three vagueness expression categories identified by prior studies (e.g., Ivanic (1991); Channell (1994)) that Arinas (2012) uses to construct the list of vague expressions used in US patents as shown in Appendix D.

1) **Vague category identifiers**. Vague category identifiers are expressions that are vague enough to refer to a set of more specific concepts and, at the same time, unclear, as they can be used to refer to a concept introduced previously in a given text. Consider the following example from a US patent.

Example 1. "Thus, ***the present invention is not limited by*** *the above description but is defined by the appended claims." (US Patent 7,557,072)*

The expression in bold is vague because, first, it is unclear as to what "the present invention" is precisely referring to. It can refer to either a particular aspect of the described invention or the invention in its entirety. Second, the expression "is not limited by" serves the purpose of warning readers that the description covers other potential claims not explicitly described in the patent disclosure.

2) **Vague quantities**. Vague quantities can either refer to expressions that designate intervals of concrete numbers/quantities or whose truth can be interpreted within a scale in relation to a context.

Example 2. "via a clearance so as to cover a region ***ranging from*** *the vicinity of the upper end* ***to*** *the lower end vicinity of the internal door 22" (US Patent 6,764,234)*

Example 3. "the engine 22 includes a lubricating system for providing lubricant to the various ***portions of*** *the engine." (US Patent 6,763,795)*

The bold expressions above are vague because they refer to a range of possible quantities or values that make the statements true.

3) **Lack of Interpretation Standard.** Lack of interpretation standard refers to a set of expressions that open the interpretation of the patent disclosure to nondescribed aspects.

Example 4. "Ball 503 ***may be*** *a neodymium magnet, as described above, or* ***may be*** *any other permanent magnet …" (US Patent 7,557,727)*

This example demonstrates that the vague expression "may be" opens the interpretation of the referenced object (i.e., Ball 503) to various types of magnets.

Appendix D. Vague Expressions Used for Textual Analysis

Vague category identifiers		
According to + In accordance with + In + It is +	an/the alternate + an/the alternative + an/the + another + one + the above described + a (still) further exemplary + a further + an illustrative + a predetermined + a preferred + an + still/yet another + a broad +	***embodiment*** of the present ***invention*** ***aspect*** of the present ***invention***
This + The present + The +	***invention*** is not limited +	by in this respect thereto
The present ***disclosure*** relates + The present ***invention*** relates + This ***invention*** is related +	to *generally* to *in general* to	
Vague quantities		
between, at least, ranging from, preferably, preferred, a plurality of, a ratio of, a set of, a subset of, a member of, a section of, a mixture of, a segment of, portions of, components of, embodiments of		
Lack of interpretation standard		
may be, may also be, can be, can also be, if, substantially, selectively		

Notes: This table is the list of vague expressions used in this study and originally compiled by Arinas (2012).

Internet Appendix
to

Mandatory Corporate Patent Disclosures and Innovation

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Table of Contents (Additional Analyses)

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Internet Appendix

Table IA1. Sample Selection

Panel A. Patent Sample			
All patent applications filed by publicly listed firms on CRSP from 1996 through 2005			632,104
Exclude:			
	Patents owned by firms without technology and product-market distance measures	(355,245)	
	As well as firms that did not patent at least once prior to and after the AIPA		
	Patents owned by firms without relevant Compustant, CRSP and patent characteristics	(17,491)	
			259,368
			(525 firms over 1996-2005)

Panel B. Inventor Sample			
Inventors from Harvard Business School's Patenting Database matched to my sample of patents			439,087
Exclude:			
	Inventors that are neither a stayer, leaver, nor new	(398,650)	
	(i.e., must have patented at least once prior to and after the AIPA)		
			40,437
			(stayer (33,219), leaver (4,143), or new (3,075))

Notes: Panel A presents the data restrictions applied in creating this study's firm-patent sample with 259,368 observations comprised of 525 unique publicly traded firms spanning the years 1996–2005. Panel B presents the inventor-level sample from HBS's patenting database with 40,437 unique inventors matched to my patent-level data over the period 1996–2005.

Table IA2. Sensitivity Analyses

Panel A. Alternative Citation Measures and Model Specifications

	(1) Raw Citations (OLS)	(2) ln(1+Citations) (OLS)	(3) Raw Citations (OLS Firm-Quarter Sample)	(4) Scaled Citations (OLS Firm-Quarter Sample)	(5) Scaled Citations (Negative Binomial)	(6) Scaled Citations (Zero-Inflated Negative Binomial)	(7) Scaled Citations (Zero-Inflated Poisson)
TECHExchange*PostAIPA (β1)	2.146***	0.075**	2.084***	0.031**	0.020**	0.023**	0.021*
	(3.13)	(2.41)	(2.82)	(2.33)	(2.05)	(2.08)	(1.69)
PRODExchange*PostAIPA (β2)	-1.969***	-0.096***	-1.852***	-0.083***	-0.055***	-0.057***	-0.063***
	(-3.80)	(-3.25)	(-3.42)	(-5.18)	(-2.76)	(-2.59)	(-2.84)
TECHExchange	-	-	-	-	-0.039**	-0.059***	-0.061***
	-	-	-	-	(-2.56)	(-3.39)	(-3.30)
PRODExchange	-	-	-	-	0.044**	0.036**	0.037*
	-	-	-	-	(2.46)	(2.03)	(1.91)
PostAIPA	-	-	-	-	0.068***	0.070**	0.100***
	-	-	-	-	(2.68)	(2.56)	(3.36)
Constant	-	-	-	-	0.321***	-0.243	-0.109
	-	-	-	-	(5.62)	(-1.36)	(-0.54)
Magnitude (β1)	12.78%	3.52%	12.19%	3.07%	1.98%	2.28%	2.08%
(β2)	-11.72%	-4.51%	-11.03%	-8.22%	-5.45%	-5.64%	-6.24%
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	No	No	No
Year FE	Yes	Yes	Yes	Yes	No	No	No
Obs. (Firm-Patent)	259,368	259,368	17,271	17,271	259,368	259,368	259,368

Table IA2 [Continued]

Panel B. Alternative Firm-Link Measures 1: Variants to Bloom et al.

		(1)	(2)	(3)	(4)	(5)	(6)
		Scaled Citations	Raw Citations	Scaled Citations	Raw Citations	Scaled Citations	Raw Citations
LnTECHExchange*PostAIPA	(β1)	0.037***	2.842***	-	-	-	-
		(2.69)	(3.07)	-	-	-	-
LnPRODExchange*PostAIPA	(β2)	-0.053**	-1.981***	-	-	-	-
		(-2.56)	(-3.98)	-	-	-	-
TECHExchange_Jaffe*PostAIPA	(β1)	-	-	0.030**	2.414***	-	-
		-	-	(2.26)	(2.62)	-	-
PRODExchange_Jaffe*PostAIPA	(β2)	-	-	-0.051**	-2.032***	-	-
		-	-	(-2.46)	(-4.09)	-	-
D_TECHExchange*PostAIPA	(β1)	-	-	-	-	0.138***	9.254***
		-	-	-	-	(2.81)	(2.69)
D_PRODExchange*PostAIPA	(β2)	-	-	-	-	-0.175**	-5.832***
		-	-	-	-	(-2.41)	(-3.19)
Magnitude	(β1)	3.66%	16.92%	2.97%	14.37%	13.66%	55.10%
	(β2)	-5.25%	-11.80%	-5.05%	-12.10%	-17.33%	34.73%
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
Obs. (Firm-Patent)		259,368	259,368	259,368	259,368	259,368	259,368
Adjusted R-squared		0.04716	0.17773	0.04737	0.17712	0.04715	0.17702

Table IA2 [Continued]

Panel C. Alternative Firm-Link Measures 2: Bio-Chem Tech Class & Hoberg and Phillips

	(1)	(2)	(3)	(4)	(5)	(6)
	Scaled Citations	Raw Citations	Scaled Citations	Raw Citations	Scaled Citations	Raw Citations
TECHExchange_BioChemElec	0.033*	1.329**	0.033*	1.401**	-	-
	(1.81)	(2.15)	(1.82)	(2.11)	-	-
PRODExchange_HobergPhillips	-0.017***	-1.002***	-	-	-0.010**	-0.930***
	(-4.83)	(-4.41)	-	-	(-2.53)	(-4.50)
PRODExchange	-	-	-0.035***	-1.393***	-	-
	-	-	(-2.73)	(-2.89)	-	-
TECHExchange	-	-	-	-	0.024**	0.600
	-	-	-	-	(2.52)	(1.08)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	255,526	255,526	255,526	255,526	255,526	255,526
Adjusted R-squared	0.04703	0.18112	0.04687	0.17582	0.04610	0.18098

Table IA2 [Continued]

Panel D. Alternative Fixed Effect Structures

	(1) Raw Citations	(2) Raw Citations	(3) Raw Citations
TECHExchange*PostAIPA	1.518***	0.923***	0.591***
	(3.15)	(6.36)	(2.71)
PRODExchange*PostAIPA	-0.947**	-0.420***	-0.088
	(-2.06)	(-3.06)	(-0.21)
Controls	Yes	Yes	Yes
Type of FE	Patent Class*Year	Industry*Year	Firm*Year
Observations	259,368	259,368	259,368
Adjusted R-squared	0.19121	0.17072	0.20791

Notes: This table presents coefficient estimates based on equation (5)—corresponding results in Table 2—using different variables definitions for innovation, model specifications, and information exchange measures. Panel A uses *Raw Citations* and *ln(1+Citations)* as alternative ways of measuring innovation quality. Different model specifications include using a negative binomial, a zero-inflated negative binomial, a zero-inflated Poisson model, and collapsing the data at the firm-quarter level, all of which are indicated in the parentheses below the dependent variable headings. Ln(market equity) is the explanatory variable in the first stage of the zero-inflated models. Panel B considers different firm exchange measures, such as logged (first two rows), the Jaffe (third and fourth row), and decile portfolio versions (last two rows) of $TECHExchange_i$ and $PRODExchange_i$. Panel C uses new firm exchange measures, $TECHExchange_i\_BioChemElec_i$, defined as the proportion of patents a firm files in either chemistry, biology, or electronics classes during the pre-AIPA period, motivated by Ouellette (2017) finding that these technology sectors tend to produce patents with the most useful technical information; and $PRODExchange\_HobergPhillips_i$, which is the firm's average pre-AIPA product market "similarities" measure, provided by Hoberg and Phillips (2016). Panel D considers alternative fixed effect structures—Patent Class*Year, Industry*Year (two-digit SIC), and Firm*Year using *Raw Citations* instead of *Scaled Citations* as the main dependent variable. The discussion of the information exchange measures is provided in section 3.3. *PostAIPA* is a dummy variable equal to one if a patent is filed on or after the enactment of the AIPA and zero otherwise. Control variables included in the regressions are *Firm Age*, *R&D*, *Size*, *Profitability*, *Book-to-Market*, *Cash Holdings*, *Filing-Month-Returns*, *Review Months*, *Number of Claims Granted*, and *Patent Word Count*. All variables definitions are in Appendix A. *Magnitude* is the ratio of the estimated coefficient to the pre-AIPA average of the dependent variable. The *t*-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm and year-month. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels, respectively.

Table IA3. Firm-Level Productivity

		(1) Tobin's Q	(2) Sales on Assets	(3) Return on Assets	(4) Altman Z Score
TECHExchange*PostAIPA (β1)		0.0637**	0.0056**	0.0029***	0.8044***
		(2.51)	(2.20)	(2.99)	(3.92)
PRODExchange*PostAIPA (β2)		-0.1477***	-0.0051*	-0.0020*	-1.0609***
		(-4.51)	(-1.69)	(-1.90)	(-3.78)
Magnitude	(β1)	3.76%	2.31%	3.27%	1.91%
	(β2)	-8.73%	-2.11%	-2.26%	-2.52%
Controls		Yes	Yes	Yes	Yes
Firm FE		Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes
Obs (Firm-Quarter)		17,271	17,271	17,271	17,271
Adjusted R-squared		0.76811	0.76635	0.48061	0.51286

Notes: This table examines firm-level productivity effects induced by the AIPA. Performance metrics include *Tobin's Q*, *Sales on Assets*, *Return on Assets*, and *Altman Z Score*, as defined in Appendix A. The unit of observation is at the firm-quarter level. *PostAIPA* is a dummy variable equal to one if a patent is filed on or after the enactment of the AIPA and zero otherwise. $TECHExchange_i$ and $PRODExchange_i$ are proxies for the likelihood of firm i collectively exchanging scientific and business-related information with all other firms, respectively conditional on a disclosure shock (Bloom et al. (2013)). *Magnitude* is the ratio of the estimated coefficient to the pre-AIPA average of the dependent variable. The *t*-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm and quarter. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels, respectively.

Internet Appendix

Table IA4. Likelihood of Exercising Secrecy Option (Logit)

	(1) Likelihood of Secrecy	(2) Likelihood of Secrecy (Marginal Effects)
TECHExchange (β1)	-0.245**	-0.010**
	(-2.34)	(-2.26)
PRODExchange (β2)	0.107**	0.004**
	(2.50)	(2.51)
Scaled Citations	0.032***	0.001***
	(8.37)	(7.51)
Controls	Yes	Yes
Obs. (Firm-Patent)	126,456	126,456
Pseudo R-Squared	0.199	

Notes: This table presents the effect of $TECHExchange_i$ and $PRODExchange_i$ on the likelihood that a firm exercises its opt-out option. A firm is allowed to opt-out of the 18-month disclosure for any US patent that does not seek foreign protection. *Secrecy* is a dummy variable equal to one if a patent chooses to exercise the secrecy option and zero otherwise. The sample for this analysis is restricted to patents that do not seek foreign protection. Coefficient estimates are based on logit regressions. $TECHExchange_i$ and $PRODExchange_i$ are proxies for the likelihood of firm i collectively exchanging scientific and business-related information with all other firms, respectively, conditional on a disclosure shock (Bloom et al. (2013)). The t-statistics reported below the coefficient estimates in parentheses are computed based on robust standard errors. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels, respectively.

Table IA5. Heterogeneity and Falsification

	(1) Scaled Citations (High Patent Information = 1)	(2) Scaled Citations (Low Patent Information = 0)	(3) Scaled Citations (Low Opt Out Option = 1)	(4) Scaled Citations (Low Opt Out Option = 0)
TECHExchange*PostAIPA (β1)	0.064**	0.029*	0.038***	0.011
	(2.01)	(1.85)	(3.12)	(0.13)
PRODExchange*PostAIPA (β2)	-0.073***	-0.025**	-0.074***	-0.021
	(-3.34)	(-1.99)	(-2.87)	(-0.89)
Magnitude (β1)	6.33%	2.87%	3.76%	1.08%
Magnitude (β2)	-7.22%	-2.48%	-7.32%	-2.08%
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs. (Firm-Patent)	69,433	189,935	135,325	124,043
Adjusted R-squared	0.05875	0.05321	0.05345	0.04221

Notes: This table reports two sets of subsample tests to the results presented in Table 2. First, in columns (1) and (2) *High Patent Information* equals one if a firm is in a two-digit SIC industry where 50% or more of the patents are filed in chemistry, biology, and electronics, based on pre-AIPA patenting patterns, and zero otherwise. This is based on Ouellette (2017) survey-based evidence that patents filed in these industries are most used/read by industry researchers. Second, in columns (3) and (4) *Low Opt Out Option* equals one if a firm is in a two-digit SIC industry where 50% or more of the patents file for foreign protection based on pre-AIPA patenting patterns and zero otherwise. This is based on the AIPA's opt-out rule that allows a firm to opt out of the 18-month disclosure rule for any US patent that does not seek foreign protection. *PostAIPA* is a dummy variable equal to one if a patent is filed on or after the enactment of the AIPA and zero otherwise. $TECHExchange_i$ and $PRODExchange_i$ are proxies for the likelihood of firm i collectively exchanging scientific and business-related information with all other firms, respectively, conditional on a disclosure shock (Bloom et al. (2013)). *Magnitude* is the ratio of the estimated coefficient to the pre-AIPA average of the dependent variable. The *t*-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm and year-month. *, **, *** indicate that the coefficient is statistically significant at the 10%, 5%, 1% levels, respectively.