Patent Fees and Legal Status among SMEs: Evidence from the America Invents Act

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Abstract

Patenting at the United States Patent and Trademark Office has traditionally been dominated by large entities. In an effort to mitigate this disparity, Congress recently introduced reforms aimed at lowering patenting costs for small businesses. Although these measures appear beneficial, they remain contested: existing studies indicate that fee reductions can raise filing volumes while diminishing patent quality. Importantly, this critique is derived almost exclusively from analyses of large firms, leaving evidence on the implications for smaller businesses scarce and qualitative in nature. This paper attempts to fill this gap by examining the impact of lower fees on smaller inventors. In March 2013, the America Invents Act introduced a new fee discount for micro entities. Using small firms as controls, I use a matched difference-in-difference design to verify whether lower fees affected the outcome and quality of applications filed by the treated group. The evidence shows that, post-reform, micro entities significantly reduced the quality of their applications and were 37.36-percentage-point less likely to be granted a patent. While effects are stable across individual characteristics, large universities and private firms were worst affected by the provision. The impact is persistent and spills over to patent continuation, pointing to important consequences for strategic patenting. By retrospectively examining the effects of lower fees on micro entities, this research aims to draw practical implications for the design of future statutory fees.

JEL Codes: K11, O31, O34, O38
Keywords: Patent Fees, Legal Status, Patent Quality, America Invents Act

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I thank my advisors, David A. Jaeger, Andy Zapechelnyuk, and Min Zhang for their valuable comments and suggestions. This work was financially supported by the Economic and Social Research Council (ESRC), grant number ES/P000681/1.

1 Introduction

In the United States, small entities[1] represent over 99.9% of all businesses and employ nearly half of the active population (U.S. Chamber of Commerce 2023). While intellectual property (IP) is an important asset for their growth, small entities are less likely than large ones to file and be granted a patent (USPTO 2011).

Several reasons can explain this differential. Previous scholarships demonstrate that patent acceptance heavily depends on entity size (Sterba 1997), the presence of in-house counsels (Gaudry 2012; De Rassenfosse et al. 2023), and the ability of examiners to assess novelty or inventiveness (Meurer 2009; Lemley and Sampat 2012). In theory, IP policy can address some of these concerns by changing the patent fees paid by small entities. The rationale is that, by reducing the cost of patenting, the law should affect their willingness to seek protection and, indirectly, the number of applications. As demonstrated by Picard and van Pottelsberghe de la Potterie (2013), however, lower fees may increase the count of filings, reduce patent quality, and strain the examination units, with side effects on the prosecution process (De Rassenfosse and Jaffe 2018). Thus, the net effect of patent fees on the examination outcome remains unclear and controversial (Hall and Harhoff 2012).

In this paper, I examine how the introduction of lower fees for a class of small entities has affected the status and quality of patent applications at the United States Patent and Trademark Office (USPTO). In particular, I use the enactment of the 2011 Leahy-Smith America Invents Act (Pub. L. 112-29; henceforth AIA) as a natural experiment to conduct a difference-in-difference estimation based on a sample of applications filed between 2010 and 2014. After announcing the move from a first-to-invent to first-to-file system, the law introduced a fee reduction for micro entities[2]. Starting from March 19, 2013, micro entities could claim a 75% discount upon application, while small entities would continue to pay 50% less than the statutory rate. This change was effected in response to the Small Business Administration's (SBA) concerns that the new filing system could favor large entities over small ones.

The key identifying assumption is that, had the AIA not been enacted, changes in the legal status of applications among micro and small entities would not have significantly differed. Specifically, I intend to identify the impact of fees from the difference in legal outcomes between small and micro entities before and after the provision. Throughout, I hypothesize that lower fees will reduce the grant rate of applications filed by entities affected by the

[1] The definition of small entity is codified in 37 CFR § 1.27. See Section 509 of the *Manual of Patent Examining Procedure* (hereinafter MPEP) for further reference.

[2] See 37 CFR § 1.29 for a formal definition.

reform.

To test this prediction, I first construct a dataset using a matched sample of utility patents filed by small and micro entities at the USPTO between January 1, 2010, and December 31, 2014. The sample includes data on 389387 applications filed by small entities and 29669 applications filed by micro entities[3]. Since patent corpora collect limited information about inventors, examiners, and legal counsels, I take two steps. First, I use the WIPO's World Gender Name Dictionary (WGND) and the US Social Security Administration's (SSA) register of newborn babies to predict their probable gender at birth. Second, I collect data from the roster of active attorneys licensed to practice at the USPTO and the Office of Enrollment and Discipline (OED) to record information about attorneys' location, license type, and sanctions.

Next, I ask whether the anticipated surge in rejections stems from the filing of lower quality patents. I retrieve data on quality indicators from the USPTO Patent Claim Research Dataset and the OECD/STI Micro-data Lab. These sources contain detailed claim- and innovation-level information, such as the average number of dependent and independent claims (Marco et al. 2019), the count of backward and forward citations (Harhoff et al. 2003), as well as metrics of originality, generality, and radicalness (Hall et al. 2001). By including a rich set of indicators, I aim to assess how quality changes pre- and post-reform, separating applicants' from examiners' influence on the outcome of the prosecution process.

I find that the enforcement of lower fees substantially reduced the likelihood of patent grant among micro entities. In my preferred specification with inventor, examiner and attorney controls, I demonstrate that, post-reform, patents filed by micro entities are 37.36 percentage points less likely to be granted. This result is robust to the exclusion of foreign patents, top filing classes, government and university applications, as well as alternative specifications. Further, results are stable across inventors' and attorneys' country of residence, as well as examiners' gender.

Through a sequence of regressions, I also show that this pattern extends to most quality indicators. In particular, I find that all citation metrics decrease significantly after AIA, consistent with the fact that the fee provisions affected the novelty and technological breadth of filings. While I do not detect significant changes to claim-level indicators, I show that both *Family Size* and *Backward Citations* fell by 20.63% and 19.85%, respectively. This sharp drop is important as it suggests that applications filed post-reform exhibit lower quality and value.

[3]The count includes continuation applications. See Table C.1 for a general overview.

Having documented these changes, I extend the analysis to show that lower fees encouraged the filing of patent continuations. Within the scope of the available data, I document a surge in continuing applications in March 2013 and a related increase in rejections among micro entities, both absent in the pre-reform period. These effects resonate with a large literature positing that continuation is a strategic asset, often used to appropriate the rents of a *partially* valid patent (i.e., Lemley 2004).

This paper is not without limitations. First, a key challenge in identification is effectively handling the noise associated with the enactment of the Act that could directly affect the legal status of patent applications. As previously hinted, the reduction in fees for micro entities was designed to prevent any consequence of the first-to-file system on smaller businesses. Thus, any effect on the legal status of filings should be read as an unintended consequence of the Act. While this should, in principle, enable to control for observed and unobserved heterogeneity among entities, I perform additional tests to ensure that the parallel trend assumption is met. For instance, as the passing of the AIA was the culmination of eight years of Congressional debate, it is likely that micro entities adjusted their legal strategies in expectation of the fee reduction. To control for this potential source of variation, I run a placebo regression where I assign treatment to large entities. During the reform period, the fee provisions had no impact on this class. Consequently, I would expect to observe a null effect.

Further, there may be concerns of selection bias if examiners in the same art unit dealt with similar filings overtime. In particular, problems of endogeneity would arise if unit supervisors assigned filings based on inventor or applicant characteristics. As examiners spend on average nineteen hours to review one application (Frakes and Wasserman 2017), it seems unlikely that a supervisor could systematically affect workload assignment based on a quick review of filings. As argued by Lemley and Sampat (2012), there is little to no evidence that the USPTO's application assignment mechanism is non-random and purposively driven by applicants' observables.

Another drawback is the inability to match patent data with administrative records of firms housed at the U.S. Census Bureau. This is a clear limitation which prevents me from controlling for applicants' characteristics other than the probable gender at birth, type, and place of residence at the time of filing. Further, it could be a major concern if small businesses systematically undereported their status and registered as large entities. While this seems unlikely, it cannot be ruled out. In the late 1990s, the definition of small entity used at the USPTO was heavily contested by the SBA. Following several controversial court cases[4],

[4]Examples include the case of *DH Technology, Inc. vs. Synergystex International, Inc.* 937 F. Supp.

there was evidence that a few *marginal* entities registered as large businesses to avoid the costs of misrepresentation under 13 C.F.R. § 121.108(e). Although the *Manual of Patent Examining Procedures* has since clarified which classes of inventors qualify for reduced fees, the Office still relies on a "good faith" basis to screen applications[5].

Understanding the relationship between fees and legal outcomes holds significance for two key reasons. From the firm's perspective, the interaction between patenting costs and decision status plays a key role in its future commercialization strategies and ability to secure venture capital. Further, from a regulatory standpoint, this question provides valuable insights into the limitations of current IP law and the potential for patent reform to effect systemic changes. Overall, this paper could speak to the future of US patent policy. In December 2022, Congress further reduced patent fees for small and micro entities. As part of the Unleashing America Invents Act (UAIA), the Biden administration announced an increase in the discount rate from 50% to 60% for small entities and from 75% to 80% for micro entities. My findings suggests that such incentives may have indirect consequences on the quality of patents and their enforceability.

Organization. The rest of the paper proceeds as follows. Section 2 briefly reviews the legislation and the relevant literature. Section 3 examines potential responses to the policy. Section 4 and Section 5 discuss, respectively, the data and methodology used in the analysis. Section 6 presents the results, while Section 7 performs additional robustness checks. Section 8 reviews the findings in the light of patent continuation data. Section 9 briefly concludes.

2 Background

In this section, I outline the key provisions of the AIA and discuss its precursors. Next, I provide a review of the relevant literature.

2.1 America Invents Act

The 2011 Leahy-Smith America Invent Act or, more commonly, America Invents Act has effected the most substantive changes to US patent law since the Patent Act of 1952. After repeated attempts to improve the system in 2005, 2007, and 2009, Congress passed the AIA in August 2011, which was subsequently signed into law on September 16, 2011.

902, 40 U.S.P.Q.2d (BNA) 1754 (N.D. Cal. 1996).

[5]See 37 CFR § 1.28.

One of the main provisions of the Act was the move from a first-to-invent (FTI) to a first-to-file (FTF) rule. Under the FTI, the invention process consists of two stages: *i*) a conceptualization step in which a novelty or improvement is formulated; *ii*) its reduction to practice. This system requires that the official filing date coincides with the date of conception[6] and assigns priority to the inventor.

By switching from a FTI to a FTF system, the US closely aligned to the filing rules used by the majority of countries. Under the FTF, the first person who files a patent application and is granted protection is entitled to appropriate the rights of the invention, taking precedence over all other parties. While proponents of the reform highlighted potential benefits such as reduced litigation and a streamlined application process; opponents raised significant concerns by citing the example of Canada. In 1989, Canada introduced the FTF system but had minimal impact on total R&D activity. Further, the system favored large corporations over small businesses and individual inventors, casting doubts on its effectiveness (Lo and Sutthiphisal 2009).

In response to such concerns, the law substantially modified the patent fee requirements, introducing a discount for micro entities. While the USPTO started registering entity sizes in the early 1980s, micro entities were initially counted as small entities for the purpose of paying reduced patent fees. In the following paragraph, I outline the antecedents leading to the legislation and the principal changes that were enacted.

2.2 Entity Definition and Fee Discounts

Under the 1980 Regulatory Flexibility Act (Pub. L. 96-354), the U.S. government first required agencies to examine the effects of federal regulations on small entities and adopt corrective measures where legislation was deemed "burdensome" (U.S. Congress 1980). The intent of the Act was to favor the growth of small businesses and ban anti-competitive measures that could threaten their survival. In an effort to apply these guidelines, the USPTO began a period of consultation with the SBA in 1982, which culminated in a 50% reduction in the major statutory and non-statutory fees[7] for small entities (Pub. L. 97-247).

While, following the Omnibus Budget Reconciliation Act (Pub. L. 101-508), patent fees were revised on a periodic basis to reflect changes in the Consumer Price Index, the provisions for small entities remained in force until the enactment of America Invents Act in

[6] See 2138 Pre-AIA 35 U.S.C. 102(g) (2022).

[7] Statutory fees include all filing, issuance, and maintenance fees. In contrast, non-statutory fees refer to all other patent processing fees, including post-issuance, trial and appeal, petition, service, and enrollment fees. Of relevance are also Patent Cooperation Treaty (PCT) fees, only applicable to international applications filed through the Office.

2011. Under the new legislation, micro entities could benefit from a 75% reduction in patent fees; in contrast, small entities would continue to receive a 50% discount[8].

To enforce this statute, the *Manual of Patent Examining Procedure* codifies the definitions of small and micro entities. In particular, reduced fees apply exclusively to independent inventor(s) and non-profit organizations as defined by the Director[9], and small business concerns as defined by the SBA Business Size Standard[10]. To obtain micro entity status, further requirements must be met - specifically, (1) the patentee must qualify as a small entity, (2) the patentee must satisfy the gross income or, where applicable, the institution of higher education basis, **and** (3) the patentee must use a certification to prove its micro entity status at the time of filing or at the renewal stage. According to this definition, applicants who "assign, grant, convey, or license, any rights in the invention" (37 CFR § 1.27) to a large enterprise do not quality as small entities and should not be granted special status.

2.3 How Much Does a Patent Cost?

Patent fees vary substantially depending on the complexity of the case, the type of application, and the engaging of a patent practitioner. At a minimum, they involve two major components: (i) statutory fees and, if professional advice is sought, (ii) attorney fees. The introduction of a micro entity status solely changed the first, leaving lawyers' compensation unchanged.

Figure A.4 provides a breakdown of statutory fees, that is fees levied by the USPTO to fund its operations[11]. All figures refer to the 2013 fiscal year and reflect costs charged to small entities[12]. As shown in the diagram, patent fees are closely tied to the prosecution process. Priority and filing fees are requested upon submission of the first application. While relatively low, these costs can cover the initial reviewing and service charges. Examination fees are also requested upfront and normally bundled with the filing fees. This payment formally initiates the search process through which an examiner evaluates the novelty and non-obviousness of the invention against the prior art. Following correspondence with the applicant, a patent may be granted upon payment of an issue fee. Once in force, renewal fees are payable to maintain the patent during its twenty-year term. Throughout this process, additional costs may be incurred for extensions, appeals, or expedited examination.

[8]See Part A of the Appendix for a breakdown of statutory patent fees at the USPTO prior to the implementation of the reform. Estimates refer to small entities, such that micro entities were entitled to 25% discount after the enactment of the reform.

[9]See 35 U.S.C. §41(h)(1) (2024).

[10]See 37 C.F.R. §1.27 (2024).

[11]An earlier provision, enacted under America Invents Act in September 2011, gave the USPTO fee-setting authority, allowing the Office to tailor the payment schedule to its operational needs.

[12]Starting on March 19, 2013, micro entities could claim a 25% discount on top of this discounted rate.

It is important to note that statutory fees often represent only a small fraction of the total costs, typically around 10-20%. If inventors seek professional advice, fees may quickly escalate. According to the American Intellectual Property Law Association (2007), preparing an application of low complexity averaged $\$8,548$ in 2007, while biotechnology and pharmaceutical cases settled at $\$15,398$. Technologies of higher complexity, including mechanical and software patents, commanded a premium, then estimated at $\$11,482$ and $\$13,684$, respectively (*ibid.*). Despite the differences across Census regions and IP firms, these figures show that attorney fees may serve as a key determinant in the decision to file and maintain the patent over its lifecycle.

The bottom line is that statutory fees are a prerequisite to process a patent application. While they may constitute a relatively small share of the overall costs, they play a critical role for Office. As established by Section 10 of America Invents Act[13], the USPTO uses the proceedings to meet its financial obligations and ensure the smooth functioning of its services.

2.4 Literature Review

The effect of patent fees on applicants' behavior is a classic question in innovation economics. While lower filing fees should, in principle, increase the count of filings, earlier findings are controversial. On the one hand, fee reductions seem to increase the quantity of applications and decrease their quality (i.e., Picard and van Pottelsberghe de la Potterie 2013; Comino and Graziano 2015). On the other, targeting such policies to small businesses seems to reduce their cost barriers and encourage them to seek patent protection (i.e., Hall et al. 2014). My paper speaks to this debate, demonstrating that patent fees have an indirect effect on the grant rate and the quality of filed applications.

Thematically, the paper closest to mine is De Rassenfosse and Jaffe (2018). They exploit the implementation of the Patent Law Amendment Act of 1982 to evaluate the effect of higher fees on the value and quality of patents. While my argument aligns closely with their initial predictions as we both posit that fees influence both the quantity and quality of patents; I introduce an additional layer to their analysis by examining the effects of IP law on legal outcomes. Further, our papers diverge significantly in terms of data and methodology used.

Another closely related paper is Kani and Nishimura (2025). They study the effect of lower fees on patent quality following the 2011 reform enacted at the Japan Patent Office (henceforth, JPO). Distinguishing between pre- and post-grant quality, they find a small

[13] See Pub. L. No. 112-29, § 10 (2011).

reduction in pre-examination outcomes and no changes to the latter. Their result contrasts markedly with mine, where lower fees introduce differential trends in post-grant indicators. Here, however, the focus is on micro entities; conversely, they consider all applications received by the JPO.

Methodologically, this study relates to the literature evaluating the impact of IP law on different measures of innovation, including both backward and forward outcomes. Hegde et al. (2023) analyze the passing of the American Inventor Protection Act (AIPA) of 1999 on technology diffusion and R&D. In particular, they ask whether the disclosure requirements introduced by the AIPA increased the rate of patenting and innovation among filings. Throughout, they use a difference-in-difference design, leveraging the AIPA as a natural experiment. In comparing quality outcomes for US and EU patents, they note that the reform significantly increased the count of citations received by former. In a similar spirit, I exploit the AIA as a policy experiment to identify the impact of patent fees on the legal status of filings. Similar to their study, I use a quasi-experimental approach to identify the impact of the provision on patent quality. Here, however, I restrict my focus to the US context, asking how the passing of the provisions affected SMEs.

Less related is a stream of research that explores the relationship between firms' investment in R&D and their decision to patent. A key paper in this area is Hunt (2006). Using a theoretical model, he demonstrates that firms seek protection when patent fees are low relative to R&D expenses and the value of final output. While I do not explicitly control for R&D expenses, my setup resonates well with his predictions.

3 Conceptual Framework

As posited by De Rassenfosse and van Pottelsberghe de la Potterie (2013), changes to patent fees may hinder or improve the efficiency of the examination process. This factor may, in turn, influence applicants' willingness to seek protection and, more generally, use patenting as an incentive for growth. In this section, I propose a theoretical argument to demonstrate that patent fees can indirectly affect both the patent grant rate and the quality of filings.

Consider first a dynamic patenting problem in which a principal can price discriminate based on a firm's size. In a perfectly competitive market, agents should respond by increasing their demand for patents if the net benefits from disclosure exceed the costs. In a patent race, however, firms' willingness to disclose their invention depends on two additional factors: first, the uncertainty about the examination outcome; second, the expected discounted value of their inventions. While lower fees directly reduce the cost of patenting, they may indirectly

increase the expected value of the invention for which protection is sought.

I develop two hypotheses. The first addresses the consequences of patent fees on the patent grant rate. While the benefits of patent protection likely vary among classes, lower fees should, in principle, reduce the cost of disclosure and attract more applicants. This, in turn, will likely increase the number of filings, with negative consequences on the time examiners dedicates to each submission. Assuming that hiring decisions are constrained in the short run, I would anticipate observing an increase in the issuance of final rejections[14].

Hypothesis I. *The fee provisions implemented by the AIA may increase the likelihood of rejections among applications filed by micro entities.*

The second hypothesis concerns the effect of the new rule on patent quality. As posited by De Rassenfosse and van Pottelsberghe de la Potterie (2013), patent fees have direct influence on applicants' behavior. Despite a reduction in fees, however, applicants with limited access to financial resources may be unable to afford legal assistance. De Rassenfosse et al. (2023) report that attorneys' fees may vary between $\$6,000$ - $\$14,000$ depending on the region and complexity of the case. In this light, assuming that a patent is a relatively elastic good, potential patentees may decide to apply without legal support and produce low-quality filings.

Hypothesis II. *Following the implementation of new fee provisions under the AIA, micro entities may be more likely to file applications of increased breadth and lower quality.*

Implications. As theorized above, I expect that lower fees may lead to an increase in the probability of final rejections among micro applicants; further, I would anticipate observing marked differences in post-reform quality outcomes for this class of filers. As applicants and examiners are both given equal weight in the prosecution process, the direction of the change is unclear and likely vary depending on the class of filing.

4 Data

As of 2000, the USPTO began publishing patent applications eighteen months after the official filing date. Since then, a large literature has exploited the information contained in patent applications to measure the effects of IP policy on quality and follow-on innovation. In this paper, I analyze how the introduction of reduced patent fees for micro entities has

[14]For a discussion on the patent prosecution process, see Lemley (2004).

affected the legal status of applications at the USPTO. To this end, I collect data from four main sources: the USPTO's PatentsView repository, the Harvard USPTO Patent Dataset (Suzgun et al. (2022), henceforth HUPD), the OECD/STI Micro-data Lab, and PatStat. In what follows, I describe the data in further detail.

4.1 Application Data

Filings, Inventors, Examiners. I retrieve detailed patent information from the HUPD for the years 2010-2014. In the analysis, I focus on utility patents and exclude design, plant, reissue, defensive, and statutory invention registrations[15]. The reason is that utility patents account for approximately 90% of all filings and comprise new or improved processes, products, machines or substances from the manufacturing and non-manufacturing sector.

Variables of interest are titles, examiners' full names and art units, decision status, small entity indicators, filing and publication dates, International Patent Classification (IPC) codes[16], and foreign entity indicators. I complement this data with the USPTO's Bulk Storage System, which offers open access information about inventors' names and contact details. Since the USPTO does not provide any demographic information about examiners, I follow Suzgun et al. (2022) and use the Social Security Administration (SSA)'s record on Security Card Applications to estimate their probable gender at birth. Consistent with previous work (i.e., Jensen et al. 2018), I define a 95% threshold of accuracy and only classify individuals with highly gendered names.

The total number of utility applications filed between 2010 and 2014 is 1706106. Once I exclude undiscounted filings, continuation, and pending patents, I retain information about 282725 small entities and 25422 micro entities.

Legal Counsels. The previous literature highlights that the availability of in-house counsels and private practice attorneys is associated with improved examination outcomes and a higher likelihood of acceptance at different stages of the patent lifecycle (Gaudry 2012). To control for this, I retrieve the full name and contact information[17] of patent

[15]Utility patents include processes, machines, and objects of novel composition or manufacture. See the USPTO (https://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/patdesc.htm) for a formal definition of each type.

[16]The IPC is the World Intellectual Property Organization's (WIPO) patent classification system. It is based on a hierarchical definition and commonly used to standardize the subject of each application. The WIPO has dedicated resources explaining the main features of this tool. See https://www.wipo.int/classifications/ipc/en/ for an overview.

[17]Data include the first, last, middle and any post-nominal name of attorneys, the name of their business or firm, the city, state, and postal code of practice.

attorneys from the USPTO's Bulk Storage System. To understand whether the attorney operates in-house or privately, I check this record against the inventors' and assignees' data. Throughout, I define an in-house counsel as any individual or unit whose address matches the address of the inventor or patent assignee. As this strategy may underestimate the number of in-house practitioners, I supplement the data with the register of active attorneys licensed to practice at the USPTO. At the time of writing, the roster contains information about 13472 agents and 37284 patent attorneys. Further to the above, the roster provides the phone and registration number, an indication of specialty (i.e., attorney, agent, design, limited recognition, government), and the employee status. Inactive practitioners are not included in the count. For completeness, I use data from the USPTO's Office of Enrollment and Discipline to manually record the names and addresses of attorneys who were disciplined in the sample period. This includes an average of 41 legal practitioners between 2010 and 2014. For each entry, I perform the gender coding exercise described in Part C of the Appendix. To prevent double-counting, records of attorneys whose names are already listed in the USPTO's database are omitted.

For the period of study, there is little information about the average salaries of patent attorneys in the United States. A useful resource is the annual AUTM's Salary Survey, which reports the mean salary of a patent manager for the years of interest. While these documents provide general guidance on the subject, I do not explicitly control for attorney's mean salaries in my specification.

Throughout, I do not plan on linking patents with administrative data on firms housed at the Census Bureau. At the time of writing, datasets of interest include the Business Register (BR) and the Longitudinal Business Database (LBD). Both are restricted access and only available to accredited federal employees.

US Patenting Patterns (2010-2014). For completeness, I include an overview of the application outcome for all utility patents filed with the USPTO between 2010 and 2014[18]. Table C.2 shows that the majority of applicants registered as a large entity. At the examination stage, large entities were more likely to be granted a patent and less likely to be rejected than either small or micro entities. During the same period, micro entities had higher acceptance, rejection, and pending rates than small entities. While there are few studies on the subject (USPTO 2012), this evidence seems to suggest that micro entities

[18]As in the HUPD, metadata on applications - including grant and rejections information - are based on the USPTO Patent Examination Research Datasets (PatEx) downloaded in February 2021.

are more likely to promote breakthrough inventions and seek protection in high-tech fields where patenting can help them secure a competitive advantage. As demonstrated by the late provisions of the Act[19], observed differences in the patent grant rate between micro and large entities may be driven by the differential access to financial resources or legal assistance.

Overall, these estimates provide compelling evidence that patenting was (and remains) less common among smaller businesses. While traditionally underrepresented in the patenting race, micro entities seem to produce applications with a higher degree of novelty and inventiveness.

4.2 Patent Quality

To test Hypothesis II, I collect bibliographic information from two main sources, the USPTO Patent Claims Research Dataset and the OECD/STI Micro-Data Lab. As there is widespread disagreement regarding the effectiveness of existing metrics (i.e., Harutyunyan and Matcham 2025; Higham et al. 2021), I assemble a rich array of indicators à la Squicciarini et al. (2013), including both pre- and post-publication outcomes. This exercise should enable me to observe how and whether quality changes during the prosecution process[20]. Hereby, I provide an overview of the main indicators, leaving a detailed definition to Part B of the Appendix.

4.2.1 Claim-Level Data

Measuring quality typically starts with an analysis of embodiments contained in patent claims[21]. Claims are lists of statements that explain the novelty and non-obviousness of the invention, defining the scope for which protection is sought. Generally, claims consist of a dependent and an independent component. Independent claims are standalone entities that broadly characterize the scope of the invention; dependent claims describe the subject matter in detail by explaining the main features of the specification. Previous scholarships find that a higher number of independent claims is associated with broader scope and lower quality; in contrast, applications with multiple dependent claims have higher probability of grant and shorter examination lags (Marco et al. 2019).

The USPTO's Patent Claims Research Dataset provides claim-level data on utility applications filed between 2001 and 2014. The variables are assembled by the Office of the Chief

[19] In 2015, the PTO introduced the Patent Pro Bono Program, a federally sponsored program to support solo inventors and micro entities in the drafting and application stage. See https://www.uspto.gov/patents/basics/using-legal-services/pro-bono/patent-pro-bono-program.

[20] Although applicants draft claims at the filing stage, examiners may lengthen or shorten the content of the claimed matter during prosecution.

[21] This analysis builds on the doctrine of "peripheral" claiming as defined in Burk and Lemley (2009).

Economist (OCE) and constructed by parsing both independent and dependent claims. As these metrics serve different purposes and contain different information, I analyze them separately.

Independent Claims In patent drafting, independent claims are self-supporting assertions of novelty and non-obviousness. They require the applicant to disclose the core of the invention, imposing a minimum restriction on the subject claimed. Kuhn and Thompson (2019) report that the first independent claim can be a good indicator of patent scope. In particular, they find that the most valuable inventions contain fewer words in the first assertion and expand the matter using dependent claims.

In Figure C.1, I plot the monthly average evolution of claim-level metrics for micro entities before and after the changes to the fee schedule. In each graph, I fit a pre-trend line showing how the indicators would have evolved in the absence of the reform. While there is no departure from the mean until July 2014, all metrics exhibit higher variability after this date. While initially ranging from 2.3 to 3.4, the average number of independent claims falls below 2 at publication. Alongside a lower number of claims, the panel shows a reduction in the average word count 18 months after filing. Specifically, the count decreases from about 325 pre-reform to a low of 140 post-reform. Similarly, the average number of words moves downward, from around 135 pre-AIA to less than 50 in 2014. In Figure C.4, I perform the same analysis on small entities. The panel shows significant deviations starting from early 2014, but no visible departure in the immediate aftermath of the reform.

Dependent Claims Applicants specify the features of the invention using dependent claims. In practice, dependent claims add restrictions to an independent or a dependent component. While rarely used to assess infringement (Brean 2019), dependent claims can reduce the risks of litigation by defining the core of the invention. The lower section of Figure C.1 plots the monthly average evolution of dependent claims for the years of interest. As before, the trend indicates how the metrics would have changed in the absence of the provision. While there is no significant departure from the mean pre-AIA, all indicators exhibit higher variability following publication. The number of dependent claims and the average word count clearly deviate from the trend from 2014. The first falls from an average of 15 to a trough of 10 in July 2014, displaying substantial variability thereafter; the latter moves from about 550 pre-AIA to a low of 430. In Figure C.4, I repeat the same exercise using data on small entities. Similar to Figure C.1, all outcomes jump discontinuously after July 2014. Together, this evidence indicates that factors others than patent fees may have influenced claim construction.

Overall, this evidence points in two directions. First, it suggests that neither small nor micro entities adjusted their claim strategies in the initial post-reform period. Second, it shows that micro entities may have only mildly responded to the USPTO fee schedule, which penalizes the use of independent claims in favor of dependent ones[22].

4.2.2 Other Quality Indicators

The EPO's PatStat and the OECD/STI Micro-data Lab maintain detailed, bibliographic information about patent applications filed with the major patent offices worldwide. Both repositories are periodically updated and can provide citation- and technology-based metrics of breakthrough innovations.

Citation-Based Metrics The use of citations as proxies for patent quality has been widely studied (i.e., Trajtenberg 1990). According to Hall et al. (2005), patent citations positively correlate with R&D investments and market value. Despite their popularity, citation-based variables may suffer from truncation bias. Since citations to patents filed pre-reform have had more time to accumulate, all indicators are here reweighed as in Hall et al. (2001).

Backward Citations are references made by the filer to the patent literature. While the PTO requires applicants to disclose the prior art at the filing stage, this evidence is reviewed by the examiner and modified during the prosecution process. According to Trajtenberg (1990) and Silverberg and Verspagen (2007), backward citations positively correlate with patent renewal and stock market value. Similarly, *NPL Citations* are references made by the applicant to the non-patent literature. Especially relevant in the software and biotechnology industry, NPL citations summarize the contributions of the invention to the scholarly literature. Harhoff et al. (2003) demonstrate that this indicator positively associates with the patent's private and social value.

The upper segment of Figure C.2 plots the monthly average evolution of *Backward* and *NPL Citations* for micro entities. Post-treatment, neither *Backward Citations* nor *NPL Citations* depart meaningfully from the average; despite this, data points are substantially less sparse. Figure C.5 repeats the analysis for small entities. The panel shows that *Backward Citations* follow an s-shaped pattern, evolving non-linearly in both the pre- and post-reform period. In contrast, *NPL Citations* exhibit less variability and move in line with the trend throughout the period.

[22] See 37 C.F.R. § 1.16(h)-(j) (2013).

Forward Citations include references to a focal application made by subsequent inventors. According to Hall et al. (2005), forward citations are good predictors of economic value and firm performance. Further, patents with a higher number of forward citations are less likely to be infringed or upheld in court (Lanjouw and Schankerman 2001). Consistent with the literature, I consider a five- and seven-year lag post-filing.

The lower panel of Figure C.2 plots the monthly average change in the log of *Forward Citations*. In both plots, data points become progressively less scattered, falling below the trend post-AIA. Figure C.5 illustrates the evolution of this indicator for small entities. In this case, the mean gradually increases, while remaining consistent with the green line. More generally, this evidence supports Hypothesis II, showing that reduced fees had a seemingly small and negative effect on *Forward Citations*.

Technology-Based Metrics Alongside bibliographic data, the literature employs additional indicators to evaluate the contribution of a patent to follow-on innovation. Generally constructed from citations and classification codes, these metrics offer valuable insights into the novelty of a patent and its potential to effect change.

Many Field summarizes the number of the technological domains to which a patent belongs. The variable is compiled by converting the IPC codes listed in the application into a descriptive framework that facilitates cross-country comparisons. According to the WIPO, inventions belong to thirty-five different fields[23]. Each field maps into five major sectors: *Electrical Engineering*, *Instruments*, *Chemistry*, *Mechanical Engineering*, and *Other Fields*.

Scope identifies the breadth of the invention and its potential to generate social value. As in Lerner (2002) and Squicciarini et al. (2013), this indicator counts the occurrences of 4-digits IPC codes contained in each filing. The variable is normalized by dividing its maximum value for each year to adjust for potential outliers. Overall, applications with a higher number of IPC codes signal broader innovation capabilities (i.e., Lerner 1994).

Family Size counts the number of jurisdictions where the inventor seeks protection. Putnam (1996) and Harhoff et al. (2003) find that larger family sizes positively correlate with patent renewal and life span. Here, family size reflects two aspects of applicants' behavior: first, their ability to invest in the invention at an early stage; second, the perceived market value of the patent. As for *Scope*, the indicator is scaled by its yearly maximum.

Figure C.3 provides a summary of these metrics for micro entities. While less scattered than in the pre-AIA period, data points drop below the trend post-reform and do not rebound until mid-2014. Conversely, monthly averages for small entities are more concentrated around the mean pre-AIA and jump discontinuously six months after its implementation (see Figure

[23] See World Intellectual Property Organization (2008) for a structured overview.

C.6). I interpret this as a signal that, after a period of initial adjustment, the FTF system may have had an impact on small entities' filing behavior.

Another relevant metric is *Radicalness*. This indicator measures the distance between the patent and the existing technology, anticipating its future demand and economic potential. As in Squicciarini et al. (2013), it is computed as the ratio of 4-digit IPC codes used in a backward filing and included in a focal patent to the count of its 7-digit IPC codes. On average, the higher the index, the higher the likelihood of patent issuance (i.e., Trajtenberg et al. 1997). In Shane (2001), radicalness positively affects new firm formation and serves as a proxy for technical innovation.

The lower panel of Figure C.3 shows how the monthly mean of this outcome evolves around the date of implementation. On average, data points are considerably less sparse post-reform. Unlike other variables, *Radicalness* shows an increase post-reform. In Figure C.6, I repeat the analysis for small entities. Point averages are closely distributed around the trend pre-reform and exhibit a marked deviation after six months. Again, this suggests that the new filing system may have introduced an important source of bias that has to be controlled for.

5 Empirical Strategy

5.1 Baseline Approach

I exploit the introduction of reduced fees under the AIA as a natural experiment to divide the sample into pre- and post-treatment months, comparing the decision status of filings among matched micro entities (*treatment group*) and small entities (*control group*) before and after the enactment of the provision. The general model takes the following form:

$$y_{it}^{k} = \beta_0 Post_t + \beta_1 Treat_i + \beta_2 Treat_i \times Post_t + \epsilon_{it}$$

where y_{it}^{k} with $(k = 0, 1)$ is a dummy variable equal to 0 for accepted and 1 for rejected patents[24]; $Post_t$ is a dummy equal to 1 for post-treatment periods and 0 for pre-treatment periods; $Treat_i$ is equal to 1 for micro entities and 0 for small entities and ϵ_{it} is random noise.

To control for covariates, class and time fixed effects, I augment the general model by

[24]Similar to Suzgun et al. (2022), I exclude continuity patents from the main estimation and perform separate analysis on them.

estimating the following regression:

$$Status_{it}^{k} = \alpha + \lambda_i + \mu_t + \beta_1 Ent_i + \beta_2 Ent_i \times Post_t + \gamma' \mathbf{X}_{it} + \delta' \mathbf{Z}_{it} + \theta' \mathbf{C}_{it} + u_{it} \quad (1)$$

where y_{it}^{k} is legal status of an application filed by applicant i in month t; λ_i and μ_t are class[25] and month fixed effects, respectively; $\mathbf{X}_{it}$ is a vector of examiners' controls, including art unit, years of employment at the USPTO, and probable gender at birth; $\mathbf{Z}_{it}$ is a vector of attorneys' observables, controlling for country of origin, license type, sanctions, and probable gender at birth; $\mathbf{C}_{it}$ are a set of inventor level characteristics, including gender, previous patenting experience, country of residence at the time of filing. Throughout, I cluster standard errors at the applicant level.

In this specification, I am interested in the interaction term which, under the assumption of parallel trends, captures the impact of lower fees on legal outcomes after passage of the AIA.

I next evaluate whether the introduction of a micro entity status affected the quality of patents filed on or after March 19, 2013. To this end, I modify (1) to account for the innovation metrics defined in Section 4.2. The empirical specification is:

$$Qual_{it} = \alpha + \lambda_i + \mu_t + \beta_1 Ent_i + \beta_2 Ent_i \times Post_t + \gamma' \mathbf{X}_{it} + \delta' \mathbf{Z}_{it} + \theta' \mathbf{C}_{it} + u_{it} \quad (2)$$

where i is a patent application filed in month t; u_{it} is an unobserved error component. As before, the regressor of interest is β_2. Under the assumption of parallel trends, the coefficient on the interaction term should capture the effect of lower fees on patent quality. The specification in (2) further controls for time-variant patent covariates (i.e., inventor, attorney, and examiner characteristics) and time-invariant factors, including IPC and month fixed effects. Standard errors are one-way clustered by applicant.

5.2 Dynamic Approach

I further extend the specification in (1) and (2) to analyze the dynamic effect of the provision on treated applicants. Specifically, I estimate a matched event-study regression to compare the impact of lower fees on micro entities to matched counterfactual entities as in (3):

[25] Here, I control for IPC class fixed effects, where the IPC variable is measured at the most disaggregated level. The IPC, or International Patent Classification, consists of seven alphanumeric characters. Traditionally, most of the literature has relied on the first four digits, which identify the group, class, and subclass of reference (i.e., Levine et al. 2017). Including all characters allows me to control for the broad and heterogeneous fields of specialization among a broader class of technologies.

$$Status_{it}^{k} = \beta + \lambda_i + \sum_{\tau=2010m1}^{2014m12} \delta_t 1[t=\tau] + \sum_{\tau=2010m1}^{2014m12} \gamma_t 1[t=\tau] \times Ent_i + \zeta' \mathbf{W}_{it} + v_{it} \quad (3)$$

where $Status_{it}^{k}$ is the legal status of a patent application filed by entity i in month t. The estimating equation includes class fixed effects, λ_i; a control vector, $\mathbf{W}_{it}$; a full set of month indicators (with one omitted), interacted with the treatment status. Standard errors are clustered at the applicant level.

The coefficient of primary interest is γ_t. Conditional on parallel trends, the coefficient measures the average change in the legal status of a patent application for micro relative to small entities and relative to the t months before and after the introduction of lower fees. To ensure identification, the dummy that corresponds to the month prior to the reform is omitted.

5.3 Identification

The identification strategy rests on the assumption of parallel trends: in the absence of the AIA, changes to the legal status of filings among small and micro entities would have been comparable over time. To ensure I meet this requirement, I intend to perform a series of tests, which I describe in this section.

First, I restrict attention to a small window around the passing of the AIA in 2011. As the USPTO introduced minor reforms in 2005, 2007, and 2009, the inclusion of any year prior to 2010 would invalidate my identification strategy and confound the estimates. In addition, on 29 April 2015, Congress passed a new Patent Reform to prevent and alleviate the consequences of litigation on small businesses. As these provisions could systematically affect the decision status of new and existing filings, I restrict my observation period to years 2010-2014.

Although the main purpose of the law was to simplify the application process and avoid the anti-competitive effects of the FTF, I should be mindful of eventual endogeneity concerns that could systematically bias my estimates. As highlighted by Lerner (2002) and Moser (2005), the legal system often strives to shape the incentives of firms to seek protection using patent law. However, if such reforms have a direct effect on the outcome of interest (i.e., legal status of applications), the treatment is likely endogenous.

In my specification, selection bias could arise if the provisions of the Act were designed to directly affect the decisions of examiners or the strategies of patent attorneys. Because modifications to the fee structure were introduced to ensure fairness in the application process,

any effect on the legal status of the filings should be considered an unintended consequence of the reform. However, the equal trend assumption could still be violated if micro entities adjusted their patenting strategies in expectation of the fee reduction. Since the AIA was the result of years of intense negotiations, it is likely that micro entities' behavior changed in the run-up to its enactment. To control for this source of variation, I run a placebo regression in which I assign treatment to large entities. As large entities were untreated throughout the sample period, I take these observations as the null distribution to test the hypothesis that the difference between the treatment and control group is zero for each application.

Further, concerns of endogeneity may arise if examiners were consistently paired with the same applicant or patentee exhibiting specific characteristics. For example, I cannot completely rule out that Supervisory Patent Examiners (SPE) could intentionally assign specific applications to particular individuals. In addressing a similar concern, Lemley and Sampat (2012) circulated a survey among USPTO's staff confirming that, within a specific art unit, application assignment occurs randomly and is mostly based on internal structures and docket flows. Furthermore, since the average time for examiners to review an application is 19 hours (Frakes and Wasserman 2017), it does not seem credible that the SPE could systematically affect workload assignment based on a quick review of documents.

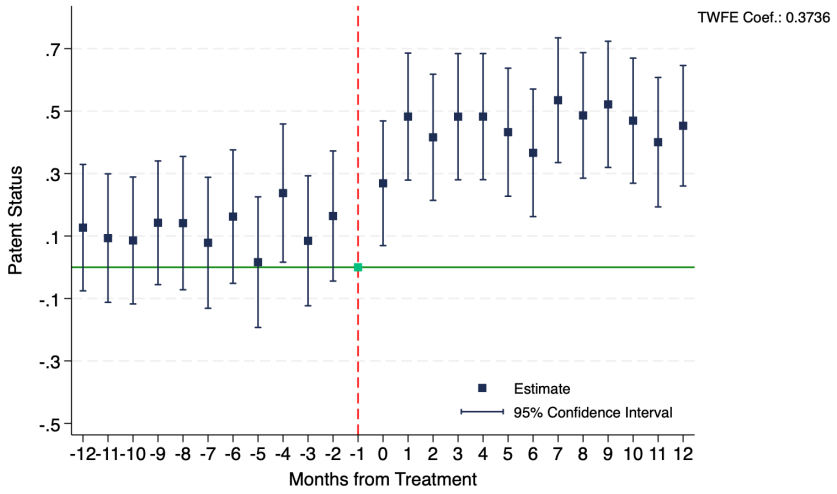
Likewise, there may be concerns about the behavior of patent attorneys. If legal counsels systematically changed their strategy based on entity size, the interaction term in (1) may not capture the average treatment effect on the treated. Due to ethical obligations, attorneys are generally expected to act in the best interest of their clients. What is more probable is that a private practitioner handling patent applications for entities of different sizes might exhibit different conduct. In the absence of further data on patent attorneys, this possibility cannot be ruled out.

6 Main Results

Table D.1 summarizes the results of the difference-in-difference estimate, showing that the policy had a positive impact on rejections. Column (1) presents the results for the baseline model with month and class fixed effects, without covariates. Columns (2), (3), and (4) add, respectively, inventor, attorney, and examiner covariates to the baseline. In Column (5), I include both examiner and attorney controls. In Column (6), I allow for inventor and attorney controls, while in Column (7) I substitute attorney with examiner covariates. My preferred specification in Column (8) indicates that the passage of lower fees increased the probability of rejection among micro entities by 37.36 percentage points. In all specifications, the coefficient on the interaction term is significant at the 1% level and consistent with the

dynamic effect plotted in Figure 1.

Figure 1: Dynamic Effects of the Provision on U.S. Patent Status, 2010-2014.



Notes: The figure shows the regression coefficients and the 95% confidence intervals for the difference between matched treated and control entities relative to the 12 months before and after treatment (2010-2014). The coefficient at $\tau = -1$ is normalized to zero. The outcome variable is the legal status of a new patent application. The x-axis indexes event time. Controls include invention count, inventor gender and country of residence; attorney predicted gender at birth, country of practice, qualification and sanction status; examiner gender at birth and experience level. Standard errors are clustered at the applicant level. Quantitative estimates are summarized in Table D.1.

Table D.2-Table D.8 exploit individual-level data to explore the heterogeneous effects of the policy on patent grant. As before, Column (1) presents the simplest estimates without covariates. Columns (2)-(7) add inventor, attorney, and examiner controls; Column (8) repeats the analysis including all the variables. In Table D.2, the coefficient on the triple interaction term indicates that female and gender-neutral inventors were equally likely to be rejected as their male counterparts. This finding suggests that the provision did not lead to varying trends among different gender identities. Unlike Table D.3, Table D.4 shows that foreign inventors were no less likely to receive a rejection than US-based ones. In Table D.5 and Table D.6, I repeat the analysis interacting the difference-in-difference coefficient with attorneys' gender and license type, respectively. Together, these regressions show no effect of attorneys' observables on the application outcome. As an additional test, Table D.7 verifies whether examiners' gender can explain the surge in rejections. The estimates are quantitatively similar, small in magnitude, and statistically insignificant. Finally, I check whether the issuance of rejections differs across patenting sectors. Table D.8 shows that, compared to Electrical Engineering patents, less sophisticated inventions have 10.25 percentage points

higher probability of rejection. This is consistent with the idea that patents with limited technical and commercial value are less likely to be deemed novel and defended during prosecution. Overall, these findings show that rejections were largely homogeneous across most inventor, attorney, and examiner observables, with salient exceptions in particular technology sectors. Further, while the data attest to the presence of a gender gap in patenting, I do not find evidence of a home bias caused by the provision.

Table 1: Effect of Micro Entity Status on Independent Claims, 2010-2014.

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$\text{Ent}_i \times \text{Post}_t$	-0.0659	-6.3435	1.2791	0.6636
	(0.040)	(6.770)	(2.474)	(2.583)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	198,925	198,925	198,891	198,891
$Adj.R^2$	0.193	0.176	0.294	0.279
Dep. Var. Mean	2.529	313.031	109.813	132.577

Notes: The table reports the effect of lower fees on independent claims. All outcomes are in levels. Examiners' controls include years of employment at the USPTO and probable gender at birth. Attorneys' controls include type of registration, country of practice, and probable gender at birth. Inventor controls include country of residence and probable gender at birth. Standard errors are clustered at the applicant level.

Table 2: Effect of Micro Entity Status on Dependent Claims, 2010-2014.

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$\text{Ent}_i \times \text{Post}_t$	-0.2090	-18.5820	0.9162*	-0.3999
	(0.233)	(14.413)	(0.533)	(0.848)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	198,925	198,925	195,864	195,864
$Adj.R^2$	0.204	0.198	0.497	0.437
Dep. Var. Mean	15.613	592.643	19.423	40.354

Notes: The table reports the impact of new fee provisions on dependent claims. All outcomes are in levels. Examiners' controls include years of employment at the USPTO and probable gender at birth. Attorneys' controls include type of registration, country of practice, and probable gender at birth. Inventor controls include country of residence and probable gender at birth. Standard errors are clustered at the applicant level.
Asterisks denote statistical significance: *10%.

Table 3: Effect of Micro Entity Status on OECD Quality Indicators, 2010-2014.

	Many Fields	Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Ent}_i \times \text{Post}_t$	-0.0461***	-0.1233***	-0.6010***	-0.1985***	-0.1514***	-0.1434***	-0.1518***	0.0292***
	(0.016)	(0.036)	(0.104)	(0.036)	(0.034)	(0.040)	(0.042)	(0.010)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
N	97,452	97,452	97,452	97,452	97,452	97,452	97,452	88,742
$Adj.R^2$	0.168	0.173	0.206	0.144	0.167	0.165	0.166	0.192
Dep. Var. Mean	0.342	1.695	2.914	2.190	0.548	1.467	1.703	0.453

Notes: The table reports the impact of a micro entity status on eight quality outcomes. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the applicant level.
Asterisks denote statistical significance: ***1%.

In addition to changes to the grant rate, the legislation may have reduced the quality of applications filed by micro entities post-reform (see Hypothesis II). In Table 1 and Table 2, I estimate the effect of the provision on the claim-level outcomes reviewed in Section 4. In particular, Table 1 considers whether lower fees had an impact on independent claims. All coefficients on the interaction term are economically small and statistically insignificant. Table 2 extends the analysis to dependent claims. Estimates are nearly all negative, except for the *Minimum Average Word Count*. More generally, these patterns indicate that the provision did not generate systematic differences in claim-level measures of patent quality.

This finding contrasts with a large body of evidence that highlights how applications with broader claims have, on average, a higher probability of rejection.

Table 3 considers the impact of the provision on several OECD indicators. Except for Column (8), the estimates are all negative and statistically significant at the 1% level, showing that the policy had an adverse effect on micro entities. This finding is consistent with Hypothesis II, and the data points presented in Figure D.3-D.4. In particular, the impact was larger for *Family Size* (-20.63%) and *Backward Citations* (-19.85%). In Column (7) and (5), I further show that, on average, lower fees reduced *Forward Cites (7Y)* and *NPL Citations* by 15.18% and 15.14%, respectively. Both estimates are statistically significant at the 1% level and consistent with the plots presented in the Appendix. Economically less relevant is the impact of lower fees on *Patent Scope* and the *Radicalness* index. Unlike other outcomes, *Radicalness* increased mildly, indicating that, post-reform, patentees cited a broad range of technologies beyond their primary field. However, since the index ranges from 0 to 1 and is based on retrospective technologies, it remains difficult to establish its relevance for follow-on innovation.

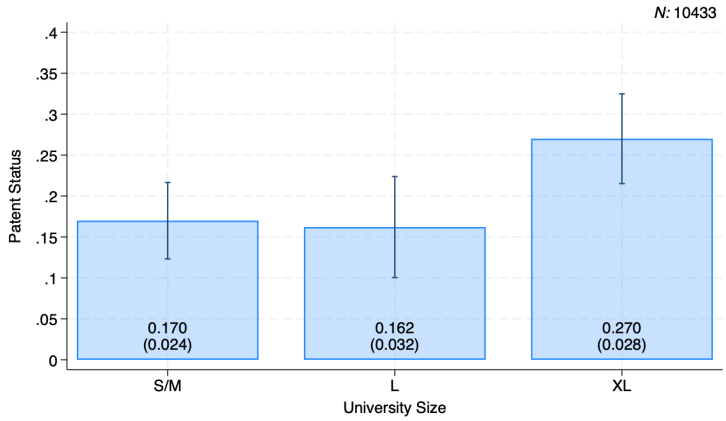
7 Mechanisms and Robustness

In this section, I probe whether the findings are robust to (*i*) alternative functional forms, (*ii*) fixed effects specifications, and (*iii*) a placebo regression. Overall, the sensitivity tests confirm the practical and statistical significance of the core results.

Institutions of Higher Education. To study the effect of micro entity fees on universities, I proceed in two steps. First, I perform a triple difference-in-difference to show how rejections differ among institutions of varying size. Second, I eliminate all applications filed on behalf of academic employees to demonstrate that the findings are unaffected by their exclusion.

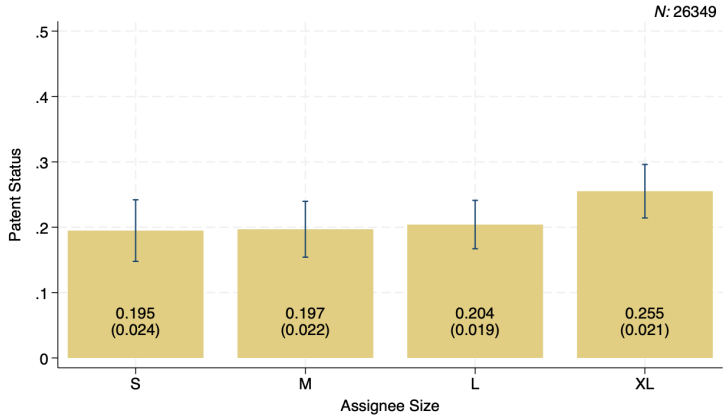
Figure 2 estimates the impact of lower fees on universities based on their size. I split entities into three employment-based groups, dividing the sample into small/medium (1-5000), large (5001-10000), and very large (10001+) establishments. On average, rejections rose significantly for institutions in the upper tercile. While statistically significant, small and medium-sized universities exhibit relatively better performance. Yet, because there is no meaningful variation in quality-level outcomes, the differential may stem from the heavier workload experienced by larger Technology Transfer Offices (TTOs) prior to the introduction of the FTF rather than to poor communication by the USPTO. Although it is not possible

Figure 2: Gap in Patent Rejections among Universities of Varying Size, 2010-2014.



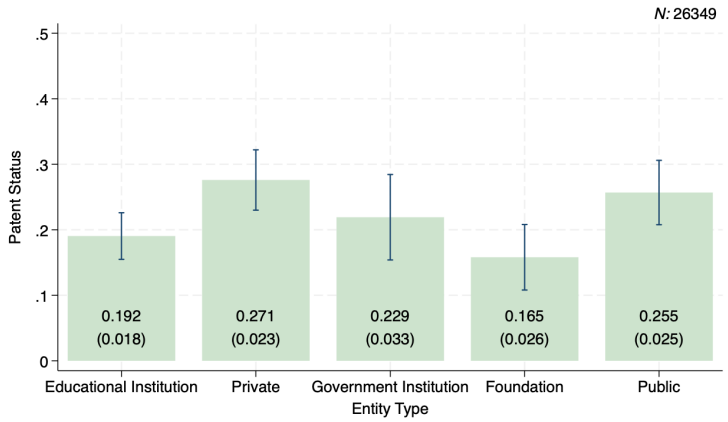
Notes: The figure examines how the introduction of micro entity fees affects patentees differently based on their employee count, using a matched sample of universities and research institutions (2010-2014). From left to right, entities are labeled as S/M (1–5000 employees 45.16%), L (5001 − 10000 employees 17.18%), and XL (10001+ employees 37.65%). Controls include inventors' country of residence, gender, and invention count; examiners' experience at the USPTO and probable gender at birth; attorneys' type of registration, country of practice, and probable gender at birth. Vertical bars represent the 95% confidence intervals. Standard errors are clustered at the applicant level.

Figure 3: Small and Micro Entities with more than 5 Patents at the USPTO, 2010-2014.



Notes: The figure examines how the introduction of micro entity fees affects patentees differently based on their employee count, using a matched sample of entities with more than five applications on record at the USPTO (2010-2014). From left to right, entities are labeled as S (1–50 employees, 26.94%), M (51–250 employees, 23.57%), L (251 − 5000 employees, 29.54%), and XL (5001+ employees, 19.95%). Controls include inventors' country of residence, gender, and invention count; examiners' experience at the USPTO and probable gender at birth; attorneys' type of registration, country of practice, and probable gender at birth; total IP count, year of establishment, ownership type, and region of incorporation as of 2025. Vertical bars represent the 95% confidence intervals. Standard errors are clustered at the applicant level.

Figure 4: Rejections among Large Patentees by Entity Type, 2010-2014.



Notes: The figure examines how the introduction of micro entity fees affects patentees differently based on their ownership type, using a matched sample of entities with more than five applications on record at the USPTO (2010-2014). Controls include inventors' country of residence, gender, and invention count; examiners' experience at the USPTO and probable gender at birth; attorneys' type of registration, country of practice, and probable gender at birth; total IP count, year of establishment, ownership type, and region of incorporation as of 2025. Vertical bars represent the 95% confidence intervals. Standard errors are clustered at the applicant level.

to disentangle the two sources, this evidence contrasts with Dahl (2021), showing that larger employers were worse affected.

Next, I eliminate all patents filed by universities. Due to the nature and purpose of university-led research, TTOs can produce applications whose quality and value are harder to measure (i.e., Hsu et al. 2021). The results, reported in Table D.12 and Table D.59-Table D.61, yield very similar estimates across all outcomes. Interestingly, dropping applications filed by research institutions increases the probability of rejection and reduces the average quality of patents.

IP-Intensive Industries. I next turn to explore variations in outcomes among applicants experienced in patenting. As shown by extant scholarships (i.e., Webster and Jensen 2011), firms with vast IP portfolios are better able to navigate prosecution and commercialize their inventions. To account for this potential source of variation, I estimate separate effects across workforce-size quartiles to verify whether the provision affected large filers differently. In Figure 3, I use a matched sample of 26349 entities and divide the data into quartiles[26]. Results reveal that entities at both tails of the distribution had higher probability of rejection post-AIA. The change was coupled with meaningful reductions in both pre- and post-quality indicators. Using the same sample, Figure 4 further shows that there is variation across own-

[26]Data are hand-coded and derived from S&P Capital IQ Pro, Crunchbase, and Pitchbook.

ership types: private and public entities were worst affected by the provision. Interestingly, both estimates are highly significant and of similar magnitude, inconsistent with the large disparities in assignee types observed in previous work (i.e., Bessen 2008).

Together, these findings provide a first snapshot into the heterogeneity of the policy among large filers: the reform's harshest impact fell on the upper half of the tail, whereas the lower quartile - one of the key targets - was not the most adversely affected.

Alternative Fixed Effects Specifications. In the analysis, I use class-fixed effects to control for technology-specific nuisance. In Table D.9, I propose five alternative specifications. Column (1) uses Art Unit fixed effects; Column (2) and (3) account for the unobserved variation in WIPO Fields and Sectors, respectively. Column (4) substitutes IPC with USPC fixed effects, while Column (5) controls for applicant-level attributes. The coefficients on the interaction term range from 0.3590 to 0.3998, showing that the initial estimate is largely unchanged. In Table D.36 through Table D.50, I repeat this exercise for all quality outcomes and obtain similar estimates. Both findings provide compelling evidence that the results are not driven by industry- or applicant-specific characteristics.

Excluding Foreign Applicants. Table D.11 excludes patents filed by foreign applicants (21.13% of the sample). Column (8) suggests that lower fees are associated with a 37.56 percentage point increase in rejections among micro entities. In Table D.54-Table D.56, I perform the same analysis on the quality outcomes. Again, I reach similar conclusions: the interaction term is negative for all measures of patent quality, except for *Radicalness*. This is evidence that dropping foreign applications does not meaningfully affect the magnitude and significance of the initial estimates.

Excluding Top Filing Classes. I follow Hegde et al. (2023) and remove applications from the top five filing classes based on examiners' Art Units[27]. As shown in Table D.12 and Table D.57-Table D.59, point estimates are no more sensitive to this specification. Rather, the coefficients on the interaction term are slightly smaller in every column. This fact provides strong evidence that the original estimates are robust to the exclusion of the main technology codes and to potential macroeconomic trends.

[27]Between 2010 and 2014, the top five classes came from "Mechanical Engineering, Manufacturing and Products" (Art Units 3765, 3754, 3711), "Transportation, Electronic Commerce, Construction, Agriculture, Licensing and Review" (Art Unit 3643), and "Semiconductors, Electrical and Optical Systems and Components" (Art Unit 2875).

Patents of Government Interest. To ensure that federally funded patents were no more likely to be issued[28], I remove all applications funded by the US Government. During our sample period, a total of 23028 applications received federal funding. Of these, the National Institutes of Health (40.26%), the National Science Foundation (14.69%), and the Department of Energy (12.21%) held the leading title in research proceedings. Table D.13, Table D.60, and Table D.62 show very similar results to those reviewed before.

Extended Data. To prove that the impact of lower fees was not transitory, I extend the observation period to the end of 2016. I estimate the regression model using the same dependent variable and controls specified in Table D.1. Consistent with the previous specification, Table D.14 shows that the provision is associated with a 40.05% higher probability of rejection. While larger in magnitude, the coefficient exhibits a significant and persistent effect over time. This evidence points in two directions. First, it rules out that the effect resulted from a post-enforcement adjustment. Second, it demonstrates that the policy deepened the divide it was aiming to close.

Placebo Estimates. To more credibly assess the effect of the policy on micro entities, I run a placebo regression where I assign treatment to large entities. While affected by the transition from a FTI to a FTF system, large entities were not affected by the introduction of a new entity status.

Table D.15 reveals that the results do not change appreciably. All estimates are economically small and statistically insignificant. In particular, the coefficients range between 0.39 and 0.50 percentage points, providing reassurance that large entities were not affected by the introduction of a micro entity status. This test resonates with the previous evidence, showing that only micro entities responded to the change in fees.

Listed Companies and R&D. I use patent data from Kogan et al. (2017) (henceforth, KPSS) to estimate the stock market response to the introduction of lower fees under the AIA. If traded micro entities benefited from the provision, I would anticipate a sharp increase in their stock market valuation on the date of grant. Indeed, as found by Kogan et al. (2017), a favorable trading response at issuance can anticipate higher innovation and technological development among grantees. In Column (1) and Column (2) of Table E.1, results show no impact of the policy on KPSS measures of innovation. Although the analysis has limited power due to a small sample, this evidence show no effect of the policy on R&D

[28] See Babina et al. (2023).

even among micro entities with an established presence.

Taken together, these findings suggest that rejections among micro entities increased substantially post-reform, with marked changes to the quality of applications filed thereafter. This evidence is consistent with Hypothesis II and the literature on patent fees.

8 Scarecrowing or Fencing In?

A natural question is whether the introduction of a micro entity status had a broader impact on the US patent system. In this section, I employ data on continuing applications to show that there are at least two additional mechanisms through which the policy influenced filing patterns, namely *patent scarecrows* and *patent fences*.

Patent continuation enables applicants to submit a second filing for the same invention, adding or subtracting matter from the original claims. If used strategically, continuation can serve to broaden claims, delay prosecution, or adapt to new technologies at a reduced cost. As documented by Lemley (2004), this practice can deter market entrance and limit follow-on innovation[29]. Figure F.1 visualizes the surge in patent continuations filed by micro entities around the passing of the reform. In particular, it suggests that subsequent applications increased by 102.08% in March 2013. Figure F.2 expands on this dimension, showing that the percentage of rejections increased with the enforcement of the provisions.

To obtain a more accurate assessment, I use the following regression model:

$$Cont.Status_{it}^{k} = \alpha + \lambda_i + \mu_t + \beta_1 Ent_i + \beta_2 Ent_i \times Post_t + \gamma' \mathbf{X}_{it} + \delta' \mathbf{Z}_{it} + u_{it} \qquad (4)$$

where $Cont.Status_{it}^{k}$ is the legal status of a continuation application filed by applicant i at time t. As in (1), λ_i and μ_t are class and month fixed effects; $\mathbf{X}_{it}$ and $\mathbf{Z}_{it}$ are vectors of examiners' and attorneys' controls, respectively. Table 4 shows that rejections of continuations filed by micro entities increased on average by 37.82-38.37 percentage points post-reform. Overall, these results offer confirmative evidence that the policy increased the practice of continuation among eligible entities. Consistent with the original filings, the magnitude of the increase suggests that continuing applications did not meet the standard patentability requirements.

[29] See, for example, the extensive literature on patent thickets in the pharmaceutical industry (i.e., Righi and Simcoe 2023; Hall et al. 2020; Ayres and Parchomovsky 2007).

Table 4: Effect of Micro Entity Status on Patent Continuation.

	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	0.3837***	0.3791***	0.3819***	0.3782***
	(0.027)	(0.027)	(0.027)	(0.027)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
Examiner controls	-	-	✓	✓
Attorney controls	-	✓	-	✓
N	82,350	81,496	82,350	81,496
$Adj.R^2$	0.286	0.285	0.292	0.291
Dep. Var. Mean	0.208	0.209	0.208	0.209

Notes: The dependent variable is an indicator for whether a continuation application is granted a patent or not. Non-linear probability estimates produce analogous results. All regressions include attorneys' and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

How to explain this phenomenon? Since the 15% reduction extended to all major patent fees, one channel through which the reform could have affected continuation was by facilitating the filing of *scarecrow patents*. In a discussion of patent pools, Morrow (1945) refers to scarecrows as speculative applications that systematically deter competitors from entering a market. Nowadays, the American Bar Association (ABA) identifies *scarecrows* as strategic applications whose matter can only in part be held valid. Filed to discourage potential infringers, scarecrows contain broad and narrow claims. While their validity hinges on the latter, they could easily be invalidated if the subject matter is fully disclosed during prosecution[30].

An alternative way by which the reform could have affected continuation was by incentivizing *patent fences*. According to Sternitzke (2013), fences expand the patent portfolio by enabling inventors to capitalize on closely substitutable technologies. As a major route to maintain competitive advantage, fencing creates a barrier to entry and increases legal leverage (*ibid.*).

Although neatly separating these channels is not possible with the available data, the findings are consistent with the view that strategic patenting is no longer the sole prerogative of large entities.

[30]See *Hoganas AB v. Dresser Indus., Inc.*, 9 F.3d 948, 950 at n.6 (Fed. Cir. 1993).

9 Conclusion

The introduction of the AIA has been one of the major changes in US patent law since 1952. One of its provisions was the reduction of patent fees for micro entities. Under this policy, the discount for eligible applicants increased from 50% to 75%, effective on March 19, 2013. Although seemingly positive, the evidence on the merits of similar reforms remains limited and contested (De Rassenfosse and Jaffe 2018). Here, I exploit this provision to identify its effect on the status and quality of filed applications.

I find that, following the introduction of lower fees, micro entities were 37.36 percentage points more likely to be rejected. Patterns of rejection are homogeneous across inventors' and attorneys' countries of residence, as well as examiners' gender. While the point estimate is larger for female inventors, it is not statistically distinguishable from zero, and therefore there is no evidence of heterogeneous trends by gender. Overall, results are robust to the exclusion of foreign patents filed under the PCT, classes of top filing, and alternative specifications.

The results further show that, post-reform, micro entities filed patents with narrower scope, family size, and lower citation count. Coupled with a surge in patent continuations, these findings suggest that the reform had a negative effect on patent quality and value.

I close this analysis by noting some limitations. First, the inability to link entities to administrative data means that I cannot assess the consequences of the reform at a finer level. In particular, I do not distinguish all entities based on the number of employees, nor do I differentiate them based on the year of establishment. A second drawback is that the screening of the entity status at the USPTO is based on "good faith". However, if applicants underreported their status (i.e., registered as small while eligible for micro entity status), the estimated effect in Table D.1 would be systematically biased. While data pre-cleaning helps alleviate this concern, I cannot rule out any instance of misreport.

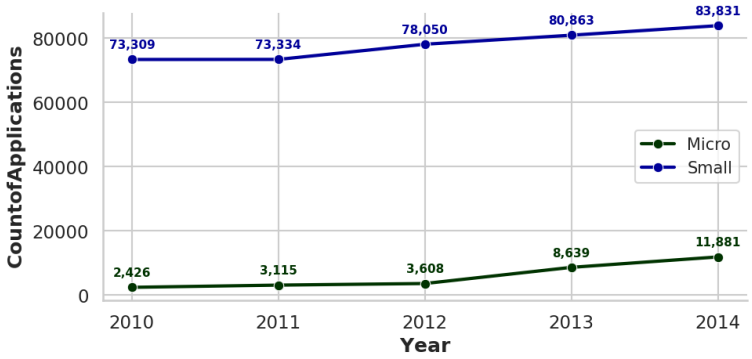
Overall, the central message of this paper is that, while seemingly beneficial to micro applicants, lower fees can be detrimental to patent quality. Although this finding holds for the United States, the discussion can be extended to other Offices, currently considering amendments to statutory fees.

Appendix

A Institutional Background

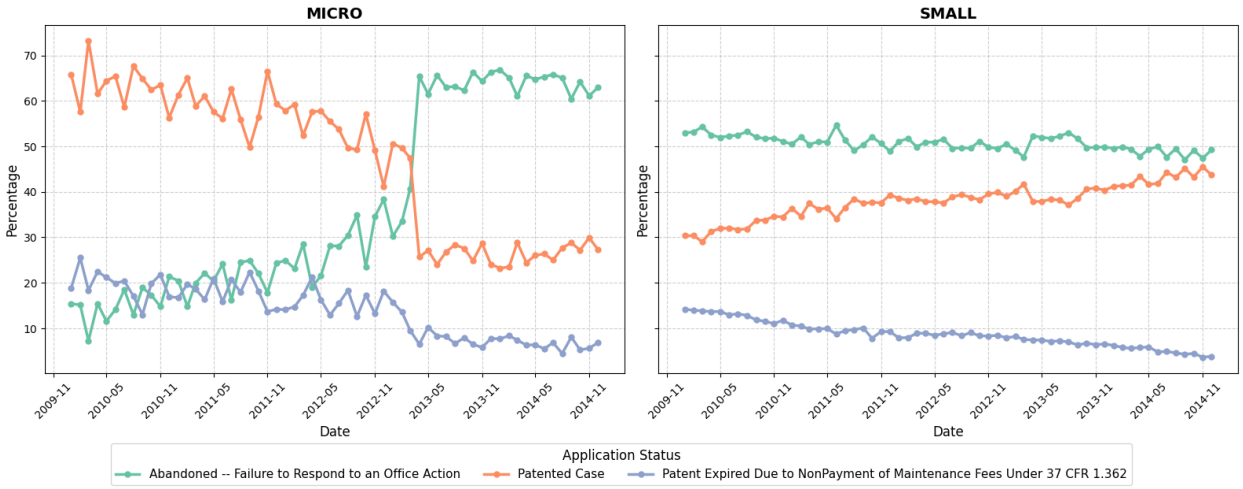
A.1 Patent Count, Status, and Fees

Figure A.1: Count of Patent Applications by Entity Type (2010-2014).



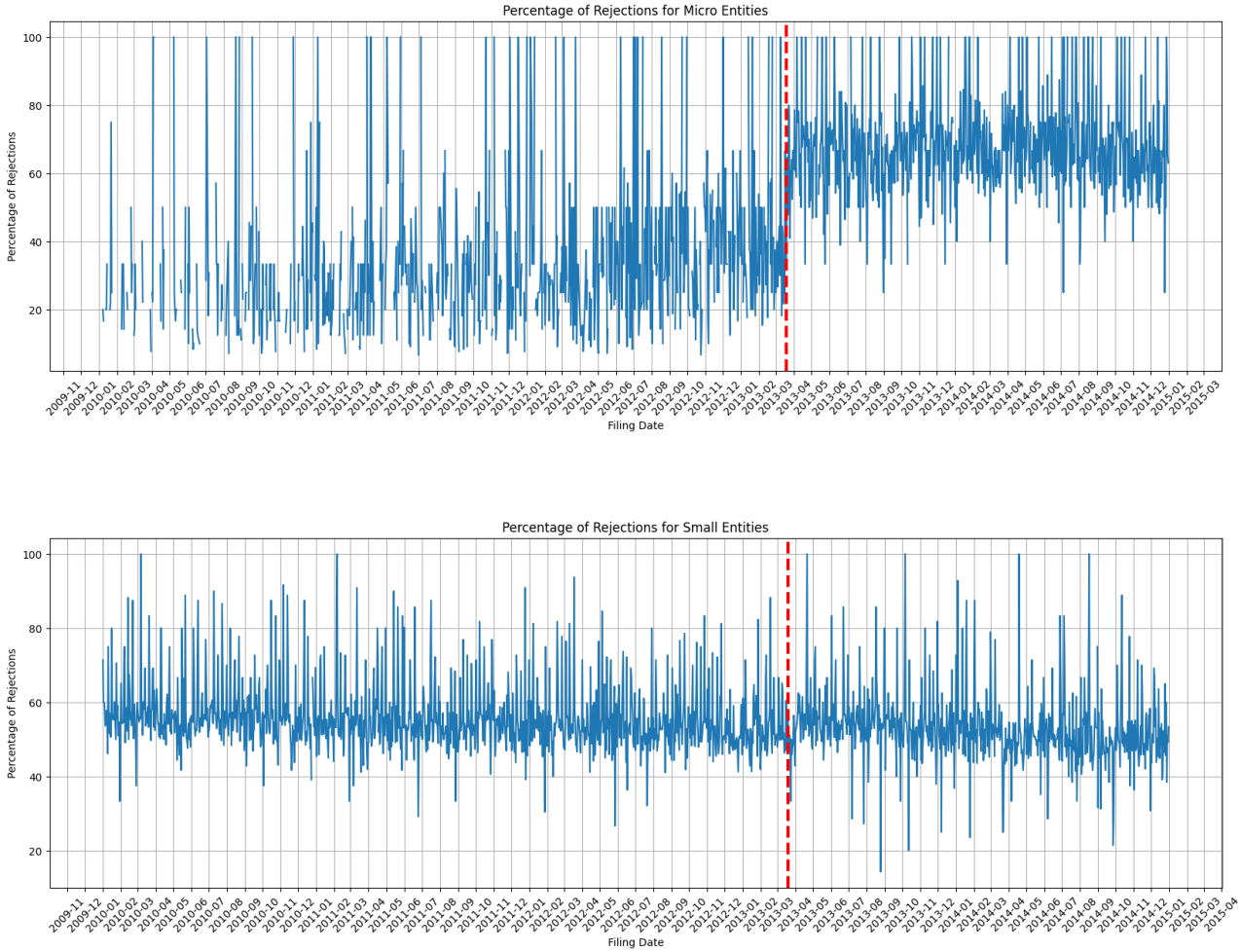
Notes: The figure plots the count of patent applications filed by small and micro entities against the filing year (2010-2014). For treated entities, the number of filings increased the most between 2012 and 2013 (82.2%). While small entities show an ascending trend, they exhibit smaller year-on-year growth throughout the sample period.

Figure A.2: Monthly Patent Status Percentage by Entity Type, 2010-2014.



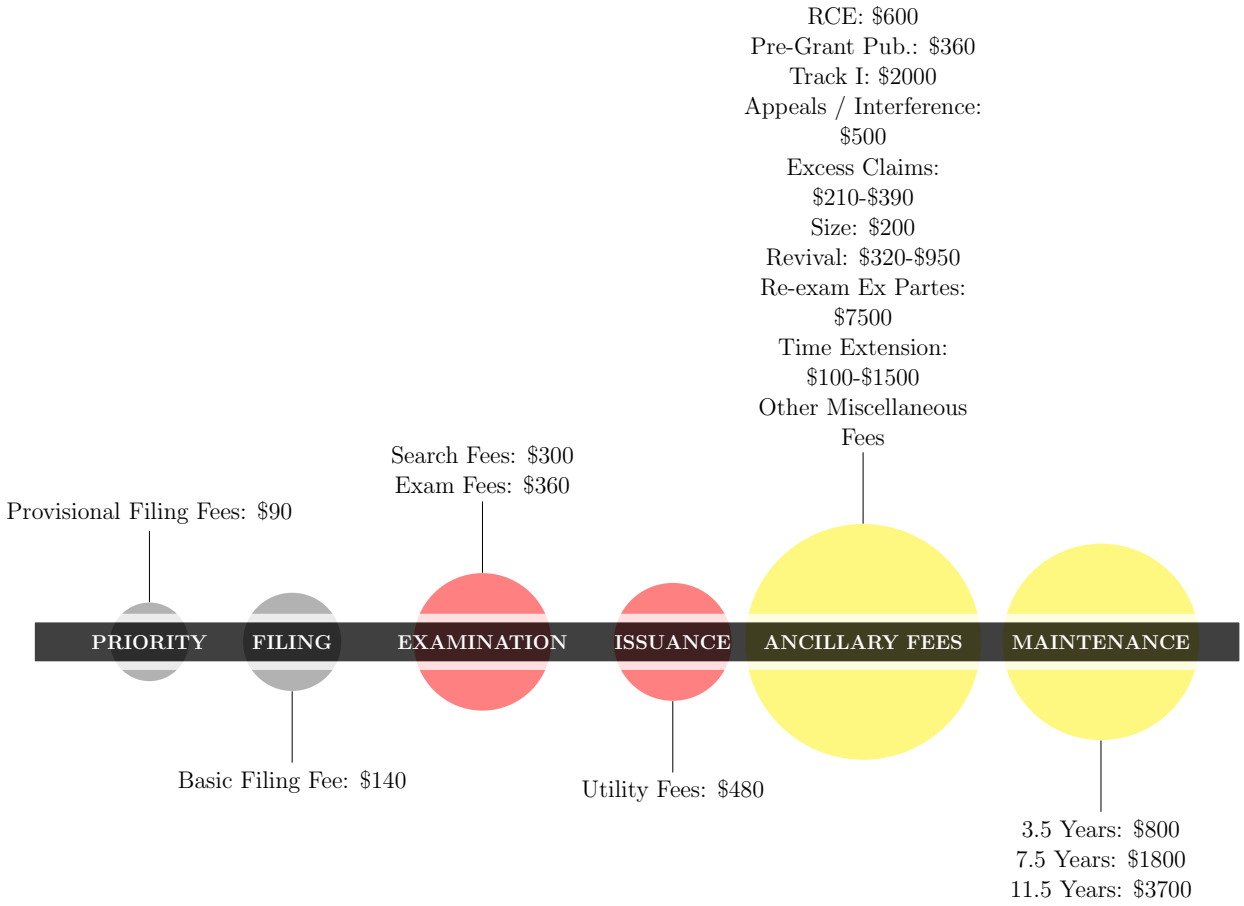
Notes: The panel plots the decision status for new applications filed by small and micro entities against the filing month. Among treated entities, the number of patented cases dropped from around 48% to 27% in March 2013, fluctuating between 25% and 30% thereafter. During the same period, the percentage of abandoned applications due to non-response increased from around 40% to 68% and remained persistently high in the months following the implementation of new fee provisions.

Figure A.3: Percentage of Rejections for New Applications by Filing Date.



Notes: The figures plot the daily percentage of patent rejections for new applications filed by micro and small entities against the filing date. The red vertical line indicates the date of the reform (19 March 2013).

Figure A.4: Statutory Patent Fees for a Small Entity.



Source: Author's Analysis.

Notes: The figure provides a breakdown of the patent prosecution process and the fees paid by small entities in 2013. Post-reform, micro entities were entitled to a 25% reduction in all the fees shown in the diagram.

B Variable Definition

Table B.1: USPTO's Patent Claims Research Dataset.

Variable	**Definition**
Independent Claims	
Avg. Claim. Count	Average number of independent claims at publication
Avg. Word Count	Average number of words contained in independent claims at publication
Min. Avg. Word Count	Minimum number of words contained in independent claims at publication
Word Avg.	Average number of words within each independent claims at publication
Dependent Claims	
Avg. Dep. Claim Count	Average number of dependent claims at publication
Avg. Dep. Word Count	Average number of words contained in dependent claims at publication
Min. Avg. Dep. Word Count	Minimum number of words contained in dependent claims at publication
Dep. Word Avg	Average number of words within each dependent claims at publication

Notes: The table offers a description of the pre-grant quality metrics used in the analysis. Definitions are based on USPTO's Patent Claims Research Dataset (covering activity through 2014). A detailed glossary may be found in the Variable Codebook.

Table B.2: Bibliographic Indicators of Patent Quality (OECD/STI Micro-data Lab).

Variable	**Definition**
Many Fields	Number of technology fields recorded according to the IPC Technology Concordance Table
Patent Scope	Number of distinct 4-digit IPC subclasses at publication
Family Size	Number of filing offices in which the invention has been registered
Backward Citations	Total number of citations made to the prior art (including self-citations)
NPL Citations	Number of citations received by the patent in the non-patent literature
Forward Citations (5y)	Number of citations received by the patent five years after its publication
Forward Citations (7y)	Number of citations received by the patent seven years after its publication
Radicalness	Ratio between the count of all IPC-4 digits codes contained in a backward filing and cited by the patent to the count of its 7-digit IPC codes

Notes: The table offers a description of the post-grant quality metrics used in the analysis. Definitions are based on Squicciarini et al. (2013).

C Data

This section provides a detailed overview of the datasets, addressing some of the limitations.

C.1 Sample Construction and Methodology

Examination Outcome

At the USPTO, decisions on patent status are publicly available through the Patent Examination Research Dataset (*PatEx*). In this article, I follow Suzgun et al. (2022) and include metadata on utility patents from the 2019 update covering applications filed through August 2020. To recover the full text of each patent, data were further merged by the authors using the USPTO Bulk Data Storage System.

In the analysis, I include information on accepted and rejected applications. As in Suzgun et al. (2022), I term *accepted* a patent that has been issued and published by the USPTO. In *PatEx*, this definition maps into the following events: *Mail Notice of Allowance* (MN/=), *Notice of Allowance Data Verification Completed* (N/=), *Application is Considered Ready for Issue* (PILS), *Issue Fee Payment Verified* (N084), *Recordation of Patent Grant Mailed* (PGM/), *Issue Notification Mailed* (WPIR), *Issue Fee Payment Received* (IFEE), and *Application is Considered Ready for Issue* (PILS). I term *rejected* a filing that received a Final or Non-Final Rejection, and was later abandoned by the applicant. Corresponding events are *Non-Final Rejection* (CTNF), *Mail Non-Final Rejection* (MCTNF), *Mail Final Rejection* (MCTFR), and *Final Rejection* (CTFR).

Throughout, I extend this mapping to continuation patents and exclude pending applications from the sample.

Quality Indicators

Pre-grant quality indicators provide textual information about dependent and independent claims. Data are derived from the USPTO's Patent Claims Research Dataset, covering both pre- and post-grant applications for the 2001-2014 period. All indicators are pre-computed by Marco et al. (2019) using natural language processing. In the analysis, I rely on the `document_stats.csv` file to collect information about the pre-prosecution outcomes shown in Table B.1. Here, all counts reflect data available at publication, which occurs 18 months after filing[31].

Post-grant indicators of quality are derived from the OECD/STI Micro Data Lab. They include data from the March 2023 release and only record information about granted appli-

[31] See MPEP § 1120-1121.

cations. As in Squicciarini et al. (2013), all measurements are normalized to enable analysis across time and technology cohorts. Matching this data with the Harvard USPTO Patent Dataset is non-standard and requires access to the `uspto_equiv.txt` file. A description of the matching procedure and concordances are left to the code.

Limitations. A number of caveats accompany this analysis. First, since examiner decisions may be appealed or reverted over time, grants and rejections may resolve on different timelines and influence cohort comparisons. To overcome right-censoring, I include filing metadata from the 2019 update of *PatEx*. On average, applicants wait close to 22 months for an examiner's *First Office Action*, followed by an additional 3-6 months of prosecution. Currently, it takes applicants between 2-3 years before a *Final Office Action* is released[32]. Here, using a recent update of *PatEx* should systematically reduce this source of bias.

Second, some quality metrics mature over a period of years. For example, 2010-2011 patentees had a relatively longer window to accumulate forward citations compared to the 2013-2014 cohorts. While this is practically important, two steps are taken to avoid skewed assessments. To begin, forward citations are normalized by the maximum count of citations for each technology cohort and measured five and seven years after filing. This approach aims to reduce truncation bias, but may not fully eliminate it. Further, a broad range of quality metrics is considered, some of which could only be modified by the applicants or the examiner during prosecution.

Third, quality indicators may provide no indication of patent value. In practice, the inability to link entities with U.S. Census data is a major limitation that prevents further analysis on commercialization outcomes. This is especially important in light of mounting evidence that a small firm's ability to generate patent proceeds is key for its survival and long-term viability.

C.2 Gender Coding

The previous literature has emphasized the gender disparities in the patenting process (e.g. Jensen et al. 2018). As there is no information on gender in public patent corpora, I perform a coding exercise to predict the probable gender at birth of examiners and their legal representatives. As customary, I mostly rely on the WIPO's World Gender Name Dictionary (henceforth, WGDN 2.0). Further, I complement this resource with a list of foreign names and hand-collected data.

[32] Although pendency rates vary substantially across fields, fast-track timelines are possible at an additional fee. This is adjusted yearly to reflect changes in the median household income for the preceding calendar year.

Table C.1: Gender Coding Predictions (WGDN 2.0).

	Examiners	**Attorneys**
Percent female	28.62	7.20
Percent male	65.32	89.91
Percent unknown	6.06	2.89
N	419,056	345,150

Notes: The table reports the percentage of gender matches for examiners and attorneys obtained using the WGDN 2.0 Dictionary. Estimates refer to applications filed with the USPTO by small and micro entities between 2010 and 2014 (including pending and continuation applications).

The WGDN 2.0 is one of the largest records of gender-name pairings, containing more than 25 million names from WIPO's member states. The dictionary helps researchers identify applicants' and representatives' genders based on their main name. The repository distinguishes between *Male*, *Female*, and *Unknown* names. While the first two include highly gendered names, the latter comprises non-binary and infrequent names. After an initial pre-cleaning step, the WGDN 2.0 library may be used by calling function `gender-it` in Python. As shown in Table C.1, the algorithm achieves the highest match with attorneys' names where the share of *Unknown* values is 2.89%. For examiners, the matching is considerably lower, with 6.06% of names left unassigned.

Since the majority of *Unknown* entries comprise Asian-sounding names[33], I complement the WGDN 2.0 Dictionary with the CJKI's Comprehensive Database of Chinese Personal Names. The repository contains the original character and romanized version of more than 4 million Chinese names and associated gender at birth[34]. Overall, this exercise does not meaningfully increase the percent of matches, providing reassurance that unassigned names are not the result of missing entries.

[33]This should strike a note of caution for other researchers who plan to use the WGDN 2.0 for gender assignment. While the WIPO argues that the number of Chinese and Korean names recently added is substantial, there is still a need to integrate this source with outside corpora.

[34]The CJKI's Database includes both Mandarin and Cantonese names.

C.3 Data Summary

Table C.2: Summary Statistics for US Patenting (Full Sample, 2010-2014).

	Micro	Small	All U.S.
Total count	29669	389387	1706106
Percent accepted	37.50	31.55	42.45
Percent rejected	39.52	34.92	23.81
Percent pending	8.67	6.10	8.21
Percent cont-accepted	7.61	14.04	15.91
Percent cont-rejected	4.84	10.52	6.43
Percent cont-pending	1.86	2.83	3.81

Notes: Estimates summarize information about all utility patents filed with the USPTO between 2010 and 2014. Pending and continuation patents are included in the count.

Table C.3: Summary Statistics - Utility Patents, 2010-2014.

	Small Entity		Micro Entity	
	Mean	Std. Dev.	Mean	Std. Dev.
Patent level:	#237900		#16891	
Legal Status	0.36	(0.64)	0.27	(0.65)
Claim level:	#226641		#14838	
Independent Claim Count	2.61	(2.01)	2.45	(1.69)
Independent Word Count	313.50	(313.44)	316.83	(279.46)
Independent Word Minimum	106.95	(96.06)	114.73	(109.77)
Independent Word Average	128.77	(100.39)	138.92	(114.45)
Dependent Claim Count	16.62	(11.21)	14.50	(8.69)
Dependent Word Count	618.89	(564.71)	571.70	(566.05)
Dependent Word Minimum	18.41	(19.79)	21.08	(54.09)
Dependent Word Average	39.16	(31.03)	42.79	(61.70)
Quality level:	#99191		#7528	
Many Fields	0.34	(0.47)	0.35	(0.48)
Scope	1.70	(1.06)	1.69	(1.05)
Family Size	2.97	(3.38)	2.86	(3.33)
Backward Citations	15.95	(40.47)	16.22	(31.75)
NPL Citations	3.21	(13.99)	3.21	(12.61)
Forward Cites (5Y)	11.00	(46.46)	10.80	(49.52)
Forward Cites (7Y)	15.32	(61.42)	14.41	(62.69)
Radicalness	0.46	(0.30)	0.45	(0.29)

Notes: The table reports the data summary of key variables of interest for utility patents filed at the USPTO between 2010 and 2014. Standard deviations are reported in parentheses. Estimates exclude pending, re-issuance, and continuation applications.

Table C.4: Propensity Score Matching Balance Test for Patent Level Data, 2010-2014.

	Unmatched			Matched		
	Micro	Small	Δ	Micro	Small	Δ
	(1)	(2)	(3)	(4)	(5)	(6)
Inventor						
Gender	0.271	0.275	-0.002	0.268	0.275	-0.007
			(0.003)			(0.002)
Country	0.128	0.343	-0.199	0.327	0.329	-0.002
			(0.003)			(0.002)
Invention Count	0.573	0.796	-0.219	0.789	0.782	0.007
			(0.003)			(0.002)
Attorney						
Predicted Gender	0.196	0.132	0.064	0.174	0.137	0.037
			(0.003)			(0.002)
Practice	0.125	0.096	0.029	0.134	0.098	0.036
			(0.002)			(0.001)
Sanctioned	0.031	0.008	0.014	0.009	0.010	-0.001
			(0.001)			(0.000)
Examiner						
Predicted Gender	0.384	0.407	-0.022	0.404	0.405	-0.002
			(0.004)			(0.002)
Experience Level	0.437	0.514	-0.087	0.511	0.509	0.002
			(0.003)			(0.002)
Observations		#308147			#254791	

Notes: Columns (1) and (2) report the unmatched means for each regressor. Columns (4)-(5) display the inverse probability–weighted means, where treated and control observations receive weights of $1/p_i$ and $1/(1-p_i)$. Columns (3) and (6) shows the difference between reweighted treatment and control entities, with standard errors reported in parentheses.

Table C.5: Propensity Score Matching Balance Test for Claim Level Data, 2010-2014.

	Unmatched			Matched		
	Micro	Small	Δ	Micro	Small	Δ
	(1)	(2)	(3)	(4)	(5)	(6)
Inventor						
Gender	0.267	0.276	-0.008	0.267	0.276	-0.008
			(0.004)			(0.002)
Country	0.132	0.347	-0.199	0.328	0.334	-0.006
			(0.003)			(0.002)
Invention Count	0.584	0.802	-0.214	0.795	0.788	0.006
			(0.003)			(0.002)
Attorney						
Predicted Gender	0.197	0.131	0.066	0.171	0.136	0.036
			(0.004)			(0.002)
Practice	0.126	0.095	0.032	0.132	0.097	0.035
			(0.003)			(0.001)
Sanctioned	0.029	0.008	0.012	0.009	0.009	0.000
			(0.001)			(0.000)
Examiner						
Predicted Gender	0.381	0.409	-0.027	0.404	0.407	-0.003
			(0.004)			(0.003)
Experience Level	0.451	0.520	-0.080	0.518	0.516	0.002
			(0.004)			(0.002)
Observations		#290821			#241479	

Notes: Columns (1) and (2) report the unmatched means for each regressor. Columns (4)-(5) display the inverse probability–weighted means, where treated and control observations receive weights of $1/p_i$ and $1/(1-p_i)$. Columns (3) and (6) shows the difference between reweighted treatment and control entities, with standard errors reported in parentheses.

Table C.6: Propensity Score Matching Balance Test for Patent Quality Data, 2010-2014.

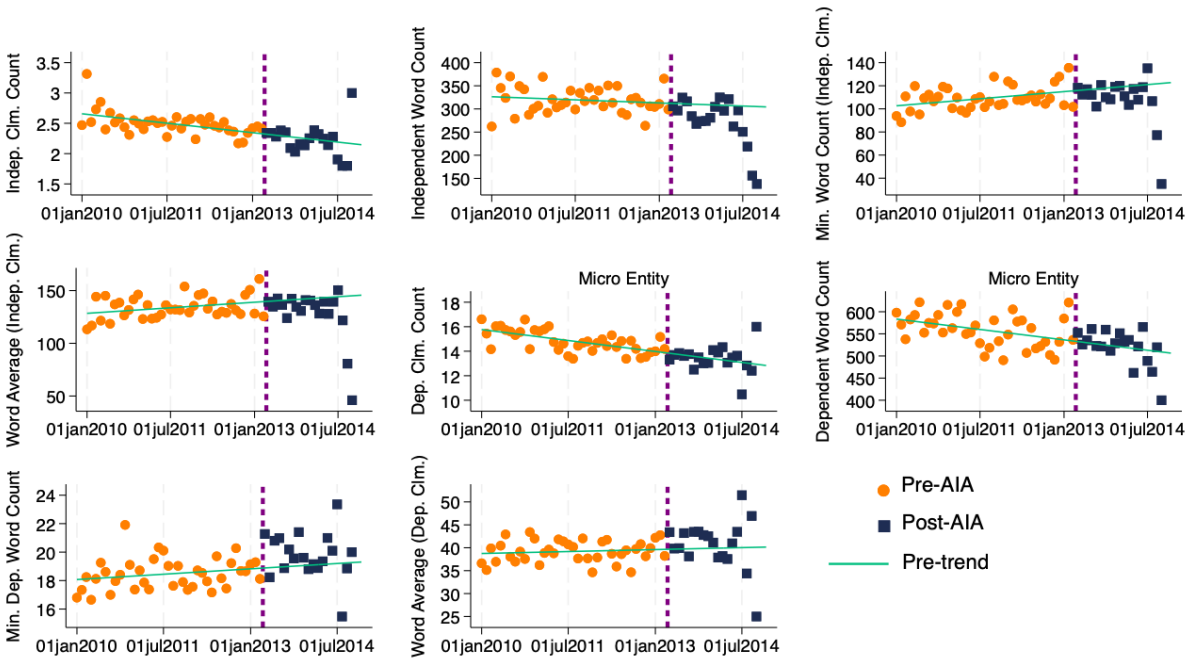
	Unmatched			Matched		
	Micro	Small	Δ	Micro	Small	Δ
	(1)	(2)	(3)	(4)	(5)	(6)
Inventor						
Gender	0.281	0.273	0.011	0.266	0.273	-0.008
			(0.005)			(0.004)
Country	0.108	0.296	-0.167	0.279	0.282	-0.003
			(0.004)			(0.003)
Invention Count	0.553	0.780	-0.220	0.764	0.768	0.004
			(0.004)			(0.003)
Attorney						
Predicted Gender	0.200	0.138	0.062	0.174	0.143	0.032
			(0.005)			(0.003)
Practice	0.101	0.118	0.016	0.136	0.103	0.033
			(0.004)			(0.002)
Sanctioned	0.035	0.009	0.015	0.011	0.011	0.000
			(0.001)			(0.000)
Examiner						
Predicted Gender	0.394	0.406	-0.022	0.398	0.405	-0.007
			(0.004)			(0.004)
Experience Level	0.439	0.532	-0.007	0.524	0.525	-0.001
			(0.005)			(0.003)
Observations		#137444			#106719	

Notes: Columns (1) and (2) report the unmatched means for each regressor. Columns (4)-(5) display the inverse probability–weighted means, where treated and control observations receive weights of $1/p_i$ and $1/(1-p_i)$. Columns (3) and (6) shows the difference between reweighted treatment and control entities, with standard errors reported in parentheses.

C.4 Graphical Analysis (Micro Entities)

Claim-Level Data

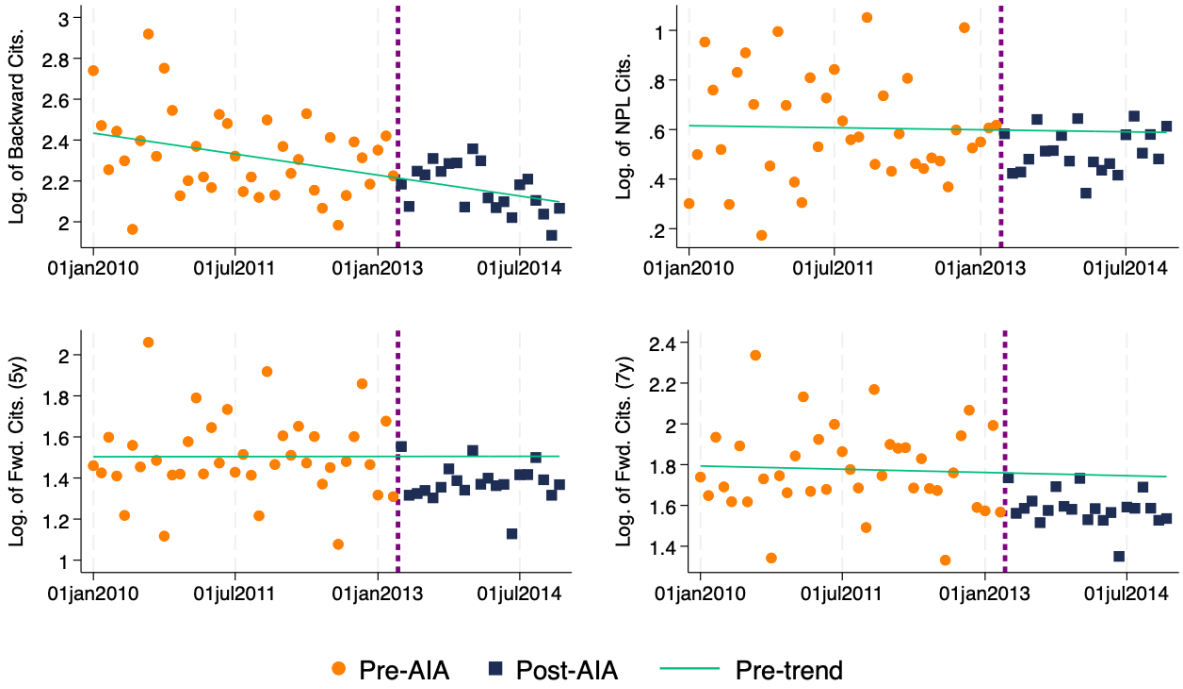
Figure C.1: Pre-Grant Claim-Level Analysis (Micro Entities, 2010-2014).



Notes: The panel plots the monthly average number of dependent claims, the monthly total, average, and minimum average word count among independent claims for new applications filed by micro entities with the USPTO from January 2010 to December 2014 (excluding pending and continuation patents). The purple dotted line indicates the AIA's enactment date (19 March 2013).

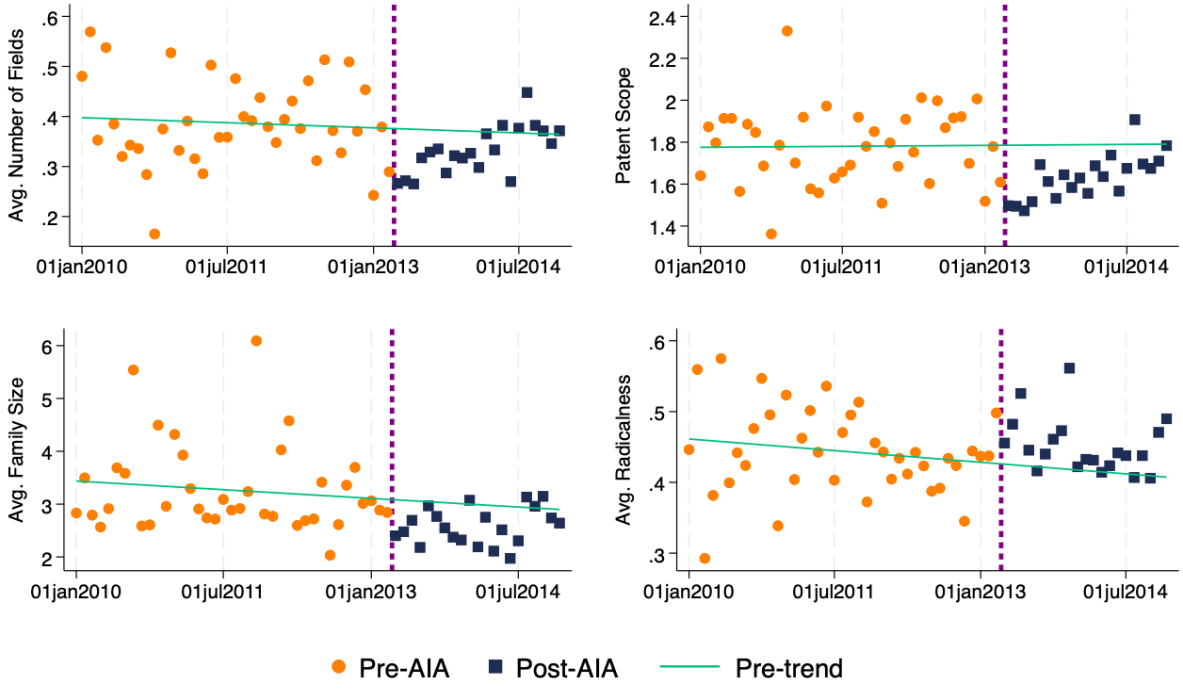
Other Bibliographic Indicators

Figure C.2: Citation Metrics (Micro Entities, OECD / PatStat).



Notes: The panel plots the monthly logarithm of backward citations, citations to the non-patent literature, forward citations five and seven years after filing. Data refer to applications sent by micro entities to the USPTO between January 2010 and December 2014 (excluding pending and continuation patents). The purple dotted line indicates the AIA's enactment date (19 March 2013).

Figure C.3: Other Quality Metrics (Micro Entities, OECD / PatStat).

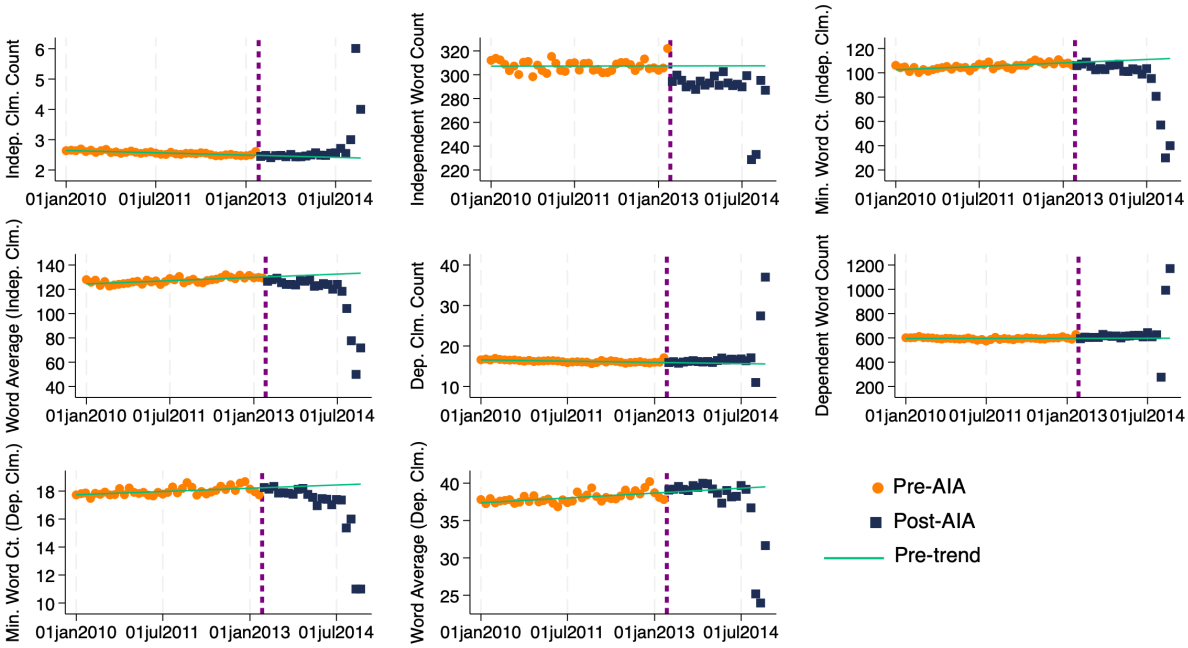


Notes: The panel plots the monthly number of fields, scope, family size, and radicalness for new applications filed by micro entities at the USPTO between January 2010 to December 2014 (excluding pending and continuation patents). The purple dotted line indicates the AIA's enactment date (19 March 2013).

C.5 Graphical Analysis (Small Entities)

Claim-Level Data

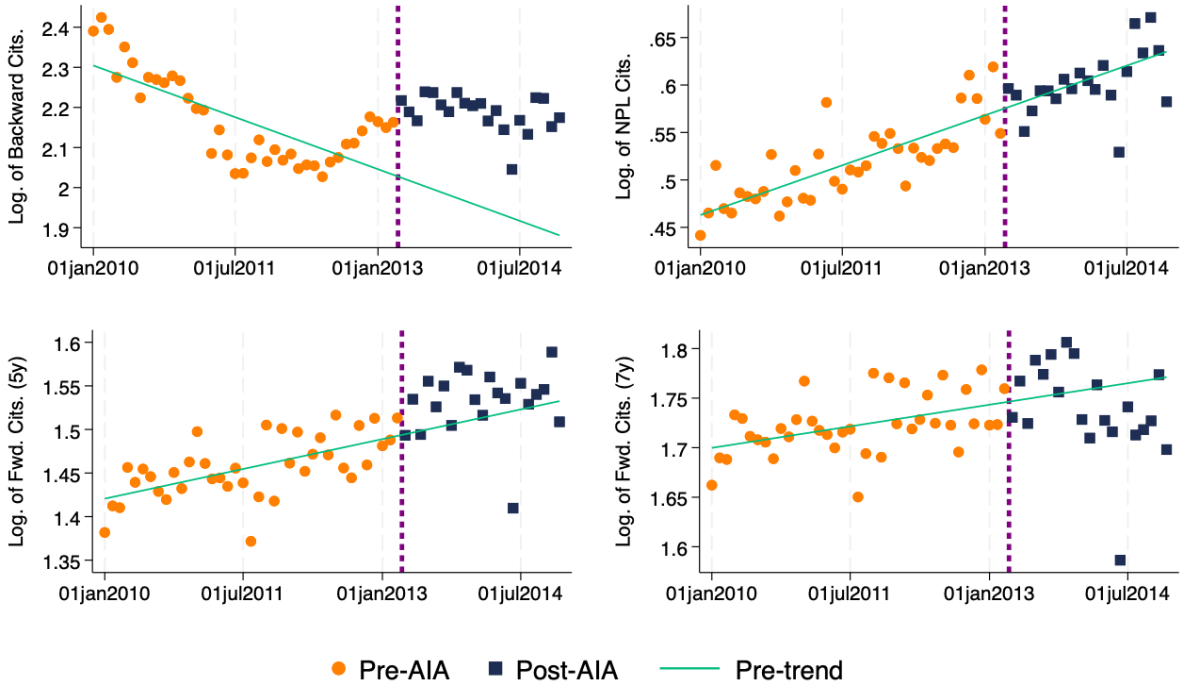
Figure C.4: Pre-Grant Claim-Level Analysis (Small Entities, 2010-2014).



Notes: The panel plots the monthly average number of dependent claims, the monthly total, average, and minimum average word count among independent claims for new applications filed by small entities with the USPTO from January 2010 to December 2014 (excluding pending and continuation patents). The purple dotted line indicates the AIA's enactment date (19 March 2013).

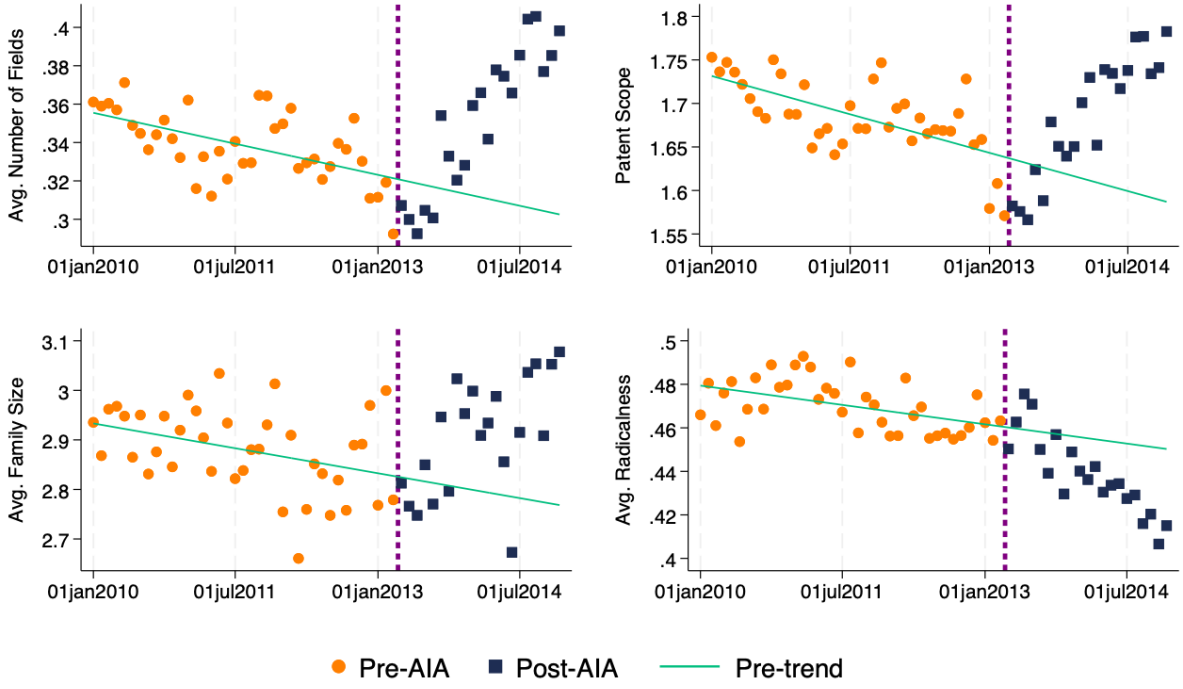
Other Bibliographic Indicators

Figure C.5: Citation Metrics (Small Entities, OECD / PatStat).



Notes: The panel plots the monthly logarithm of backward citations, citations to the non-patent literature, forward citations five and seven years after filing. Data refer to applications sent by small entities to the USPTO between January 2010 and December 2014 (excluding pending and continuation patents). The purple dotted line indicates the AIA's enactment date (19 March 2013).

Figure C.6: Other Quality Metrics (Small Entities, OECD / PatStat).



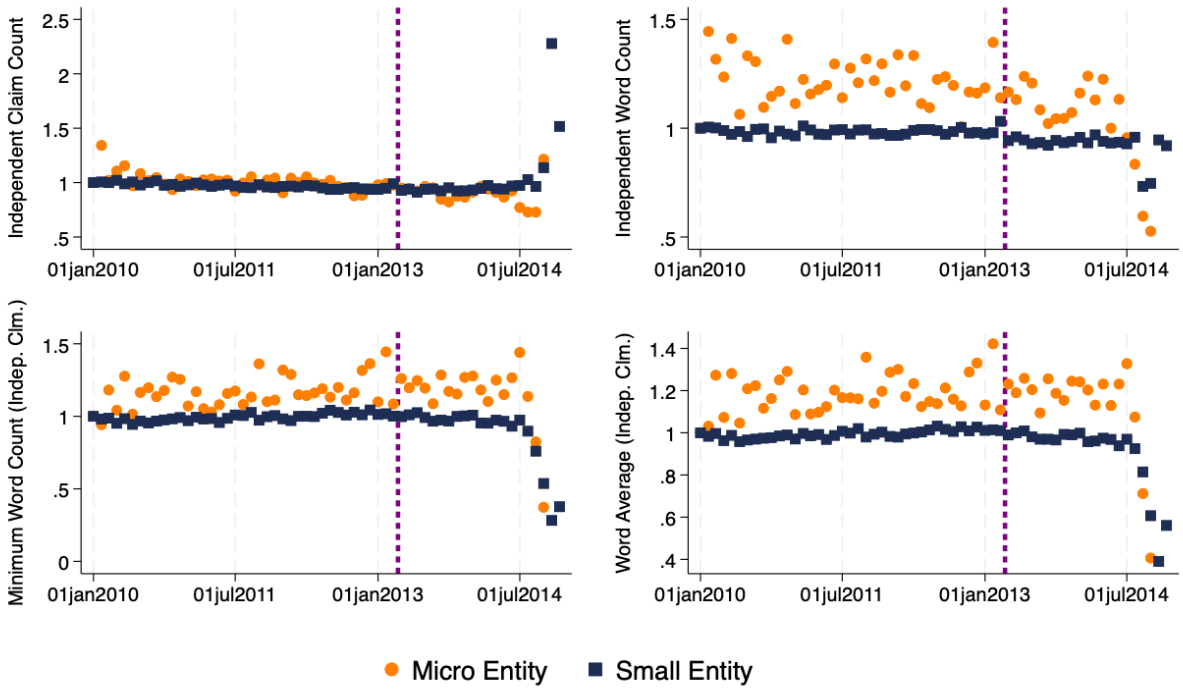
Notes: The panel plots the monthly number of fields, scope, family size, and radicalness for new applications filed by small entities at the USPTO between January 2010 to December 2014 (excluding pending and continuation patents). The purple dotted line indicates the AIA's enactment date (19 March 2013).

D Additional Evidence

D.1 Figures

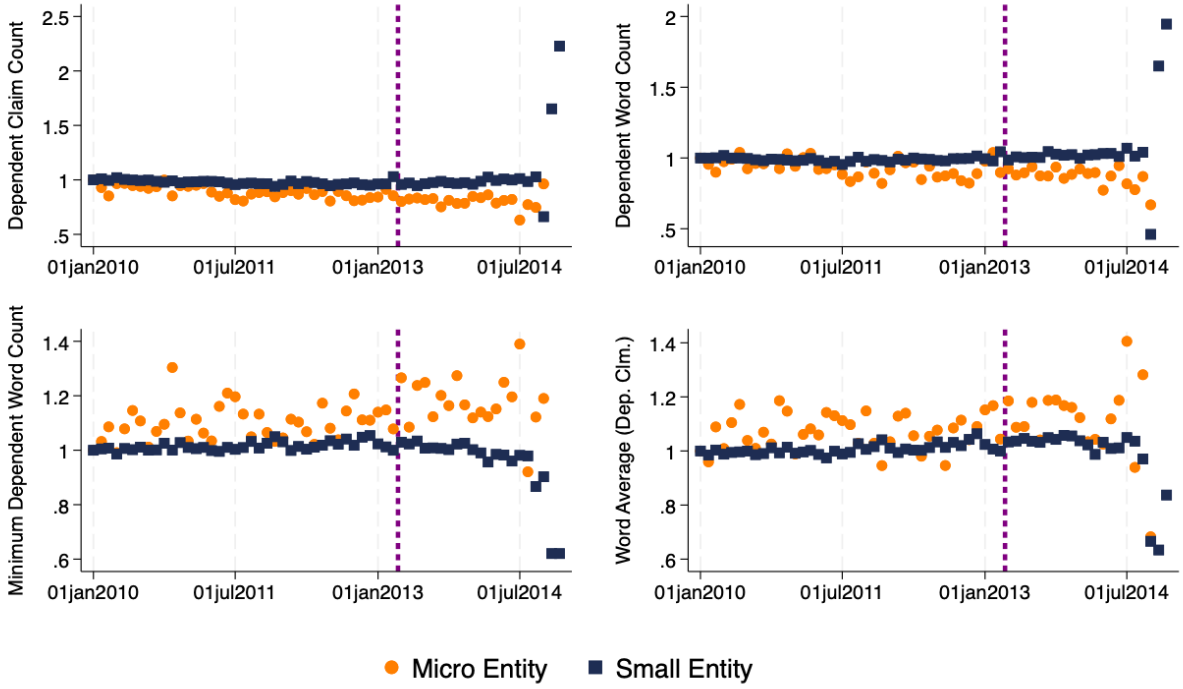
Claim-Level Data

Figure D.1: Independent Claims before and after the AIA (USPTO, 2010-2014).



Notes: The panels present an analysis of pre-grant independent claims for new applications filed by small and micro entities with the USPTO from January 2010 to December 2014 (excluding pending and continuation patents). The purple line indicates the date of implementation (19 March 2013).

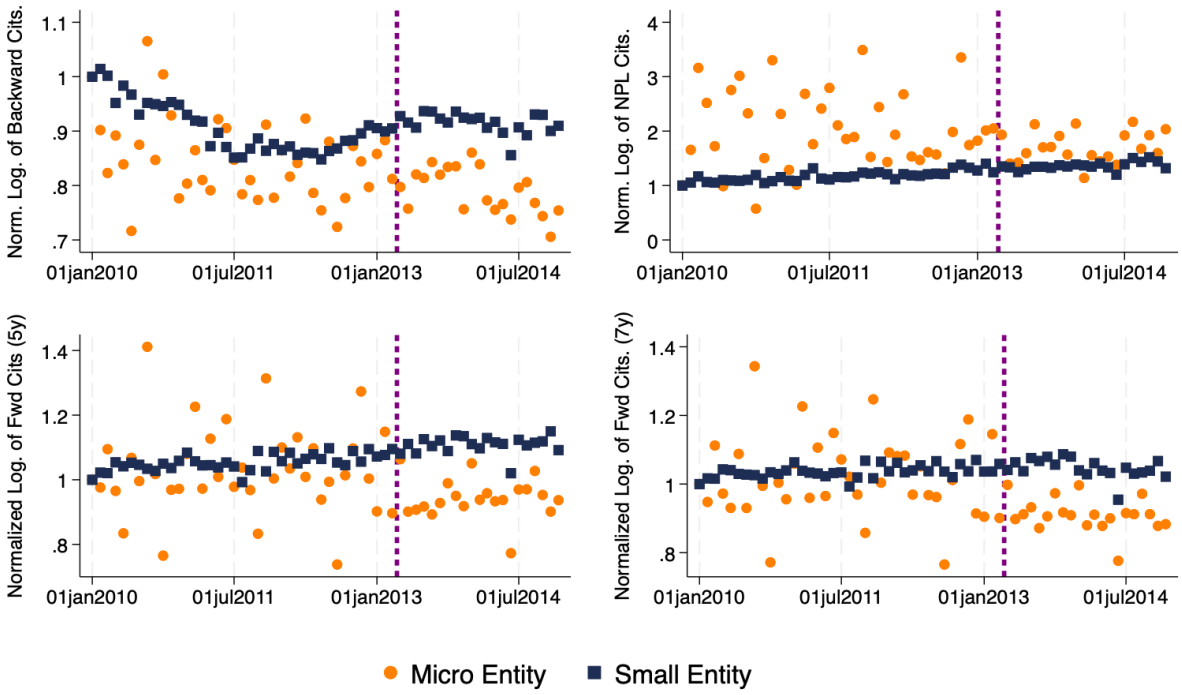
Figure D.2: Dependent Claims before and after the AIA (USPTO, 2010-2014).



Notes: The panels present an analysis of pre-grant dependent claims for new applications filed by small and micro entities with the USPTO from January 2010 to December 2014 (excluding pending and continuation patents). The purple line indicates the date of implementation (19 March 2013).

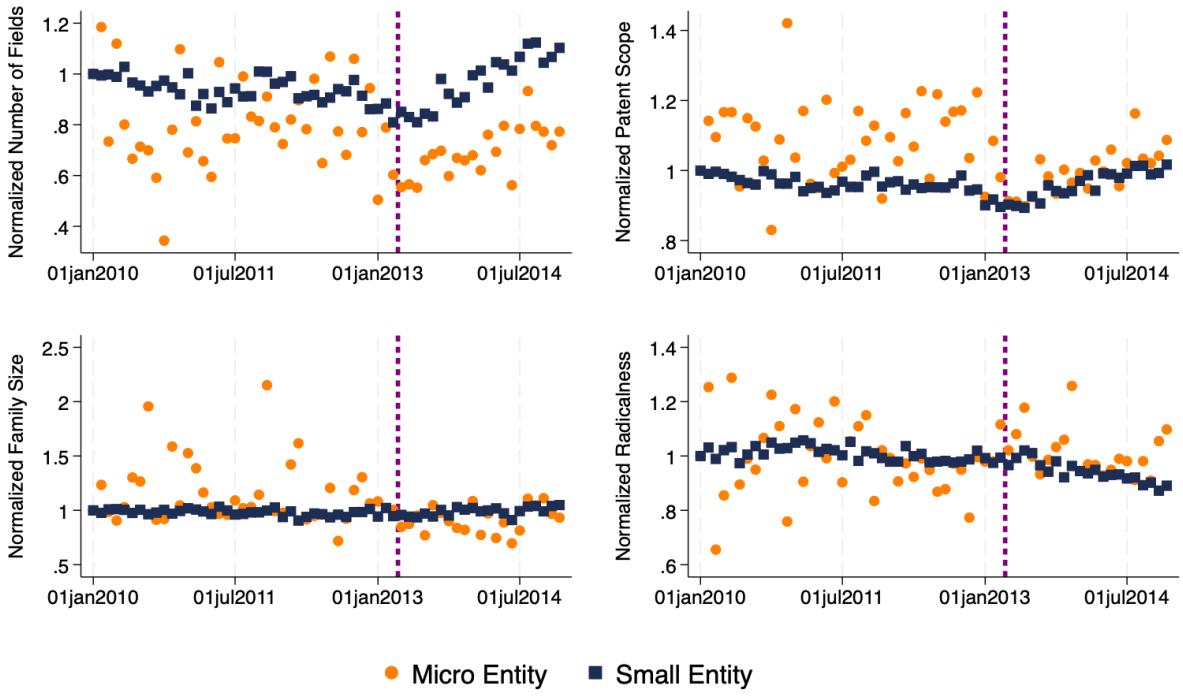
OECD Indicators

Figure D.3: Citation Metrics before and after the AIA (OECD / PatStat, 2010-2014).



Notes: The panels presents an overview of OECD citation metrics for new applications filed by small and micro entities with the USPTO from January 2010 to December 2014 (excluding pending and continuation patents). The purple line indicates the date of implementation (19 March 2013).

Figure D.4: Other Quality Indicators before and after the AIA (OECD/ PatStat, 2010-2014).



Notes: The panels present an analysis of OECD quality indicators for new applications filed by small and micro entities with the USPTO from January 2010 to December 2014 (excluding pending and continuation patents). The two grey lines indicate the date in which the rule was first proposed (30 May 2012) and the date in which the final rule was published (19 December 2012); the black line indicates the date of implementation (19 March 2013).

D.2 Tables

Table D.1: Linear Probability Estimates for U.S. Patent Application Outcome, 2010-2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	0.3886***	0.3819***	0.3821***	0.3862***	0.3796***	0.3761***	0.3794***	0.3736***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	244,464	244,068	241,263	244,464	241,263	240,871	244,068	240,871
$Adj.R^2$	0.211	0.218	0.213	0.215	0.217	0.220	0.223	0.224
Dep. Var. Mean	0.319	0.318	0.318	0.319	0.318	0.317	0.318	0.317

Notes: The dependent variable is an indicator for whether a newly filed application is granted a patent or not. Non-linear probability estimates produce analogous results. Inventors' controls include country of residence and probable gender at birth. Examiners' controls include years of employment at the USPTO and probable gender at birth. Attorneys' controls include type of registration, country of practice, and probable gender at birth. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Legal Status: Heterogeneity Analysis

Table D.2: Heterogeneous Effects of AIA - Inventor Gender.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times Gender_i$								
$Female_i$	0.0413	0.0405	0.0445	0.0417	0.0454	0.0436	0.0408	0.0443
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
$Unknown_i$	0.0531	0.0522	0.0505	0.0550	0.0515	0.0462	0.0541	0.0473
	(0.058)	(0.058)	(0.059)	(0.058)	(0.059)	(0.059)	(0.058)	(0.059)
$Ent_i \times Post_t$	0.3790***	0.3731***	0.3724***	0.3764***	0.3698***	0.3673***	0.3704***	0.3647***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	244,464	244,068	241,263	244,464	241,263	240,871	244,068	240,871
$Adj.R^2$	0.211	0.219	0.213	0.215	0.217	0.220	0.223	0.224
Dep. Var. Mean	0.319	0.318	0.318	0.319	0.318	0.317	0.318	0.317

Notes: The table reports the heterogenous effects of AIA on the legal status by inventor gender. Using the assignment mechanism described in PatentsView, I code gender as 0 if male, 1 if female, and 2 if unknown. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.3: Heterogeneous Effects of AIA - Inventor Ethnicity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times Ethnicity_i$								
$Asian_i$	-0.0684	-0.0716	-0.0733	-0.0744*	-0.0795*	-0.0784*	-0.0773*	-0.0843*
	(0.044)	(0.044)	(0.045)	(0.044)	(0.045)	(0.045)	(0.044)	(0.044)
$Hispanic_i$	-0.0007	-0.0005	-0.0101	0.0005	-0.0084	-0.0084	0.0003	-0.0069
	(0.056)	(0.057)	(0.057)	(0.056)	(0.057)	(0.057)	(0.057)	(0.057)
$NH\ Black_i$	0.0124	0.0062	0.0298	0.0194	0.0360	0.0248	0.0132	0.0310
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.068)	(0.067)	(0.068)
$Ent_i \times Post_t$	0.3949***	0.3927***	0.3893***	0.3931***	0.3876***	0.3878***	0.3908***	0.3860***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	147,729	147,471	145,976	147,729	145,976	145,725	147,471	145,725
$Adj.R^2$	0.235	0.245	0.236	0.239	0.240	0.246	0.249	0.250
Dep. Var. Mean	0.323	0.323	0.323	0.323	0.323	0.322	0.323	0.322

Notes: The table reports the heterogeneous effects of AIA on the legal status by inventor ethnicity. Here, the reference category is *Non Hispanic White* (*NH-White*). Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%, ***1%.

Table D.4: Heterogeneous Effects of AIA - Inventor Country.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times US_i$	-0.0075	-0.0073	-0.0123	-0.0088	-0.0139	-0.0132	-0.0087	-0.0148
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
$Ent_i \times Post_t$	0.3935***	0.3898***	0.3885***	0.3913***	0.3864***	0.3850***	0.3876***	0.3829***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	244,464	244,464	241,263	244,464	241,263	241,263	244,464	241,263
$Adj.R^2$	0.211	0.214	0.213	0.215	0.217	0.216	0.218	0.220
Dep. Var. Mean	0.319	0.319	0.318	0.319	0.318	0.318	0.319	0.318

Notes: The table reports the heterogeneous effects of AIA on the legal status by inventor country of residence. I code variable US_i as 0 if the inventor's last known address is in the United States or code it as 1 if foreign. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.5: Heterogeneous Effects of AIA - Attorney Gender.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times AttGen_i$								
$Female_i$	0.0163	0.0036	0.0226	0.0174	0.0230	0.0103	0.0045	0.0104
	(0.046)	(0.046)	(0.047)	(0.046)	(0.046)	(0.046)	(0.045)	(0.046)
$Unknown_i$	0.0901	0.0855	0.0804	0.0918	0.0828	0.0833	0.0874	0.0860
	(0.060)	(0.059)	(0.062)	(0.059)	(0.061)	(0.061)	(0.059)	(0.060)
$Ent_i \times Post_t$	0.3821***	0.3772***	0.3770***	0.3795***	0.3745***	0.3717***	0.3745***	0.3691***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	244,464	244,068	241,263	244,464	241,263	240,871	244,068	240,871
$Adj.R^2$	0.211	0.219	0.213	0.216	0.217	0.220	0.223	0.224
Dep. Var. Mean	0.319	0.318	0.318	0.319	0.318	0.317	0.318	0.317

Notes: The table reports the heterogeneous effects of AIA on the legal status by attorney gender. After using the assignment mechanism described in the *Appendix*, I code gender as 0 if male, 1 if female, and 2 if unknown. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.6: Heterogeneous Effects of AIA - Practitioners' License Type.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times Practice_i$	0.0201	0.0261	0.0050	0.0201	0.0050	0.0145	0.0262	0.0145
	(0.038)	(0.038)	(0.039)	(0.038)	(0.039)	(0.039)	(0.038)	(0.039)
$Ent_i \times Post_t$	0.3864***	0.3793***	0.3820***	0.3840***	0.3797***	0.3747***	0.3768***	0.3723***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	244,464	244,068	241,263	244,464	241,263	240,817	244,068	240,871
$Adj.R^2$	0.211	0.219	0.213	0.215	0.217	0.220	0.223	0.224
Dep. Var. Mean	0.319	0.318	0.318	0.319	0.318	0.317	0.318	0.317

Notes: The table reports the heterogeneous effects of AIA on the legal status by attorney license type. I code variable $Practice_i$ as 0 if the counsel is registered as attorney or code it as 1 if registered as an agent. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.7: Heterogeneous Effects of AIA - Examiner Gender.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times ExamGen_i$								
$Female_i$	0.0170	0.0220	0.0141	0.0165	0.0137	0.0201	0.0214	0.0196
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
$Unknown_i$	-0.0000	-0.0046	0.0005	0.0033	0.0032	-0.0029	-0.0010	0.0001
	(0.060)	(0.060)	(0.061)	(0.060)	(0.061)	(0.060)	(0.060)	(0.060)
$Ent_i \times Post_t$	0.3832***	0.3754***	0.3775***	0.3809***	0.3753***	0.3700***	0.3731***	0.3677***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	244,464	244,068	241,263	244,464	241,263	240,871	244,068	240,871
$Adj.R^2$	0.211	0.219	0.213	0.215	0.217	0.220	0.223	0.224
Dep. Var. Mean	0.319	0.318	0.318	0.319	0.318	0.317	0.318	0.317

Notes: The table reports the heterogeneous effects of AIA on the legal status by examiner gender. After using the assignment mechanism described in the *Appendix*, I code gender as 0 if male, 1 if female, and 2 if unknown. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.8: Heterogeneous Effects of AIA - WIPO Sectors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times WIPO\ Sector_i$								
$Chemistry_i$	-0.0578	-0.0490	-0.0645	-0.0590	-0.0655	-0.0533	-0.0503	-0.0563
	(0.044)	(0.043)	(0.044)	(0.044)	(0.044)	(0.044)	(0.043)	(0.044)
$Instruments_i$	-0.0220	-0.0258	-0.0218	-0.0248	-0.0241	-0.0252	-0.0287	-0.0276
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
$Mechanical\ Engineering_i$	0.0089	0.0129	0.0043	0.0043	-0.0001	0.0074	0.0083	0.0032
	(0.037)	(0.036)	(0.037)	(0.037)	(0.037)	(0.036)	(0.036)	(0.036)
$Other\ Fields_i$	0.1093***	0.1137***	0.1060***	0.1025***	0.0996***	0.1089***	0.1068***	0.1025***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
$Ent_i \times Post_t$	0.3785***	0.3687***	0.3751***	0.3799***	0.3762***	0.3662***	0.3700***	0.3673***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	243,472	243,078	240,292	243,472	240,292	239,902	243,078	239,902
$Adj.R^2$	0.212	0.220	0.214	0.217	0.218	0.222	0.224	0.226
Dep. Var. Mean	0.319	0.318	0.318	0.319	0.318	0.317	0.318	0.317

Notes: The table reports the heterogeneous effects of AIA on the legal status by WIPO Sector. Here, the reference category is *Chemistry*. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Legal Status - Robustness

Table D.9: Alternative Controls and Fixed Effects Specifications.

	Art Unit	WIPO Field	WIPO Sector	USPC	Applicant
	(1)	(2)	(3)	(4)	(5)
$Ent_i \times Post_t$	0.3639***	0.3882***	0.3998***	0.3757***	0.3797***
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)
Month FE	✓	✓	✓	✓	✓
Inventor controls	✓	✓	✓	✓	-
Examiner controls	✓	✓	✓	✓	✓
Attorney controls	✓	✓	✓	✓	✓
Applicant controls	-	-	-	-	✓
N	227,524	250,253	250,253	251,209	241,263
$Adj.R^2$	0.229	0.077	0.055	0.107	0.217
Dep. Var. Mean	0.313	0.313	0.313	0.313	0.318

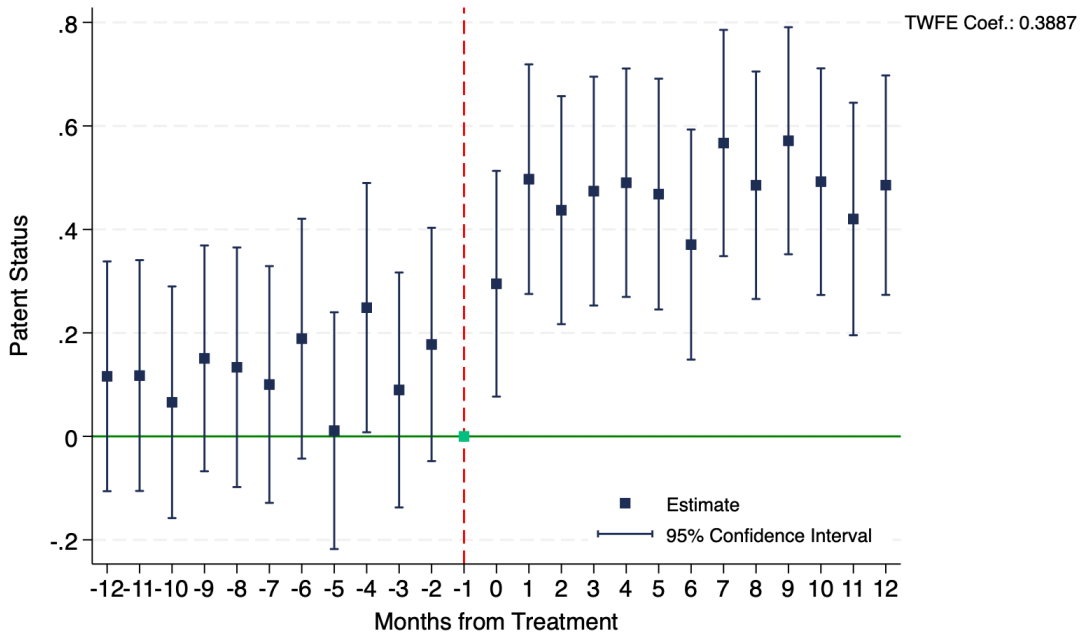
Notes: The dependent variable is an indicator for whether a new application is granted a patent or not. Column (1) reports estimates with USPTO's Art Unit fixed effects. Column (2) uses WIPO Field fixed effects; WIPO Fields include 35 categories ranging from "Analysis of Biological Materials" to "Transport". Column (3) presents estimates using WIPO Sector fixed effects, including "Chemistry", "Electrical Engineering", "Instruments", "Mechanical Engineering", and "Other Fields". Column (4) substitutes the IPC fixed effects with United States Patent Classification (USPC) codes. Column (5) uses applicant controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.10: Drop University Patents.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	0.4036***	0.3978***	0.3962***	0.4009***	0.3937***	0.3913***	0.3951***	0.3887***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	213,924	213,537	211,087	213,924	211,087	210,704	213,537	210,704
$Adj.R^2$	0.212	0.220	0.214	0.216	0.218	0.222	0.224	0.226
Dep. Var. Mean	0.327	0.327	0.327	0.327	0.326	0.326	0.327	0.326

Notes: The dependent variable is an indicator for whether a new application is granted a patent or not. Non-linear probability estimates produce analogous results. Dropped variables include all patents whose raw assignee organization contains the word "University", "Institute", "Research" or "Foundation". A total of 42753 entities is excluded from the count. All regressions include inventors', attorneys', and examiners' controls. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Figure D.5: Drop All University Patents, 2010-2014.



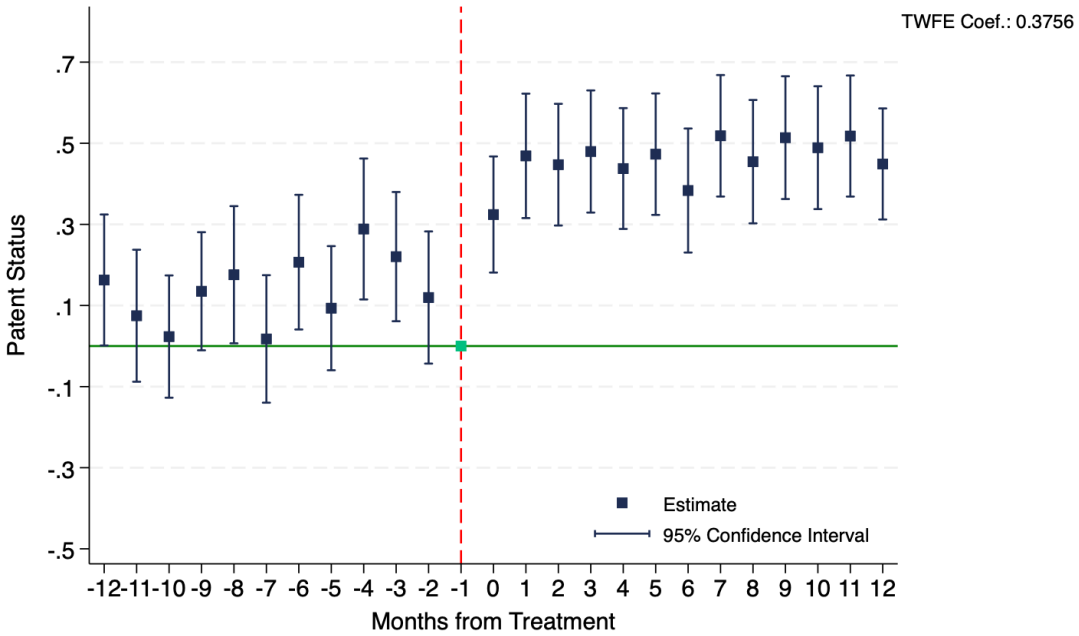
Notes: The figure shows the matched regression coefficients and the 95% confidence intervals for patents filed by small and micro entities at the USPTO between 2010 and 2014. Dropped observations include patents whose raw assignee organization contains the word "University", "Institute", "Research" or "Foundation" as in Table D.12. The coefficients at τ =-1 are normalized to zero. The outcome variable is the legal status of a newly filed application. The x-axis indexes event time.

Table D.11: Drop Foreign Patents.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	0.3896***	0.3820***	0.3853***	0.3879***	0.3818***	0.3773***	0.3802***	0.3756***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	161,519	161,195	159,372	161,519	159,372	159,052	161,195	159,052
$Adj.R^2$	0.195	0.203	0.198	0.199	0.202	0.205	0.207	0.209
Dep. Var. Mean	0.326	0.325	0.326	0.326	0.326	0.325	0.325	0.325

Notes: The dependent variable is an indicator for whether a new application is granted a patent or not. Non-linear probability estimates produce analogous results. After dropping pending applications, patents filed by foreign entities are 88538 (21.13%). The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Figure D.6: Drop Foreign Patents, 2010-2014.



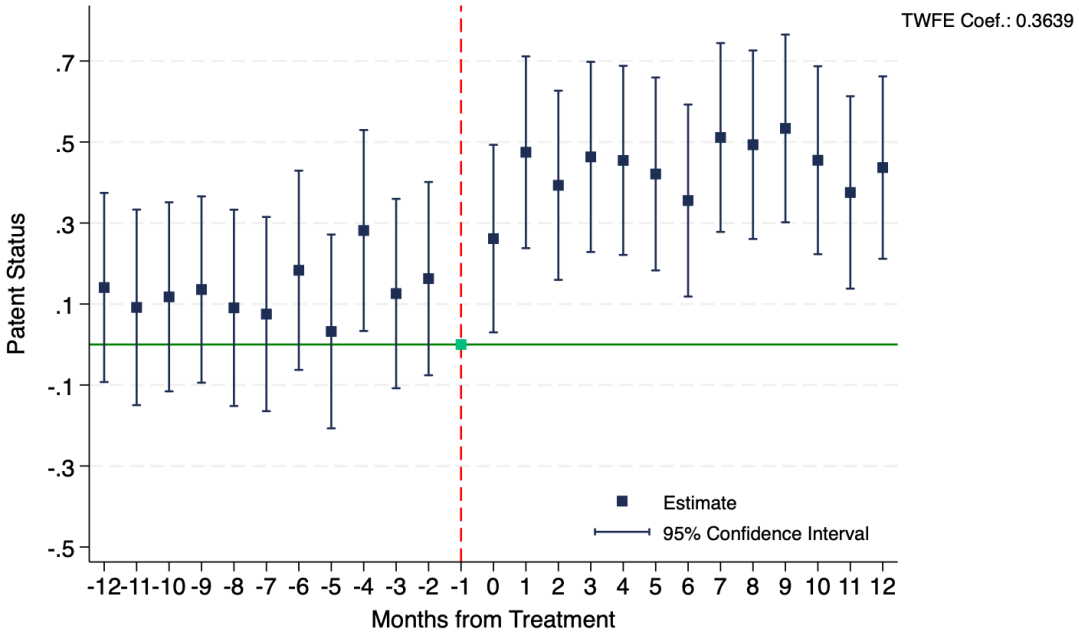
Notes: The figure shows the matched regression coefficients and the 95% confidence intervals for patents filed by small and micro entities at the USPTO between 2010 and 2014. Dropped observations include patents filed by foreign entities as in Table D.11. The coefficients at τ =-1 are normalized to zero. The outcome variable is the legal status of a newly filed application. The x-axis indexes event time.

Table D.12: Drop Top Five Patent Classes.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	0.3776***	0.3712***	0.3720***	0.3753***	0.3696***	0.3663***	0.3687***	0.3639***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	230,881	230,522	227,879	230,881	227,879	227,524	230,522	227,524
$Adj.R^2$	0.216	0.224	0.218	0.220	0.222	0.226	0.228	0.229
Dep. Var. Mean	0.313	0.312	0.312	0.313	0.312	0.311	0.312	0.311

Notes: The dependent variable is an indicator for whether a new application is granted a patent or not. Non-linear probability estimates produce analogous results. During our sample period, Art Unit 3765, 3711, 3754, 2875, and 3643 received the highest number of applications. A total of 17354 applications is dropped from the count. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Figure D.7: Drop Top Five Patent Classes, 2010-2014.



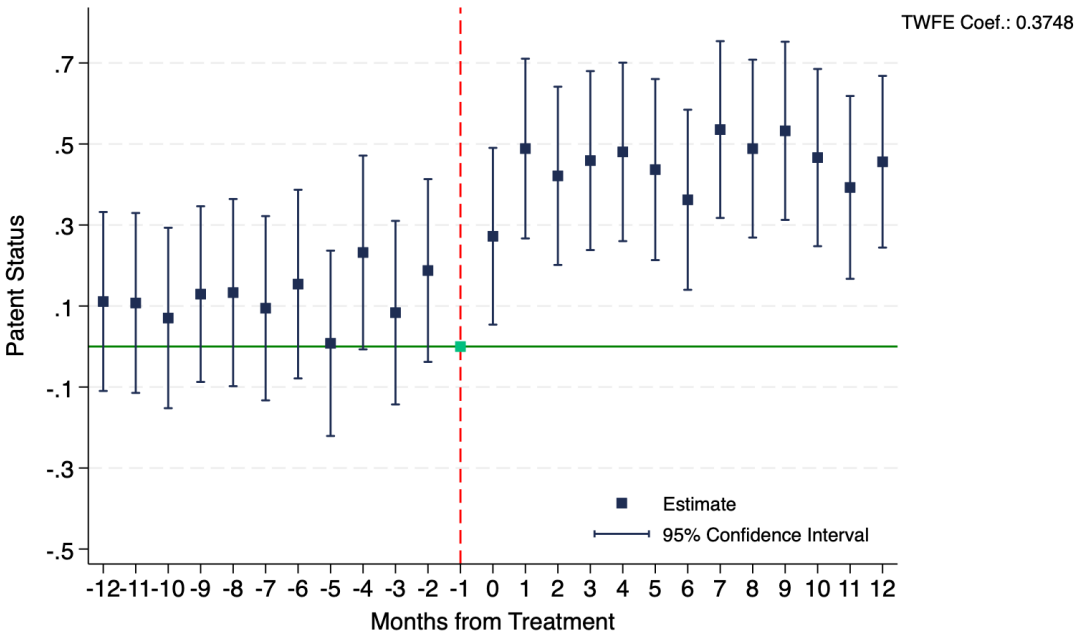
Notes: The figure shows the matched regression coefficients and the 95% confidence intervals for patents filed by small and micro entities at the USPTO between 2010 and 2014. Dropped observations include patents in Art Unit 3765, 3711, 3754, 2875 and 3643 as in Table D.12. The coefficients at τ =-1 are normalized to zero. The outcome variable is the legal status of a newly filed application. The x-axis indexes event time.

Table D.13: Drop All Patents of Government Interest.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	0.3901***	0.3838***	0.3882***	0.3874***	0.3805***	0.3776***	0.3810***	0.3748***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	235,631	235,240	232,489	235,631	232,489	232,102	235,240	232,102
$Adj.R^2$	0.212	0.220	0.214	0.216	0.218	0.222	0.224	0.226
Dep. Var. Mean	0.322	0.321	0.321	0.322	0.321	0.320	0.321	0.320

Notes: The dependent variable is an indicator for whether a new application is granted a patent or not. Non-linear probability estimates produce analogous results. A total of 23028 applications were funded by the US Government during our sample period. Top filing agencies include the Department of Energy (12.21%), the National Institutes of Health (40.26%), and the National Science Foundation (14.69%). The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Figure D.8: Drop Patents of Government Interest, 2010-2014.



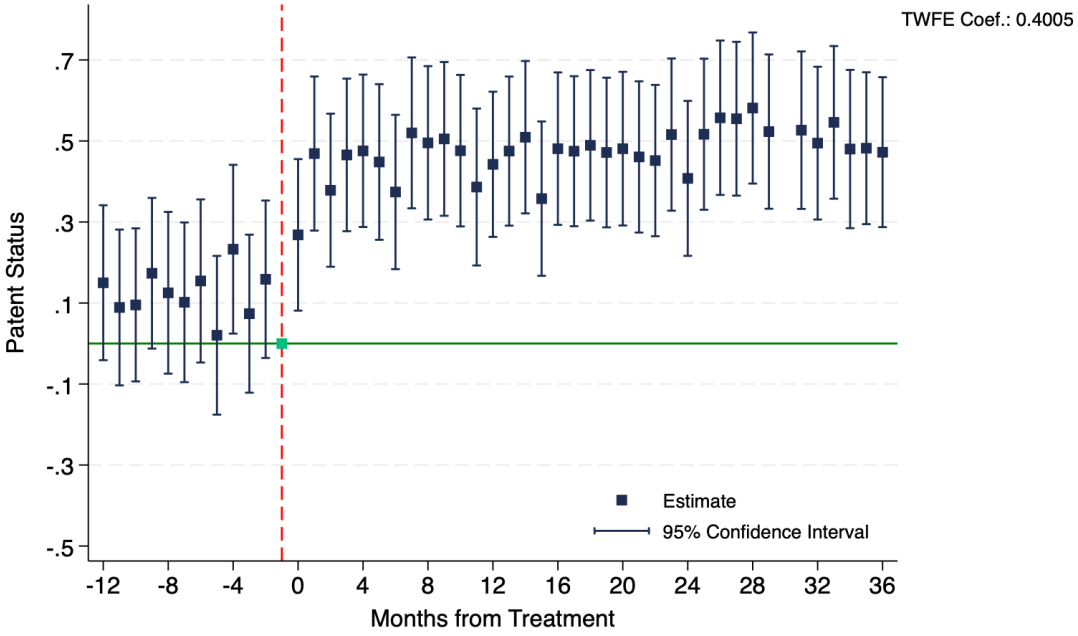
Notes: The figure shows the matched regression coefficients and the 95% confidence intervals for patents filed by small and micro entities at the USPTO between 2010 and 2014. Dropped observations include documents funded by the US Government. The outcome variable is the legal status of a newly filed application. The x-axis indexes event time.

Table D.14: Extended Timeline - Effect of Micro Entity Status, 2010-2016.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	0.4162***	0.4062***	0.4116***	0.4140***	0.4094***	0.4028***	0.4038***	0.4005***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	346,562	346,099	343,082	346,562	343,082	342,619	346,099	342,619
$Adj.R^2$	0.182	0.189	0.184	0.185	0.187	0.190	0.192	0.193
Dep. Var. Mean	0.273	0.273	0.273	0.273	0.273	0.273	0.273	0.273

Notes: The dependent variable is an indicator for whether a new application is granted a patent or not. The observation period runs from January 2010 to December 2016. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Figure D.9: Dynamic Effect of Lower Fees on Patent Outcome, 2010-2016.



Notes: The figure shows the regression coefficients and the 95% confidence intervals for the difference between matched treated and control entities relative to the 12 months before and after treatment (2010-2016). The coefficient at τ =-1 is normalized to zero. The outcome variable is the legal status of a newly filed application. The x-axis indexes event time. Controls include invention count, inventor gender and country of residence; attorney predicted gender at birth, country of practice, qualification and sanction status; examiner gender at birth and experience level. Standard errors are clustered at the applicant level.

Table D.15: Placebo Test: "Undiscounted" Status as Treatment.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	0.0050	0.0038	0.0048	0.0053	0.0050	0.0036	0.0041	0.0039
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	1,143,810	1,143,033	1,134,298	1,143,810	1,134,298	1,133,529	1,143,033	1,133,529
$Adj.R^2$	0.108	0.113	0.108	0.113	0.113	0.114	0.119	0.119
Dep. Var. Mean	0.246	0.246	0.247	0.246	0.247	0.246	0.246	0.246

Notes: The table performs a placebo test where treatment is arbitrarily assigned to "Undiscounted" entities. The dependent variable is an indicator for whether a new application is granted a patent or not. Controls include invention count, inventor gender, and country of residence; attorney predicted gender at birth, country of practice, qualification and sanction status; examiner gender at birth and experience level. Standard errors are clustered at the application level.

Patent Quality: Heterogeneity Analysis

Table D.16: Heterogeneous Effects of AIA - Inventor Gender (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t \times Gender_i$				
$Female_i$	0.0014	-11.4847	-10.1744	-10.6302
	(0.101)	(18.219)	(7.730)	(7.992)
$Unknown_i$	0.1508	-57.0930*	-32.6693**	-36.4300**
	(0.129)	(29.376)	(14.169)	(14.604)
$Ent_i \times Post_t$	-0.0744*	-1.9076	4.2901	3.9537
	(0.045)	(7.634)	(2.719)	(2.837)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	198,925	198,925	198,891	198,891
$Adj.R^2$	0.193	0.176	0.296	0.280
Dep. Var. Mean	2.529	313.031	109.813	132.577

Notes: The table reports the heterogeneous effects of AIA on independent claims by inventor gender. After using the assignment mechanism described in Part C of the Appendix, I code gender as 0 if male, 1 if female, and 2 if unknown. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%, **5%.

Table D.17: Heterogeneous Effects of AIA - Inventor Gender (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t \times Gender_i$				
$Female_i$	0.2388	54.1707	2.3801	3.5152*
	(0.930)	(59.623)	(1.732)	(2.098)
$Unknown_i$	0.3110	-41.7759	1.8015	-3.8687
	(0.777)	(106.097)	(2.911)	(8.716)
$Ent_i \times Post_t$	-0.1418	-21.4645*	-0.0056	-1.2885
	(0.207)	(11.483)	(0.830)	(0.951)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	198,925	198,925	195,864	195,864
$Adj.R^2$	0.204	0.199	0.497	0.438
Dep. Var. Mean	15.613	592.643	19.423	40.354

Notes: The table reports the heterogeneous effects of AIA on dependent claims by inventor gender. After using the assignment mechanism described in Part C of the Appendix, I code gender as 0 if male, 1 if female, and 2 if unknown. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%.

Table D.18: Heterogeneous Effects of AIA - Inventor Gender (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times Gender_i$								
$Female_i$	-0.0846**	-0.1491	-0.5891**	-0.0168	0.0635	-0.0263	0.0137	-0.0116
	(0.041)	(0.093)	(0.277)	(0.090)	(0.078)	(0.102)	(0.105)	(0.027)
$Unknown_i$	-0.0676	0.0383	-0.4781	0.0996	-0.1816	0.1777	0.1566	0.0494
	(0.077)	(0.166)	(0.591)	(0.167)	(0.161)	(0.181)	(0.202)	(0.047)
$Ent_i \times Post_t$	-0.0303*	-0.1040***	-0.4858***	-0.2049***	-0.1523***	-0.1524***	-0.1668***	0.0286**
	(0.018)	(0.040)	(0.109)	(0.041)	(0.039)	(0.045)	(0.047)	(0.011)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
N	97,452	97,452	97,452	97,452	97,452	97,452	97,452	88,742
$Adj.R^2$	0.168	0.173	0.206	0.145	0.167	0.165	0.166	0.192
Dep. Var. Mean	0.342	1.695	2.914	2.190	0.548	1.467	1.703	0.453

Notes: The table reports the heterogeneous effects of AIA on other quality indicators by inventor gender. After using the assignment mechanism described in Part C of the Appendix, I code gender as 0 if male, 1 if female, and 2 if unknown. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level. Asterisks denote statistical significance: *10, **5%, ***1%.

Table D.19: Heterogeneous Effects of AIA - Inventor Ethnicity (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t \times Ethnicity_i$				
$Asian_i$	0.1949	32.9559	7.3523	12.2261
	(0.124)	(23.207)	(10.350)	(10.553)
$Hispanic_i$	-0.3037*	-45.4294*	-4.5999	-3.9932
	(0.170)	(27.603)	(8.667)	(9.411)
$NH\ Black_i$	0.2253	80.6136	1.8926	19.7833
	(0.198)	(55.157)	(10.433)	(13.564)
$Ent_i \times Post_t$	-0.0769	-18.1168*	-1.5539	-4.7267*
	(0.055)	(9.496)	(2.655)	(2.828)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	123,411	123,411	123,388	123,388
$Adj.R^2$	0.219	0.188	0.298	0.283
Dep. Var. Mean	2.526	312.124	109.086	131.906

Notes: The table reports the heterogeneous effects of the AIA on independent claims by inventor ethnicity. The sample is composed of 68.65% Non-Hispanic White individuals (used as the reference category), 22.10% Asian, 5.90% Hispanic, and 3.36% Non-Hispanic Black. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%.

Table D.20: Heterogeneous Effects of the AIA - Inventor Ethnicity (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t \times Ethnicity_i$				
$Asian_i$	0.4975	48.3245	3.1114	5.6763**
	(0.993)	(61.345)	(—)	(2.663)
$Hispanic_i$	0.2735	41.4477	-1.2840	-0.2575
	(0.983)	(46.592)	(—)	(2.369)
$NH\ Black_i$	2.7295**	196.7099**	2.0923	3.7506
	(1.143)	(93.582)	(—)	(4.863)
$Ent_i \times Post_t$	-0.2493	-36.4418**	0.7850	-1.4960*
	(0.317)	(14.542)	(—)	(0.837)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	123,411	123,411	121,418	121,418
$Adj.R^2$	0.204	0.166	0.533	0.283
Dep. Var. Mean	15.429	580.116	19.079	39.598

Notes: The table reports the heterogeneous effects of the AIA on dependent claims by inventor ethnicity. Here, the reference category is Non-Hispanic White (*NH-White*). Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level. Standard errors for *Min Avg Wrd Ct* cannot be computed due to insufficient variation. Coefficients are reported for completeness.
Asterisks denote statistical significance: *10%, **5%.

Table D.21: Heterogeneous Effects of AIA - Inventor Ethnicity (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
$Ent_i \times Post_t \times Ethnicity_i$								
$Asian_i$	-0.0656	-0.2923**	-0.4657	-0.0805	-0.1882	0.1077	0.1044	0.0575
	(0.057)	(0.144)	(0.376)	(0.133)	(0.123)	(0.186)	(0.202)	(0.036)
$Hispanic_i$	-0.0993	-0.4879**	0.5892	0.1642	-0.4858***	0.1800	0.1661	0.0147
	(0.079)	(0.219)	(0.000)	(0.167)	(0.172)	(0.176)	(0.176)	(0.049)
$NH\ Black_i$	-0.0930	-0.1695	-0.2964	0.2836	0.0034	-0.1667	-0.2217	0.0411
	(0.097)	(0.202)	(0.000)	(0.191)	(0.149)	(0.197)	(0.217)	(0.053)
$Ent_i \times Post_t$	-0.0350*	-0.0636	-0.5383***	-0.2360***	-0.1080**	-0.1810***	-0.1901***	0.0194
	(0.021)	(0.047)	(0.124)	(0.047)	(0.043)	(0.051)	(0.054)	(0.013)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Inventor controls	-	✓	-	-	-	✓	✓	✓
Examiner controls	-	-	-	✓	✓	-	✓	✓
Attorney controls	-	-	✓	-	✓	✓	-	✓
N	58,466	58,466	58,466	58,466	58,466	58,466	58,466	53,204
$Adj.R^2$	0.181	0.196	0.236	0.159	0.170	0.177	0.178	0.201
Dep. Var. Mean	0.342	1.700	2.905	2.200	0.540	1.446	1.683	0.453

Notes: The table reports the heterogeneous effects of AIA on other quality indicators by inventor ethnicity. Here, the reference category is *Non-Hispanic White (NH-White)*. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%, **5%, ***1%.

Table D.22: Heterogeneous Effects of AIA - Inventor Country (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t \times US_i$	0.1361	11.8812	-8.7971	-5.0747
	(0.116)	(18.606)	(8.422)	(8.502)
$Ent_i \times Post_t$	-0.1356***	-12.2906*	4.0604**	2.1936
	(0.042)	(6.809)	(2.016)	(2.207)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	199,287	199,287	199,253	199,253
$Adj.R^2$	0.172	0.168	0.277	0.267
Dep. Var. Mean	2.529	312.961	109.787	132.548

Notes: The table reports the heterogeneous effects of AIA on independent claims by inventor country. I code variable US_i as 1 if the inventor's last known address is in the United States or code it as 2 if foreign. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%, **5%, ***1%.

Table D.23: Heterogeneous Effects of AIA - Inventor Country (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t \times US_i$	-0.1645	-18.9113	2.3032*	0.6962
	(0.587)	(41.577)	(1.370)	(2.702)
$Ent_i \times Post_t$	-0.5724**	-24.0779**	0.2075	-0.7778
	(0.258)	(12.250)	(0.474)	(0.653)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	199,287	199,287	196,214	196,214
$Adj.R^2$	0.172	0.191	0.493	0.427
Dep. Var. Mean	15.608	592.418	19.423	40.351

Notes: The table reports the heterogeneous effects of AIA on dependent claims by inventor country. I code variable US_i as 1 if the inventor's last known address is in the United States or code it as 2 if foreign. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%, **5%.

Table D.24: Heterogeneous Effects of AIA - Inventor Country (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times US_i$	0.0088	0.0631	-0.0270	0.2336**	-0.0185	0.0240	0.0357	0.0486*
	(0.051)	(0.116)	(0.350)	(0.118)	(0.125)	(0.137)	(0.145)	(0.028)
$Ent_i \times Post_t$	-0.0455***	-0.1335***	-0.6290***	-0.2269***	-0.1516***	-0.1541***	-0.1554***	0.0223**
	(0.016)	(0.036)	(0.104)	(0.037)	(0.033)	(0.041)	(0.043)	(0.010)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
N	97,710	97,710	97,710	97,710	97,710	97,710	97,710	88,971
$Adj.R^2$	0.166	0.171	0.205	0.142	0.165	0.160	0.161	0.188
Dep. Var. Mean	0.342	1.694	2.913	2.190	0.547	1.467	1.703	0.453

Notes: The table reports the heterogeneous effects of AIA on other quality indicators by inventor country. I code variable US_i as 1 if the inventor's last known address is in the United States or code it as 2 if foreign. Only key coefficients are reported for brevity. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%, **5%, ***1%.

Table D.25: Heterogeneous Effects of AIA - Attorney Gender (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t \times Gender_i$				
$Female_i$	-0.1260	-7.9912	8.8228	7.3593
	(0.155)	(23.540)	(7.830)	(8.126)
$Unknown_i$	0.0896	-53.0131	-24.4580	-27.4388
	(0.149)	(39.457)	(26.878)	(26.991)
$Ent_i \times Post_t$	-0.0644	-5.6483	0.7965	0.2570
	(0.043)	(7.230)	(2.244)	(2.400)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	198,925	198,925	198,891	198,891
$Adj.R^2$	0.193	0.177	0.296	0.281
Dep. Var. Mean	2.529	313.031	109.813	132.577

Notes: The table reports the heterogeneous effects of AIA on independent claims by attorney gender. After using the assignment mechanism described in Part C of the Appendix, I code gender as 0 if male, 1 if female, and 2 if unknown. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.

Table D.26: Heterogeneous Effects of AIA - Attorney Gender (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t \times Gender_i$				
$Female_i$	-0.8979	-36.7455	3.0436*	3.2249
	(0.679)	(39.306)	(1.844)	(2.607)
$Unknown_i$	-2.0330***	-189.3594	3.2271	-3.7313
	(0.770)	(152.445)	(1.990)	(12.363)
$Ent_i \times Post_t$	-0.0625	-12.4178	0.4733	-0.8415
	(0.258)	(14.007)	(0.563)	(0.740)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	198,925	198,925	195,864	195,864
$Adj.R^2$	0.204	0.201	0.497	0.439
Dep. Var. Mean	15.613	592.643	19.423	40.354

Notes: The table reports the heterogeneous effects of AIA on dependent claims by attorney gender. After using the assignment mechanism described in Part C of the Appendix, I code gender as 0 if male, 1 if female, and 2 if unknown. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%, ***1%.

Table D.27: Heterogeneous Effects of AIA - Attorney Gender (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times Gender_i$								
$Female_i$	0.0558	-0.0003	0.0573	0.1467	0.0894	0.1418	0.1078	0.0199
	(0.057)	(0.142)	(0.320)	(0.150)	(0.114)	(0.202)	(0.219)	(0.038)
$Unknown_i$	0.1672**	0.0836	-0.6145	0.1816	-0.2837	-0.4615***	-0.4953**	0.0766
	(0.069)	(0.163)	(0.750)	(0.184)	(0.201)	(0.171)	(0.196)	(0.047)
$Ent_i \times Post_t$	-0.0570***	-0.1268***	-0.5870***	-0.2172***	-0.1500***	-0.1381***	-0.1428***	0.0248**
	(0.017)	(0.039)	(0.110)	(0.038)	(0.036)	(0.041)	(0.043)	(0.011)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
N	97,452	97,452	97,452	97,452	97,452	97,452	97,452	88,742
$Adj.R^2$	0.168	0.173	0.206	0.145	0.167	0.165	0.167	0.192
Dep. Var. Mean	0.342	1.695	2.914	2.190	0.548	1.467	1.703	0.453

Notes: The table reports the heterogeneous effects of AIA on other quality indicators by attorney gender. After using the assignment mechanism described in Part C of the Appendix, I code gender as 0 if male, 1 if female, and 2 if unknown. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level. Asterisks denote statistical significance: **5%, ***1%.

Table D.28: Heterogeneous Effects of AIA - Practitioners' License Type (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t \times Practice_i$	-0.0615	-9.4258	6.0976	3.3675
	(0.122)	(21.343)	(10.734)	(10.939)
$Ent_i \times Post_t$	-0.0640	-6.3546	0.3786	0.0003
	(0.043)	(7.171)	(2.212)	(2.346)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	198,925	198,925	198,891	198,891
$Adj.R^2$	0.193	0.176	0.295	0.280
Dep. Var. Mean	2.529	313.031	109.813	132.577

Notes: The table reports the heterogeneous effects of AIA on independent claims by attorney license type. I code variable $Practice_i$ as 0 if the counsel is registered as attorney or code it as 1 if registered as an agent. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.

Table D.29: Heterogeneous Effects of AIA - Practitioners' License Type (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t \times Practice_i$	-0.8121	15.2528	2.3272	4.1525
	(0.611)	(58.390)	(1.537)	(4.558)
$Ent_i \times Post_t$	-0.1349	-20.9068	0.6364	-0.9261
	(0.254)	(14.200)	(0.545)	(0.733)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	198,925	198,925	195,864	195,864
$Adj.R^2$	0.204	0.198	0.497	0.437
Dep. Var. Mean	15.613	592.643	19.423	40.354

Notes: The table reports the heterogeneous effects of AIA on dependent claims by attorney license type. I code variable $Practice_i$ as 0 if the counsel is registered as attorney or code it as 1 if registered as an agent. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.

Table D.30: Heterogeneous Effects of AIA - Practitioners' License Type (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times Practice_i$	-0.0556	-0.1583	-0.3552	0.1905	0.0387	-0.0841	-0.1628	0.0517*
	(0.053)	(0.123)	(0.344)	(0.126)	(0.105)	(0.156)	(0.170)	(0.031)
$Ent_i \times Post_t$	-0.0400**	-0.1066***	-0.5626***	-0.2201***	-0.1568***	-0.1358***	-0.1357***	0.0233**
	(0.017)	(0.038)	(0.109)	(0.037)	(0.036)	(0.041)	(0.042)	(0.010)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
N	97,452	97,452	97,452	97,452	97,452	97,452	97,452	88,742
$Adj.R^2$	0.168	0.173	0.206	0.145	0.167	0.165	0.167	0.192
Dep. Var. Mean	0.342	1.695	2.914	2.190	0.548	1.467	1.703	0.453

Notes: The table reports the heterogeneous effects of AIA on other quality indicators by attorney license type. I code variable $Practice_i$ as 0 if the counsel is registered as attorney or code it as 1 if registered as an agent. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%, **5%, ***1%.

Table D.31: Heterogeneous Effects of AIA - Examiner Gender (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t \times Gender_i$				
$Female_i$	-0.0999	4.9626	3.1825	0.7527
	(0.084)	(15.099)	(5.312)	(5.480)
$Unknown_i$	0.1779	-27.7896	-14.1212	-17.4780
	(0.165)	(36.808)	(12.887)	(13.690)
$Ent_i \times Post_t$	-0.0463	-6.1725	1.2175	1.5451
	(0.050)	(8.066)	(2.708)	(2.892)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	198,925	198,925	198,891	198,891
$Adj.R^2$	0.193	0.176	0.294	0.279
Dep. Var. Mean	2.529	313.031	109.813	132.577

Notes: The table reports the heterogeneous effects of AIA on independent claims by examiner gender. After using the assignment mechanism described in Part C of the Appendix, I code gender as 0 if male, 1 if female, and 2 if unknown. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.

Table D.32: Heterogeneous Effects of AIA - Examiner Gender (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t \times Gender_i$				
$Female_i$	0.0762	4.1418	0.9179	1.1378
	(0.389)	(22.031)	(1.605)	(1.836)
$Unknown_i$	-0.4678	10.2080	3.5313	1.7191
	(1.180)	(71.027)	(2.489)	(4.746)
$Ent_i \times Post_t$	-0.2484	-20.5989	0.5852	-0.4841
	(0.309)	(17.811)	(0.817)	(0.999)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	198,925	198,925	195,864	195,864
$Adj.R^2$	0.204	0.198	0.497	0.438
Dep. Var. Mean	15.613	592.643	19.423	40.354

Notes: The table reports the heterogeneous effects of AIA on dependent claims by examiner gender. After using the assignment mechanism described in the Part C of the Appendix, I code gender as 0 if male, 1 if female, and 2 if unknown. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.

Table D.33: Heterogeneous Effects of AIA - Examiner Gender (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times Gender_i$								
$Female_i$	-0.0095	-0.0416	-0.1085	-0.0248	0.1341*	0.0079	0.0247	0.0085
	(0.034)	(0.075)	(0.219)	(0.079)	(0.070)	(0.090)	(0.095)	(0.022)
$Unknown_i$	-0.0075	-0.0043	0.1303	0.1477	-0.0261	-0.1676	-0.1533	0.0099
	(0.070)	(0.164)	(0.412)	(0.137)	(0.131)	(0.157)	(0.175)	(0.040)
$Ent_i \times Post_t$	-0.0427**	-0.1106**	-0.5768***	-0.1996***	-0.1921***	-0.1360***	-0.1504***	0.0258**
	(0.020)	(0.045)	(0.136)	(0.045)	(0.042)	(0.048)	(0.050)	(0.012)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
N	97,452	97,452	97,452	97,452	97,452	97,452	97,452	88,742
$Adj.R^2$	0.168	0.173	0.206	0.144	0.167	0.165	0.166	0.192
Dep. Var. Mean	0.342	1.695	2.914	2.190	0.548	1.467	1.703	0.453

Notes: The table reports the heterogeneous effects of AIA on other quality indicators by examiner gender. After using the assignment mechanism described in the Part C of the Appendix, I code gender as 0 if male, 1 if female, and 2 if unknown. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%, **5%, ***1%.

Table D.34: Heterogeneous Effects of AIA - WIPO Sectors (Independent and Dependent Claims).

	Independent Claims				Dependent Claims			
	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
$Ent_i \times Post_t \times WIPO\ Sector_i$								
Chemistry$_i$	0.1961	47.2910**	-4.7755	4.8083	0.4638	65.1814	-1.1981	-2.9164
	(0.139)	(23.054)	(7.170)	(7.808)	(0.793)	(54.238)	(1.928)	(3.245)
Instruments$_i$	-0.1269	23.1775	20.8312**	18.7937**	-1.1193	-10.7621	2.3456	4.8999
	(0.142)	(22.657)	(9.430)	(9.580)	(0.909)*	(53.755)	(1.762)	(3.208)
Mechanical Engineering$_i$	0.0616	13.4449	2.2033	3.4312	-1.2139*	-32.7025	7.4552***	8.9713***
	(0.109)	(22.537)	(7.704)	(8.061)	(0.676)	(50.978)	(2.403)	(3.462)
Other Fields$_i$	0.0062	16.2595	6.5068	8.2368	-1.0481	-37.0721	1.9318	2.6228
	(0.114)	(20.121)	(6.614)	(6.917)	(0.662)	(48.522)	(1.620)	(2.964)
$Ent_i \times Post_t$	-0.1004	-24.6636	-3.5502	-5.9189	0.3185	-13.2510	-1.1408	-4.0330
	(0.086)	(16.466)	(5.483)	(5.635)	(0.581)	(44.529)	(1.494)	(2.745)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
N	198,110	198,110	198,077	198,077	198,110	198,110	195,060	195,060
$Adj.R^2$	0.194	0.177	0.296	0.280	0.204	0.199	0.498	0.438
Dep. Var. Mean	2.529	313.113	109.835	132.617	15.61	592.614	19.424	40.360

Notes: The table reports the heterogeneous effects of AIA on dependent and independent claims by WIPO Sector. Here, the reference category is *Electrical Engineering*. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level. Asterisks denote statistical significance: *10%, **5%, ***1%.

Table D.35: Heterogeneous Effects of AIA - WIPO Sectors (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t \times WIPO\ Sector_i$								
$Chemistry_i$	0.0403	0.0465	-0.0765	-0.3098**	-0.0938	-0.0272	-0.0904	0.0076
	(0.058)	(0.134)	(0.338)	(0.128)	(0.114)	(0.137)	(0.146)	(0.035)
$Instruments_i$	0.0189	-0.1069	-0.6377**	-0.0664	-0.1717*	0.0124	-0.0120	-0.0326
	(0.051)	(0.116)	(0.325)	(0.111)	(0.099)	(0.131)	(0.139)	(0.031)
$Mechanical\ Engineering_i$	-0.0074	-0.1466	-0.8370**	-0.0896	-0.1521	0.0038	0.0005	-0.0348
	(0.048)	(0.111)	(0.328)	(0.109)	(0.103)	(0.129)	(0.137)	(0.029)
$Other\ Fields_i$	-0.0859*	-0.1489	-0.4668*	-0.1401	-0.2292**	-0.0238	-0.0238	-0.0169
	(0.046)	(0.099)	(0.272)	(0.104)	(0.097)	(0.118)	(0.126)	(0.028)
$Ent_i \times Post_t$	-0.0308	-0.0499	-0.2099	-0.0995	-0.0284	-0.1380	-0.1349	0.0448**
	(0.034)	(0.075)	(0.200)	(0.074)	(0.065)	(0.093)	(0.102)	(0.020)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓		
Controls	✓	✓	✓	✓	✓	✓	✓	✓
N	97,013	97,013	97,013	97,013	97,013	97,013	97,013	88,333
$Adj.R^2$	0.169	0.174	0.207	0.145	0.169	0.166	0.167	0.192
Dep. Var. Mean	0.342	1.695	2.914	2.190	0.548	1.466	1.702	0.453

Notes: The table reports the heterogeneous effects of AIA on eight OECD quality indicators by WIPO Sector. Here, the reference category is *Electrical Engineering*. Only key coefficients are reported for brevity. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%, **5%.

Patent Quality: Robustness

Table D.36: Art Unit Fixed Effects (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.0509	-11.2569*	-0.8307	-1.5523
	(0.040)	(6.513)	(2.706)	(2.812)
Month FE	✓	✓	✓	✓
Art Unit FE	✓	✓	✓	✓
N	208,690	208,960	208,656	208,656
$Adj.R^2$	0.100	0.066	0.123	0.106
Dep. Var. Mean	2.522	312.661	110.329	133.081

Notes: The table reports the effect of AIA on independent claims using art unit fixed effects. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%.

Table D.37: Art Unit Fixed Effects (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.3236*	-37.1264***	0.7102	-1.2229
	(0.190)	(13.915)	(—)	(1.238)
Month FE	✓	✓	✓	✓
Art Unit FE	✓	✓	✓	✓
N	208,690	208,690	205,627	205,627
$Adj.R^2$	0.145	0.061	0.057	0.087
Dep. Var. Mean	15.563	591.868	19.542	40.508

Notes: The table reports the effect of AIA on dependent claims using art unit fixed effects. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level. Standard errors for *Min Avg Wrd Ct* cannot be computed due to insufficient variation. Coefficient is reported for completeness.
Asterisks denote statistical significance: *10%, ***1%.

Table D.38: Art Unit Fixed Effects (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	-0.0432***	-0.0961***	-0.6317***	-0.1774***	-0.1295***	-0.1726***	-0.1771***	0.0360***
	(0.015)	(0.034)	(0.113)	(0.033)	(0.031)	(0.036)	(0.037)	(0.009)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Art Unit FE	✓	✓	✓	✓	✓	✓	✓	✓
N	105,070	105,070	105,070	105,070	105,070	105,070	105,070	96,335
$Adj.R^2$	0.044	0.046	0.051	0.045	0.047	0.040	0.042	0.058
Dep. Var. Mean	0.344	1.697	2.917	2.194	0.548	1.458	1.693	0.453

Notes: The table reports the effect of AIA on other quality indicators using art unit fixed effects. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.39: Applicant Controls (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.1313***	-10.6228	4.0607	2.7895
	(0.035)	(5.822)	(1.926)	(2.593)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	199,287	199,287	199,253	199,253
$Adj.R^2$	0.155	0.160	0.270	0.264
Dep. Var. Mean	2.529	312.961	109.787	132.548

Notes: The table reports the effect of AIA on independent claims using applicant controls. The regression includes attorneys' and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.40: Applicant Controls (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.6598***	-24.0177	1.4202**	0.4749
	(0.239)	(14.673)	(0.562)	(0.891)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	199,287	199,287	196,214	196,214
$Adj.R^2$	0.143	0.188	0.490	0.417
Dep. Var. Mean	15.608	592.418	19.423	40.351

Notes: The table reports the effect of AIA on dependent claims using applicant controls. The regression includes attorneys' and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance:**5%, ***1%.

Table D.41: Applicant Controls (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	-0.0455***	-0.1252***	-0.6217***	-0.1975***	-0.1545***	-0.1503***	-0.1629***	0.0294***
	(0.016)	(0.036)	(0.104)	(0.036)	(0.034)	(0.039)	(0.041)	(0.010)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
N	97,710	97,710	97,710	97,710	97,710	97,710	97,710	88,971
$Adj.R^2$	0.165	0.170	0.200	0.141	0.164	0.159	0.160	0.187
Dep. Var. Mean	0.342	1.694	2.913	2.190	0.547	1.467	1.703	0.453

Notes: The table reports the effect of AIA on other quality indicators using applicant controls. The regression includes attorneys' and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.42: WIPO Field Fixed Effects (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.0429	-9.0384	-0.4632	-1.0844
	(0.041)	(6.790)	(2.895)	(2.997)
Month FE	✓	✓	✓	✓
WIPO Field FE	✓	✓	✓	✓
N	207,886	207,886	207,853	207,853
$Adj.R^2$	0.086	0.045	0.093	0.074
Dep. Var. Mean	2.522	312.762	110.356	133.126

Notes: The table reports the effect of AIA on independent claims using WIPO Field fixed effects. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.

Table D.43: WIPO Field Fixed Effects (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.3159	-35.0893**	0.7468	-1.1848
	(0.203)	(15.310)	(—)	(1.333)
Month FE	✓	✓	✓	✓
WIPO Field FE	✓	✓	✓	✓
N	207,886	207,886	204,836	204,836
$Adj.R^2$	0.128	0.037	0.035	0.066
Dep. Var. Mean	15.560	591.838	19.544	40.515

Notes: The table reports the effect of AIA on dependent claims using WIPO Field fixed effects. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level. Standard errors for *Min Avg Wrd Ct* cannot be computed due to insufficient variation. Coefficient is reported for completeness.
Asterisks denote statistical significance: **5%.

Table D.44: WIPO Field Fixed Effects (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	-0.0456***	-0.1119***	-0.6690***	-0.1878***	-0.1402***	-0.1719***	-0.1763***	0.0363***
	(0.016)	(0.036)	(0.121)	(0.035)	(0.033)	(0.038)	(0.040)	(0.009)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
WIPO Field FE	✓	✓	✓	✓	✓	✓	✓	✓
N	104,648	104,648	104,648	104,648	104,648	104,648	104,648	95,939
$Adj.R^2$	0.022	0.025	0.030	0.023	0.024	0.020	0.022	0.029
Dep. Var. Mean	0.344	1.698	2.917	2.194	0.549	1.457	1.692	0.453

Notes: The table reports the effect of AIA on other quality indicators using WIPO Field fixed effects. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.45: WIPO Sector Fixed Effects (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.0565	-8.3506	0.3415	-0.4173
	(0.041)	(6.856)	(2.934)	(3.033)
Month FE	✓	✓	✓	✓
WIPO Sector FE	✓	✓	✓	✓
N	207,886	207,886	207,853	207,853
$Adj.R^2$	0.077	0.034	0.075	0.058
Dep. Var. Mean	2.522	312.762	110.356	133.126

Notes: The table reports the effect of AIA on independent claims using WIPO Sector fixed effects. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.

Table D.46: WIPO Sector Fixed Effects (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.2876*	-27.7809***	0.3643	-1.1995
	(0.163)	(9.884)	(0.875)	(0.989)
Month FE	✓	✓	✓	✓
WIPO Sector FE	✓	✓	✓	✓
N	207,886	207,886	204,836	204,836
$Adj.R^2$	0.110	0.018	0.040	0.059
Dep. Var. Mean	15.560	591.838	19.544	40.515

Notes: The table reports the effect of AIA on dependent claims using WIPO Sector fixed effects. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%, ***1%.

Table D.47: WIPO Sector Fixed Effects (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	-0.0497***	-0.1215***	-0.6892***	-0.1926***	-0.1466***	-0.1765***	-0.1809***	0.0345***
	(0.016)	(0.037)	(0.122)	(0.035)	(0.033)	(0.038)	(0.040)	(0.009)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
WIPO Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
N	104,648	104,648	104,648	104,648	104,648	104,648	104,648	95,939
$Adj.R^2$	0.017	0.020	0.026	0.020	0.021	0.017	0.018	0.020
Dep. Var. Mean	0.344	1.698	2.917	2.194	0.549	1.457	1.692	0.453

Notes: The table reports the effect of AIA on other quality indicators using WIPO Sector fixed effects. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.48: USPC Fixed Effects (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.0382	-9.2168	-0.6982	-1.1981
	(0.041)	(6.554)	(2.829)	(2.914)
Month FE	✓	✓	✓	✓
USPC FE	✓	✓	✓	✓
N	208,701	208,701	208,667	208,667
$Adj.R^2$	0.095	0.063	0.122	0.106
Dep. Var. Mean	2.522	312.688	110.332	133.085

Notes: The table reports the effect of AIA on independent claims using USPC fixed effects. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.

Table D.49: USPC Fixed Effects (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.3067	-34.0002**	0.5561	-1.3011
	(0.201)	(14.871)	(0.776)	(1.089)
Month FE	✓	✓	✓	✓
USPC FE	✓	✓	✓	✓
N	208,701	208,701	205,640	205,640
$Adj.R^2$	0.141	0.060	0.203	0.183
Dep. Var. Mean	15.563	591.880	19.542	40.509

Notes: The table reports the effect of AIA on dependent claims using USPC fixed effects. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: **5%.

Table D.50: USPC Fixed Effects (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	-0.0494***	-0.1155***	-0.6738***	-0.1892***	-0.1376***	-0.1864***	-0.1902***	0.0341***
	(0.015)	(0.035)	(0.113)	(0.033)	(0.032)	(0.036)	(0.037)	(0.009)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
USPC FE	✓	✓	✓	✓	✓	✓	✓	✓
N	105,084	105,084	105,084	105,084	105,084	105,084	105,084	96,345
$Adj.R^2$	0.038	0.043	0.046	0.044	0.042	0.038	0.039	0.060
Dep. Var. Mean	0.344	1.697	2.918	2.194	0.549	1.458	1.693	0.453

Notes: The table reports the effect of AIA on other quality indicators using USPC fixed effects. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.51: Drop University Patents (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.0398	-2.0925	1.3103	1.0280
	(0.043)	(7.181)	(2.520)	(2.651)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	171,758	171,758	171,724	171,724
$Adj.R^2$	0.191	0.172	0.291	0.275
Dep. Var. Mean	2.488	317.487	112.911	135.903

Notes: The table reports the effect of AIA on independent claims (excluding universities and research institutes). Dropped variables include all patents whose raw assignee organization contains the word "University", "Institute", "Research" or "Foundation". A total of 42753 entities is excluded from the count. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.

Table D.52: Drop University Patents (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.1073	-20.0498	1.0334*	-0.3589
	(0.248)	(13.720)	(0.569)	(0.751)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	171,758	171,758	168,855	168,855
$Adj.R^2$	0.197	0.190	0.495	0.441
Dep. Var. Mean	15.379	588.829	19.688	40.512

Notes: The table reports the effect of AIA on dependent claims (excluding universities and research institutes). The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%.

Table D.53: Drop University Patents (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	-0.0405**	-0.1184***	-0.5299***	-0.1887***	-0.1379***	-0.1409***	-0.1471***	0.0255**
	(0.017)	(0.037)	(0.104)	(0.037)	(0.035)	(0.042)	(0.044)	(0.010)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
N	86,276	86,276	86,276	86,276	86,276	86,276	86,276	78,483
$Adj.R^2$	0.162	0.169	0.206	0.140	0.155	0.160	0.161	0.189
Dep. Var. Mean	0.337	1.682	2.891	2.190	0.529	1.462	1.697	0.454

Notes: The table reports the effect of AIA on other quality indicators (excluding universities and research institutes). The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: **5%, ***1%.

Table D.54: Drop Foreign Patents (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.0817*	-7.9271	1.9206	0.4609
	(0.042)	(6.803)	(1.950)	(2.143)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	129,344	129,344	129,313	129,313
$Adj.R^2$	0.154	0.148	0.217	0.213
Dep. Var. Mean	2.736	331.899	101.624	127.204

Notes: The table reports the effect of AIA on independent claims (excluding foreign filings). After dropping pending applications, patents filed by foreign entities are 88538 (21.13%). The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%.

Table D.55: Drop Foreign Patents (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.1855	-18.5050	0.1292	-1.1876**
	(0.262)	(12.319)	(0.368)	(0.562)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	129,344	129,344	127,171	127,171
$Adj.R^2$	0.152	0.106	0.503	0.414
Dep. Var. Mean	16.945	596.203	17.356	36.257

Notes: The table reports the effect of AIA on dependent claims (excluding foreign filings). The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: **5%.

Table D.56: Drop Foreign Patents (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	-0.0545***	-0.1414***	-0.6054***	-0.2353***	-0.1344***	-0.1558***	-0.1610***	0.0316***
	(0.015)	(0.035)	(0.102)	(0.035)	(0.031)	(0.039)	(0.040)	(0.010)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
N	68,795	68,795	68,795	68,795	68,795	68,795	68,795	62,213
$Adj.R^2$	0.025	0.029	0.035	0.015	0.018	0.033	0.034	0.067
Dep. Var. Mean	0.335	1.675	2.706	2.180	0.525	1.462	1.702	0.462

Notes: The table reports the effect of AIA on other quality indicators (excluding foreign filings). The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

Table D.57: Drop Top Five Patent Classes (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.0879**	-10.5489	-1.0476	-0.1376
	(0.042)	(7.382)	(2.712)	(2.823)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	188,488	188,488	188,454	188,454
$Adj.R^2$	0.194	0.182	0.303	0.289
Dep. Var. Mean	2.551	315.920	109.927	132.877

Notes: The table reports the effect of AIA on independent claims (excluding top five patent classes). During our sample period, Art Unit 3765, 3711, 3754, 2875, and 3643 received the highest number of applications. A total of 17354 applications is dropped from the count. The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: **5%.

Table D.58: Drop Top Five Patent Classes (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.2570	-17.2056	1.2047**	0.0532
	(0.256)	(15.840)	(0.592)	(0.932)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	188,488	188,488	185,621	185,621
$Adj.R^2$	0.204	0.204	0.507	0.449
Dep. Var. Mean	15.738	599.607	19.482	40.626

Notes: The table reports the effect of AIA on dependent claims (excluding top five patent classes). The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: **5%.

Table D.59: Drop Top Five Patent Classes (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	-0.0354**	-0.1128***	-0.5725***	-0.1954***	-0.1363***	-0.1233***	-0.1364***	0.0325***
	(0.017)	(0.039)	(0.112)	(0.038)	(0.036)	(0.043)	(0.046)	(0.011)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
N	91,446	91,446	91,446	91,446	91,446	91,446	91,446	83,325
$Adj.R^2$	0.176	0.184	0.221	0.155	0.179	0.176	0.177	0.200
Dep. Var. Mean	0.347	1.703	2.927	2.182	0.553	1.474	1.709	0.455

Notes: The table reports the effect of AIA on other quality indicators (excluding top five patent classes). The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: **5%, ***1%.

Table D.60: Drop All Patents of Government Interest (Independent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.0537	-6.5509	1.0050	0.3712
	(0.042)	(7.071)	(2.580)	(2.696)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	187,977	187,977	187,944	187,944
$Adj.R^2$	0.196	0.176	0.302	0.286
Dep. Var. Mean	2.485	314.257	112.308	135.008

Notes: The table reports the effect of AIA on independent claims (excluding all patent of government interest). A total of 23028 applications were funded by the US Government during our sample period. Top filing agencies include the Department of Energy (12.21%), the National Institutes of Health (40.26%), and the National Science Foundation (14.69%). The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.

Table D.61: Drop All Patents of Government Interest (Dependent Claims).

	Avg Clm Ct	Avg Wrd Ct	Min Avg Wrd Ct	Wrd Avg
	(1)	(2)	(3)	(4)
$Ent_i \times Post_t$	-0.1785	-21.5311	0.9433*	-0.5579
	(0.240)	(14.804)	(0.572)	(0.886)
Month FE	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓
N	187,977	187,977	184,975	184,975
$Adj.R^2$	0.201	0.203	0.501	0.441
Dep. Var. Mean	15.289	591.181	19.814	41.021

Notes: The table reports the effect of AIA on dependent claims (excluding all patent of government interest). The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: *10%.

Table D.62: Drop All Patents of Government Interest (Other Quality Indicators).

	Many Fields	Patent Scope	Family Size	Bwd Cites	NPL Cites	Fwd 5Y	Fwd 7Y	Radicalness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Ent_i \times Post_t$	-0.0527***	-0.1369***	-0.6481***	-0.2202***	-0.1825***	-0.1617***	-0.1634***	0.0323***
	(0.017)	(0.040)	(0.111)	(0.039)	(0.036)	(0.042)	(0.044)	(0.011)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
IPC FE	✓	✓	✓	✓	✓	✓	✓	✓
N	80,345	80,345	80,345	80,345	80,345	80,345	80,345	72,263
$Adj.R^2$	0.210	0.211	0.251	0.204	0.226	0.207	0.206	0.244
Dep. Var Mean	0.317	1.631	2.787	2.101	0.472	1.422	1.660	0.464

Notes: The table reports the effect of AIA on other quality indicators (excluding all patent of government interest). The regression includes inventors', attorneys', and examiners' controls. Standard errors are clustered at the application level.
Asterisks denote statistical significance: ***1%.

E Publicly Traded Entities and R&D

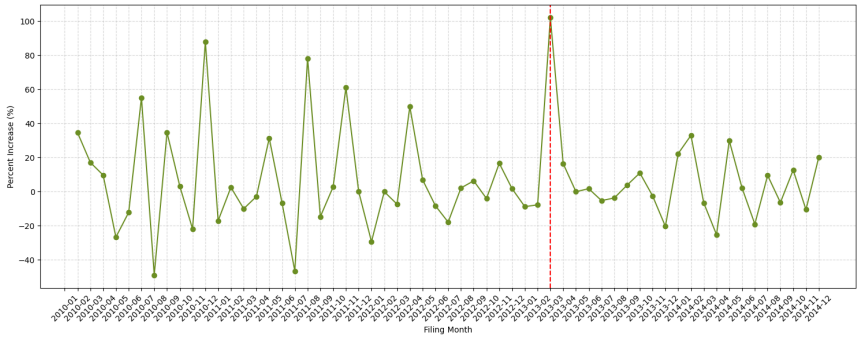
Table E.1: Effect of Micro Entity Status on KPSS Indicators, 2010-2014.

	Nominal Value	Real Value
	(1)	(2)
$Ent_i \times Post_t$	12.3403	4.3569
	(15.550)	(5.941)
Month FE	✓	✓
PERMCO FE	✓	✓
N	3,794	3,794
$Adj.R^2$	0.767	0.773
Dep. Var. Mean	6.977	2.854

Notes: The table reports the effect of AIA on the measures of innovation proposed by Kogan et al. (2017). Standard errors are clustered at the CRSP PERMCO level, the unique permanent identifier used in the WRDS repository (See https://libguides.stanford.edu/library/wrds/identifiers-linking/files).

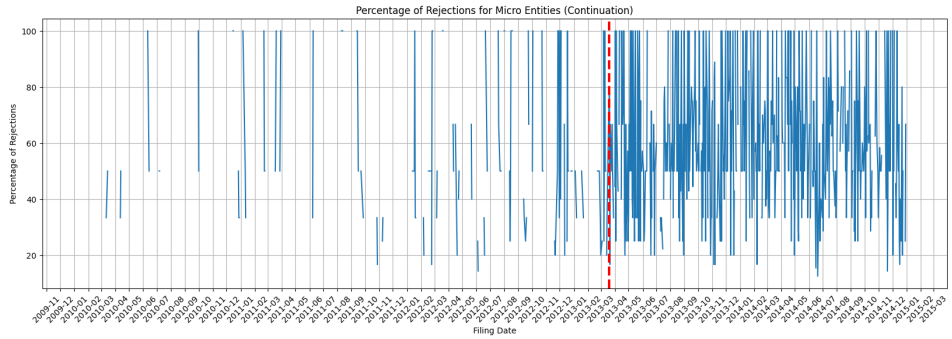
F Patent Continuation

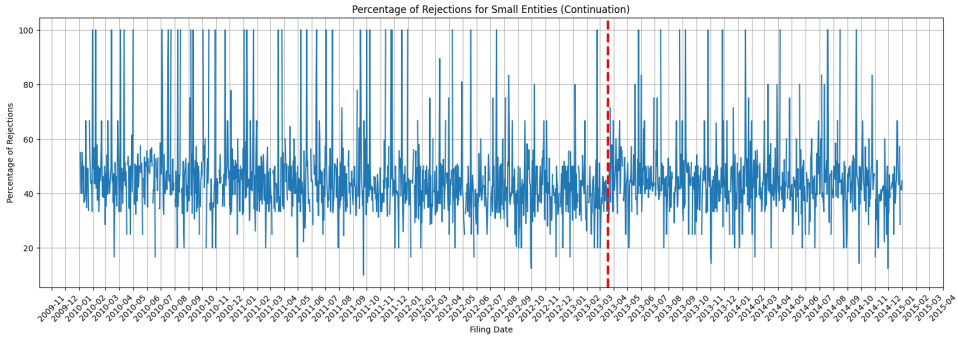
Figure F.1: Percentage Increase in Continuation Applications, 2010-2014.



Notes: The figure plots the monthly percentage increase in continuation applications among micro entities. The red vertical line indicates the month of the reform (March 2013).

Figure F.2: Percentage of Rejections for Continuation Applications by Filing Date.





Notes: The figures plot the daily percentage of patent rejections for continuation applications filed by micro and small entities against the filing date. The red vertical line indicates the date of the reform (19 March 2013).

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