Patents and knowledge diffusion: The effect of early disclosure

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ABSTRACT

We study how the timing of information disclosure affects the diffusion of codified technical information. On November 29, 2000, the American Inventors Protection Act (AIPA) reduced the default publication time of patents at the United States Patent and Trademark Office (USPTO) to 18 months. We analyze the effects of this change by means of a regression discontinuity design with time as an assignment variable and a complementary difference-in-differences analysis. Our study shows that information flows from patents measured by forward citations, increased. Interestingly, the degree of localization within geographic boundaries remained unchanged and technological localization even increased moderately. Moreover, the effect of early disclosure on citations from patents filed by patent attorney service firms is particularly strong. These results imply that knowledge diffusion stemming from speedier disclosure of technical information is confined to the existing attention scope and absorptive capacity of specific inventors and organizations.

Keywords: knowledge diffusion; patent citations; information disclosure; patent policy, technology spillovers, AIPA

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1. INTRODUCTION

The innovation potential of modern economies rests strongly on the diffusion of knowledge (Romer 1986; Audretsch and Feldman, 1996). Scientific and technological advances tend to follow cumulative trajectories where new results build on previous findings (Scotchmer 1991; Belenzon 2011). Information disclosure is an important antecedent of diffusion and can be a driver of cumulative innovation and reduce wasteful duplication of R&D effort (Murray and O'Mahony, 2007; Romer, 1986). As a result, institutions often support or require disclosure of codified knowledge (Denicolo and Franzoni, 2003; Furman and Stern, 2011). The spread of information and communication technologies (ICTs) has also increased the role of disclosure quite dramatically since once disclosed, ICTs make information available almost instantly worldwide (e.g. Hilbert and Lopez, 2011). However, an overwhelming stock of information poses problems for innovators who face increasing screening and cognitive costs when accessing external information (Jones, 2009; Piezunka and Dahlander, 2015). Moreover, in contexts where information diffusion costs are very low, disclosure requirements are a source of concern related to the increased risks of imitation and unintended knowledge spillovers (Arrow, 1962; Modigliani, 1999).

One concrete information diffusion channel is the patent literature, which arguably constitutes a huge and continuously growing repository of technological information. However, there is an ongoing debate over the effectiveness of patent information for cumulative innovation. Some studies suggest that patents have improved the diffusion of knowledge (e.g. Furman et al. 2018; Moser 2011; Ouellette 2012) but there remains concern over whether patents are effective for informing other inventors (Bessen, 2005). This somewhat sceptical view is supported indirectly by the observation that knowledge flows often are strongly localized within geographical, technological and organizational boundaries (Feldman and Kogler, 2010; Jaffe et al., 1993). In the context of technology clusters, this can be a sign of a thriving innovation environment (Audretsch and Feldman, 1996). At the same time, strong localization of knowledge flows could reflect limited effectiveness of codified knowledge and of the patent literature as a knowledge diffusion channel. Also, whether improved disclosure of patent information affects knowledge diffusion and its localization remains especially unclear (Murray and O'Mahony, 2007; Williams, 2017).

In this paper, we analyze the impact of *disclosure timing* of codified patent information on its diffusion. Although timing is a rather understudied determinant of knowledge diffusion (Williams, 2017), we argue that it is highly relevant. The publication of codified R&D information such as scientific results, or the technical information contained in patents tends to occur with substantial delay which can render the information obsolete for inventors working on similar technologies (Hall and Harhoff, 2012; Katila and Mang, 2003; Ouellette, 2012). Delayed disclosure may imply also that other inventors have to invest more to generate the knowledge needed for follow-on inventions which might prevent or slow project completion. In aggregate terms, the rate of technological progress more generally could be affected (Fromer, 2009; Seymore, 2010). Faster disclosure increases the visibility of codified information and can be expected to increase its diffusion. However, visibility can have varying implications depending on the characteristics of the information disclosed and the information recipients, possibly leading to heterogeneous effects.

In some contexts, there may be alternative channels for the diffusion of codified information. In the case of substitute channels, increasing the visibility of codified information becomes less important. Moreover, visibility per se is not a sufficient condition for information use. First, visibility matters only if individuals direct attention towards the information disclosed (Haas et al., 2015). Second, conditional on the actual and attentive observation of information, accessibility of the underlying knowledge is a function of the nature of the information and the absorptive capacity of potential recipients (see Zahra and George, 2002; Haas et al., 2015).[1] Accordingly, while some groups of innovators may have a more urgent need to have timely access to codified R&D outcomes due to the lack of substitute channels, others may have superior ability to internalize information and benefit from its early disclosure (Cohen and Levinthal, 1990).

We address relevant corresponding contingency conditions. First, we explore how the effect of early disclosure varies based on the characteristics of the information such as complex or discrete technological nature, and the source of the information such as industry or academia, and the size of the firm. Second, we study the types and characteristics of information recipients in terms of their technological and geographic distance to the knowledge source. As we develop further in the theory section, geographic and technological proximity are related to the possibility for inventors to access alternative sources of information, but also ease identification of relevant information and influence absorptive capacity. Finally, we study the effect of the presence of patent attorney

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[1] By accessibility, we are not referring to legal access rights to patent protected underlying knowledge (Murray and O'Mahony 2007).

services firms (PASFs) as specialized information intermediaries (Wagner et al., 2014). These organizations are renowned for their screening abilities and understanding of the patent literature.

In the empirical analysis, we exploit the American Inventors Protection Act (AIPA), which was passed on November 29, 1999 and became effective on November 29, 2000. This act implied a significant reduction in the disclosure times for patents filed at the United States Patent and Trademark Office (USPTO) (Graham and Hegde, 2015; Hegde and Luo, 2017). Before the act came into force, patents were published at the moment of patent grant and after the act, the USPTO started to publish patents 18 months after the patent application date. However, inventors not seeking patent protection outside the US can opt out of the new disclosure requirements. We use patent citations as a first order indicator of patents being used as a source of information. We consider the number of forward citations for measuring the rate of information diffusion. Second, we study the composition of these citations along three main dimensions. We examine the geographic and technological distance of citations to assess changes to the localization of information flows. Also, we distinguish citations that originate from patents filed by PASFs as an exemplary case of organizations with specialized competencies in the use of patents as information source.

We demonstrate the feasibility of exploiting AIPA as an exogenous change to publication timing in a regression discontinuity design (RDD) analysis with time as an assignment variable – i.e. regression discontinuity design in time (RDiT) as labelled by Hausman and Rapson (2018). There are obvious concerns that patentees respond strategically to AIPA, e.g. by not seeking patent protection for valuable inventions (Johnson and Popp, 2003; Spiegel and Aoki, 1999). However, the possibility to opt out mostly eliminates similar incentives. Our validation tests support this assumption since we found no evidence of discontinuities in the co-variates. We replicated our analysis employing a difference-in-difference (DID) approach using unaffected patent families as our control group. In our main specifications, which rely on a conservative construction of citation counts, we find that a one-year reduction in disclosure time increases citations by 12%. Interestingly, we find mostly no change in geographic distance apart from a weakly significant relative increase in the number of citations beyond a very short distance (over 50 kms), while the share of citations from technologically proximate domains increased slightly. Moreover, we find evidence that citations by patents with PASFs grow twice as much than from other patents. Additional robustness analyses broadly confirm our results.

This paper makes several contributions to the literature. First, we add to the debate on the informativeness of patents for cumulative innovation by highlighting the timing dimension (Furman et al., 2017; Moser, 2011; Murray and O'Mahony, 2007). Second, our findings on the contingency effects of technological and geographic distance contribute to the debate on knowledge spillovers (Bloom et al. 2013; Modigliani 1999) and effective firm search behavior (e.g. Rosenkopf and Almeida, 2003; Tallman and Phene, 2007; Wagner et al., 2014) by identifying whether proximate or distant inventors are more strongly responding to early disclosure. Third, our work provides some micro-foundations for the emerging body of firm-level studies, which use AIPA as a shock to firms' information environment (e.g. Chondrakis et al. 2019; Hoffmann et al., 2018; Mohammadi et al., 2018; Saidi and Zaldokas, 2019). In the conclusion, we elaborate on these contributions and the policy and managerial implications.

2. THEORETICAL BACKGROUND

2.1 Early disclosure and the value of patent information

Uncodified knowledge tends to remain secret and tacit (Polanyi, 1966), diffuses more slowly, and remains confined within geographical and social boundaries (Breschi and Lissoni, 2009; Jaffe et al., 1993; Singh and Marx, 2013). The patent system represents a comprehensive repository of codified information, and patents can constitute a knowledge input for other inventors (Scotchmer, 1991). Technological opportunities typically emerge and diminish within relatively short time windows (Katila and Mang, 2003; Reinganum, 1989). Publication delay can mean that the information disclosed in the patent document is outdated by the time it becomes available (Hall and Harhoff, 2012). Survey evidence suggests that delays to patent disclosure can be an impediment to inventors' ability to learn about state-of-the-art technologies (Ouellette, 2012, 2017). Consequently, we expect timely disclosure of patent information to increase the visibility of information and the rate of diffusion of knowledge.

There are some factors that might attenuate this effect. Specifically, the nature of the information contained in the patent may limit its accessibility. First, inventors can file patents that contain no information of any value to third parties; in this case, crucial knowledge may remain tacit. Alternatively, only technologies that would become available via channels such as reverse engineering or scientific publication, may be patented (Bloch and Markowitz, 1996; Horstmann et al., 1985). Second, the legal language of the patent can render the description of the technology unintelligible (Seymore, 2010). Third, inventors may be reluctant to read patents due to risk of willful patent infringement (Moore, 2004; Powers and Carlson, 2001). These impediments imply that the answer to the simple question of whether improvements to disclosure time would affect knowledge diffusion is not obvious as doubts remain about the de-facto value of patent documents as sources of knowledge (Bessen and Meurer, 2008; Hall and Harhoff, 2012).

2.2 Heterogeneous effects of early disclosure

The effectiveness of patents as sources of information is likely not homogeneous and might depend on the characteristics and the source of the information For instance, in discrete technology domains, codified knowledge is usually more useful for learning about a technology than in complex knowledge domains (von Graevenitz et al., 2013) because the description of a particular complex technology typically is fragmented across several patents. This condition is illustrative of the case where visibility would barely equate to accessibility because cognitive effort is required to recombine dispersed pieces of information. Variation across sectors in the notification function of a patent (Bessen and Meurer, 2008), i.e. its effectiveness in defining clear intellectual property boundaries, also may have implications for the incentive to screen patents. Similarly, patents might be more relevant in domains where other substitutes for codified knowledge are not available. For instance, patents originating from universities might more frequently be backed up by scientific publications and accompanied by an open disclosure policy to attract potential licensees. There might be differences also in relation to firm size with larger firms attracting more attention from competitors and smaller firms achieving comparatively greater visibility through early disclosure of patent information (Modigliani, 1999). Overall, variation across these dimensions could be informative about the mechanisms leading to diffusion.

2.3 Early disclosure and the geographic and technological localization of knowledge flows

The effect of early disclosure on knowledge diffusion is likely heterogeneous, and likely will depend on the characteristics of potential recipients and their possibility to identify and access visible information. In particular, we argue that the absorption of information which is disclosed early will depend on follow-on inventors' geographic and technological proximity to the invention.

The theoretical predictions about early disclosure and localization of knowledge flows are a priori ambiguous. One the one hand, those inventors who cannot substitute codified information may benefit more from early disclosure than inventors with alternative (and thus redundant) access to the same information (Crane, 1972).[2] This argument implies that geographically and technologically proximate inventors may react less strongly to early disclosure. Geographically proximate firms and inventors can exploit proximity-based channels such as personal contacts, local networks and local employee mobility as learning mechanisms (Almeida and Kogut, 1999; Klevorick et al., 1995; Rosenkopf and Almeida, 2003). Similarly, inventors from technologically close domains meet at scientific and technical conferences whose participants typically tend to be scientists and engineers with similar interests and backgrounds (Autant-Bernard, 2001; Garud, 2008; Maskell, 2014). Hence, for technologically and geographically distant inventors early disclosure of codified information may be comparatively more important and would help to overcome the localization of knowledge flows.

On the other hand, it might be expected that early disclosure would favor proximate inventors and increase the localization of knowledge flows. Geographically and technologically proximate inventors may have complementary skills to allow the transformation of visible patents into accessible information. First, codified information may require complementary tacit knowledge which is more likely to be available locally (Audretsch and Feldman, 1996). Second, there are costs associated to the identification of, access to, and assimilation of codified information. While the stock of available information is increasing rapidly (Jones, 2009), the attention scope of innovators remains limited. Innovators have limited cognitive capacity and resources for monitoring the technological landscape which implies the need to focus on selected sources of information (Haas et al. 2015; Piezunka and Dahlander, 2015; Simon, 1955), and specialization in their inventive activity (Jones, 2009; Wuchty et al., 2007). Accessing knowledge requires a certain level of absorptive capacity (Cohen and Levinthal, 1990; Zahra and George 2002), and faster information disclosure may increase the need to focus, and strengthen absorptive capacity. The patent literature represents a huge and continuously increasing knowledge repository, which can be characterized

[2] In an analogous context, Crane (1972: 121), reflecting on the opportunity to access "unrefereed" material before publication (e.g. working papers), hypothesized that more isolated scientists may benefit disproportionally. She notes also that the sudden availability of additional possibly lower quality literature as the result of lack of quality control requires additional information screening effort.

not only by its size but also a high variability in the quality of the patents and information (Czarnitzki et al., 2011; Griliches et al., 1986; Scherer and Harhoff, 2000). In the context of geographical proximity, Bikard and Marx (2018) show that innovators focus selective attention on geographic hubs, and tend to more often cite publications from these locations. Similarly, technologically proximate inventors are able to monitor each other's work (see Haas et al. 2015). In other words, cognitive proximity combined with a focus on similar sources of information complement the increased visibility of information. Therefore, early disclosed patent information might be absorbed more especially by inventors located in the immediate technological and geographical space. Overall, whether early disclosure leads to increasing or decreasing localization of knowledge flows remains an empirical question.

2.4 Early disclosure and information brokerage by Patent Attorney Services Firms

The above discussion implies that the patterns of codified knowledge diffusion ultimately are the outcome of search and cognitive ability. Firms have strong incentives to search and recombine distant knowledge to generate innovative products (Laursen and Salter, 2006). At the same time, they need to develop efficient search routines which might constrain their absorptive capacity, and reinforce the tendency to search locally (Phene et al., 2006; Rosenkopf and Nerkar, 2001; Tallman and Phene, 2007). Acquiring the ability to screen and absorb external knowledge requires specific investments and learning. Recent studies show that firms are using PASFs in order to cope with the increasing costs of screening information, and to reduce the tendency to engage in excessive localized search. Wagner et al. (2014) show that PASFs serve as inter-firm knowledge brokers especially for firms that are geographically distant. Mayer at al. (2012) highlight the role and path dependency of firms' human capital. The decision to outsource the patenting process to PASFs results in lack of relevant human resources. Meanwhile, PASFs are specializing increasingly in the capability to search effectively for patent information. Improved disclosure of patent information is likely to enhance the value of these organizational competences. Accordingly, we analyze the extent to which a plausible increase in the use of patent information is explained by use of PASFs.

3. EMPIRICAL SETTING AND DATA

3.1 AIPA as a shock to patent disclosure

The AIPA became effective on November 29, 2000. Previously, patents granted by the USPTO were published on the patent grant date; after the policy came into effect, they must be published 18 months from the patent application date. Notably, patents subject to the Patent Cooperation Treaty (PCT) to be awarded patent protection outside the US have always been subject to "early disclosure" since other patent authorities already publish patents after 18 months. AIPA includes the possibility of opt out of pre-grant disclosure for patentees who do not want to patent their inventions abroad. Therefore, AIPA should primarily affect patents filed exclusively at the USPTO whose applicants do not opt-out, or international patents via early publication of the US documents. The risk that AIPA would induce more strict selection of inventions to be patented seems limited a priori by the opt-out feature. Inventors have no need to abandon the intent to patent; they can simply opt out of the new disclosure requirements (Graham and Hegde, 2015). However, the number of inventors that opt out is quite small: Graham and Hegde (2015) found that between 2001 and 2005, 85% of patentees did not opt out.[3]

The introduction of AIPA has raised concerns about its potentially negative effects on the US economy (Modigliani, 1999) while scholars tend to highlight the potential benefits of knowledge diffusion (Gallini, 2002). Gallini (2002: 140) suggests that "the disclosure requirement under AIPA […] may improve the flow of information from patent applications". A number of recent studies examine some of the possible effects: Hegde and Luo (2017) argue that AIPA has facilitated licensing transactions. Johnson and Popp (2003) observe that an early disclosure regime has a stronger effect on higher quality inventions since quality is associated to longer grant time lags. Other studies found that AIPA has had positive effects for innovative firms' capital market activities, such as corporate venture capital investments (Khashabi and Mohammadi, 2016). However, it remains unclear whether patents facilitate transactions based on disclosure of technological content, or their signal of existing property rights (De Rassenfosse et al., 2016).

[3] Cockburn and Henderson (2003) show that only 5% of a sample of senior IP managers in the US reported a negative impact of the introduction of AIPA.

3.2 Data and sampling

Our main source of data is the European Patent Office (EPO) Worldwide Patent Statistical Database 2017 ("PATSTAT"). Our initial sample includes patents subject to AIPA, and to maintain comparability of the sample of patents before and after AIPA, we select on:

(i) patents filed at the USPTO within the time window 12 months before and 12 months after November 29, 2000;

(ii) patents with grant lags longer than 18 months: This excludes a small share of patents for which AIPA had no de-facto impact on disclosure timing;

(iii) patents where at least one inventor resides in the US: This restriction allows a focus on inventions developed in the US where the policy change took place, and enables us to measure diffusion to inventors abroad relative to inventors in the US;

(iv) patents granted with a maximum 8 year grant lag: This avoids truncation and excludes non-granted patents not observable before AIPA.

We obtained a sample of 160,232 USPTO patent families including 122,909 with US filings only, and 37,323 with filings abroad. We merged the information on all citing patents for a total of 2,772,013 citations, consolidated at the citing patent family level.

To measure geographic distance, we use the geographic locations of inventors on USPTO patents included in the USPTO *PATENTSVIEW* dataset if a patent family contains at least one US filing. For other patent families, we complemented this information with the Organisation for Economic Co-operation and Development (OECD) *REGPAT* 2016 database. A small percentage (12%) of citing patents, belonging to families for which the inventors' location could not be retrieved from any of these sources, are not included in the analysis of geographic distance.

3.3 Dependent variables

We construct the outcome variables based on patent forward citations. A citation occurs if a (cited) patent contains relevant prior-art for another (citing) patent. Although patent citation data have limitations, they are used frequently to analyze spatial patterns of diffusion (Jaffe et al., 1993; Roach and Cohen, 2013). In our context, citations constitute first-order evidence of patents being informative for follow-on patents.

In the first analysis, we use number of citations as an indicator of the rate of information diffusion. We exclude self-citations from inventors or applicants. We consider citations at the DOCDB family level to avoid multiple counting. To avoid truncation, we count citations within a 10-year time window starting from the priority date of the cited patent. We also restrict on the "left-hand side" the year in which we start to count citations. In the first specification, we consider all citations from patents with a filing date later than the priority date of the cited patent (henceforth citations "from priority"), and label the variable *Citations - Priority*. After AIPA, we observe citations to patent applications that originate from patents appearing before the grant date of the cited patent, which would not be observable before AIPA. These citations may still reflect a true information diffusion effect caused by early disclosure but it is not possible to distinguish such cases from mere mechanical appearance of a citation that otherwise would not be observable.

For this reason, we counted citations for two more restrictive time windows based on the rationale that we could observe these citations both before and after AIPA. First, we count citations starting from first disclosure of a patent document, which for patents in the pre-AIPA regime is the grant document, and for patents in the post-AIPA setting is the search report (*Citations - Disclosure*). The second and more restrictive criterion is counting only citations from citing patents with a *filing date* later than the *grant date* of the cited patent. We label this variable *Citations - Grant*. We use this more conservative indicator for all the analyses related to the composition of citations but verified that more permissive counts provided equivalent results. [4]

Next, we study the composition of citations. First, we look at geographic distance. We distinguish citations from patents with at least one inventor located in the US from patents where none of the inventors is located in the US (*Citations - Grant: Country* and *Citations Grant: Abroad*). We calculated an average distance measure for patents with follow-on citations *(Min-distance - Average)*. To determine distance, we consider the minimum distance between inventor pairs from cited and citing patents, and then computed the average for all pairs; Note that our results are robust to considering either the maximum or the average distance. Also, we compute counts

[4] Consider the patent with the publication number US2003087632A1. The priority date of this patent is Nov.2, 2001, it was first disclosed on May 8, 2003, and was granted on March 8, 2005 (US6865384B2). For different specifications of the dependent variable, we count a citation if the filing date of the citing patent document is after one of these dates. In this example, we observe 59 citations starting from the priority date, 55 citations from the date of first disclosure, and 41 citations from the grant date (all citations are consolidated by citing patent family).

based on discrete changes (*Citations – Grant – ‘Distance threshold’*), using the thresholds 50 km, 500 km, 2,500 km and 10,000 km. These thresholds are arbitrary; however, different threshold choices, and groups based on centiles provided very similar results.

For technological distance, first we compute the share of common International Patent Classification (IPC) codes between citing and cited patents at the IPC 4-digit level: this is the ratio of number of unique IPC codes present in both patents and the count of all unique IPC codes in both patents. We build an average distance measure (*Avg. tech distance*), and five citation count variables based on different (20%) similarity thresholds which can vary between 0 and 100 (*Citations - Grant: Tech distance*). For example, a citation is counted in the *Tech distance 0-20* category if the overlap in patent classes between the citing and the cited patent is below or equal to 20%.

To capture the presence of a PASF in the citing patents, we used information from the USPTO *PATENTSVIEW* database. We computed two main variables: *Citations – Grant: PSF* and *Citations – Grant: Corporate*. This information was available only for a subset of citing patents (around 62%) with at least one US patent within the patent family. To create the variable, we used keywords for law firms and its typical legal forms (such as “Law”, “Associates”, “Law office”, “LLP”), and also conducted a manual inspection of the raw data. In addition to lawyers which clearly work for corporations (e.g. “Xerox Corporation”, “Intel Corporation”, “HP Legal Department”), we classified all lawyers with missing information, or not categorized as “Corporate”. We also computed two derivative variables of *Citations – Grant: PSF* to differentiate between large and small PASFs where large (small) PASFs handled more (less) patents than the median number of patents covered by disambiguated PASFs in the *PATENTSVIEW* dataset.

3.4 Publication time and control variables

The main variable of interest is *Publication time,* which is the time in years from the patent’s priority date and first publication by the USPTO. In the case of patent families with multiple filings, all filed exclusively at the USPTO, the latter date corresponds also to first appearance in the patent literature (Martínez, 2011). However, families with international filings were published within 18 months by the foreign jurisdiction even before AIPA. In robustness analyses, we distinguish the samples of US-only and international families.

Other variables include *AIPA*, a dummy which is equal to 1 for patents filed after November 29, 2000, and *Distance AIPA* which is the distance (number of days) of the filing to/from November 29, 2000. We include a comprehensive set of covariates. The number of patent claims and the number of inventors proxy respectively for patent scope and patent value. Patent family size, grant lag and year of last patent renewal payment have been shown to be correlated strongly to private patent value.[5] The number of citations is often used also as an indicator of patent quality. However, in our analytical framework, patent value is held constant which is in line with the fact that all the other covariates proxying for patent value do not change significantly (see section 4.2). Therefore, the number of citations can be distinguished from patent value and can be interpreted as information flows.

We next include number of *backward citations* and share of *non-patent literature* backward citations, and a series of applicant and inventor level variables. To measure inventor experience, we count the number of unique granted patents filed by inventor(s). Similarly, we proxy applicant's patent portfolio size by number of granted patents filed by the applicant. Based on the median value of the applicant's patent portfolio, we created the indicator variables (small vs. large firms) for the subsample analysis reported in table 4. We also use the number of different patent offices where the applicant filed patents to indicate experience in international patenting.[6] For the few patents with multiple applicants, we consider only the first inventor. We also include a dummy for whether the applicant is based in a university using a comprehensive list of keywords and university names.

Finally, we include state dummies for inventor location, and sector dummies for patent technology sector. We take sectors from the World Intellectual Property Organization (WIPO) IPC-technological field concordance table (WIPO, 2013). In subsample analyses, we distinguish discrete and complex technologies using the taxonomy proposed by Von Graevenitz et al. (2013: 560). Around 67% of our sample patents are assigned to complex technological areas, and 33% to discrete areas. Table 1 presents the descriptive statistics for all the variables.

[5] Note that some of these variables are determined after AIPA and may also be affected. Adding them could raise the problem of a "bad control" (see Angrist and Pischke, 2008: 47). We added the variables under the assumption that they are predetermined by the value of the invention at the moment of patent filing. Our analyses suggest that this was the case. Note that our results vary only marginally with the inclusion of these controls.

[6] To disambiguate inventors, we relied on the standardized name identifiers provided by PATSTAT and ECOOM (KU Leuven), and the ID for the DOCDB standardized name. For applicants, we also used the ID of harmonized applicant names (HAN) provided by the OECD.

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4. ECONOMETRIC METHODOLOGY

4.1 Regression discontinuity design in time (RDiT)

We rely on a RDiT methodology. The basic assumption in this methodology is that unobservable characteristics vary as a continuous function of time, which serves as the assignment variable, while the probability of treatment changes discontinuously around a given threshold for the same variable (Lee and Lemieux, 2010). The time distance to AIPA is used as the assignment variable in an empirical setting otherwise analogous to a Regression Discontinuity Design (RDD). The use of time as the assignment variable has precedents in several contributions (Auffhammer and Kellogg, 2011; Busse et al., 2006; Davis, 2008; Hausman and Rapson, 2018). RDiT compared to the more general RDD comes with the limitation that observations are not comparable cross-sectionally but only before and after a given point in time. Hausman and Rapson (2018) provide a discussion of the resulting shortcomings, and describe a series of relevant robustness tests which we use in this paper. We also complemented our analyses with a DID methodology.

The existence of the opt-out option implies that not all patents necessarily are treated after AIPA. Consequently, AIPA can be understood as a discontinuity in the probability of being "offered the treatment" (i.e. early disclosure). Patentees that refuse earlier publication are described as non-compliers. This characteristic makes the analysis equivalent to "fuzzy" RDiT. Imbens and Lemieux (2008: 619–620) provide a detailed explanation of the analytics behind the model where "fuzziness" pertains not to the threshold which is precise and known but to the fact that not all observations "comply" with the treatment.

The possibility to exploit AIPA as a shock relies on the assumption that patentees do not select strategically into the old or new policy regime, or worse, change their propensity to patent (Hausman and Rapson, 2018). This assumption is not specific to RDiT. However, for the RDD methodology, treated subjects must not be able (or willing) perfectly to manipulate the assignment variable (Lee and Lemieux, 2010). This assumption is violated if patentees accelerated (or delayed) filing in order to select their regime status, or choose not to patent (Spiegel and Aoki, 1999). However, importantly, the possibility of opting out mitigates this concern. In principle, inventors have no incentive to act strategically because they can opt out. We discuss and test the validity of this assumption later in the paper.

Under the above assumption, AIPA represents an exogenous discontinuity in time in the probability of patentees being subject to the treatment of early publication while compliance with the treatment remains optional. The effect of AIPA can be estimated in a regression that includes a dummy to capture this discontinuity while controlling for a flexible functional form of the assignment variable (time). In the following equation, Y_i is the outcome variable, *AIPA* is a dummy variable which is equal to 1 if the filing date of patent *i* is later than AIPA, *Distance_AIPA* is the time distance in days to AIPA, and *Controls* is a matrix of potential additional controls (not necessary for identification):

$$\mathrm{Y_i = \theta * AIPA_i + f(Distance\_AIPA_i, \vartheta) + \lambda' Controls_i + \eta_i} \qquad (1)$$

We then move to the fuzzy RDiT design to account for the presence of non-compliers in our sample. The real variable of interest is the endogenous variable, *Publication Time,* which substitutes for the dummy whether the patent complies or not with AIPA.[7] The model can be written as a two-stage-least-square (2SLS) regression:

$$\mathrm{PublicationTime_i = \theta * AIPA_i + f(Distance\_AIPA_i, \vartheta) + \lambda' Controls_i + \eta_i} \qquad (2)$$

$$\mathrm{Y_i = \beta * PublicationTime_i + f(Distance\_AIPA_i, \gamma) + \delta' Controls_i + \varepsilon_i} \qquad (3)$$

The β coefficient can be interpreted as the causal effect of one additional year of publication delay. Regarding the functional form of the assignment variable, we included *Distance_AIPA* and the square of *Distance_AIPA*, and their interactions with *AIPA* (Lee and Lemieux, 2010). Adding third and fourth order polynomials does not affect our results (see appendix A-4). In order to take account of inter-temporal correlations between the error terms, we cluster errors at the level of weekly periods. This gives us a local average treatment effect (LATE): the causal effect is estimated on the sub-population of patents around the threshold, complying with the treatment.

Equation (1) can be considered a reduced form equation but the underlying identification assumptions remain the same. Note that the exogeneity of the decision to comply (not opt out) is

[7] Note that this choice comes without loss of generality with respect to the model's identifying assumptions. Ultimately, this has implications with respect mostly to interpretation of the unit of measure of the magnitude of the coefficients.

not among them. In general, opting out is an endogenous decision and opt-out patents may differ from complier patents (Graham and Hegde, 2015). We studied the probability of opt-out (analyses available upon request). Applicant size and the year of last renewal are positively correlated to the decision to opt out, whereas inventor experience, applicant experience in international filing, family size and grant lag are negatively correlated to this decision. This implies that the estimates may be more representative of non-opt out patents. However, importantly, as already noted, the majority of patentees did not opt out of AIPA, so the complier sample is the larger group. In our case, this corresponds to 81% of our sample patents after AIPA, and 76% excluding international families. Consequently, the estimates are based on the variation in the majority of the patents in the sample (close to the threshold).

4.2 Patent selection into AIPA and RDiT assumption

We provide evidence supporting the assumption that the selection induced by the AIPA if any, was marginal. The analysis consists of testing for the presence of a discontinuity in the covariates. This type of validation requires a more cautious verification in the RDiT context compared to the typical RDD (Hausman and Rapson, 2018). In particular, the time frequency of the observations in a typical RDiT may imply the existence of a small mass of observations around the threshold. However, in our application, the data frequency is daily, with multiple observations per period: the number of observations around the threshold is sizeable.[8] Therefore, testing for the presence of discontinuities in the covariates around the threshold remains meaningful (Hausman and Rapson, 2018). For instance, patentees may speed up their filings of high-value inventions to ensure they are before AIPA, and may choose not to patent after AIPA (Johnson and Popp, 2003). In this hypothetical case, we would observe a discontinuous decrease in patenting and in the indicators associated to patent value around AIPA. Similar concerns might apply to other covariates. Figure 1 is a graphical analysis of the covariates around the policy change; it provides no prima-facie evidence of strategic filing behavior since we observe no apparent discontinuity in the covariates.

[8] More precisely, our setting is akin to one that relies on asymptotics in the number of observations N. This differs from the more typical RDiT setting where there is only one observation per time period, and consequently, the numbers of observations around the thresholds do not increase with N.

-- Figure 1 about here –

We test this formally in regressions where the covariates are the dependent variables in the RDiT models (appendix A-1). In line with the graphical analysis, we find no significant effect of AIPA except for a weak correlation to the number of backward citations. Since backward citations are not a strong indicator of patent quality, we believe it to be unlikely that this outcome implies any selection bias. None of these tests on their own prove the absence of selection. However, it is likely that any relevant selection would become evident in discontinuous changes among several covariates. This analysis shows also that while there may be overall trends, differences in levels and changes to trends before and after AIPA, the RDiT estimates exclusively capture significant and discontinuous shifts around the threshold.

These results suggest also that AIPA did not impose a different selection of inventions into patents. This is in line with previous evidence indicating that maintaining secrecy until patent grant was not a major concern for the majority of patentees before and after the AIPA (Cockburn and Henderson, 2003). In the context of the present analysis, we propose that patents filed immediately before and immediately after AIPA are of comparable value so that variations in the outcome variables can be attributed mostly to the treatment. We also checked for shifts between the number of filings of international or US-only families. We would expect the number of patent filings for US-only patents to decrease in favor of international patents (which were always subject to early disclosure in foreign jurisdictions) if before AIPA, some patent assignees filed US-only patents because the longer secrecy period made this relatively more attractive. In other words, we could expect applicants either to refrain from patenting or to favor international patents rather than filing for US-only patents. However, a graphical inspection (Appendix A-2) does not provide any grounds for such concerns.

4.3 Difference in Differences (DID) approach

We complement our analysis with a DID methodology to check robustness. We selected a control group of patent families not affected by AIPA and independent of the treated US families. We use patent families without a US equivalent filed at the EPO, and also national patent families filed at the German, UK, French and Italian patent offices. This control group contains 31,307 observations in the bandwidth one year before and one year after the policy change. We constructed the variables for this control sample in the same way as for the treated sample. However, we only have data on PASFs for US patents covered by *PATENTSVIEW* so we cannot replicate the corresponding analysis in this framework. The corresponding model can be written as:

$$\mathrm{Y_i} = \beta\, \mathrm{AIPA_i} * \mathrm{USpatent_i} + \gamma\, \mathrm{AIPA_i} + \delta\, \mathrm{USpatent} + \lambda' \mathrm{Controls_i} + \eta_i \quad (4)$$

USpatent is a dummy that is equal to 1 for the group of US patents affected by AIPA and 0 for the control group. We include monthly period fixed effects and all the covariates.

There are pros and cons to the use of a DID compared to an RDiT (Bertrand et al., 2004; Hausman and Rapson, 2018). It should be noted that an effect of selection due to AIPA would bias the estimates in both approaches. Similarly, the opt-out feature implies that in both models the identifying variation derives completely from the presence of complier patents. In contrast to the RDiT, the DID offers a control group which is appealing intuitively and yields estimates that rely on cross-sectional differences between the treated and control groups over the entire period. In the RDiT framework, the pre-event observations serve as controls for the observations immediately after the event; observations around the threshold are weighted disproportionately implying that the estimates are strongly localized (LATE).

Potential confounding factors are a concern in the RDiT framework but could have more severe consequences in the DID model. Several concurrent changes and patent-related events occurred in the years around AIPA (Gallini, 2002).[9] However, none of these changes occurred in the week of AIPA implementation. In the RDiT framework, we are able to rule out their influence by showing the coincidence between an effect and the date of implementation of AIPA (see appendix A-4, columns 3-5). The fact that the RDiT exploits variation mostly around the exact date of introduction of AIPA is an advantage in this case. For all these reasons, RDiT is our preferred econometric approach but it is reassuring that the results do not change in the DID specifications.

[9] We collected detailed information and asked the USPTO directly about changes that occurred close to the AIPA (see appendix A.3). There were several changes including publication of full-text patent grant data with embedded TIFF images from January 2001.

5. RESULTS

5.1 AIPA and reduced publication time

First, we quantify the effect of AIPA on publication time. Figure 2 depicts the variable *Publication time*, averaged over 7-day periods, as a function of time around the AIPA. We distinguish between patent families with US-only filings (left side of figure 2a) and patent families with international filings (right side of figure, 2b). Figure 2a shows that compliers experienced a significant drop in publication time whereas for non-compliers (opt-out) we observe an increasing trend. As expected, AIPA reduced publication time for all US documents but had no impact on the timing of disclosure of international documents for international families. Table 2 presents the first-stage regressions – corresponding to equation (2) – and allows us to quantify the reduction in publication time. We include the controls and second order polynomials of the assignment variable (distance policy) one by one to test the stability of the estimates (columns 1 to 5). Including the controls does not change the estimates significantly.

-- Insert Figure 2 and Table 2 about here –

After AIPA, publication time decreased by an average of 1.13 years. Average publication delay before AIPA was around 1,000 days, with the 5th percentile, median and 95th percentiles 550, 867 and 2,139 days respectively. After AIPA, opt-out patents experienced a comparable delay (970 days on average, 550, 770, 2,080 days for 5th percentile, median and 95th percentiles). The large majority (95%) of non-optout patents are published at 18 months. There are a few exceptions due possibly to imprecisions in the raw data, or differences in the processing of patents. In particular, within DOCDB patent families, publication delays can be less than 18 months if the patent priority date refers to a patent filing which later is not considered part of the same DOCDB family. These few exceptions do not affect our findings.

5.2 Total counts of citations

We explore the impact of AIPA graphically. Figure 3 plots seven-day period averages for our main dependent variables. We display the three specifications *Citations – Priority*, *Citations –*

Disclosure, and *Citations – Grant*, respectively. We find clear discontinuous increases for all three variables around AIPA, although the discontinuity is slightly less pronounced for the most restrictive variable *Citations – Grant*. For brevity, we report only the results of the second stage of the two-stage regression model. The reduced form model for our main result – based on equation (1) – is reported in appendix A-4, column 1. Table 3 reports the second-stage estimates of our main specifications. We present the results with and without patent-level controls.[10] The coefficients differ only marginally between the models with and without controls which further supports the absence of notable selection. The effect of *Publication Time* on citations is consistently highly significant at the 1% level. Specifically, we find that a one-year decrease in *Publication time* increases the number of citations from priority by 13%, from disclosure by 19%, and from grant by 11%. These findings are evidence that earlier disclosure enhances information and knowledge diffusion.

-- Insert Table 3 and Figure 3 about here --

5.3 Testing for heterogeneous effects

In table 4, we investigate the heterogeneity of these main effects along a series of dimensions of interest. Columns 1 and 2 distinguish between patents with a university applicant and other types of applicants. Columns 3 and 4 differentiate patent applicants by size, defined by the median cumulative number of patents. Columns 5 and 6 report the estimates for complex and discrete technologies. As expected, the effect is stronger for discrete technologies. It has been acknowledged that patents are often a more valuable source of technical information in discrete settings (Bessen and Meurer, 2008; Graham et al., 2009): a 1-year reduction in disclosure time implies a 15% increase in citations to discrete technologies compared to 9.3% for complex technologies. This difference is statistically significant (p-value 0.000). We find a relatively smaller coefficient of university patents and small applicants. The coefficient of disclosure timing the sample of university patents also is not significant. This is in line with the hypothesis that patent

[10] To improve readability, we do not report the coefficients of all the covariates but the full results are available upon request.

disclosure is more relevant if alternative access to knowledge would be more difficult. However, we acknowledge that there is little difference in the economic magnitudes across these pairs of subsamples although the difference between small and large firms is also statistically significant. The coefficient of publication time is not significant for university patents, and the relatively large standard error may indicate that the sample of university patents is not sufficiently large.

-- Insert Table 4 about here –

5.4 Composition of citations with regard to geographic and technological distance

In this subsection, we report the results for geographical and technological distance. Geographical distance is presented in figure 4 and table 5. We observe notable discontinuities for all the outcome variables, with a somewhat weaker pattern only for citations that originate from very proximate inventors. Columns (1) and (2) show the results for the count of citations from patents with at least one inventor located in the same country (US), and for inventors located abroad. Column (3) presents the average distance of inventors between cited and citing patents, and columns (4)-(8) consider citations based on five distance thresholds. The regression results suggest that the count of citations increases in a similar manner, regardless of the distance between inventors. For instance, a reduction in publication time of one year leads to an 8.1% increase in citations from inventors located in the US, and a 9.8% increase from inventors located abroad. Formal testing confirms that this difference is not statistically significant. Similarly, publication time has no effect on average distance. Regressions estimating citations from different distance groups do not reveal any clear pattern. We observe that the coefficients for the count of citations at different discrete levels of geographical distance vary in some instances. The coefficient is lower in magnitude for the count of citations at very low (less than 50km), and very high (over 10000km) distances. While the latter result might be driven by the rather low number of citations in this category, the small magnitude for very short distances may imply that alternative proximity-based informal channels make the effects of earlier disclosure obsolete. However, while we acknowledge this possibility, we interpret these differences to be insufficient to conclude that any significant pattern in the geographic distance of citations exists, particularly given the lack of any evidence of a change in the average distance and in the probability of citations from abroad.

-- Insert Table 5 and Figure 4 about here –

In the following, we analyze the technological distance of citations. Figure 5 shows some interesting patterns; namely, the discontinuity is strongest for citations from closely related technological domains. The regression results reported in table 6 support this interpretation. Column (1) shows the effect of publication time on the average technology overlap. In columns (2)-(6) we estimate citation counts depending on the similarity between citing and cited patents. In line with our graphical results, we find that a reduction in publication time leads to a stronger increase in citations by technologically similar patents. In the highest overlap category, a 1-year reduction leads to an increase in citations of 9.0% (column 6) but there is no statistically and economically significant impact for citations to patents with low similarity (column 2). The evidence is also consistent with gradually increasing magnitudes from low to high similarities. Therefore, early disclosure appears to strengthen technological localization of diffusion.

-- Insert Table 6 and Figure 5 about here –

In analyses not reported but available upon request, we tested whether a similar pattern emerges for proximity in the end-market space, i.e. within industries. Indeed, product market competition, rather than technological proximity, may serve as a driver of attention for different sources of information. To test this we matched our data to applicant level information on industry of operation (NACE code) with data from Kogan et al. (2017). The sample for this analysis is limited to 45,943 observations. We found no significant results for heterogeneous citation patterns. Therefore, we tend to conclude that technological proximity rather than proximity in the product-market space determines attention on the sources of technical information. However, due to the limited availability of industry information, this finding should be interpreted with caution.

5.5 Regression results: Composition of citations – Presence of PASF

We also investigated citations originating from patents filed by PASFs. The regression analysis reported in table 7 shows that citations by patents filed with a PASF increase disproportionately. A one-year reduction in publication time increases citations by patents with PASF by 12.1% (column 1) whereas citations by patents with corporate (or undefined) patent attorneys increase by only 5.7% (column 2). This difference is statistically significant. Early publication affects citations by small and large PASFs (columns 3 and 4) by a similar magnitude. These results suggest that actors who search the patent system systematically are the most responsive to early disclosure which is in line with the evidence in Wagner et al, (2014) on the brokerage role of PASF, and similarly consistent with our findings for technological distance.

-- Insert Table 7 about here –

6. DID ANALYSES

We present the complementary DID analysis which confirms all the results discussed previously. In the graphical analysis (figure 6), we plot outcome variables related to overall citation counts and the composition of citations with regard to technological and geographical distance.[11] We detect no discontinuity in the control group which is additional evidence that our results are not driven by factors unrelated to the AIPA. In the regressions in table 8, we replicate the RDiT analysis reported in tables 3, 5, and 6 in a DID setting. Panel A presents the results for total citation counts for the three different time windows and technological distance, Panel B presents the results for geographical distance. The results of the regression analysis are in line with the magnitudes of our RDiT estimates, and in some cases, are stronger. Note that these results are not directly comparable. The fuzzy RDiT estimates represent a change in publication time of one year for patents complying with AIPA (LATE) while the DID estimates reflect the overall effect of AIPA (relative to the control group), corresponding to an average decrease of 1.13 years in publication time (see table 2) considering all patents including opt-out patents.

-- Insert Table 8 and Figure 6 about here –

We can see that the trends between the treated and control groups appear to converge slightly for the citations count variables. However, formal tests of significance of trend differences fail to reject the assumption of parallel trends for *Log Citations – Priority* and for *Log Citations – Grant*.

[11] Additional DID plots are available upon request and were made available to the reviewers.

Within a slightly narrower window of 10 months before and after AIPA the parallel trend assumption holds for all the variables, and the results for the dependent variable remain significant.

We also implemented a matched sample DID specification (results not reported but available upon request). We use Coarsened Exact Matching (CEM) to balance patent characteristics between the treated and control groups, and to group patents into strata with similar characteristics.[12] We obtained a sample of 152,276 patents in matched strata (with at least one treated and control patent) for a total of 5,043 strata. We ran DID regressions with strata fixed effects which allows us to control for variance deriving from changes over time in the composition of the patents in the treated and control groups, at a very fine-grained level. In this specification, all the main results are confirmed, and the assumption of parallel trends holds for all the outcome variables.

7. ROBUSTNESS ANALYSES

Appendix A.4 reports the results for a series of robustness analyses. First, we report the RDiT reduced-form model and a model without AIPA as an exogenous shock. Column (1), shows the results of the reduced form estimation with AIPA as the independent variable of interest. The dummy variable shows a 12.5% increase in citations which is in line with our main results. Column (2) shows the results for publication time without the preceding first-stage regression and without the RDiT time controls. This shows that for this main outcome variable, the effect would be underestimated in a simple regression that does not address endogeneity.

7.1 Sensitivity analyses

We estimate different RDiT model specifications with increasingly narrow windows of observation around AIPA. This is a standard robustness test for RDD models, and in our analytical context, increases confidence about the robustness of our results to potential confounding events around the time of the AIPA. We reduced the sampling time window (bandwidth) to 6, 3, and 1 month before and after AIPA (columns 3-5). Importantly, the effect remains strongly statistically

[12] As matching variables we use number of inventors, applicant size, inventor size, and patent offices, with cutoff levels determined by Sturge's rule, and university patent, month of filing of the patent and technological sector with exact matching. We omit variables whose values differ structurally between the USPTO and EPO (e.g. number of backward citations or claims) since this would lead to misleading matching.

and economically significant. Second, we add RDD time polynomials of third and fourth-order and obtained nearly identical results (columns 6-7). Third, in column (8), we show the results of the discrete AIPA variable when applying nearest-neighbor matching (1:1) on all patent-level co-variates, and found a similarly positive and significant effect.

7.2 Intensity of treatment

We designed additional tests to verify the hypothesis that the reduction in time of publication is the main explanation of the effect of AIPA on citations. First, we designed a placebo test based on a count of citations within 18 months starting from priority which should not be affected by AIPA. As expected, AIPA has no impact on these citations (column 9). Second, in columns (10)-(12) in a reduced form estimation we interact, AIPA with grant lag. The intuition is that the policy change should have a stronger impact if the grant lag is long since the time difference between disclosure in the new and old regimes is increasing. Alternatively, this can be considered a DID type model with continuous treatment (Khashabi and Mohammadi, 2016). We find positive and significant interaction effects for the time windows *Citations – Priority* and *Citations – Disclosure.* The model is not applicable to the outcome variable *Citations – Grant*. This variable counts citations only after patent grant (and within a maximum window of time). Consequently, while longer grant lag exposes a patent to a stronger AIPA treatment, it simultaneously shrinks the time window in which citations are counted.

7.3 International families and citations origin

We also (appendix A.5) created two subsamples based on patents with families only in the US, and also in foreign jurisdictions. For each subsample, we distinguish the citing authority (USPTO vs. foreign patent office), and applicant vs. examiner-added citations (Alcacer and Gittelman, 2006; Baruffaldi and Raffo, 2017; Criscuolo and Verspagen, 2008). Inventor citations are sometimes considered a better proxy for knowledge flows than examiner citations but there is no consensus on this in the literature (Atal and Bar, 2010; Lampe, 2007; Michel and Bettels, 2001; Thompson, 2006). However, a particularly strong effect of early disclosure on examiner citations would suggest improvements to the examination process rather than direct knowledge flows between inventors.

For the sample of US-only patent families (appendix A.5, panel A), where we would expect the strongest effects, we find positive and significant effects of AIPA on citation counts regardless of citation categories. We also find positive significant effects for patents with international family documents (panel B) of surprisingly large magnitudes.[13] In the case of those patents where the information is disclosed after 18 months by a foreign jurisdiction, we would not expect notable effects of AIPA. Interestingly, citations by US authorities increased substantially after AIPA but we found no effect for citations from non-US authorities. This observation may reflect language and legal provisions which bring examiners to prefer citing patent documents within their own jurisdiction. This result suggests an attention focus or preference among inventors and patent authorities for documents within their own institutional boundaries.

We replicated the entire main analysis reported in section 5 using only applicant citations; the results remained consistent. Due to the abovementioned lack of agreement about whether applicant or examiner citations are better indicators of knowledge flows, and to maintain comparability of citations for the DiD regression analysis, we did not limit our analysis to applicant citations.

8. DISCUSSION AND CONCLUSION

This study examined the effect of reduced disclosure time of patents on information flows. We analyzed whether the effect was contingent on information characteristics such as whether the patent covers a complex or a discrete technology. We investigated recipient characteristics and considered the geographical and technological distance between the focal and subsequent inventions, and the presence of Patent Attorney Service Firms (PASF). The baseline finding is that early disclosure facilitates information diffusion which is consistent with the view that technological knowledge may become obsolete rather quickly, making timing of disclosure a relevant determinant for the usefulness of the information for future inventions. In this regard, we find stronger effects for discrete technologies where the technical description in the relevant patents is more informative. Concerning the role of technological and geographical distance, our results support the theory that proximate inventors might be better placed to access knowledge contained

[13] Differences in magnitude likely can be attributed to the fact that international patents are more valuable and receive more citations than US-only families which makes the reduction in disclosure time particularly important.

in visible information as result of early disclosure, reflecting the roles of their attention scope, screening abilities and absorptive capacity.

The effect of faster disclosure is largely unaffected by geographical distance, perhaps with the minor exception that diffusion is confined to distances beyond very short ones, and we find evidence of stronger effects of early disclosure on follow-on inventions from proximate technological domains. In other words, improved disclosure timing and associated availability of patent information are disproportionately visible to inventors in related technology domains. This finding is supported by the result that citations increase from patents that are filed using PASFs' which assist inventors' search of the patent landscape. It should be stressed that citation rates increase generally, i.e. early disclosure leads to increasing information diffusion overall, but the magnitude of this diffusion differs substantially. The differential effects with regard to technological distance and PASFs support the notion that the growing stock of patent literature makes it increasingly difficult for inventors and organizations to monitor relevant developments. Here, AIPA may contribute directly to the growing importance of PASFs since in the new policy regime, disclosure applies also to low-quality patents which are not granted, thus increasing the variability in the quality of the disclosed patent information. Overall, our findings indicate that early disclosure disproportionately increases the diffusion of knowledge from organizations that already were well positioned to make effective use of it.

The implications are notable. The findings support the view that early disclosure of knowledge is important but on its own is not a driver of knowledge diffusion across existing boundaries. The expectation that disclosure requirements for codified information would disproportionately benefit distant inventors and lead to widespread knowledge diffusion appears mistaken. In other words, while improved visibility of codified information may generate knowledge flows, our evidence challenges the view that disclosure would automatically promote equality in knowledge diffusion (Eeckhout and Jovanovic, 2002). Policymakers concerned about the effective diffusion of information need to tackle other persistent costs which innovators are likely to face related to the screening and use of increasingly overwhelming amounts of technical information. Beyond early disclosure, continuous investments in databases and powerful screening tools with low access costs could further increase the visibility of information, thus enhancing the possibilities for firms to identify relevant information. Moreover, policy initiatives which indirectly support firms' development of absorptive capacity (e.g. R&D tax credits, support schemes for hiring PhD trained graduates), remain complementary to improvements to the disclosure of technical information (see Gruber et al. 2013; Margolis and Miotti 2017).

Similarly, managers willing to cross technological and geographical boundaries in their search for new knowledge may need to invest deliberately in specialized information systems, rely more heavily on information brokers and intermediaries such as PASFs, and develop adequate in-house screening and monitoring routines to allow more efficient processing of distant information. In addition to PASFs, other information brokers such as Ocean Tomo have emerged and are likely becoming helpful resources for firms with limited means to develop strong intellectual property screening abilities. Moreover, firms interested in creating intentional spillovers for instance to influence the development of technological trajectories or complementary technologies, may have to leverage additional channels to the patent system such as scientific publications, in order to achieve the desired information diffusion (Alexy et al., 2013; Harhoff, 1996). Our findings should be informative for firms concerned about undesired outgoing spillovers and imitation (Modigliani 1999, Bloom et al. 2013). If patent citations are indicative of technology spillovers, early disclosure could increase spillovers. The finding that knowledge diffusion is promoted by increased technological proximity implies that existing competitors which already scrutinize the focal firm's inventive outputs, might be more responsive than new competitors from different technology areas.

The results of our study contrast in part with existing findings on the role of patent literature as a relevant knowledge repository and decreasing geographical localization effects (Furman et al., 2017; Moser, 2011, 2013). First, we examined the timing of publication, holding other dimensions constant. Increased patenting propensity (Moser, 2011) and novel access to the patent literature (Furman et al., 2017) may have different implications, and likely may remain important for the diffusion of distant knowledge in that case. Second, the historical context of previous studies may limit their generalizability to recent years: the diffusion of technical information through different channels, may have been facilitated by the use of ICTs (Furman et al., 2017). In other words, patent disclosure might play a smaller part in the diffusion of knowledge today compared to the past. Third, it is also plausible that first access to an information repository may lead to initial exploration of distributed knowledge, while marginal improvements and further additions to an already sizable information pool could lead to a relative increase in the localization of knowledge flows. These aspects should be investigated in future research.

Our study also informs research that examines the effects of AIPA, and provides micro-level validation for ongoing work studying firm-level outcomes. Recent contributions propose that AIPA increased the firm information environment overall, subsequently stimulating the market for acquisitions or firms' access to financing (e.g. Chondrakis et al. 2019; Mohammadi et al. 2018; Saidi and Zaldokas 2019). Analysis of AIPA at firm level poses additional methodological challenges. Moreover, the first-order effect of AIPA on the diffusion of technical information has been rather overlooked. As our study confirms that AIPA had relevant first-order impacts on information diffusion within the patent system, it seems plausible that it also had effects beyond the context of follow-on invention and the patent system. At the same time, our finding that the effect of AIPA was stronger among inventors and organizations with good screening and absorptive capacities likely imposes some boundary conditions on the effects of AIPA outside the patent system. A deeper understanding of the mechanisms underlying the second-order effects linked to the nature of patents as sources of information, together with more detailed consideration of the specificities of AIPA as a policy change, ought to be better taken into account.

We acknowledge the limitations of our study. First, as AIPA exclusively affected the disclosure timing of US patent documents, any conclusions are subject to external validity issues. Our robustness analysis, shows that US patents with international equivalents also received more citations but only within the US patent system. Second, in our framework, micro-level search strategies remain a potential mechanism explaining the observed dynamics of information diffusion; future research could address more explicitly the role of individual and firm-level strategies. Finally, both RDiT and DID methodologies applied to AIPA have limitations. In theory, DID methods are more sensitive to biases from shocks that are contemporaneous or close in time to AIPA, and remain subject to considerations about the appropriateness of the selected control group. In the RDiT case, it is important to acknowledge that the comparison is between patents filed before and after AIPA which does not allow cross-sectional comparison (Hausman and Rapson, 2018). Our analysis provides strong support for the assumption that AIPA induced very limited if any, changes to patenting propensity and as well as active sorting of inventors into the pre- or post AIPA regimes. Nonetheless, the possibility that this assumption is not fully met remains a possible concern in both methodologies.

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TABLES AND FIGURES

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Mean (before)	Mean (after)
Citations - Priority	160,232	17.30	25.59	0.00	1375.00	16.78	17.83
Citations - Disclosure	160,232	15.81	23.75	0.00	1168.00	14.85	16.76
Citations - Grant	160,232	13.79	20.83	0.00	1168.00	13.82	13.75
Citations - Grant: Country	160,232	8.59	16.07	0.00	955.00	8.75	8.43
Citations - Grant: Abroad	160,232	5.20	8.82	0.00	390.00	5.07	5.32
Min-distance (average)	151,961	3907.55	2617.58	0.00	19173.00	3881.80	3933.27
Citations - Grant: Geo Distance 0-50km	160,232	2.00	7.53	0.00	573.00	2.06	1.94
Citations - Grant: Geo Distance 50-500km	160,232	2.47	6.59	0.00	295.00	2.50	2.44
Citations - Grant: Geo Distance 500-2500km	160,232	5.32	11.24	0.00	434.00	5.40	5.24
Citations - Grant: Geo Distance 2500-10000km	160,232	5.68	10.65	0.00	602.00	5.67	5.69
Citations - Grant: Geo Distance > 10000km	160,232	1.30	4.02	0.00	213.00	1.27	1.33
Avg. tech distance	154,820	0.63	0.23	0.00	1.00	0.63	0.63
Citations - Grant: Tech distance 0 - 20	160,232	0.96	3.24	0.00	472.00	0.97	0.94
Citations - Grant: Tech distance 20-40	160,232	2.11	5.42	0.00	582.00	2.10	2.12
Citations - Grant: Tech distance 40 - 60	160,232	3.61	7.04	0.00	464.00	3.63	3.59
Citations - Grant: Tech distance 60 - 80	160,232	2.09	5.71	0.00	432.00	2.07	2.11
Citations - Grant: Tech distance 80 - 100	160,232	5.02	10.47	0.00	420.00	5.06	4.99
Citations - Grant: PASF	160,232	7.46	12.75	0.00	712.00	7.62	7.30
Citations - Grant: Corporate IPR unit	160,232	1.20	2.59	0.00	82.00	1.24	1.15
Publication Time (in years)	160,232	2.22	1.36	0.28	8.00	2.80	1.64
BWD citations	160,232	18.54	20.69	1.00	203.00	18.07	19.00
Share NPL citations	160,232	0.13	0.22	0.00	1.00	0.13	0.13
Claims	160,232	21.43	16.73	1.00	525.00	21.01	21.86
Number Inventors	160,232	2.40	1.69	1.00	51.00	2.41	2.40
Applicant size	160,232	9328.87	21743.45	0.00	122754.00	9123.20	9535.13
Inventor size	160,232	36.66	117.78	0.00	3320.00	37.09	36.22
Patent offices	160,232	17.02	17.12	1.00	67.00	17.16	16.88
University Patent	160,232	0.03	0.17	0.00	1.00	0.03	0.03
Renewal payments - last year	160,232	2011.33	4.21	2001.00	2017.00	2010.90	2011.75
Family size	160,232	3.00	3.58	1.00	150.00	3.07	2.94
Grant lag (in years)	160,232	3.15	1.38	1.56	8.00	3.13	3.17

Table 2: First stage regression: the effect of the policy change on the publication delay

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Publication delay (in years)	Publication delay (in years)	Publication delay (in years)	Publication delay (in years)	Publication delay (in years)
Sample	Full	Full	Full	Full	Full
AIPA	-1.147***	-1.152***	-1.153***	-1.154***	-1.132***
	(0.029)	(0.014)	(0.014)	(0.013)	(0.018)
Patent-level controls	NO	YES	YES	YES	YES
RDD time controls	LINEAR	LINEAR	LINEAR	LINEAR	QUADRATIC
Technology controls	NO	NO	YES	YES	YES
State controls	NO	NO	NO	YES	YES
Observations	160,232	160,232	160,232	160,232	160,232
F-test	3750.86	2589.93	1738.14	12363.86	30234.81

Table 2 represents the first-stage regression models in which the effect of the binary "AIPA" variable on publication timing is tested. A different set of control variables is added stepwise from column (1) - column (5). The set of patent-level controls includes the number of backward citations (log), the share of NPL citations (log), the number of claims (log), the number of inventors (log), inventor experience (log), the size of the applicant (log), international patenting experience (number of offices applied, in logs), university patent (dummy), the grant lag (log), patent family size, and patent renewal - last year.

Standard errors robust to weekly periods clusters in parentheses

*** p<0.001, ** p<0.01, * p<0.05

Table 3: The effect of early disclosure on knowledge diffusion

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Log Citations - Priority	Log Citations - Priority	Log Citations - Disclosure	Log Citations - Disclosure	Log Citations - Grant	Log Citations - Grant
Sample	Full	Full	Full	Full	Full	Full
Publication time	-0.133***	-0.137***	-0.183***	-0.191***	-0.094***	-0.109***
	(0.016)	(0.015)	(0.015)	(0.015)	(0.014)	(0.016)
Patent-level controls	NO	YES	NO	YES	NO	YES
RDD time polynomials	YES	YES	YES	YES	YES	YES
Observations	160,232	160,232	160,232	160,232	160,232	160,232
F-test	46.63	3241.91	120.00	5457.77	29.97	49954.88

Table shows regression results with regards to the number of forward citations within specific time windows. In models (1)-(2), citations are counted starting from the priority date of the focal patent. In Models (3)-(4), citationsa are counted starting from the first publication of a patent. In models (5)-(6), citations are counted starting from patent grant only. The set of patent-level controls includes the number of backward citations (log), the share of NPL citations (log), the number of claims (log), the number of inventors (log), inventor experience (log), the size of the applicant (log), international patenting experience (number of offices applied, in logs), university patent (dummy), the grant lag (log), patent family size, and patent renewal - last year. Instrument relevance of the first stage (Cragg-Donald Wald F-statistics) is supported with F = 3667.19 (Stock-Yogo weak IV critical test value F = 16.38). Use of IV regression is supported by Durbin-Wu-Hausman test (F-stat: 23.27, p-value 0.000)

Standard errors robust to weekly periods clusters in parentheses

*** p<0.001, ** p<0.01, * p<0.05

Table 4: Organizational and knowledge heterogeneity in knowledge diffusion

Sample	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Log Citations - Grant	Log Citations - Grant	Log Citations - Grant	Log Citations - Grant	Log Citations - Grant	Log Citations - Grant
Sample	University Patent	Industry Patent	Small Firms	Large Firms	Complex Tech	Discrete Tech
Publication time	-0.085	-0.111***	-0.122***	-0.102***	-0.093***	-0.150***
	(0.056)	(0.016)	(0.027)	(0.015)	(0.013)	(0.024)
Patent-level controls	YES	YES	YES	YES	YES	YES
RDD time controls	YES	YES	YES	YES	YES	YES
Observations	4,950	155,282	70,319	89,913	106,960	53,272
F-test	2168.9	5306.73	18389.34	3.34E+03	259.44	128.48

Table shows the results of subsample regressions according to the following dimensions: (1)-(2) University Patent / Industry patent, (3)-(4) Small firms / Large firms, and (5)-(6) Complex /Discrete technologies. All regressions contain RDD time controls of second order, plus the full set of patent-level controls, technology and US-State dummies. For all regressions, the citation window starting from patent grant (see Table 3, column 6) is applied. The set of patent-level controls includes the number of backward citations (log), the share of non-patent literature citations (log), the number of claims (log), the number of inventors (log), inventor experience (log), the size of the applicant in terms of cumulative patent applications (log), international patenting experience (number of offices applied, in logs), university patent (dummy), the grant lag (log), patent family size, and patent renewal - last year. Formal testing of the effect of publication time across models (1)-(2) yields: chi2(1) = 2.67 (p-value: 0.102), across models (3)-(4): chi2(1): 11.20 (p-value 0.001), and models (5)-(6): chi2(1) = 31.54 (p-value 0.000)

Standard errors robust to weekly periods clusters in parentheses

*** p<0.001, ** p<0.01, * p<0.05

Table 5: Composition of citations: geographic distance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Log Citations - Grant - US	Log Citations - Grant - abroad	Min-distance (Average)	Log Citations - Grant - Distance < 50km	Log Citations - Grant - Distance 50 - 500 km	Log Citations - Grant - Distance 500 - 2500 km	Log Citations - Grant - Distance 2500 - 10000 km	Log Citations - Grant - Distance > 10000 km
Sample	Full	Full	Patents with >= 1 citation	Full	Full	Full	Full	Full
Publication time	-0.081***	-0.098***	0.003	-0.024*	-0.063***	-0.103***	-0.087***	-0.037***
	(0.018)	(0.012)	(0.015)	(0.012)	(0.013)	(0.014)	(0.015)	(0.010)
Patent-level controls	YES	YES	YES	YES	YES	YES	YES	YES
RDD time controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	160,232	160,232	151,961	160,232	160,232	160,232	160,232	160,232
F-test	35270.35	10478.15	12470.42	5.3e+05	11254.78	4964.03	23963.64	1810.84

Table shows regression results with regard to the geographic distance of cited and citing patents. Models (1) and (2) count citations separately depending on whether inventors of citing patents are located in the US or abroad. Model (3) estimated the average minimum distance between the inventors of the cited and citing patents for a subsample of patents with citations. Models (4) - (8) count citations separately for different distance clusters. All regressions contain RDD time controls of second order, plus the full set of patent-level controls, technology and US-State dummies. The set of patent-level controls includes the number of backward citations (log), the share of non-patent literature citations (log), the number of claims (log), the number of inventors (log), inventor experience (log), the size of the applicant in terms of cumulative patent applications (log), international patenting experience (number of offices applied, in logs), university patent (dummy), the grant lag (log), patent family size, and patent renewal - last year. Formal testing of the effect of publication time across equations (1)-(2) yields: chi2(1) = 1.29 (p-value: 0.256), and across equations (4)-(8): chi2(4): 38.23(p-value 0.000)

Standard errors robust to weekly periods clusters in parentheses

*** p<0.001, ** p<0.01, * p<0.05

Table 6: Composition of citations: technological distance

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Avg tec codes overlap	Log Citations - Grant - Tech distance 0% - 20%	Log Citations - Grant - Tech distance 20% - 40%	Log Citations - Grant - Tech distance 40% - 60%	Log Citations - Grant - Tech distance 60% - 80%	Log Citations - Grant - Tech distance 80% - 100%
Publication time	-0.006*	-0.005	-0.038***	-0.057***	-0.054***	-0.090***
	(0.003)	(0.008)	(0.010)	(0.010)	(0.014)	(0.015)
Patent-level controls	YES	YES	YES	YES	YES	YES
RDD time controls	YES	YES	YES	YES	YES	YES
Observations	154,820	160,232	160,232	160,232	160,232	160,232
F-test	1.40E+05	2.15E+04	1776.29	22736.23	5946.57	10866.34

Table shows regression results with regard to the technological distance between cited and citing patents. All regressions contain RDD time controls of second order, plus the full set of patent-level controls, technology and US-State dummies. The set of patent-level controls includes the number of backward citations (log), the share of non-patent literature citations (log), the number of claims (log), the number of inventors (log), inventor experience (log), the size of the applicant in terms of cumulative patent applications (log), international patenting experience (number of offices applied, in logs), university patent (dummy), the grant lag (log), patent family size, and patent renewal - last year. Formal testing of the effect of publication time across equations (2)-(6) yields: chi2(4) = 31.25 (p-value: 0.000).

Standard errors robust to weekly periods clusters in parentheses

*** p<0.001, ** p<0.01, * p<0.05

Table 7: Composition of citations: presence of Patent Attorney Service Firms (PASF)

	(1)	(2)	(3)	(4)
Dependent Variable	Log Citations - Grant - PASF	Log Citations - Grant - Corporate IPR	Log Citations - Grant - Specialized Attorney Small	Log Citations - Grant - Specialized Attorney Large
Publication time	-0.121***	-0.057***	-0.087***	-0.103***
	(0.017)	(0.011)	(0.014)	(0.016)
Patent-level controls	YES	YES	YES	YES
RDD time controls	YES	YES	YES	YES
Observations	160,232	160,232	160,232	160,232
F-test	5407.48	2335.73	8182.35	40287.35

Table shows regression results with regard to the presence of patent attorney service firms (PASF) on part of the citing patents. Columns (1) and (2) display citations from patents with PASF and Corporate (incl. undefined) attorneys, and Columns (3) and (4) further decompose citations from patents with PASF into small and large PASF, as defined by the median number of patents handled in the Patentsview database. All regressions contain RDD time controls of second order, plus the full set of patent-level controls, technology and US-State dummies. The set of patent-level controls includes BWD citations (log), Share NPL citations, Claims (log), No. Inventors (log), Applicant size (log), Inventor size (log), No. patent offices (log), University Patent, Renewal payments - last year, Family size (log), and Grant lag (in years). Formal testing of the effect of publication time across equations (1)-(2) yields: chi2(1) = 22.35 (p-value: 0.000).

Standard errors robust to weekly periods clusters in parentheses

*** p<0.001, ** p<0.01, * p<0.05

Table 8: Robustness - Difference-in-difference estimation

PANEL A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Log Citations - Priority	Log Citations - Disclosure	Log Citations - Grant	Log Citations - Grant - Tech distance 0% - 20%	Log Citations - Grant - Tech distance 20% - 40%	Log Citations - Grant - Tech distance 40% - 60%	Log Citations - Grant - Tech distance 60% - 80%	Log Citations - Grant - Tech distance 80% - 100%
AIPA X Treated	0.162***	0.225***	0.130***	0.015	0.046***	0.064***	0.064***	0.094***
	(0.019)	(0.019)	(0.019)	(0.008)	(0.012)	(0.013)	(0.013)	(0.017)
Patent-level controls	YES	YES	YES	YES	YES	YES	YES	YES
Distance to AIPA (days)	YES	YES	YES	YES	YES	YES	YES	YES
Observations	191,472	191,472	191,472	191,472	191,472	191,472	191,472	191,472
F-test	2990.81	2244.79	3799.11	722.56	1273.27	2451.87	1203.25	1765.28

PANEL B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Log Citations - Grant - Country	Log Citations - Grant - abroad	Min-distance (Average)	Log Citations - Grant - Distance < 50km	Log Citations - Grant - Distance 50 - 500 km	Log Citations - Grant - Distance 500 - 2500 km	Log Citations - Grant - Distance 2500 - 10000 km	Log Citations - Grant - Distance > 10000 km
AIPA X Treated	0.098***	0.104***	-0.067	0.032**	0.044**	0.072***	0.061***	0.046***
	(0.018)	(0.017)	(0.065)	(0.011)	(0.014)	(0.015)	(0.017)	(0.009)
Patent-level controls	YES	YES	YES	YES	YES	YES	YES	YES
Distance to AIPA (days)	YES	YES	YES	YES	YES	YES	YES	YES
Observations	191,472	191,472	162,848	191,472	191,472	191,472	191,472	191,472
F-test	3576.68	1576.46	331.43	1327.47	704.84	2780.21	3215.87	1551.54

Table shows results of difference-in-difference regressions using a sample of European patents as control group that is not affected by the policy change. PANEL A reports the results with regard to the amount of follow-on citations (see Table 3) and technological distance (Table 6). PANEL B reports the results with regard to geographic distance (see Table 5). All regressions contain the daily time distance to the policy change, plus the full set of patent-level controls and technology dummies. The set of patent-level controls includes the number of backward citations (log), the share of non-patent literature citations (log), the number of claims (log), the number of inventors (log), inventor experience (log), the size of the applicant in terms of cumulative patent applications (log), international patenting experience (number of offices applied, in logs), university patent (dummy), the grant lag (log), patent family size, and patent renewal - last year.

Standard errors robust to weekly periods clusters in parentheses

*** p<0.001, ** p<0.01, * p<0.05

Figure 1: Control variables

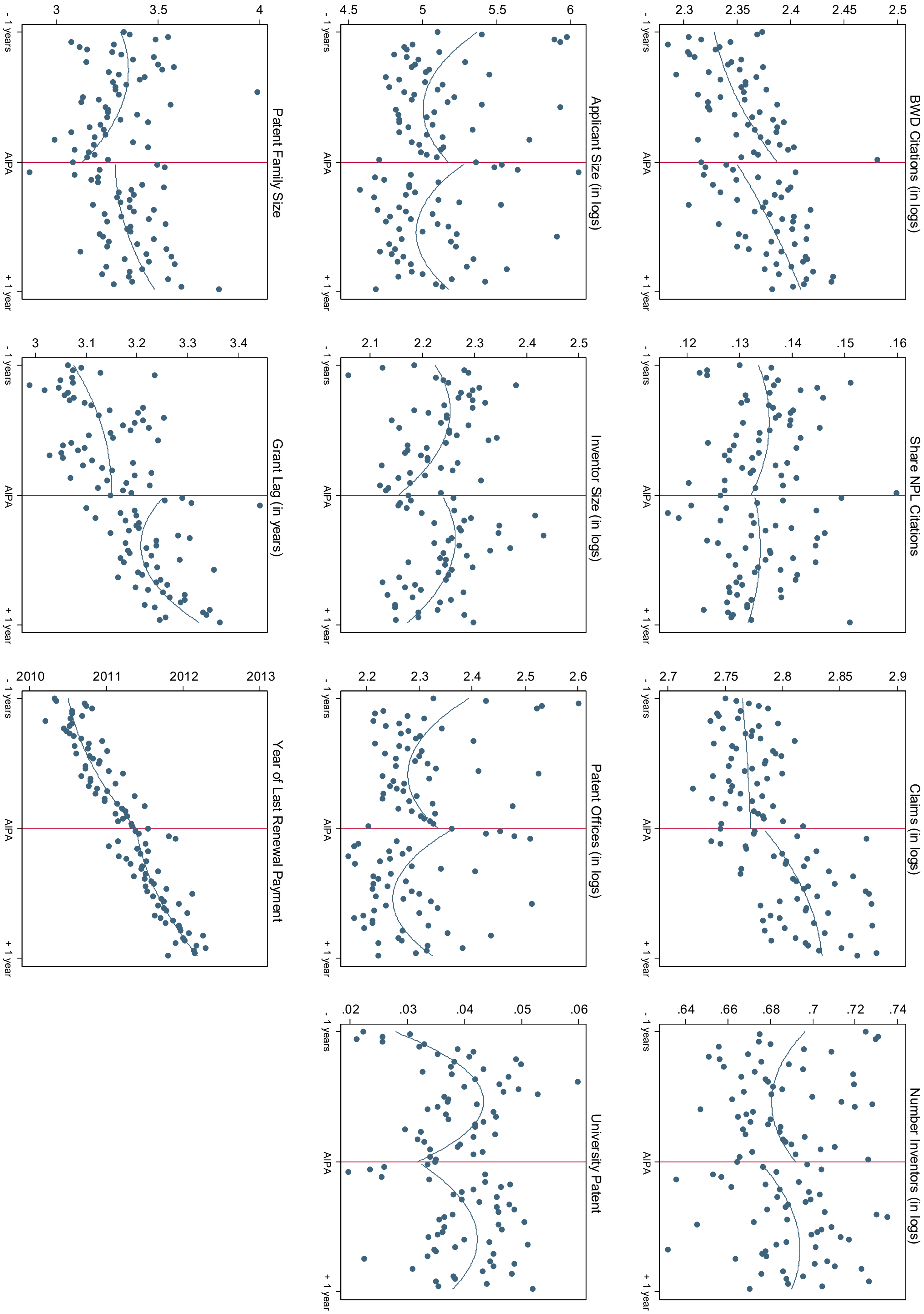


Figure 2: Reduction Publication Time

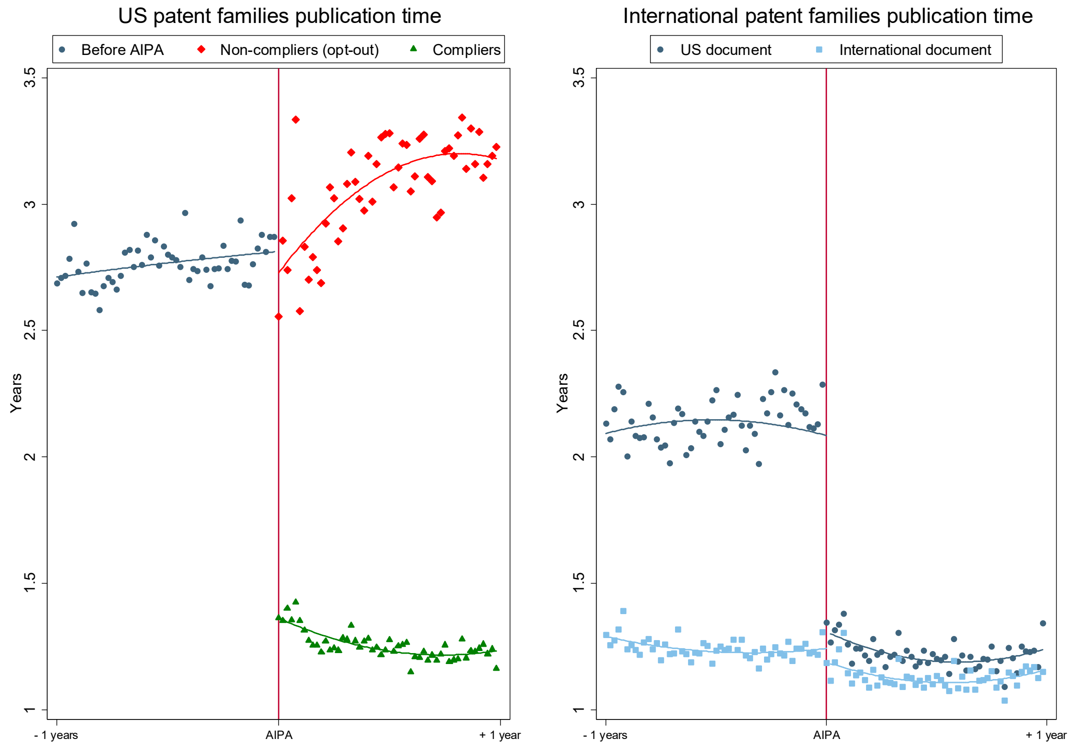


Figure 3: Citation counts

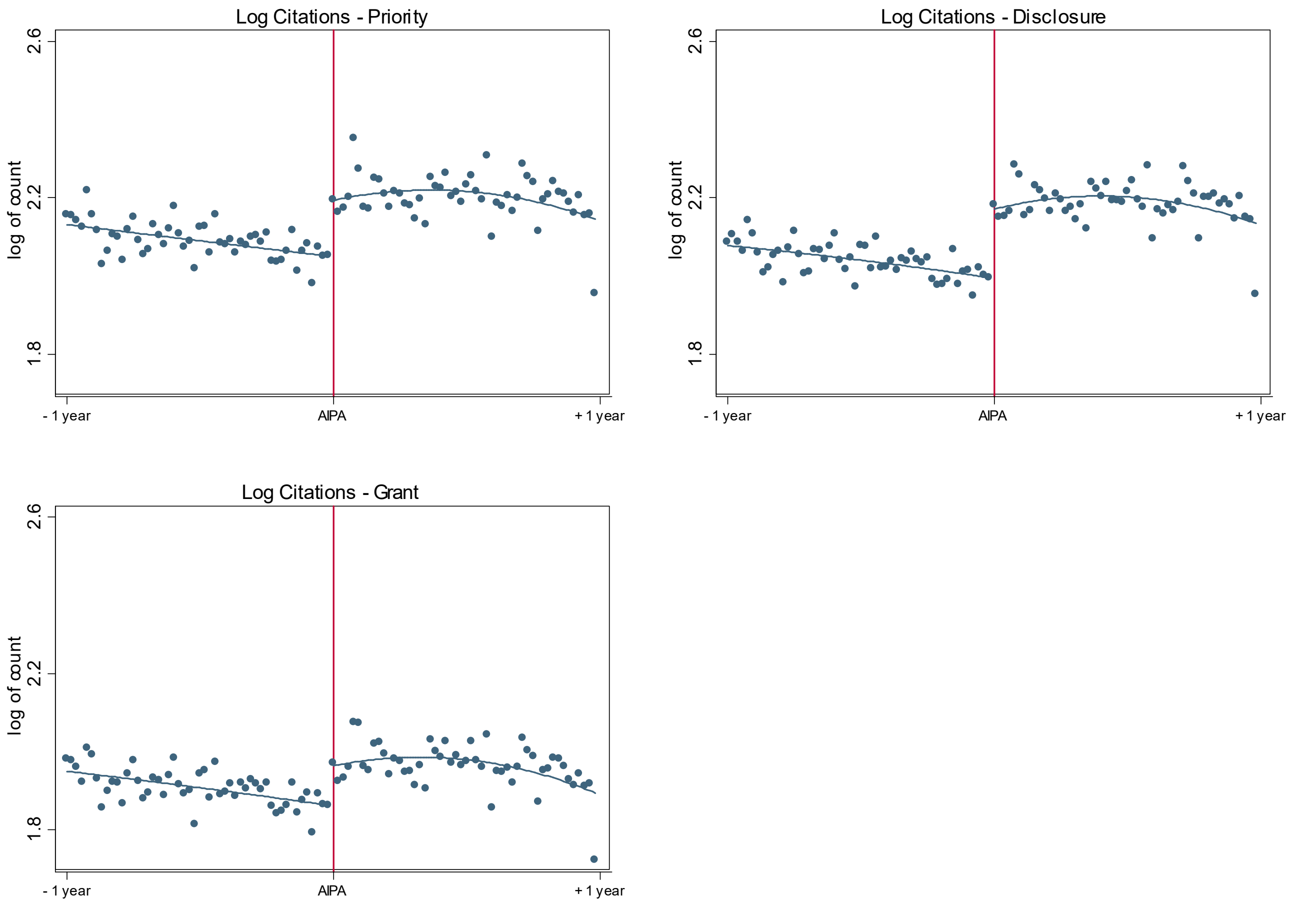


Figure 4: Citation counts – geographical distance

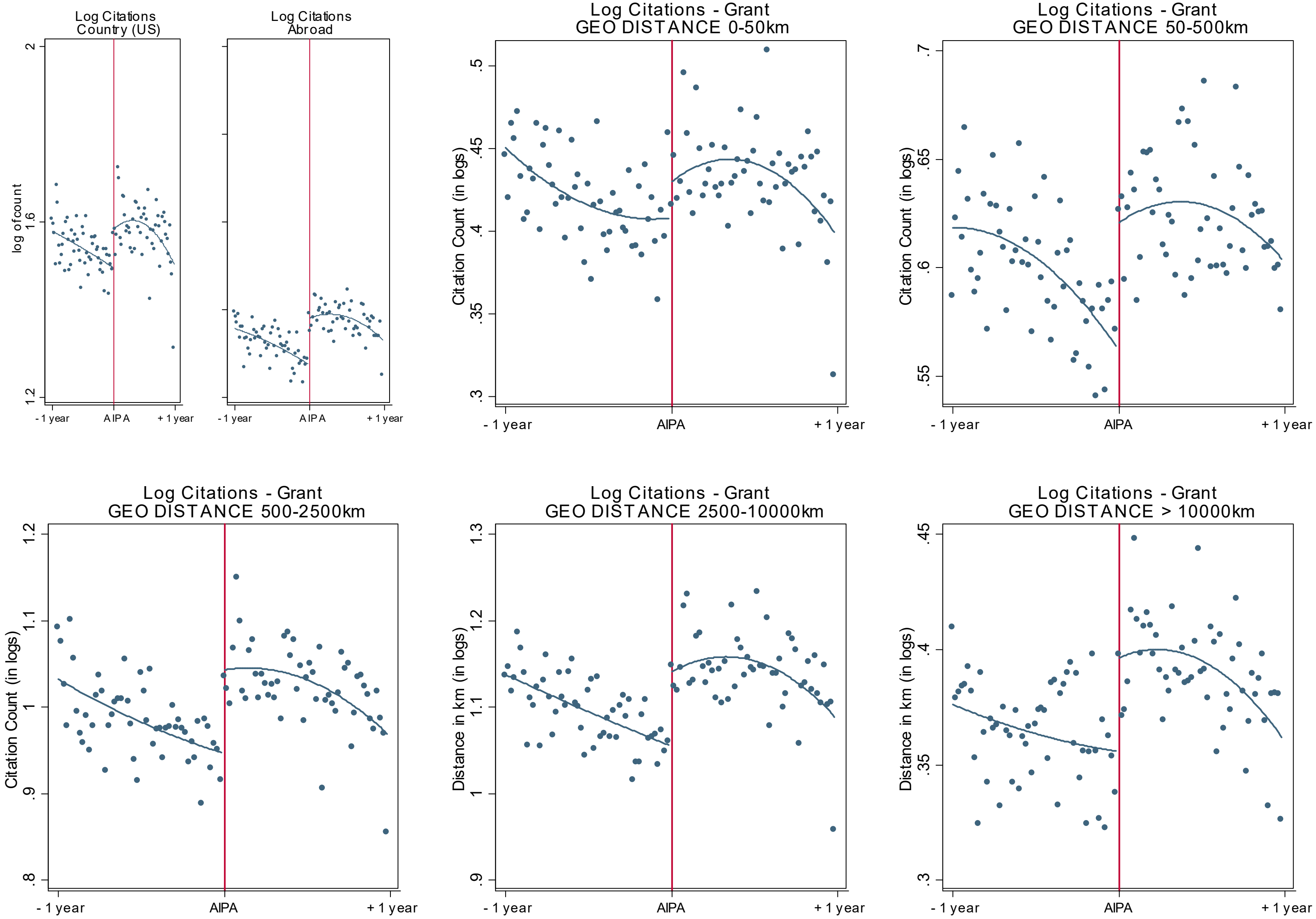


Figure 5: Citation counts – technological distance

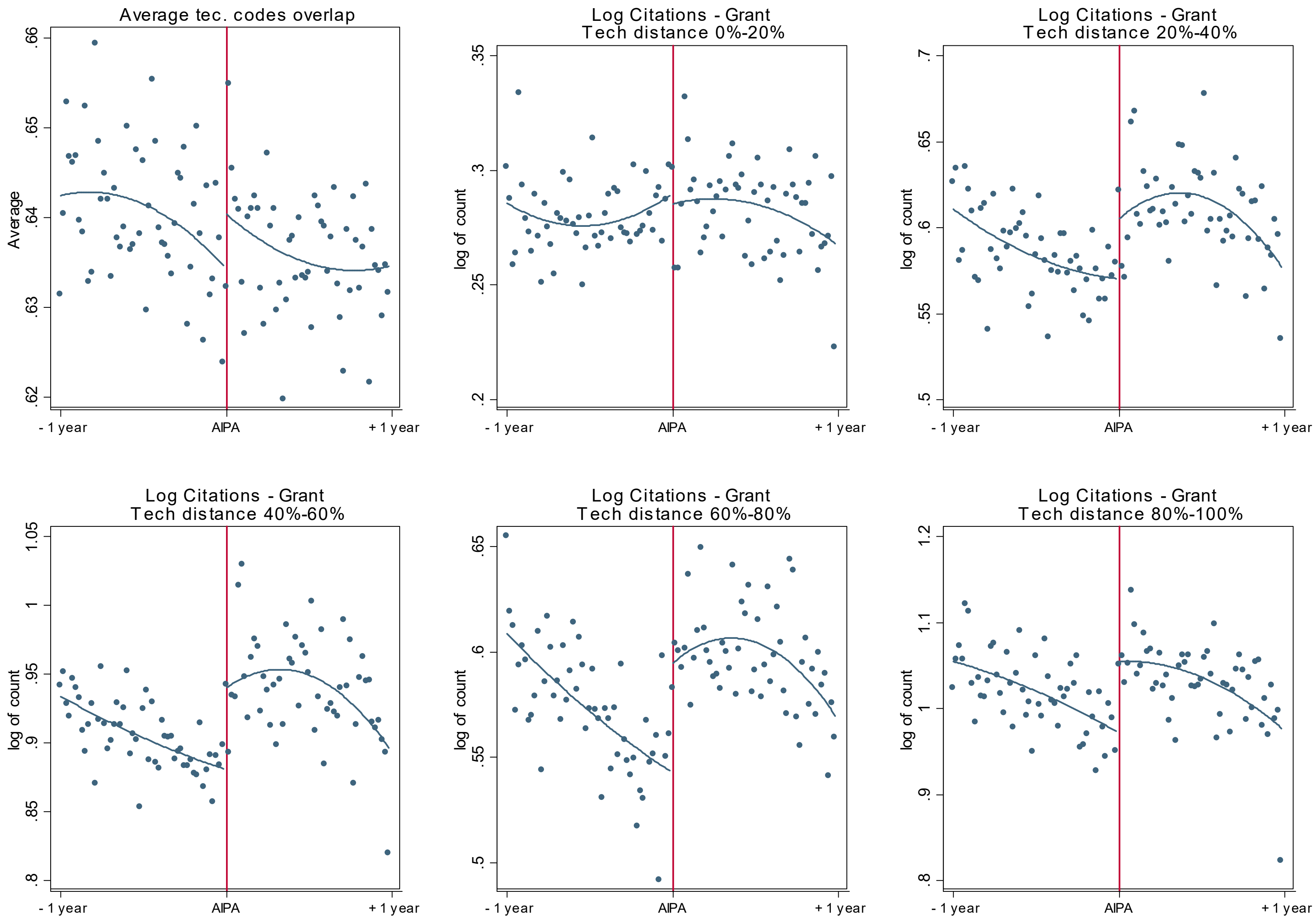
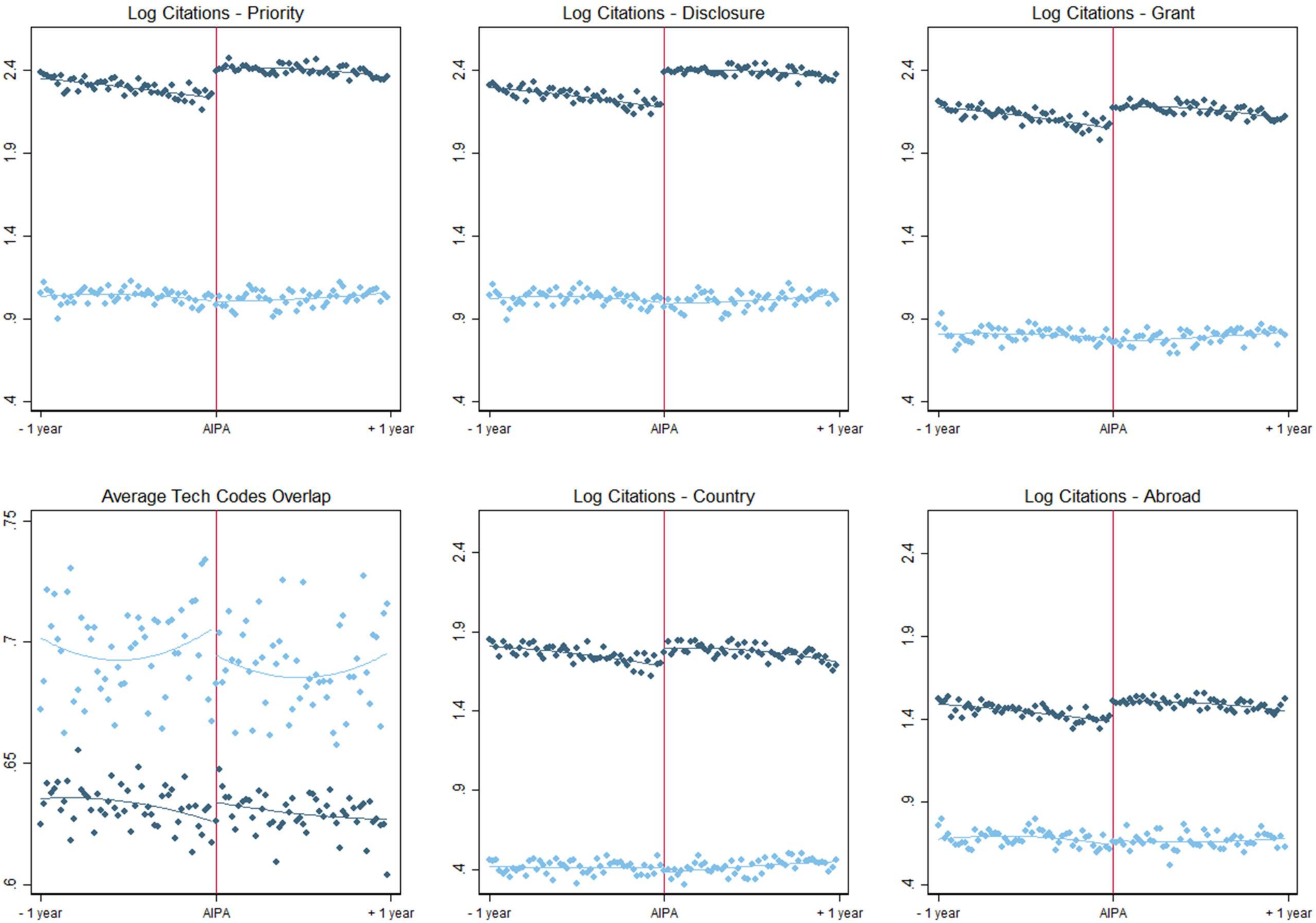


Figure 6: Graphs Outcomes by treatment and control group (DID setting)



Appendix

Appendix A-1: Control variables before and after the policy change

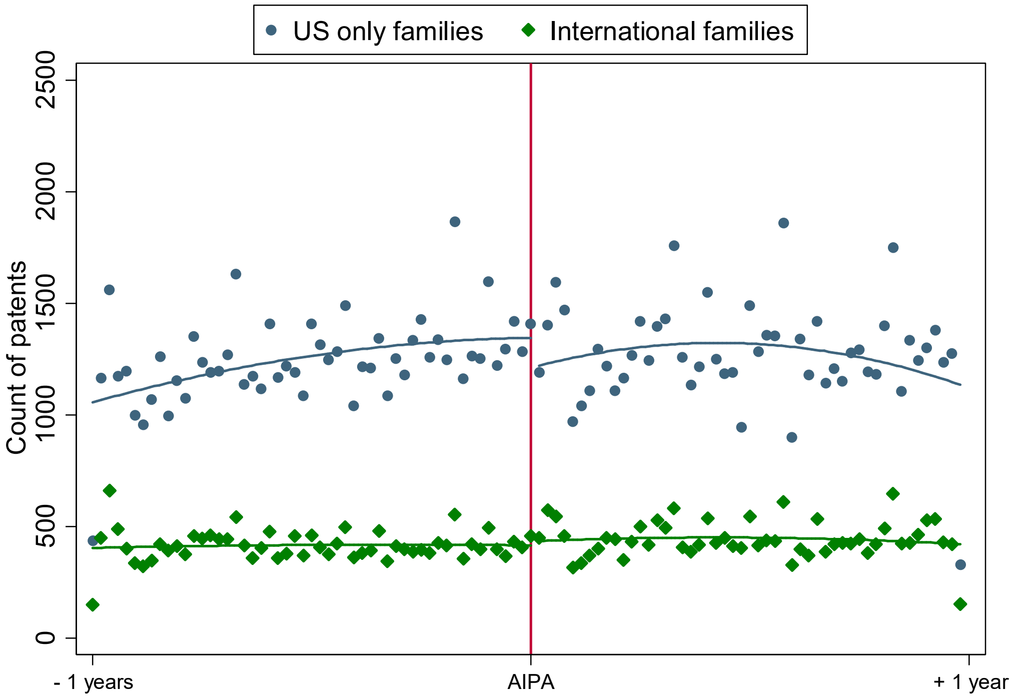
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent Variable	BWD citations (log)	Share NPL Citations	Claims (log)	Number inventors (log)	Applicant Size (log)	Inventor Size (log)	Patent offices (log)	University Patent	Grant lag (in years)	Patent renewal - last year	Patent Family Size
Sample	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full
AIPA	-0.053*	-0.001	-0.004	-0.025	0.331	0.053	0.072	-0.005	0.048	0.088	-0.093
	(0.022)	(0.007)	(0.019)	(0.013)	(0.199)	(0.041)	(0.054)	(0.003)	(0.047)	(0.111)	(0.075)
RDD time controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	160,232	160,232	160,232	160,232	160,232	160,232	160,232	160,232	160,232	160,232	160,232
F-test	19.82	1.99	18.58	0.90	2.16	3.38	2.27	7.28	7.00	200.38	8.95

This table shows whether control variables differ before and after the policy change. All regression models contain quadratic RDD time controls.

Standard errors robust to weekly periods clusters in parentheses

*** p<0.001, ** p<0.01, * p<0.05

Appendix A-2: Filing trends before and after AIPA



Appendix A.3: USPTO search infrastructure

Date	Information System	Source / Reference
Early 1990's	Dial-Up Bulletin Board System (BBS) for downloading weekly patent bibliographic (front page) text data in ASCII format (no charges)	no ref available (source: USPTO correspondence)
	BBS was substituted with weekly patent bibliographic information via an FTP site (no charges)	no ref available (source: USPTO correspondence)
	FTP site was substituted with a HTTPS site "eipweb" which offered patent and trademark bulk data for download	no ref available (source: USPTO correspondence)
	USPTO also had the Data File Delivery (DFD) system. This system offered patent bulk data for download for a fee	no ref available (source: USPTO correspondence)
Nov. 9, 1995	USPTO disclosed 20 years of Patent Bibliographic (front page) text data available for searching on the internet. This was precursor to today's Patent Full-Text Database (PATFT)	https://www.uspto.gov/about-us/news-updates/pto-announces-plan-put-patent-data-internet
June 25, 1998	USPTO announced the Patent Full-Text Database (PATFT) and the Trademark Image Capture and Retrieval System (TICRS), which became operational in Nov. 1998	https://www.uspto.gov/about-us/news-updates/uspto-make-comprehensive-patent-and-trademark-data-available-free-internet
Nov 6, 2000	USPTO expanded the coverage of the PATFT database	https://www.uspto.gov/about-us/news-updates/uspto-web-database-now-includes-all-patents-dating-1790
Nov. 27, 2000	USPTO announced that it would begin publishing patent applications. This was the beginning of the Application Full-Text database (APPFT). The first patent applications were published on March 15, 2001	https://www.uspto.gov/about-us/news-updates/uspto-will-begin-publishing-patent-applications https://www.uspto.gov/about-us/news-updates/uspto-publishes-first-patent-application
Jan 2, 2001	USPTO provided patent grant full text data with embedded TIFF Images (images, drawings, tables, mathematical expressions, chemical structures)	https://uspto.data.commerce.gov/dataset/Patent-Grant-Full-Text-Data-with-Embedded-TIFF-Ima/e84t-779s
June 2010 - June 2013	USPTO contract with Google to disseminate USPTO patent and trademark bulk data to the public (no charge)	https://www.google.com/googlebooks/uspto.html
June 2013 - now	USPTO has contract with Reed Technology to disseminate USPTO patent and trademark buld data to the public (no charge)	http://patents.reedtech.com
October 1, 2015	USPTO Bulk Data Storage System (BDSS) was created	https://bulkdata.uspto.gov

Appendix A-4: Technical robustness tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable	Log Citations - Grant	Log Citations - Grant	Log Citations - Grant	Log Citations - Grant	Log Citations - Grant	Log Citations - Grant	Log Citations - Grant	Log Citations - Grant (Matching estimator)	Log Citations - 18M after priority	Log Citations - Priority	Log Citations - Disclosure	Log Citations - Grant
Sample	Full	Full	Window 6m	Window 3m	Window 1m	Full	Full	Full	Full	Full	Full	Full
AIPA	0.125***							0.028***		0.026	-0.098***	0.130***
	(0.018)							(0.007)		(0.021)	(0.022)	(0.021)
Publication time		-0.039***	-0.108***	-0.083**	-0.136***	-0.110***	-0.086***		-0.003			
		(0.004)	(0.022)	(0.029)	(0.018)	(0.020)	(0.025)		(0.003)			
AIPA X Grant Lag										0.036***	0.073***	-0.008
										(0.004)	(0.004)	(0.004)
Patent-level controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
RDD time controls	YES	NO	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES
Observations	160,232	160,232	80,955	40,923	15,776	160,232	160,232	160,232	160,232	160,232	160,232	160,232
F-test	49415.48	12285.64	76.87	4.67	0.13	6573.26	8575.84	606.76	3209.28	6663.98	13737.82	49415.48

Table reports results of various robustness tests. Regression models contain RDD controls of second order and the full set of control variables. Regression (1) represents the reduced form regression, with the binary variable "AIPA" which has the value 1 for patents in the new post-AIPA regime, and 0 for patents in the pre-AIPA regime. In column (2), we present the reduced form regression without endogeneity correction. In columns (3-5), the sampling window is stepwise reduced from 6 months to 1 month. Regression models (6) and (7) contain RDD time controls of third and fourth order. Model (8) shows the result of the AIPA coefficient when a matching estimator (nearest neighbor matching, 1 neighbor) is estimated. Model (9) represents a placebo test with a citation window of 18 months starting from a patent's priority date. Models (10)-(12) estimate the interaction of AIPA with the grant lag. The coefficient (SE) for the variable grant lag (in years) in models (10)-(12) is -0.065 (0.003), -0.111(0.003), and -0.147(0.003).

Standard errors robust to weekly periods clusters in parentheses

*** p<0.001, ** p<0.01, * p<0.05

Appendix A.5: US and international families and citations by citing authority

PANEL A		Sample: US-only patent families (N=122,909)		
		(1)	(2)	(3)
Citing Authority		All citations	Examiner	Applicant
	AIPA	0.116***	0.112***	0.079***
US		(0.017)	(0.017)	(0.015)
	F-test	20991.39	14771.03	8139.66
	AIPA	0.052***	0.046***	0.006*
Non-US		(0.012)	(0.012)	(0.003)
	F-test	99999.00	64410.06	1290.7
PANEL B		Sample: International families (N=37,323)		
		(4)	(5)	(6)
Citing Authority		All citations	Examiner	Applicant
	AIPA	0.229***	0.235***	0.154***
US		(0.033)	(0.034)	(0.027)
	F-test	3070.24	1727.99	12447.84
	AIPA	0.031	0.033	0.003
Non-US		(0.026)	(0.023)	(0.010)
	F-test	2600.03	3353.12	729.28

Appendix table reports regression results with splitted sample, i.e. patent (families) with US documents only and patents with international families and reports citation counts based on the citation origin of USPTO or Non-USPTO documents. Columns (1) and 6 show all forward citations (starting from grant), columns (2) and (5) examiner-added citations, and columns (3) and (6) applicant-added citations.

Standard errors robust to weekly period clusters in parenthesis; *** p<0.001, ** p<0.01, * p<0.05