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Crafting Intellectual Property Rights: Implications for Patent Assertion Entities, Litigation, and Innovation†

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We show that examiner-driven variation in patent rights leads to quantitatively large impacts on several patent outcomes, including patent value, citations, and litigation. Notably, Patent Assertion Entities (PAEs) overwhelmingly purchase patents granted by "lenient" examiners. These examiners issue patents that are more likely to be litigated by both *PAEs and conventional companies, and that also have higher invalidity rates. PAEs leverage a specific friction in the patent system that stems from lenient examiners and affects litigation more broadly. These patterns indicate that there is much at stake during patent examination, contradicting the influential "rational ignorance" view of the patent office.* (*JEL* K11, K41, O31, O34, O38)

Which features of the patent system matter for innovation dynamics? In this paper, we investigate the behaviors of examiners at the United States Patent Office (USPTO) and their impact on various patent outcomes. We find that examiner-driven variation in patent rights is central to understand a much-debated feature of the US innovation system: the activities of Patent Assertion Entities (PAEs). PAEs, which acquire patents from third parties and generate revenue by asserting them against alleged infringers, are controversial as they account for a large share of patent licensing and lawsuits.[1] We show that PAEs disproportionately purchase and assert patents from "lenient" patent examiners who issue patents that are more likely to be litigated and legally invalid. Furthermore, we find that

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[1] For instance, RPX Corporation (2015) reports that the share of PAEs in overall patent lawsuits went from 35 percent in 2010 to 70 percent in 2015, while Federal Trade Commission (2016) documents that the share of PAE in licensing revenue was 80 percent in the wireless chipset sector between 2009–2014.

examiners have an impact on several important patent outcomes (conditional on patent grant), including patent value and citations.

We advance the hypothesis that these examiner effects primarily stem from the way examiners *craft* patents rather than from their choice of which patents to grant. Conceptually, the value of a patent may not be solely determined by the quality of the idea embedded in it: a patent is not a raw idea but a carefully worded legal document, conferring to its holder the right to sue for infringement.[2] Examiners are heavily involved in the process of writing the patent description and claims through a back-and-forth process with the applicant between patent filing and patent grant (known as the "prosecution" process).

Using detailed data from the prosecution process, we find empirical support for the hypothesis that patent crafting matters for many patent outcomes, particularly so for litigation and PAEs. We show that patent outcomes correlate with specific examiner traits (e.g., the propensity to change the text of the claims during prosecution), and we use flexible controls to address the potential concern that our results are driven by selection effects stemming from the decision of which patents to grant (rather than by the way patents are crafted). The finding that PAEs overwhelmingly purchase patents granted by lenient examiners cannot be accounted for by mainstream theories of PAEs (which emphasize efficient intermediation or nuisance litigation). Instead, this pattern suggests that PAEs are primarily the symptom of a specific friction in the patent system, the way patent rights are crafted by lenient examiners. This friction affects litigation more broadly.

The first part of the paper examines the importance of examiners for various patent outcomes. Examiners decide which patents to grant and, conditional on grant, affect patent rights rather than the underlying idea embedded in the patent. By law, all examiners must ensure that the patents they grant have clear, well-defined claims with appropriate scope. In practice, using prosecution data from the USPTO and Frakes and Wasserman (2017), we find that there is significant variation in the way examiners craft patent rights. Conditional on patent grant, examiner effects may therefore be interpreted as reflecting variation in patent rights that is orthogonal to other determinants of patent outcomes, such as technical merit (we discuss below how this interpretation hinges on the ability to control for potential differences in the underlying quality of examiners' granted patents).

We contribute to a growing literature (e.g., Sampat and Williams 2015; Gaulé 2015; and Farre-Mensa, Hegde, and Ljungqvist 2017) suggesting that patent applications can be treated as quasi-randomly allocated to examiners conditional on some covariates like application, year, and technology class.[3] Prior research has used examiner assignment to estimate the causal effects of obtaining a patent, as

[2] A striking feature of patent systems around the world is the enormous variation in private returns, social returns, and litigation risk across patents (e.g., Pakes 1986 and Kogan et al. 2017 on firm returns; Toivanen and Väänänen 2012 and Bell et al. 2017 on inventor returns; Jaffe, Trajtenberg, and Henderson 1993 on patent citations as a proxy for social value; and Lanjouw and Schankerman 2001 on exposure to litigation). Scientific or technical factors, such as the expertise of eminent scientists (e.g., Azoulay, Graff Zivin, and Wang 2010) or a firm's learning capacity (e.g., Cohen and Levinthal 1989), are likely to be important drivers of patent outcomes. But the way patents are crafted may also be important, which we examine in this paper.

[3] Conceptually, patent outcomes may vary because of heterogeneity in idea quality, the applicant's input into patent drafting (typically via the applicant's lawyers), and the examiner's input into patent drafting. We use variation in patent

examiners differ in their grant rates. We build on this approach but differ in two ways. First, we develop two new quasi-experimental approaches to address identification concerns about examiner specialization raised in more recent work (Righi and Simcoe 2017); second, we exploit variation in examiner prosecution behavior *conditional* on granting the patent rather than variation in the propensity of examiners to grant patents. We present evidence supporting the validity of our approach after reporting a set of baseline results.

Our baseline research design estimates examiner fixed effects on the set of granted patents conditional on technology-by-year fixed effects. Our estimator uses an empirical Bayes shrinkage correction to prevent "overfitting" of the fixed effects, which would misattribute some of the variation from noise to causal variation across examiners. We apply this methodology to a range of patent outcomes related to private returns (stock market response from Kogan et al. 2017 and payment of maintenance fees), patent citations (total citations, self-citations, and external citations), patent market dynamics (patent sales, in general and specifically to PAEs), and legal disputes (patent infringement lawsuits, in general and specifically from PAEs). The estimated examiner effects are large for many outcomes, in particular for those related to PAEs and litigation. For example, a one standard deviation change in examiner effects leads stock market capitalization to increase by \$3 million, total citations by 24 percent, patent purchases by PAEs by 63 percent, litigation by 64 percent, and litigation specifically by PAEs by 46 percent. These estimates imply that policies affecting examiner behavior can have a substantial impact on the US innovation system.[4]

We then validate the causal interpretation and magnitudes of our baseline estimates in three ways. First, regarding identification, Righi and Simcoe (2017) reports strong evidence that examiners working in the same technology-based group (called "art units")[5] in fact specialize in specific sub-technologies, in ways that may be difficult to control for using observables. We develop two complementary quasi-experimental approaches to address this concern: (i) we show that there is a large subset of art units within which patent applications are assigned to examiners based on the last digit of the application's serial number, implying that examiner assignment is orthogonal to potential confounds in these art units; and (ii) we show that an examiner's "busyness" can be used as an instrument for application assignment; examiners with recently disposed applications are much more likely to be assigned the next incoming application, which provides variation in assignment

drafting from examiners rather than from lawyers because examiners are quasi-randomly assigned to patents, while lawyer assignment may be correlated with idea quality across applicants.

[4] As a point of comparison, the teacher value-added literature has documented sizable but much smaller effects of teachers on student outcomes. Chetty, Friedman, and Rockoff (2014a, b) estimates that a one standard deviation improvement in teacher effects in one grade raises student earnings by about 1 percent at age 28.

[5] Examiners at the USPTO are divided into more than 600 working groups called "art units," each composed of about 20 examiners who handle patent applications on relatively homogeneous technologies. Following qualitative evidence on assignment of applications to examiners reported in Cockburn, Kortum, and Stern (2003); Lemley and Sampat (2010); and Lemley and Sampat (2012), the recent literature treats assignment of patent applications to examiners within the same art unit as "as good as random" (e.g., Sampat and Williams 2015; Gaulé 2015; and Farre-Mensa, Hegde, and Ljungqvist 2017).

even in art units with significant specialization. These two alternative sources of variation yield estimates that are similar to our baseline results.

Second, we address the potential concern that selection effects (from the patent grant decision) may confound our results. Since examiners differ in their grant rates, it could be the case that patent outcomes vary across examiners because of underlying differences across examiners' pools of granted patents, independently of the crafting of patent rights. For instance, examiners with a low grant rate might only grant patents of high technical merit; this examiner "selection effect" is not related to patent crafting. To assess the magnitude of this potential bias, we introduce flexible controls for the examiner's average grant rate as well as proxies for the technical merit of patent applications (including the number of claims and the patenting histories of the assignee and inventors). We find that there is equally large causal variation in patent outcomes across examiners with these additional controls, which suggests that our estimates do not capture selection effects from grant decisions.

Third, we validate our baseline estimates in out-of-sample tests. We find that the empirical Bayes shrinkage correction is important to suitably account for excess variance from noise and obtain unbiased estimates of examiner effects, in particular for rare outcomes such as PAE purchase and litigation.

In the second part of the analysis, we investigate why examiner effects are an important driver of the wave of patent purchases and lawsuits by PAEs, a major and controversial feature of the US innovation system. We focus on outcomes related to PAEs because they rank among the outcomes that are most sensitive to examiner effects, and because PAEs have generated substantial academic and policy debate.[6] There are two main hypotheses about PAEs' behaviors: (i) PAEs may be useful intermediaries in the patent market, fostering incentives to innovate by lowering the cost of matching patent holders to patent buyers (e.g., Hagiu and Yoffie 2013 and Abrams et al. 2019) and helping enforce the patents of small inventors who lack the financial resources or legal expertise to defend themselves against large infringing companies (e.g., Lu 2012 and Galetovic, Haber, and Levine 2015); or (ii) PAEs may exploit imperfections in the legal system by acquiring patents with unclear claim boundaries and by asking innovative firms for licensing fees, whether or not the asserted patent is valid or infringed, in the hope that targeted firms will settle instead of risking a costly and uncertain trial (e.g., Miller 2013; Council of Economic Advisers 2013; Cohen, Gurun, and Kominers 2016; and Federal Trade Commission 2016). Any plausible theory of PAEs should account for the new fact, documented in the first part of this paper, regarding the large sensitivity of PAEs to examiner effects. By analyzing which examiners drive patent acquisition and litigation by PAEs, we can assess which PAE theories are plausible.

[6] PAEs, also known as "nonpracticing entities," "patent monetization entities," or "patent trolls," are defined as entities that generate revenue exclusively from patent licensing and litigation, without producing or selling products (Federal Trade Commission 2016). Since there is no official list of PAEs, we follow the literature (e.g., Bessen and Meurer 2014) and rely on a list provided by the RPX Corporation, a firm that helps companies manage risks from exposure to patent litigation. Universities, individual inventors, and failed companies are excluded from the set of PAEs we consider, and we show that the results are similar with alternative PAE lists from Cotropia, Kesan, and Schwartz (2014).

We start by studying the characteristics of examiners who issue patents that are purchased and asserted by PAEs or practicing firms. We correlate the causal examiner effects from the first part of the paper with measures of examiners' prosecution behaviors based on the correspondence between examiners and applicants (from Frakes and Wasserman 2017). We find that within the same technology category, PAEs and practicing firms target patents issued by examiners with different characteristics.[7] PAEs disproportionately purchase and assert patents that were granted by "lenient" examiners, who require applicants to make fewer changes to the text of the patent, such as clarifying a claim or withdrawing a claim deemed to be obvious or to bear on non-patentable subject matter. Examiner leniency has a negligible correlation with purchases by practicing firms, a sizable correlation with litigation by practicing firms and on purchases by PAEs, and a much larger correlation with litigation by PAEs. These patterns are quantitatively important: for instance, a one standard deviation increase in a simple proxy for examiner leniency, the change in the number of words per claim between patent filing and grant, leads to an increase in litigation of 40.5 percent for PAEs and 13.9 percent for practicing firms. These results cannot be accounted for by theories of PAEs based on a generic friction in the patent market, such as matching costs or the lack of financial resources for some inventors. They are consistent with the view that PAEs have a comparative advantage in patent litigation and therefore handle patents that are subject to a higher litigation risk, induced by the way examiners handle patents during prosecution. The fact that examiner leniency is an important driver of litigation for *both* PAEs and practicing firms, although the effect is not as large for the latter, is in line with a nuanced view of PAEs (e.g., Lemley and Melamed 2013 and Schwartz and Kesan 2014). According to this view, PAEs do not exploit imperfections of the legal system in an idiosyncratic way, but behave as litigation experts. In sum, our results show that PAEs' activities are the symptom of the way patents are handled by lenient examiners who affect litigation more broadly.

Given the evidence that patent litigation by PAEs is strongly correlated with examiner leniency, we study whether lenient examiners tend to issue patents that are more likely to be invalid according to the standards set by current patent law. Several observers have hypothesized that PAEs assert invalid patents (e.g., Federal Trade Commission 2016); approaching this question in terms of examiner effects has the potential to be informative about PAEs but also about patent litigation by practicing firms, who also selectively assert patents that were issued by lenient examiners. Patent invalidity is notoriously difficult to measure because of selection effects. For instance, court rulings on patent validity are observed only for a strongly selected set of patents, as there were only a few hundred rulings over the past decade. To address this issue, we introduce a proxy for patent invalidity available in the full sample of granted patents: patent re-issuance requests, which can

[7] Given that quasi-random assignment is at the level of examiners, the only causal effect that can be recovered is the "full" examiner effect on patent outcomes, which is a bundle of observed and unobserved examiner attributes. Observed relationships between patent outcomes and specific examiner attributes can only be interpreted as correlations, which are potentially subject to omitted variable bias. As discussed in Section III, we focus on establishing correlations that are quantitatively large, robust to the inclusion of various controls, and that can be interpreted as reflecting a more general trait of the examiner, such as "leniency."

be filed by the applicant when a patent is deemed wholly or partly "inoperative or invalid" through an error in the document. Using this proxy as well as two common proxies for invalidity (decisions from court rulings and trials at the patent office), we document robust and quantitatively important evidence that lenient examiners issue patents that are more likely to be invalid. The evidence is therefore consistent with the view that PAEs are willing to purchase and assert patents for which validity is questionable, but PAEs are not the only entities to assert such patents—practicing firms do so as well.[8]

These results are surprising for several reasons. First, the very large impact of patent examiners on patent outcomes (conditional on grant) is unexpected. While previous work documented variation in examiners' propensities to grant patents (Sampat and Williams 2015; Gaulé 2015; and Farre-Mensa, Hegde, and Ljungqvist 2017), we uncover the importance of the "intensive margin" of examiner effects (the crafting of patent rights, conditional on patent grant). This margin was not previously thought of as being of paramount importance for patent outcomes, as evidenced by (i) the fact that patent examiners are not very well paid,[9] (ii) the influential "rational ignorance" view of the patent office (Lemley 2000) that states there is little at stake in the patent examination process and that low-quality patents can be rationally ignored without significant consequences, and (iii) the focus of innovation research on the "macro-determinants" of the patent system, such as laws that establish a patent system or change the set of patentable subject matters.[10] In contrast, we show the importance of the "micro-determinants" of patents by establishing that the specific way in which patent rights are crafted (by examiners who are all subject to the same patent law) has a substantial impact on a range of patent outcomes and is of first-order importance to understand certain features of the US innovation system, such as litigation (by PAEs in particular, but also by practicing firms). Additionally, our results on PAEs and litigation are also unexpected: (i) our finding that PAEs overwhelmingly purchase and assert patents from lenient examiners is not in line with mainstream theories of PAEs;[11] (ii) our findings imply that policies affecting examiner behavior could have a large impact on PAEs' activities and litigation (in contrast with prior work that does not use quasi-experimental variation, e.g., Marco and Miller 2019);[12] and (iii) the

[8] This finding does not speak conclusively to the welfare effects of PAEs because litigation of patents issued by lenient examiners could conceivably be socially valuable, even when these patents are deemed invalid by the courts, the USPTO, or applicants themselves. For instance, Galetovic, Haber, and Levine (2015) suggests that the process of litigation might be the socially efficient dynamic process through which the patent system defines the contours of what should be patentable in highly innovative, rapidly changing industries.

[9] In 2017, most patent examiners started with annual salaries between \$54,099–82,094; salary can reach around \$130,000 for senior patent examiners, which is much lower than the typical salary of patent lawyers.

[10] For theoretical contributions, see, for example, Nordhaus (1969), Klemperer (1990), and Gilbert and Shapiro (1990); for empirical studies, see, for example, Sakakibara and Branstetter (2001), Moser (2005), Lerner (2009), and Williams (2013).

[11] For recent work on PAEs, see, for example, Golden (2006); McDonough III (2006); Chien (2012); Tucker (2014); Allison, Lemley, and Schwartz (2018); and Haber and Werfel (2016).

[12] Our findings are also related to the pioneering study of Cockburn, Kortum, and Stern (2003), which documents relationships between some examiner characteristics and patent invalidity rulings. We show how to recover the full magnitude of examiner effects on patent outcomes using a fixed effects estimator with a Bayesian shrinkage correction.

examiners who drive PAEs' activities do not tend to create greater private value in general, as discussed in Section III.[13]

Our findings about PAEs should be placed in the context of recent patent reforms (e.g., inter partes reviews) and Supreme Court rulings (e.g., *eBay v. MercExchange*, *Alice v. CLS Bank*). The 27 percent fall in the number of defendants targeted by PAEs from 2016 to 2017 suggests that this new legislation may be curbing PAEs' activities. Despite this change, PAEs remain a pressing potential social concern; PAE-targeted firms still account for 56 percent of all defendants in intellectual property (IP) cases, and PAEs are also active beyond litigation (e.g., licensing). Our results suggest that policies affecting patents examiners are another potentially powerful policy lever to affect their activities.

The remainder of the paper is organized as follows. Section I presents the data and descriptive statistics. Section II estimates examiner effects on a range of patent outcomes. Section III studies the implications for PAEs' activities. Section IV concludes.

I. Data

In this section, we describe the data sources, define the samples and key variables we used in the analysis, and present summary statistics.

A. *Data Sources, Samples, and Variable Definitions*

Patent Records.—We use two types of patent data to achieve two purposes. First, we rely on data on granted patents to measure a series of post-grant patent outcomes. Specifically, we build proxies for the private returns to patents, identify high-impact patents using citations, and document transactions in the patent market. Second, we use data on both granted and ungranted patent applications to identify examiners and measure their behavior during patent prosecution.

The granted patent dataset is obtained from USPTO and extends from 1975 to 2016.[14] We rely on several proxies for the private returns to patents. Following the literature (e.g., Pakes 1986), we use the payment of patent maintenance fees as a lower bound on the private valuation of the patent by the assignee. These fees are due 4, 8, and 12 years after patent grant and are increasing over time.[15] We also use the estimates of firm-level returns to patents from Kogan et al. (2017), who runs event studies to estimate the excess stock market return realized on the grant date of patents assigned to publicly traded firms; these estimates are available for patents granted before 2010. Moreover, we use data on patent citations to identify high-impact patents. We consider alternatively total citations, self-citations (i.e., the assignee of the focal patent cites it in future patents), and citations by assignees

[13] Therefore, it is not the case that examiners with high PAE effects create more valuable patents for all agents in the patent system, as would be the case if they were just allowing greater scope.

[14] This data is obtained through the Reed Tech USPTO page: http://patents.reedtech.com/pgrbft.php.

[15] For entities that do not benefit from reduced rates, the fees are \$1,600 after 4 years, \$3,600 after 8 years, and \$7,400 after 12 years. The complete fee schedule is available from the USPTO at https://www.uspto.gov/learning-and-resources/fees-and-payment/uspto-fee-schedule.

that were not listed on the focal patent. We build these measures using the disambiguated assignee names from Balsmeier et al. (2015). To address censoring, we focus on citations that occurred in the three years following patent grant, and we document in robustness checks that the results are similar when considering all citations. Finally, we measure changes in ownership of patents by merging in data on patent reassignments from Graham, Marco, and Myers (2018).[16]

The data covering both granted and ungranted patent applications ranges from 2001 to 2015 and is obtained from the USPTO's Patent Examination Research Dataset (Graham, Marco, and Miller 2015a). We use this dataset to obtain unique numeric identifiers for each examiner during their tenure at the patent office, which are the critical inputs needed to estimate examiner effects. We then merge in data from Frakes and Wasserman (2017) on the correspondence between the examiner and the applicant. When asking applicants to amend patent documents, examiners need to ground their demands in specific sections of patent law, which we describe in Section IB.[17] To characterize an examiner's behavior during prosecution, we count the number of references made to the various sections of patent law. We also measure the examiner's grant rate, and, for granted patents, we directly measure the extent to which the text of the patent changes between application and grant by computing changes in the number of words per claim and in the number of claims.[18]

Our main analysis sample is the Patent Examination Research Dataset merged to the patent outcomes of the granted patent dataset. We implement one important sample restriction: we exclude the so-called "continuation applications," applications that follow an earlier-filed patent application. Those applications are assigned to the same examiner as the patent they follow, and, therefore, quasi-random assignment of examiner does not hold. Our main analysis sample covers each non-continuation granted patent between 2001 and 2015, for which we observe the patent outcomes of interest as well as examiners' identity and prosecution behaviors. For robustness, we estimate examiner effects on the full sample of (non-continuation) granted patents going back to 1975 by disambiguating examiner names (given the lack of numeric identifiers in this sample), but we lose information on examiners' prosecution behaviors.

Patent Litigation.—We combine three data sources to obtain a comprehensive picture of patent litigation. Specifically, we combine data from LexMachina, Darts IP, and RPX, which have been tracking intellectual property lawsuits since 2000 and

[16] Records of the assignments (transactions) affecting US patents are maintained by the US Patent and Trademark Office and available between 1970 and 2014. There is no express legal requirement for parties to disclose assignments to the USPTO, but patent laws provide incentives for recording. For instance, failure to record an assignment renders it void against any subsequent purchaser or mortgagee (35 USC 261). See Graham, Marco, and Meyers (2015b) for more details.

[17] When a patent is assigned to two examiners, a "primary" examiner with signatory authority and a "secondary" examiner who carries out most of the work, we treat the data as if the patent had been assigned to the secondary examiner only, following the example of Lemley and Sampat (2012).

[18] The USPTO's Patent Examination Research Dataset only covers published patent applications. For ungranted patents, applicants are free to opt out of publications, which occurs in about 5 percent of cases during the period we consider (Graham, Marco, and Meyers 2018). The potential selectivity issues that could arise from the omission of "nonpublic" applications are largely orthogonal to our analysis, as we only rely on ungranted applications to measure an examiner's allowance rate.

thus offer full coverage for our main analysis sample. Although the datasets have significant overlap, it is sometimes challenging to identify all the patents involved in a given lawsuit, which creates differences in the lists.[19]

Patent Assertion Entities.—Following standard practice (e.g., Bessen and Meurer 2014), we rely on a list provided by the RPX Corporation, a firm that helps companies manage litigation risk, and exclude from the list any individual inventor, university, or failed company.[20] We then build the patent portfolio of PAEs by merging the PAE list to the patent reassignment dataset of Graham, Marco, and Myers (2018) by assignee name. We only consider patents that were purchased by PAEs (a few large PAEs, such as Intellectual Ventures, also invent their own patents). To establish that our results are robust to the choice of PAE list, we repeat the analysis using alternative PAE lists from Cotropia, Kesan, and Schwartz (2014) and consider only the patent portfolio of Intellectual Ventures.[21]

B. *Summary Statistics*

Table 1 presents the summary statistics for the variables of interest, documenting heterogeneity in patent outcomes (panel A), the extent to which patent documents change between application and grant (panel B), and heterogeneity in examiner behavior (panel C).

Statistics on private returns, citations, patent sales, and patent litigation are shown in panel A of Table 1. Private returns feature high variance; the standard deviation of the firm-level patent value estimates from Kogan et al. (2017) is equal to almost three times the mean. The rates of maintenance fee payments are very high in early years but substantially lower for the more expensive twelfth-year maintenance fee payment, which also indicates heterogeneity in private valuations. Citations also feature high variance, indicating that patents greatly vary in their level of impact, regardless of whether we consider total citations, self-citations, or citations by other assignees. The panel also shows that about 20 percent of all granted patents are sold to practicing (i.e., non-PAEs) firms and 1.01 percent to PAEs. Only 0.65 percent of all granted patents are litigated. Patent litigation by PAEs involves 0.04 percent of patents; this fraction is very small, but it indicates that PAEs' litigation rate is over six times higher than average, given that they own only about 1 percent of the patent stock.[22] The purpose of Section II is to estimate the extent to which this heterogeneity in patent outcomes results from examiner effects.

Panel B of Table 1 shows how the patent document changes between application and grant. In most cases, the examiner issues a so-called "rejection" as her first decision on the application (Williams 2017), which is effectively an invitation for

[19] We manually checked a few of the differences and verified that the patents were actually involved in litigation.

[20] Excluded entities are based on classifications from RPX and Cotropia, Kesan, and Schwartz (2014).

[21] Intellectual Ventures holds an estimated 25,000–30,000 US patents and released a list of around 20,000 patents on their website in November 2013 that is available at http://patents.intven.com/data/ivpatents.csv.

[22] In addition, PAE patents are involved in about seven cases per litigated patent versus about two cases for non-PAE litigated patents, based on a simple count of district court cases per patent in the LexMachina data.

Table 1—Summary Statistics

Outcomes	Mean	Median	SD	Sample size
Panel A. Heterogeneity in patent outcomes				
Winsorized patent value from Kogan et al. (2017), \$M	8.1495	2.56	16.07	356,375
Fourth-year fee payment rate	0.8708	1	0.3354	1,247,958
Eighth-year fee payment rate	0.6098	1	0.4877	697,918
Twelfth-year fee payment rate	0.2089	0	0.4065	373,207
Total patent citation within three years of grant	0.5256	0	1.461	988,585
Patent citations by same assignee within three years of grant	0.1134	0	0.7257	988,585
Patent citations by other assignees within three years of grant	0.4122	0	1.1992	988,585
Rate of patent acquisition by non-PAEs	0.1965	0	0.3974	1,270,082
Rate of patent acquisition by PAEs	0.0102	0	0.10045	1,270,082
Rate of patent litigation by non-PAEs	0.0065	0	0.0804	1,270,082
Rate of patent litigation by PAEs	0.0004	0	0.0202	1,270,082
Panel B. Changes to patent document between application and grant				
Percent change in number of words per claim	57.32	25.24	84.58	1,110,272
Percent change in number of claims	−3.64	0	46.14	1,110,912
Use of Section 101—lack of utility or eligibility	0.0541	0	0.226	1,270,210
Use of Section 102(a)—prior art exists	0.0174	0	0.130	1,270,210
Use of Section 103(a)—obvious invention	0.419	0	0.493	1,270,210
Use of Section 112(b)—vague claims	0.056	0	0.231	1,270,210
Patent citations added by examiner	0.185	0	0.388	1,270,210
Panel C. Heterogeneity in examiner behavior				
Number of years at the US Patent Office	6.35	7	3.19	10,018
Number of art units active in	1.80	2	0.96	10,018
Total patent applications processed	190	119	215	10,018
Patent grant rate	0.55	0.57	0.27	10,018
Use of Section 101—lack of utility or eligibility	0.09	0.02	0.14	10,018
Use of Section 102(a)—prior art exists	0.02	0.006	0.03	10,018
Use of Section 103(a)—obvious invention	0.45	0.48	0.21	10,018
Use of Section 112(b)—vague claims	0.19	0.17	0.15	10,018
Rate of patent acquisition by PAEs	0.011	0	0.032	10,018

Notes: In panels A and B, patents are the unit of observation. In panel C, patent examiners are the unit of observation. All statistics are unweighted. See Section IA for details on the sample and variable definitions. Percent change in number of words per claim is an average over all claims.

the patent applicant (or their representative, typically a patent attorney) to revise the text of the patent. Panel B shows that these changes are substantial. Through the back-and-forth with the examiner, the number of words in each claim increases by 57 percent on average.[23] The lengthening of the claims can be interpreted as limiting the scope and clarifying the claims by making them more precise (Marco, Sarnoff, and deGrazia 2016). In addition, examiners tend to ask applicants to reduce the number of claims to limit the scope of the patent; while the average change is limited (−3.64 percent), the standard deviation across patents is high (46.14 percent).[24] We also observe that the examiner asks the applicant to add citations to prior patents. The changes to the patent document during the back-and-forth between the applicant and the examiner show that the examiner is engaged in an

[23] Given that the effective IP protection provided by a patent depends entirely on the content of the claims, and given that examiners affect to a great extent the words in the claims during prosecution, it is plausible that examiners may have a large impact on the legal force of the patent.

[24] Following the literature, we report statistics for independent claims, leaving dependent claims aside as in Marco, Sarnoff, and deGrazia (2016).

iterative process and does not simply make a one-time accept or reject decision. During this process, the examiner must substantiate her demands by referring to specific sections of patent law corresponding to various standards of patentability, namely that the invention is useful and its subject matter is eligible for a patent (35 U.S.C. §101), it is novel relative to the prior art (35 U.S.C. §102(a)), it is non-obvious (35 U.S.C. §103(a)), and the claims are sufficiently clear to satisfy the disclosure requirement (35 U.S.C. §112(b)). Panel B of Table 1 shows that on average non-obviousness is used significantly more frequently than other sections.

Panel C of Table 1 presents statistics at the level of examiners. We observe 10,018 examiners in our main analysis sample who work at the USPTO for 6.35 years on average. The median number of technology areas in which an examiner works (called "art units") is two. The average examiner processes close to 200 patents over the course of our sample. The panel shows that some examiners have a much higher grant rate than others, or have a stronger tendency to invoke specific sections of patent law during the back-and-forth with the applicant. We also observe large variation across examiners in the shares of their granted patents that are purchased by a PAE: the standard deviation across examiners is twice the average PAE purchase rate. This observed heterogeneity across examiners could merely reflect noise or the fact that different examiners are working on different technologies, or it could be driven by systematic (causal) differences in examiner behavior, which we investigate in the remainder of the paper.

C. *Illustration of Main Findings*

Some of our main results in Sections II and III can be previewed in a simple, graphical way. The various panels of Figure 1 document the relationship between patent acquisition or litigation and a simple measure of examiners' prosecution behavior.

For each patent, we compute the average change in the number of words per claim between application and grant for all other granted patents processed by the same examiner, leaving out the focal patent. This leave-one-out examiner measure is exogenous to the focal patent. To ensure that we compare similar examiners, we include art unit by patent filing year fixed effects in all specifications. To ensure that potential extensive-margin selection effects are not confounding the results, we control for the (leave-one-out) grant rate of the examiner. Conceptually, these specifications compare patent outcomes for examiners who have the same grant rate, work in the same art unit in the same year, but differ in the way they craft property rights, as measured by the change in the number of words per claim between application and grant.

Panel A of Figure 1 shows that the probability that a patent is purchased by a PAE is a strongly negative function of the examiner's propensity to ask applicants to add words to the patent claims (for instance to clarify them). Each dot in the binned scatter plot represents 5 percent of the data. The PAE purchase rate falls by about 25 percent of the baseline rate as we move from the left to the right along the *x*-axis, which shows very directly that the way examiners craft property rights is first order for certain patent outcomes. Similarly, large effects are found for litigation by PAEs

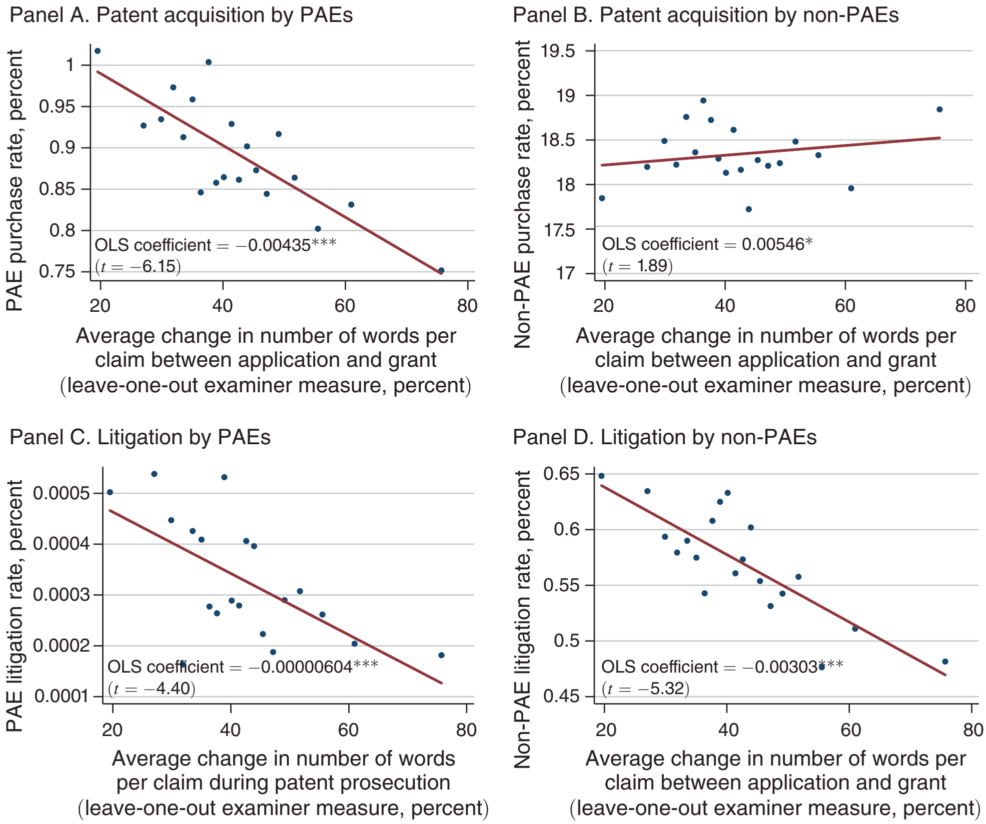

Figure 1. The Effect of Examiners on Patent Acquisition and Litigation

Notes: In the various panels of this figure, the level of observation is a patent. The average change in the number of words per claim is measured at the level of an examiner, leaving out the focal patent. All specifications include art unit-by-year fixed effects and address potential extensive margin effects by controlling for the examiner's leave-one-out patent grant rate (see text for details). The sample is the full patent grant sample described in Section IA, excluding examiners in the top 1 percent of the distribution of the total number of granted patents. The total number of patents granted by the examiner is used as weights in all panels. Each dot represents 5 percent of the data, and the OLS best-fit lines are reported. Standard errors are clustered by examiner.

and litigation by practicing firms, but not for purchases by practicing firms. The comparison of the various panels shows that PAEs and practicing firms respond in a similar way to examiners for the purpose of patent litigation (panels C and D) but not for patent acquisition (panels A and B).

This simple regression approach has the benefit that its robustness can immediately be assessed graphically. But the choice of the variable on the *x*-axis is arbitrary. This variable may capture only a small fraction of the relevant examiner behaviors, and it may be correlated with examiner traits that would suggest different interpretations. To address this limitation, we turn to a research design that can recover the full impact of examiners on patent outcomes (Section II), and we then correlate the examiner-level causal estimates with a range of examiner characteristics (Section III).

II. Estimating Examiner Effects on Patent Outcomes

In this section, we estimate the impact of examiners on a range of patent outcomes. We assess the validity of the identifying assumptions in our baseline design using additional sources of variations and alternative specifications.

A. *Research Design*

To estimate the extent to which patent outcomes depend on the way patent rights are crafted, we need variation in patent rights that is orthogonal to other determinants of patent outcomes, such as technical merit. Through their back-and-forth with the applicant between initial filing and grant, examiners may provide such variation. Conditional on patent grant, examiners affect patent rights, rather than the underlying idea embedded in the patent. Moreover, a growing literature suggests that patent applications can be treated as quasi-randomly allocated to examiners working in the same art unit in the same year (Sampat and Williams 2015; Gaulé 2015; Farre-Mensa, Hegde, and Ljungqvist 2017).

Using quasi-random allocation of patent applications to examiners raises three empirical concerns that were previewed in the introduction. First, since we are interested in recovering the full magnitude of examiner effects, conceptually we need to estimate fixed effects for all examiners, instead of projecting the data onto a specific examiner trait as in Figure 1.[25] Given that we have a large number of examiners and work with rare outcomes, such as litigation, it is likely that we may be overfitting"the fixed effects: we may misattribute some of the variation from the noise to causal variation across examiners. This "excess variance" problem is well known, and we address it using a standard Bayesian shrinkage methodology (e.g., Kane and Staiger 2008; Chetty, Friedman, and Rockoff 2014a; and Chetty and Hendren 2018). Our baseline research design focuses on addressing this issue. Second, recent evidence from Righi and Simcoe (2017) challenges the notion that the allocation of patent applications to examiners can be treated as "as good as random." Third, our examiner effects could in principle be confounded by selection effects related to grant decisions. Using alternative sources of variation and specifications, we find that the second and third potential threats turn out to leave our baseline estimates unaffected. We, therefore, proceed by presenting our baseline design and its results, before turning to validation tests addressing the other potential threats.

Our baseline research design estimates examiner fixed effects on the set of granted patents with an empirical Bayes shrinkage correction, conditional on art unit by year fixed effects. The identification assumption is that the allocation of

[25] Running a specification using examiner characteristics as regressors can only recover a lower bound for the overall effect of examiners because the observed characteristics only capture a fraction of examiner behavior. A fixed effects estimator can recover the full effect, but it must be adequately adjusted to avoid excess variance due to overfitting of the fixed effects. In addition, the regression coefficients for the various examiner characteristics included in the specification should not be interpreted as causal because random assignment occurs at the level of examiners and the observed examiner characteristics are likely to be correlated with other, unobserved examiner characteristics. For instance, in contemporaneous work, Kuhn (2016) and Kuhn and Thompson (2017) create an instrumental variable for patent scope based on an examiner characteristic they label "scope toughness," but this characteristic could be correlated with other examiner traits that may affect the patent through channels other than scope.

(non-continuation) patents to an examiner working in the same art unit in the same year is as good as random, that is, it is not correlated with other determinants of patent outcomes. Given this assumption, we estimate examiner effects using the following statistical model:

$$Y_i = a_{ut(i)} + v_{ij}, \tag{1}$$

$$v_{ij} = \mu_j + \epsilon_i,$$

where i indexes the patent, j the examiner, u the art unit, and t the year; Y_i is the patent outcome of interest, $a_{ut(i)}$ denotes art unit by year fixed effects, μ_j is the causal examiner effect of interest, and ϵ_i is an idiosyncratic patent-level shock. Our goal is to recover $\sigma_\mu \equiv \sqrt{\mathrm{var}(\mu_j)}$.

We estimate the standard deviation of the underlying distribution of examiner effects in three simple steps. We first obtain estimates of residuals $\{\hat{v}_{ij}\}$ for each patent by estimating art unit by year fixed effects in (1) by OLS. We then compute the average estimated residual per examiner in each year:

$$\bar{v}_{jt} \equiv \frac{1}{n_{jt}} \sum_{i=1}^{n_{jt}} \hat{v}_{ij} = \mu_j + \frac{1}{n_{jt}} \sum_{i=1}^{n_{jt}} \epsilon_i, \tag{2}$$

where n_{jt} is the number of patents processed by examiner j in year t. Because many examiners are assigned only a few patents per year (online Appendix Table D1), the error term cannot be expected to converge to zero for each examiner.

In a final step, we compute the covariance between an examiner's average residuals across consecutive years:

$$\hat{\sigma}_\mu = \sqrt{\mathrm{cov}\left(\bar{v}_{jt}, \bar{v}_{j(t+1)}\right)}, \tag{3}$$

which yields a consistent and unbiased estimate of σ_μ, as can be seen immediately from the second equality in (2). Excess variance in the average residual is handled by isolating the "systematic" component of the variation in average residuals that persists over time. If the examiner causal effects $\{\mu_j\}$ are close to zero, we may still observe variation in the average residuals $\{\bar{v}_{jt}\}$ across examiners in any given year because of idiosyncratic shocks, but there will be no covariance between examiners' average residuals across years because the idiosyncratic shocks are uncorrelated. We call σ_μ the "signal" standard deviation of examiner effects to contrast it with the "raw" standard deviation of residuals, which is contaminated by noise. The covariance calculation in (3) uses the counts of patents granted by each examiner $\{n_{jt}\}$ as weights to increase precision.

The signal standard deviation is our primary focus because it is informative about the overall variation from examiners, but we also compute individual estimates of causal effects for each examiner. We compute an average of the residuals $\hat{v}_{ij}$ over all

Table 2—Signal Standard Deviations of Examiner Causal Effects on Patent Outcomes

	Signal SD		Shrunk effect SD, percent of average	Sample size, patents/examiners
	Percent of average (1)	Level (2)	(3)	(4)
Patent value from Kogan et al. (2017), $M	40.80 (38.94–41.95)	3.32	29.48	356,375/7,937
Fourth-year fee payment rate	3.76 (3.64–3.91)	0.0328	2.18	1,247,958/9,543
Eighth-year fee payment rate	10.79 (10.40–10.82)	0.0658	6.32	697,918/8,580
Twelfth-year fee payment rate	22.62 (21.44–23.37)	0.0472	11.50	373,207/8,289
log total patent citation	23.79 (23.27–24.15)	0.0610	14.04	988,585/8,620
log patent citations by same assignee	46.06 (43.62–48.63)	0.0278	25.65	988,585/8,620
log patent citations by other assignees	24.47 (23.88–24.80)	0.0512	14.10	988,585/8,620
Rate of patent acquisition by non-PAEs	14.61 (13.60–15.41)	0.0287	7.66	1,270,082/9,564
Rate of patent acquisition by PAEs	62.96 (52.95–70.93)	0.0064	31.11	1,270,082/9,564
Rate of patent litigation by non-PAEs	64.25 (52.79–72.73)	0.0042	27.43	1,270,082/9,564
Rate of patent litigation by PAEs	46.04 (0–147.76)	0.0002	4.84	1,270,082/9,564

Notes: This table reports the signal standard deviations of examiner effects as a percentage of the mean (column 1) and in level (column 2), as well as the standard deviations of shrunk examiner effects (column 3). The Bayesian shrinkage methodology used to obtain these estimates is presented in Section IIA. In column 2, 95 percent confidence intervals are obtained by bootstrapping. The log patent citation variables refer to the log of one plus the number of citations within three years of grant. The patent value variable is right winsorized at the ninety-ninth percentile. See Section IA for details on the sample and variable definitions.

years for each examiner, which we denote $\bar{v}_j$.[26] We then construct the empirical Bayes posterior estimate of each examiner effect by multiplying $\bar{v}_j$ by a shrinkage factor:

$$\hat{\mu}_j = \frac{\hat{\sigma}_\mu^2}{\mathrm{var}(\bar{v}_j)} \cdot \bar{v}_j. \tag{4}$$

The shrinkage factor is the ratio of signal variance to total variance.[27] We validate this research design by documenting in Section IIC that this approach yields unbiased estimates of examiner effects in out-of-sample tests, while ignoring excess variance delivers misleading results.

B. *Baseline Estimates of Examiner Effects*

Table 2 reports the estimates of examiner causal effects for a range of patent outcomes. We find substantial examiner effects for private value and outcomes related to patent litigation.

Private value is strongly affected by examiner effects. The first row of Table 2 shows that the signal standard deviation of examiner effects corresponds to a $3.32

[26] To increase precision, $\bar{v}_j$ is computed using weights that make $\bar{v}_j$ a minimum variance unbiased estimate of μ_j for each examiner. This step requires estimating the variances of other shocks in the statistical model. Specifically, we allow for an examiner-by-year shock θ_{jt} and compute $\hat{\sigma}_\epsilon^2 = \mathrm{var}(v_{ij} - \bar{v}_{jt})$ and $\hat{\sigma}_\theta^2 = \mathrm{var}(v_{ij}) - \hat{\sigma}_\mu^2 - \hat{\sigma}_\epsilon^2$. We obtain $\bar{v}_j = \sum_t w_{jt}\bar{v}_{jt}$, with $w_{jt} = h_{jt}/\sum h_{jt}$ and $h_{jt} = 1/(\hat{\sigma}_\theta^2 + (\hat{\sigma}_\epsilon^2/n_{jt}))$. See online Appendix A for a complete discussion.

[27] Online Appendix A discusses the computation of $\mathrm{var}(\bar{v}_j)$. Because of the precision weights in $\bar{v}_j$, the shrinkage factor is lower for examiners for which more patents are observed. The estimated examiner effects $\{\hat{\mu}_j\}$ have an empirical Bayes interpretation as the Bayesian posterior estimates of the examiner effects, starting from a normal prior distribution centered around zero with signal variance σ_μ. There is also a frequentist interpretation: the shrinkage factor is the OLS coefficient in a hypothetical regression of the true (unobserved) μ_j on the (observed) $\bar{v}_j$.

million change in patent value, using the estimates from Kogan et al. (2017). In percentage terms, one signal standard deviation in examiner effects explains 40.8 percent of the average patent value for publicly traded firms. The process of creation of patent rights therefore has a first-order impact on a patent's private value to its assigned firm. We confirm this result in rows two to four of the table by considering other proxies. The rates of payment of patent maintenance fees at the various horizons are all responsive to examiner effects. Consistent with the notion that fee payments can only give a lower bound on private valuations, especially in earlier years when the fees are smaller, the examiner effects are smaller than with the Kogan et al. (2017) estimates; the signal standard deviations are under 10 percent of the average payment rate.

Citations also respond to examiner effects. Considering in turn the signal standard deviations for total patent citations, self-citations, and citations by other assignees, we consistently find significant effects. The impact is strongest for self-citations, with a signal standard deviation of 46.06 percent, while the signal standard deviation for citations by other assignees is only 24.47 percent. This finding points to the role of cumulative innovation by the assignee.[28]

We find particularly strong examiner effects for litigation and PAEs' activities. The signal standard deviation of examiner effects accounts for over 60 percent of the baseline rate of patent purchases by PAEs. In contrast, the impact of examiners on the probability that a patent is sold to a practicing firm is much smaller: the signal standard deviation is 14.6 percent of the baseline rate. The impact of examiners on the probability that a patent is litigated is very large: the signal standard deviation is about 65 percent of the baseline rate. Considering the raw standard deviation of examiner effects would be very misleading: for rare outcomes like patent litigation or PAE purchase, the raw standard deviation is implausibly high, over four times larger than the signal standard deviation (online Appendix Table D2).

We use a bootstrapping procedure for inference. We redraw samples from the application-level dataset with replacement and repeat the estimation of the signal standard deviations.[29] The 95 percent confidence intervals are reported in column 1 of Table 2 . The signal standard deviations are all precisely estimated, except for one extremely rare outcome, patent litigation by PAEs.

The standard deviation of shrunk examiner effects obtained from equation (4) is also substantial. Column 3 of Table 2 reports these results. For instance, the standard deviation of shrunk examiner effects accounts for 29.48 percent of the average patent value from Kogan et al. (2017), 31.11 percent of the baseline rate of PAE patent purchases, and 27.43 percent of the average rate of patent litigation.

The large signal standard deviations indicate that examiners play an important role in determining patent outcomes.[30] Consequently, policies affecting examiners

[28] Although this finding may also reflect strategic self-citations, the literature on strategic self-citations has emphasized the importance of strategic continuation filings, while we focus on non-continuation patents.

[29] We also bootstrapped by re-sampling within examiner or within examiner by filing year and obtained similar results (not reported).

[30] We also find sizable examiner effects on the "disruptiveness" statistics developed by Funk and Owen-Smith (2016), which are based on citation patterns. The signal standard deviation estimate for their baseline index (denoted "CD_t") is 0.0286, with a 95 percent confidence interval from 0.0272–0.0298. The underlying standard deviation

have the potential to greatly affect the US innovation system, for instance regarding litigation rates or the activities of PAEs. The large standard deviations of shrunk examiner effects indicate that, based on historical data, one can identify examiners who have a particularly large impact on specific outcomes.[31] Our analysis so far is silent on the characteristics of these examiners, which we turn to in Section III. Before doing so, we establish the validity of our identification assumptions with a series of tests and robustness checks.

C. *Validation of Baseline Design: Addressing Nonrandom Assignment and Selection*

In this subsection, we use alternative research designs and specifications to investigate potential limitations of the baseline research design.

Alternative Source of Variation #1: Allocation of Applications to Examiners Using the Last Digit of the Application's Serial Number.—A potential concern with our baseline research design is that there is specialization even across examiners working in the same art unit at the same time (Righi and Simcoe 2017). If specialization patterns are correlated with other factors that affect patent outcomes, then the examiner effects documented in Table 2 may reflect omitted variable bias.

To address this potential concern, we identify art units where application assignment to examiners is determined by the last digit of the serial number of the patent application. The last digit of an application's serial number, ranging from 0 to 9, is determined by the order of submission of applications and is therefore orthogonal to potential confounding variables such as technical factors.[32] Anecdotal evidence suggests that some art units assign applications to examiners based on the last digit of the serial number (Lemley and Sampat 2012). To determine which art units do so at different points in time, we compute an index of "concentration" of last digits across examiners working in the same art unit in the same year. If some examiners systematically get specific last digits, we will find a high degree of concentration. We use the concentration index initially developed by Mori, Nishikimi, and Smith (2005) to study industry agglomeration, which was recently applied by Righi and Simcoe (2017) to the context of patents to study examiner specialization.[33] Applied to our purposes, the test delivers an χ^2-statistic asking whether applications' last digits are less dispersed across examiners than one would expect if last digits were not used for

of the CD_t measure is 0.184. This finding indicates that examiners have an effect on the patterns of citations, in addition to the overall count.

[31] We found that examiner effects do not tend to "average out" across outcomes; for instance, there is a large share of examiners who produce patents with systematically lower value, fewer citations, and higher probabilities of litigation or of PAE purchase (not reported).

[32] When a patent application is filed, the Office of Patent Application Processing assigns it a serial number. The first part of the serial number indicates the technology category, while the last digits reflect the order of arrival of applications.

[33] Righi and Simcoe (2017) uses this test to document specialization of examiners in the same art unit and year, specifically testing for failure of random assignment with respect to technological features of the patent. We use the same test but for the opposite purpose: we use the test to identify art units that allocate applications based on their last digits, which implies quasi-random allocation with respect to technological features of the patent.

application assignment.[34] We carry out the test in each year and each art unit and find that there is a large number of art units with a p-value below 1 percent, indicating that these art units use applications' last digits to assign patents.[35] Online Appendix and Appendix Figure D1 present the methodology and results in more detail.

Panel A of Table 3 shows that the signal standard deviations estimated for art units that allocate patents using last digits are quantitatively similar to those from the baseline design. Column 1 shows the signal standard deviations for various outcomes in the subsample of art units with a p-value below 0.01 in the χ^2-test. Moreover, column 2 repeats the estimation of the signal standard deviation in the subsample of art units belonging to information technologies.[36] The results are similar in this subsample as well, which is comforting because Righi and Simcoe (2017) reports that they find no evidence of examiner specialization in information technologies.[37]

Alternative Source of Variation #2: A Busyness Instrument.—A limitation of using art units that allocate applications using last digits is that these art units account for only about a third of all art units. There is anecdotal evidence that some art units allocate applications to examiners based on the timing of arrival of applications (Lemley and Sampat (2012)). When a new application arrives at the patent office, an examiner who recently finished processing another application may be particularly likely to be assigned the new application, because they happen to have more time on their hands.

To proxy for how busy an examiner is when a given new application arrives, we measure the number of cases closed by the examiner in the two preceding weeks. For each incoming application, we compute assignment probabilities across all examiners working in the relevant art unit and time period based on the number of cases closed in the previous two weeks, art unit by year fixed effects, and examiner fixed effects. Within an art unit and year, assignment probabilities vary only because of changes in (relative) busyness across examiners. We estimate assignment probabilities using a simple linear probability model, presented in online Appendix A.

Using the estimated assignment probabilities across examiners, we instrument for the characteristics of the examiner who actually processed the application. For instance, if an application arrives in the art unit at a time when only "lenient" patent examiners (who tend to ask the applicant to make only a few changes to the patent) happen to be free, then the application should be more likely to receive a more

[34] Formally, we are testing the null that applications' assignments are independent of their last digit; this test can be viewed as a multivariate generalization of a t-statistic comparing observed frequencies to the distribution under random assignment. For details, see online Appendix A as well as Mori, Nishikimi, and Smith (2005) and Righi and Simcoe (2017).

[35] The analysis is conducted separately for each art unit-year. The total number of art unit-years is 7,695, out of which 1,456 have p-values below 0.01, 1,612 below 0.05, and 1,750 below 0.10. The number of art units is 710, out of which 249 have at least one year with p-values below 0.01, 286 below 0.05, and 329 below 0.10.

[36] This subsample includes the following technology centers: computer architecture and software (21); computer networks, multiplex, cable and cryptography/security (24); communications (26); and business method art units (3620s, 3680s, 3690s). We exclude technology center 2800 (semiconductors), which Righi and Simcoe (2017) identifies as having significant examiner specialization.

[37] The signal standard deviation for patent value from Kogan et al. (2017) is smaller in the IT subsample (3) than in the full sample (Table 2). But this is due to heterogeneity in the signal standard deviation of examiner effects across technology categories rather than to endogeneity concerns; online Appendix Table D3 reports smaller signal standard deviations for patent value in IT-related technology categories.

Table 3—Validation of Baseline Estimates of Examiner Effects

	Signal SD, percent of average		
	(1)	(2)	
Panel A. Accounting for violations of random assignment			
Patent value from Kogan et al. (2017)	44.32	15.89	
log total patent citation	21.10	22.78	
Rate of patent acquisition by non-PAEs	15.38	10.01	
Rate of patent acquisition by PAEs	40.01	41.25	
Rate of patent litigation by non-PAEs	55.65	64.36	
Sample	Art units allocating patents by last digits according to χ^2-test	Art units in information technology	
Number of art units	249	254	
	Signal SD, percent of average		
	(1)	(2)	(3)
Panel B. Accounting for extensive margin selection effects			
Patent value from Kogan et al. (2017)	40.46	41.48	40.28
log total patent citation	18.66	22.17	22.00
Rate of patent acquisition by non-PAEs	14.31	17.03	16.90
Rate of patent acquisition by PAEs	62.64	76.20	76.77
Rate of patent litigation by non-PAEs	63.06	89.93	89.88
Controls	Examiner grant rate	Examiner grant rate and application characteristics	Examiner grant rate, application characteristics, and their interactions
	SD of shrunk examiner effects, percent of average		
Panel C. Accounting for excess variance with empirical Bayes beta-binomial count model			
Rate of patent acquisition by PAEs		46.72	
Rate of patent acquisition by non-PAEs		7.99	
Rate of patent litigation by non-PAEs		48.95	

Notes: Panel A reports the signal standard deviations of several examiner effects using the Bayesian shrinkage methodology in two subsamples in which there is no examiner specialization within art unit. Panel B repeats the calculation of the signal standard deviations of examiner effects in the same sample as Table 2, but adding controls to address potential selection effects. Panel C reports the standard deviation of average shrunk examiner effects using the empirical Bayes beta-binomial count model. See Section IIC for a description of the methodologies underlying each panel.

lenient treatment. Using this source of variation, we can document the relationship between any given examiner characteristic and any patent outcomes. Specifically, we can use the estimated assignment probabilities to compute the expected examiner characteristic, which we can relate to the actual characteristic of the examiner who handled the application (the "first stage") and to any patent outcome of interest (the "reduced form").

Figure 2 presents the results of the busyness approach. The panels are based on the following specifications:

$$E_{j(i)} = \beta_1\left(\sum_{j\in ut(i)} p_{ij}E_j\right) + a_{ut(i)} + \nu_i, \tag{5}$$

$$Y_i = \beta_2\left(\sum_{j\in ut(i)} p_{ij}E_j\right) + a_{ut(i)} + \kappa_i, \tag{6}$$

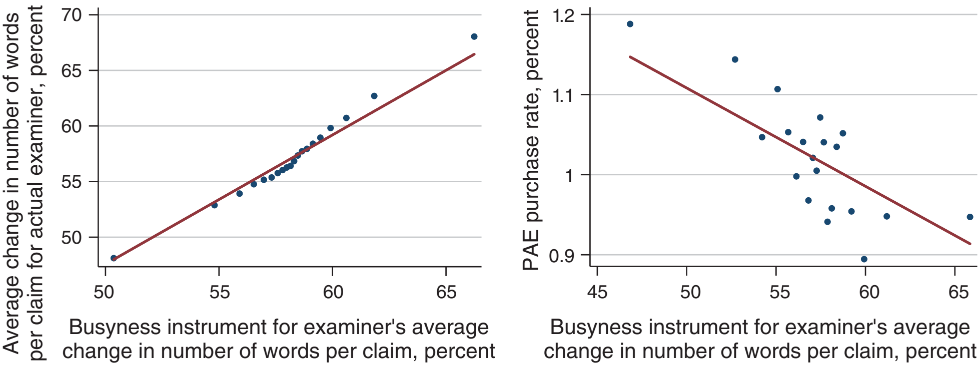

FIGURE 2. A BUSYNESS INSTRUMENT FOR THE EFFECT OF EXAMINERS ON PATENT ACQUISITION BY PAES

Notes: Panel A shows the relationship between the busyness instrument (described in the main text) for an examiner's propensity to change the number of words per claim during application and grant and the propensity of the examiner whom the application was actually assigned to. Panel B depicts the relationship between the busyness instrument and the purchase rate by PAEs. On both panels, each dot represents 5 percent of the data, and OLS best-fit lines are reported.

where i indexes the patent, j the examiner, u the art unit, and t time; p_{ij} denotes the application-specific examiner assignment probability; E_j denotes the examiner characteristic, measured using a leave-one-out procedure that does not use information on patent i; $E_{j(i)}$ is the (leave-one-out) characteristic of the examiner who actually processed application i; and Y_i is the patent outcome of interest. Figure 2 estimates these specifications, considering the (leave-one-out) change in the number of words per claim as the examiner characteristic and the (actual) purchase by a PAE as the outcome of interest. This choice of variables allows for a comparison with Figure 1, which did not use the busyness instrument and was using raw variation in the examiner's propensity to change the number of words per claim between application and grant.

Panel A of Figure 2 reports the relationship between the actual and expected examiner characteristics, as in (5). The slope is strong and positive, and the binned scatterplot is close to linear, indicating that the busyness instrument has power. Panel B of Figure 2 shows the relationship between PAE purchase and the expected examiner propensity to increase the number of words per claims; there is a strong downward relationship. These patterns are similar to Figure 1, which used the raw variation in examiner characteristic instead of the busyness instrument. These results provide additional evidence that departures from random assignment of examiners to applications do not bias our estimates.

Accounting for Potential Selection Effects on the Extensive Margin.—Another potential concern with our baseline research design is that our estimates may be confounded by selection effects stemming from the decision to grant a patent. Examiners differ in their grant rates, therefore it could be the case that patent outcomes vary across examiners because of underlying differences across examiners' pools of granted patents, independent of the crafting of patent rights. For instance, examiners with a low grant rate might only grant patents of high technical merit. To investigate this possibility, we introduce controls for the examiner's leave-one-out grant rate in equation (1) and then repeat the estimation of the signal standard deviation using equation (3). With this specification, we are now estimating the amount of systematic variation in patent outcomes across examiners who work in the same art unit, in the same year, and have the same grant rate.

Panel B of Table 3 reports the results and shows that our baseline estimates remain virtually unaffected. Column 1 controls for the grant rate in (3).[38] The estimated signal standard deviations are very similar to our baseline estimates from Table 2. In principle, it may be possible for extensive margin effects to operate even across examiners with the same grant rate. For instance, an examiner may systematically grant patents with underlying technological characteristics that appeal to PAEs, while another examiner (with a similar overall grant rate) may tend to systematically reject those patents and grant others. To assess how strong this effect might be empirically, Column 2 introduces controls for a host of initial characteristics of the patent application, namely the application's initial number of independent claims and number of words per claim; the assignee's number of applications, grants, and citations prior to the filing date; and the first inventor's number of applications, grants, and citations prior to the filing date. The estimates of signal standard deviations are not sensitive to these controls, indicating that extensive margin effects are unlikely to bias our estimates in any meaningful way. Column 3 reports the results with a more demanding specification for the controls, adding interaction terms between the examiner's grant rate and each of the eight initial application characteristics introduced in column 2. The estimated signal standard deviations remain virtually unchanged.[39]

Accurately Accounting for Excess Variance.—The preceding discussion indicates that our results are robust to failures of random assignment and extensive margin selection effects. A remaining potential concern is that the empirical Bayes shrinkage correction used in our baseline research design may fail to account for noise perfectly. To address this point, we first discuss some plausible limitations of our baseline design, in particular for rare binary outcomes such as litigation; we then present an alternative approach that addresses these limitations and produces similar

[38] To flexibly control for the grant rate, we introduce a quartic polynomial in the grant rate. The results are similar when controlling linearly for the grant rate or introducing higher order polynomials (not reported).

[39] In principle, our results could be biased by some unobserved (predetermined) characteristics of granted patents that vary systematically across examiners. However, it is reassuring that controlling for the examiner's grant rate as well as observable determinants of patent quality leaves our estimated signal standard deviation almost unchanged. Oster (2017) shows formally how selection on observables may be informative about selection on unobservables. Oster's (2017) approach can be applied informally to our setting by making a simple assumption: assume that the signal standard deviation of examiners' "selection effects" (i.e., the amount of cross-examiner variation in the technical merit of granted patents) is larger across examiners with *different* grant rates than across examiners with the *same* grant rate. Under this assumption, our specifications controlling for examiners' average grant rates can bound overall selection bias. Namely, if controlling for examiners' grant rates reduces the signal standard deviation by X percentage points (relative to the baseline specification), then the assumption implies that unobserved selection effects across examiners with the *same* grant rates can reduce the signal standard deviation by at most another X percentage points, that is, the total bias must be under $2 \times X$ percentage points. In fact, we found that controlling for examiners' grant rates leaves the results almost unaffected, that is, X is small, which suggests that overall selection effects are small.

results. Finally, we use out-of-sample tests to directly show that our baseline design accurately accounts for excess variance.

Our baseline research design yields very large signal standard deviation estimates for rare binary outcomes, such as litigation or purchase by a PAE, but the Bayesian shrinkage correction may not be appropriate in such cases. Indeed, for binary outcomes, our statistical model in equation (1) may be misspecified as it does not impose the constraint that the predicted value should lie between zero and one. Given that rare binary outcomes have a particularly high estimated signal standard deviation in Table 2, it appears important to assess whether these results are sensitive to a change in the underlying statistical model.

We repeat the analysis using an empirical Bayes beta-binomial count model, a common statistical model that can fit count data in a flexible way (Ellison and Swanson (2010)). To see how this framework operates, consider the example of patent purchases by PAEs. For each examiner j, we observe data of the form (n_j, r_j), where n_j is the examiner's total number of granted patents and r_j is the number of patents granted by the examiner that were purchased by PAEs. We assume that the probability p of granting a patent purchased by a PAE follows a beta distribution across examiners working in the same art unit in the same year: $p \sim Beta(\alpha, \beta)$. Given that we are examining the count of PAE purchases across examiners, the likelihood function for the data is a binomial distribution. Using the fact that the beta distribution is the conjugate prior of the binomial distribution, we show in online Appendix A that the integrated likelihood is

$$L(r_j | n_j, \alpha, \beta) = \binom{n_j}{r_j} \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \frac{\Gamma(r_j + \alpha)\Gamma(n_j - r_j + \beta)}{\Gamma(n_j + \alpha + \beta)},$$

which we estimate via maximum likelihood in each art unit by year. Having recovered estimates of the hyper-parameters, $\hat{\alpha}$ and $\hat{\beta}$, we compute the posterior mean for each examiner:[40]

$$\hat{\mu}_j^{BetaBinomial} = \frac{\hat{\alpha} + r_j}{\hat{\alpha} + \hat{\beta} + n_j}. \tag{7}$$

Panel C of Table 3 reports the standard deviation of the estimates; we continue to find large examiner effects. This finding indicates that our large estimates for the impact of examiner on patent litigation and purchase by PAEs is not an artifact of the statistical model used in our baseline design.

To conclude this section, we conduct out-of-sample tests of the examiner effects estimated in our baseline research design to check that we have recovered estimates of the correct magnitude. After splitting the main analysis sample into two 50 percent samples at random, we compute in each subsample the raw examiner effects using equation (2) and the shrunk examiner effects using equation (4). To test predictive accuracy, we regress the raw examiner effect from the first subsample on

[40] Intuitively, this procedure shrinks an examiner's PAE share toward the mean PAE share in the art unit. The amount of shrinkage is larger for examiners who have granted fewer patents.

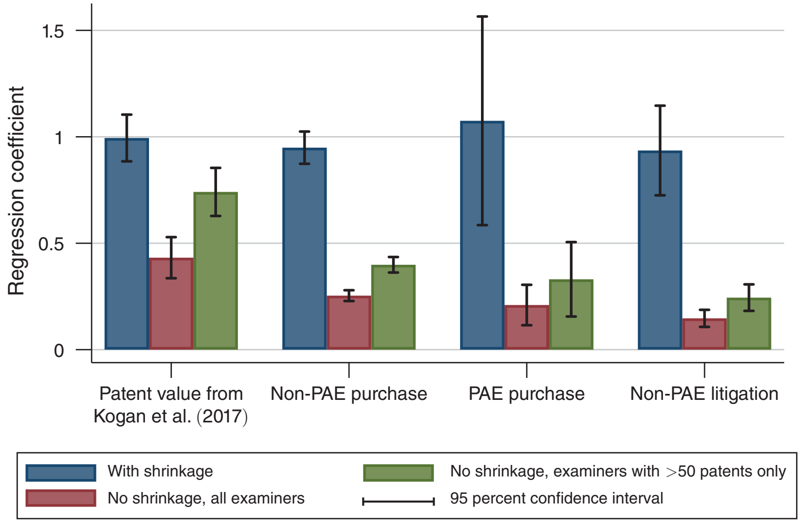

Figure 3. Out-of-Sample Tests of Baseline Estimates of Examiner Effects

Notes: This figure reports the OLS coefficients in examiner-level out-of-sample regressions. After splitting the main analysis sample into two halves at random, we compute the raw and shrunk examiner effects on each half following the methodology described in Section IIC. To test predictive accuracy, we regress the raw examiner effect from the first half on examiner effects estimated in the second half, using, in turn, as regressors the shrunk examiner effects (shrinkage), the raw examiner effects (no shrinkage, all examiners), and the raw examiner effects for the subset of examiners who have granted more than 50 patents (no shrinkage, examiners with >50 patents only). A regression coefficient of one indicates unbiased prediction. The heteroskedasticity-robust 95 percent confidence interval is reported.

the shrunk examiner effects from the second subsample.[41] We also regress the raw examiner effect from the first subsample on the raw examiner effect from the second subsample to assess whether a standard regression approach would suffer from excess variance. We do so in the full sample but also in a reduced sample of examiners who granted more than 50 patents, as measurement error may no longer be a problem if sufficiently many patents are observed per examiner.

Figure 3 reports the results and shows that the empirical Bayes shrinkage approach yields unbiased estimates of examiner effects, in contrast with standard regression analysis. A regression coefficient of one indicates unbiased prediction, while a coefficient below one indicates attenuation bias and implies that the estimates suffer from excess variance due to noise. Figure 3 shows that our baseline design delivers unbiased estimates of examiner effects even for rare outcomes such as patent purchase by PAEs or patent litigation. The point estimates are very close to one and precisely estimated. In contrast, the specifications without shrinkage always deliver a coefficient well below one, indicating that the raw variation in examiner effects contains a lot of noise. This problem is less acute for outcomes that are more common, such as the patent value measure of Kogan et al. (2017) (with a regression coefficient close to 0.5 full sample), than for rare outcomes like patent litigation

[41] We regress raw effects on shrunk effects because the shrinkage factor in the shrunk effects addresses measurement error, which poses an issue for the independent variable but not the dependent variable.

TABLE 4—ROBUSTNESS CHECKS ON EXAMINER CAUSAL EFFECTS ON PATENT OUTCOMES

	Signal SD, percent of average				
	Patent value from Kogan et al. (2017)	log total patent citations	Purchase by practicing firm	Purchase by PAE	Litigation by practicing firm
(A) Including continuations	41.8	24.9	16.8	78.9	90.7
(B) Granted patent from 1976 to 2015	36.7	22.4	15.8	72.3	62.6
(C) Including review time controls	40.8	23.2	14.6	62.9	64.3
(D) Including examiner career controls	41.5	24.6	13.5	55.8	55.4

Notes: Row (A) adds continuation applications that were filed and granted between 2001 and 2012 to our baseline analysis sample that covers the same period. Row (B) uses the sample of all non-continuation granted patents from 1976 to 2015. Row (C) controls for "time under review" in equation (1) with a quadratic polynomial in the number of years between filing and grant. Row (D) controls for examiner career effects in equation (1) with experience fixed effects, as defined in Frakes and Wasserman (2017) (namely, the examiner's general schedule (GS) level by bins corresponding to 0–1, 2–3, 4–5, 6–7, 8+ years experience at that level). All reported values are normalized by the average in the relevant sample.

(with a regression coefficient close to 0.1 in the full sample). Restricting the analysis to examiners who handle a lot of patents does not solve the problem, which offers another vindication of our baseline research design.

D. *Robustness Checks*

Table 4 shows the robustness of the signal standard deviations when using alternative samples and specifications. The first row repeats the analysis including continuation applications; the second row includes all granted patents from 1976 to 2015; the third row controls for the length of time between filing and grant to assess whether the results may be driven by delays rather than by the way patent rights are crafted; the fourth row includes fixed effects for examiner experience as in Frakes and Wasserman (2017).[42] The results are very similar across samples and specifications. Finally, the online Appendix shows that the signal standard deviations are of comparable magnitudes across technology categories (online Appendix Table D3) and reports the distributions of the shrunk examiner effects (online Appendix Figure D3).

III. Implications for Patent Assertion Entities

Our analysis so far has established that examiner effects are an important driver of a wide range of patent outcomes, in particular those related to PAEs and litigation. In this section, motivated by the large sensitivity of PAEs to examiner effects, we investigate the features of examiner behavior that drive PAEs' responses. We find that "lenient" examiners, who issue patents with higher litigation and invalidity

[42] An alternative to the inclusion of examiner experience fixed effects in our baseline specification is to look for discontinuities in patent outcomes around examiners' promotions; we find no discontinuity (online Appendix Figure D2), which confirms that examiner experience effects play a second-order role compared with the examiner fixed effects we focus on.

risks, produce a much higher share of patents purchased and asserted by PAEs. We discuss how this evidence helps discipline theories of PAE behavior.

A. *Research Design*

There are two standard views of the role played by PAEs in the patent market. According to the first view, PAEs could be useful intermediaries who address standard frictions in the patent market by lowering transaction costs and solving liquidity problems (Hagiu and Yoffie 2013; Abrams et al. 2019; Lu 2012; Galetovic, Haber, and Levine 2015). The second view suggests that PAEs do not help address any particular friction but, rather, exploit limitations of the legal system by asserting patents of questionable validity in the hope that targeted firms will pay them settlement fees instead of risking a costly and uncertain trial (Miller 2013; Council of Economic Advisers 2013; Cohen, Gurun, and Kominers 2016; Federal Trade Commission 2016).

We investigate the extent to which the two standard views can account for the (quantitatively large) patterns related to examiners in the data. Examiners have a large impact on PAEs: a one standard deviation change in examiner effects shifts the probability of patent acquisition by a PAE by over 60 percent of the baseline rate (Table 2). This fact may not be incompatible with the two standard views of PAE behavior. For instance, the process of creation of patent rights may create frictions affecting both PAEs and practicing firms (in line with the first view) or may lead to the issuance of questionable patents that only PAEs are willing to purchase and exploit via frivolous litigation (in line with the second view).

We examine this question using detailed data on the prosecution behaviors of examiners, drawing a contrast between the responses of PAEs and practicing firms. We start by characterizing the prosecution behaviors that are predictive of future purchase or litigation by a PAE or practicing firms (Section IIIB); we then investigate whether these prosecution behaviors are predictive of patent invalidity (Section IIIC). Specifically, we run regressions of the following form:

$$Y_i = \beta E_{j(i)} + a_{ut(i)} + \epsilon_i, \tag{8}$$

where i indexes the patent, j the examiner, and ut the art unit by year; Y_i is the patent outcome of interest; and $E_{j(i)}$ is a (vector of) examiner behavior(s), estimated using a leave-one-out procedure that does not use information on patent i. We scale the examiner behavior measures $E_{j(i)}$ by their signal standard deviations, which are estimated using (3). This standardization gives us the proper scaling to compare the quantitative importance of various examiner traits.[43]

We rely on a variety of proxies reflecting different aspects of examiner behavior to isolate robust correlations with the potential to inform theories of PAE behavior. The estimates from specification (8) cannot be interpreted as causal because quasi-random assignment occurs at the level of examiners working in the same art

[43] Specification (8) is analogous to the regression underlying Figure 1, except that we now use properly scaled regressors.

unit at the same time, and not at the level of examiners' traits. Given that quasi-random assignment is at the level of examiners, the only causal effect that can be recovered is the effect of the examiner "as a whole" on patent outcomes (as in Section II).[44] In contrast, the relationships between specific examiner traits and patent outcomes may be biased by potential omitted variables (i.e., other traits of the examiner that are unobserved). To address this limitation, we use several proxies to control for various aspects of examiner behavior, and we focus on establishing correlations that (i) are quantitatively large and robust to the inclusion of additional controls and (ii) can be interpreted as reflecting a more general trait of the examiner, such as the propensity to let the applicant keep the text of the claims relatively unchanged between application and grant ("leniency").

B. *PAEs and Examiner Behavior*

In this subsection, we document which examiner traits correlate with patent acquisition or litigation by PAEs and practicing entities. We use specification (8) and consider seven measures that capture different aspects of examiner behavior.

We use three general proxies for the degree of "leniency" of the examiner. By examiner leniency, we refer to the extent to which the examiner makes demands on the applicant during prosecution. First, the percentage change in the number of words per claim (averaged across claims) indicates the extent to which the examiner asks the applicant to refine the claims. Second, the percentage change in the number of claims reflects the extent to which the examiner affects the overall structure and scope of the patent document. Third, the examiner's grant rate is another natural proxy for leniency: examiners who are more demanding on applicants generally have lower grant rates.

To characterize in greater detail the examiner behaviors that drive PAEs' activities, we measure examiners' propensities to cite specific sections of patent law when asking the applicant to revise the patent. As mentioned previously, the examiner must substantiate any demand by referring to specific sections of patent law corresponding to various standards of patentability. An examiner who is less lenient should refer more often to any of the sections compared with other examiners working in the same art unit at the same time. The relative frequency of usage of the various sections may differ across examiners depending on their examination styles. Examiners who place more emphasis on the invention being useful and eligible for a patent should use Section 101 more often; those who particularly care about prior inventions should refer to Section 102 frequently; Section 103 should be invoked more often by examiners who are particularly sensitive to the requirement that the invention should be non-obvious to someone who knows the field; and Section 112(b) should be used by examiners who focus on the requirement of claim clarity.[45]

[44] One would need a quasi-experiment that directly affects specific behaviors (e.g., a training program) in order to recover more granular causal impacts.

[45] Although all examiners are supposed to apply the same standards for patent grant, which are determined by patent law, we find large causal variation across examiners in terms of their propensity to refer to the various sections (online Appendix Table D4).

Table 5—Patent Acquisition and Examiner Behavior

	Patent purchase by PAE								
Leave-one-out examiner effects	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Patent acquisition by PAEs									
% change in number of words per claim from app to grant	−0.139								−0.115
	(0.030)								(0.0490)
% change in number of claims from app to grant		0.073							0.0519
		(0.034)							(0.0345)
Grant rate			0.114						−0.0298
			(0.028)						(0.0637)
Use of Section 101 Ineligible, lack utility				−0.061				−0.0468	−0.0225
				(0.036)				(0.035)	(0.0366)
Use of Section 102(a) Prior art exists					0.007			0.0171	0.00835
					(0.021)			(0.021)	(0.0216)
Use of Section 103(a) Obvious invention						−0.0602		−0.050	−0.0223
						(0.024)		(0.026)	(0.0285)
Use of Section 112(b) Vague claims							−0.037	−0.004	−0.00392
							(0.027)	(0.026)	(0.0291)
Fixed effects	Year by art unit								
Observations	274,464	274,537	311,615	311,470	311,470	311,470	311,470	311,470	274,464
	Patent purchase by practicing firm								
Leave-one-out examiner effects	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B. Patent acquisition by practicing firms									
% change in number of words per claim from app to grant	0.0071								0.0349
	(0.0081)								(0.011)
% change in number of claims from app to grant		−0.0003							−0.0001
		(0.006)							(0.006)
Grant rate			0.022						0.062
			(0.0082)						(0.012)
Use of Section 101 Ineligible, lack utility				0.0147				0.0154	0.0174
				(0.0065)				(0.00711)	(0.0073)
Use of Section 102(a) Prior art exists					−0.0037			−0.00498	−0.007
					(0.005)			(0.00556)	(0.006)
Use of Section 103(a) Obvious invention						0.0065		0.00539	0.007
						(0.005)		(0.00633)	(0.006)
Use of Section 112(b) Vague claims							0.002	−0.00419	0.003
							(0.005)	(0.00619)	(0.006)
Fixed effects	Year by art unit								
Observations	274,464	274,537	311,615	311,470	311,470	311,470	311,470	311,470	274,464

Notes: The sample is restricted to IT patents. Regressors are standardized by their standard deviations, and coefficients are expressed as a fraction of the mean of the outcome. Standard errors are clustered by examiners.

Table 5 presents the results with patent acquisition as the outcome.[46] In both panels, the first seven columns run univariate regressions, while columns 8 and 9 consider multivariate regressions. Panel A shows that all proxies of examiner leniency deliver a similar message: more lenient examiners grant substantially more patents that are eventually purchased by PAEs. The regression coefficients are standardized by the signal standard deviations of the regressors and expressed as a percentage of the outcome. Column 1 shows that a one standard deviation increase in the distribution of

[46] The sample is restricted to art units that are part of information technologies since PAEs are primarily active in these art units (online Appendix Table D5). All results reported in this section are similar in the full sample (online Appendix Tables D6, D7, and D8) and in the subsample of art unit-years within IT that use digit-based, quasi-random assignment (online Appendix Tables D9 and D10).

examiner effects for the change in number of words per claim implies a 13.9 percent decrease in the probability of purchase by a PAE. This fraction is relatively large, given that a one standard deviation change in the overall examiner effect accounts for about 60 percent of the baseline rate (Table 2). Columns 2 and 3 show that the effect goes in the same direction, with a similar magnitude, for the other broad proxies for examiner leniency: a one standard deviation increase in the change in number of claims implies a 7.3 percent increase in the probability of PAE purchase;[47] the corresponding number for grant rates is 11.4 percent. Columns 4 to 7 show that the same finding holds when considering the use of various sections of patent law: examiners who use sections more often tend to have a lower rate of purchase by PAEs (although some specifications are noisy). Column 8 presents the results of a specification that simultaneously includes all types of references to patent law. In this specification, the section relating to the obviousness of the invention is the most important. Finally, specification (9) includes all regressors simultaneously. The results become more noisy because of collinearity, but the coefficient on the change in the number of words per claim remains large, significant, and similar in magnitude to the univariate regression in column 1. These findings show that PAEs have a preference for purchasing patents that were issued by lenient examiners.[48]

Panel B of Table 5 shows the results for patent purchase by practicing firms, which stand in sharp contrast with the patterns for PAEs. First, the effects are all much smaller in magnitude than in panel A. In the first seven columns of the table, the effects are almost all insignificant and are never larger than 2 percent. Second, the relationship with examiner leniency does not appear to be robust: it switches signs across proxies or specifications. For instance, in the univariate regression in column 1 we obtain a precisely estimated zero for the correlation with the change in the number of words per claim. The regression coefficient becomes positive and statistically significant in specification (9), suggesting that practicing firms may have a preference for less lenient examiners, but the coefficient is relatively small (3.49 percent). Overall, there appears to be no quantitatively large or statistically robust relationship between purchases by practicing firms and examiner leniency.

The fact that only PAEs selectively purchase patents issued by lenient examiners is not consistent with the view that PAEs solve a generic friction in the patent market. If PAEs were primarily lowering transaction costs or solving liquidity problems, there would be no reason for them to selectively purchase patents from lenient examiners, who do not affect patent acquisitions by practicing firms. To examine whether PAEs may rather be addressing a patent-specific friction related to the patent examination process itself, we now investigate the correlates of patent litigation.

[47] More lenient examiners tend to reduce the number of claims by less, which means that a higher change in the number of claims (in absolute value) reflects higher leniency. In contrast, a more lenient examiner increases the number of words per claim by less, i.e., a higher change in the number of words per claim reflects lower leniency.

[48] As previously mentioned, the correlations between patent outcomes and specific examiner traits should not be interpreted as causal because examiner traits are correlated. To illustrate this point quantitatively, online Appendix Table D11 reports the correlations between the examiner's propensity to grant patents and other observed examiner traits. The correlations are substantial and suggest that specific examiner traits cannot be isolated. Despite this limitation, we view panel A of Table 5 as delivering a robust message: all examiner traits that are suggestive of lenient behavior (either on the extensive margin, with the grant decision, or on the intensive margin with changes to the application during prosecution) correlate with a greater probability of PAE purchase.

Table 6—Patent Litigation and Examiner Behavior

	Patent litigation by PAE								
Leave-one-out examiner effects	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Patent litigation by PAEs									
% change in number of words per claim from app to grant	−0.405 (0.083)								−0.097 (0.12)
% change in number of claims from app to grant		0.127 (0.067)							0.05 (0.07)
Grant rate			0.567 (0.099)						0.48 (0.14)
Use of Section 101 Ineligible, lack utility				−0.105 (0.077)				−0.09 (0.08)	0.05 (0.08)
Use of Section 102(a) Prior art exists					0.0178 (0.089)			0.019 (0.08)	0.023 (0.082)
Use of Section 103(a) Obvious invention						−0.156 (0.075)		−0.176 (0.083)	−0.039 (0.08)
Use of Section 112(b) Vague claims							−0.0003 (0.079)	0.102 (0.08)	0.085 (0.086)
Fixed effects	Year by art unit								
Observations	274,464	274,537	311,615	311,470	311,470	311,470	311,470	311,470	274,464

	Patent litigation by practicing firm								
Leave-one-out examiner effects	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B. Patent litigation by practicing firms									
% change in number of words per claim from app to grant	−0.138 (0.043)								0.017 (0.071)
% change in number of claims from app to grant		0.022 (0.031)							−0.015 (0.034)
Grant rate			0.24 (0.045)						0.23 (0.067)
Use of Section 101 Ineligible, lack utility				−0.068 (0.037)				−0.0205 (0.0397)	0.005 (0.04)
Use of Section 102(a) Prior art exists					−0.008 (0.04)			0.0150 (0.0406)	0.026 (0.04)
Use of Section 103(a) Obvious invention						−0.075 (0.034)		−0.0387 (0.0370)	0.008 (0.04)
Use of Section 112(b) Vague claims							−0.118 (0.032)	−0.0978 (0.0366)	−0.065 (0.04)
Fixed effects	Year by art unit								
Observations	274,464	274,537	311,615	311,470	311,470	311,470	311,470	311,470	274,464

Notes: The sample is restricted to IT patents. Regressors are standardized by their standard deviations, and coefficients are expressed as a fraction of the mean of the outcome. Standard errors are clustered by examiners.

Table 6 presents the results with patent litigation as the outcome. Panel A reports the results for patent litigation by PAEs. The patterns are similar to those found in Table 5 for PAEs, except that the magnitudes are much larger. Column 1 shows that a one standard deviation increase in the examiner effect for the change in the number of words per claim implies a 40.5 percent increase in the rate of litigation by PAEs. This effect is very large in itself but also relative of the overall examiner effects documented in Table 2, according to which the signal standard deviation of examiner effects for PAE litigation is 46 percent (although it is imprecisely estimated). This result suggests that a simple proxy for examiner leniency can account for most of the relationship between examiner effects and PAE litigation. Moreover, the other columns of Table 5 indicate that this pattern is very robust. The other general proxies for examiner leniency, the change in the number of claims and the grant rate, go in the same direction and are larger in magnitude than when considering patent purchases. Considering the use of the various sections of patent law, we find that the section relating to the obviousness of the invention is the most important, but the magnitude of the effect is now substantially larger. In the multivariate regression including all examiner effects simultaneously in column 9, the patterns still point to the role of leniency as the predictive power loads on the grant rate, with a coefficient indicating that a one standard deviation increase in the grant rate implies an increase in the rate of PAE litigation close to 50 percent.

Panel B of Table 6 reports the results for patent litigation by practicing firms, which are qualitatively similar to the patterns for PAEs but smaller in magnitude. Across all proxies and specifications in this panel, we consistently find that lenient patent examiners—who increase the number of words per claim by less, have a higher grant rate, and reference patent law less often—issue patents with a higher litigation risk. The magnitude of the effects is less strong than for litigation by PAEs but is comparable to the magnitude of the effects for purchases by PAEs (panel A of Table 5). For instance, a one standard deviation fall in the examiner effect for the change in the number of words per claim implies a 13.8 percent increase in the rate of litigation by practicing firms and 13.9 percent increase in the rate of PAE purchase.

The finding that patent litigation by both practicing firms and PAEs is driven by examiner leniency challenges the view that PAEs engage in idiosyncratic, frivolous lawsuits. The merit of the lawsuits involving patents issued by lenient patent examiners may be questionable, but PAEs are not the only entities to selectively assert patents from lenient examiners—practicing firms do so as well. PAEs purchase patents that are different from those handled by practicing firms in the market for patents (Table 5), but their propensity to assert patents issued by lenient examiners is merely a more extreme version of the litigation behavior of practicing firms (Table 6).

The patterns in the data are therefore difficult to reconcile with the mainstream views of PAEs, either as intermediaries solving a generic friction in the patent market or as perpetrators of frivolous lawsuits. Rather, it appears that much of the activities of PAEs is driven by a specific friction in the patent market, which strongly correlates with examiner leniency. Our findings are therefore in line with a nuanced view of PAEs, suggesting that PAEs' activities are the symptom of features of the patent system that affect litigation more generally (e.g., Lemley and Melamed 2013 and Schwartz and Kesan 2014). PAEs behave as litigation experts, and much of their activities stem from the way patents are handled by lenient examiners, who affect litigation more generally. Although we can only document correlations with examiner traits, we emphasize that the underlying causal examiner effects are quantitatively large and should therefore be accounted for by any convincing theory of PAEs' activities.[49]

[49] Of course, even though the causal examiner effects from Table 2 are large, they do not account for the entirety of PAEs' patent acquisition and assertion behaviors. We only speak to the (substantial) part of PAEs' activities that is caused by examiner effects and point out that the two standard views of PAEs cannot account for these patterns.

C. *PAEs and Patent Invalidity*

In this subsection we study whether lenient examiners, who play an important role for litigation in general and for litigation by PAEs in particular, tend to issue patents that are more likely to be invalid. Various observers (e.g., Federal Trade Commission 2016) have hypothesized that PAEs may be asserting patents that are "invalid," in the sense that these patents should not have been issued in the first place because they do not comply with the standards set by US patent law. Given the evidence that patent litigation by PAEs is very strongly correlated with examiner leniency, we can recast this question in terms of examiner effects: do lenient examiners tend to issue patent that are more likely to be invalid? Approaching this question in terms of examiner effects has the potential to be informative about PAEs but also about patent litigation by practicing firms, since they also selectively assert patents that were issued by lenient examiners.

Proxies for Patent Invalidity.—Patent invalidity is notoriously difficult to measure because of selection effects (e.g., Miller 2013). To assess whether a robust relationship exists between examiner leniency and patent invalidity, we rely on three complementary proxies for patent invalidity. We consider two restricted samples to study two common proxies for patent invalidity, which are subject to substantial sample selection but standard in the literature. We also introduce a third proxy available in the full sample of granted patents.

First, for a small number of cases, patent litigation does not result in a settlement, and a court trial closes the case (see Allison, Lemley, and Schwartz 2014 for a review). We obtain this data from LexMachina. The sample of cases for which trial outcomes are available is very selected: in our main analysis sample, there are only 516 cases with information on whether the court deemed the patent invalid or found an infringement.

The second common proxy for patent invalidity is a procedure for challenging the validity of a patent at the USPTO, known as an "inter partes review" (IPR). IPRs were introduced in 2012 as a defensive tool for those seeking to defeat meritless infringement claims (see Chien and Helmers 2015 for a review). The procedure can be initiated by any party other than the patent owner and requires the patent office to review the validity of the patent based on specific sections of patent law. This sample is also very selected: there are 989 IPR cases in our main analysis sample.

Third, we use patent re-issuance requests as another proxy for patent invalidity. A reissue application can be filed by the applicant "whenever any patent is, through error, deemed wholly or partly inoperative or invalid."[50] We obtain this information from the continuation data in the Patent Examination Research

[50] Patent law states that "Whenever any patent is, through error, deemed wholly or partly inoperative or invalid, by reason of a defective specification or drawing, or by reason of the patentee claiming more or less than he had a right to claim in the patent, the Director shall, on the surrender of such patent and the payment of the fee required by law, reissue the patent for the invention disclosed in the original patent, and in accordance with a new and amended application, for the unexpired part of the term of the original patent" (35 U.S.C. 251(a)). Reissue applications can petition for an increase in the scope of claims only if they are filed within two years from grant of the original patent (35 U.S.C. 251(d)). We repeat our analysis considering only reissue applications beyond this threshold to establish that attempts to increase claim scope are not driving the patterns.

Table 7—Summary Statistics on Proxies for Patent Invalidity

	Mean	Median	SD	Sample size
Rate of invalidity decision by court, conditional on ruling	0.1880	0	0.3911	516
Rate of infringement decision by court, conditional on ruling	0.3198	0	0.4668	516
Rate of IPR filing	0.0003	0	0.0164	1,833,464
Rate of IPR institution, conditional on IPR filing	0.7858	1	0.4105	719
Rate of re-issuance	0.0020	0	0.0458	1,833,464
Rate of re-issuance more than two years after grant	0.0004	0	0.0206	1,833,464

Notes: This table reports summary statistics on several proxies for patent invalidity. See Section IIIC for variable definitions and Section IA for information on the sample.

Dataset. Reissue applications are a useful metric for our purposes, as they are available for all granted patents and provide a direct measure of examiner mistakes from the perspective of the patent applicant.

Table 7 reports summary statistics on our proxies for patent invalidity. Court rulings are observed for only 516 patents, or about 0.0004 percent of our sample. Conditional on observing a court ruling, the rate of invalidity is close to 19 percent. In 31.9 percent of cases, the court declares that the patent is infringed, which indirectly attests to its validity. The panel also indicates that an IPR procedure is filed for 0.0003 percent of patents. Conditional on filing, 78.5 percent of IPRs are "instituted," meaning that the patent office deems it likely that the patent is at least in part invalid.[51] Because the "institution" rate of IPRs is very high, close to 80 percent, either the occurrence of an IPR or the institution of an IPR can be used as proxies for patent invalidity. For both court rulings and IPRs, the invalidity rates appear to be high, but they are observed conditional on a stringent form of sample selection.

Finally, Table 7 shows that reissue applications are submitted for about 0.002 percent of patents. According to patent law, a reissue application indicates that the applicant believes that the patent is wholly or in part invalid because of a mistake in the document. To address the potential concern that some applicants may violate patent law and strategically exploit reissue applications to obtain greater scope, instead of correcting a mistake, we consider reissue applications that are submitted more than two years after grant. After the two-year delay, reissue applications cannot petition for an increase in scope; they account for about 0.0004 percent of all granted patents. This fraction is very small, but it is comparable in magnitude to the number of observations for court rulings and IPRs and has the advantage of being available for the full sample of granted patents.

Results.—We run specification (8) with our patent invalidity proxies as outcomes. The regressors are examiner effects for the change in the number of words per claim and the grant rate, which were the most powerful univariate predictors of patent acquisition and assertion by PAEs in Tables 5 and 6. We also consider the best linear predictor for patent purchase by PAEs using the specification in column 9 of Table 5. The results are reported in Table 8.

[51] According to patent law, "An inter partes review may be instituted upon a showing that there is a reasonable likelihood that the petitioner would prevail with respect to at least one claim challenged" (35 U.S.C. Ch. 31, §311–§319).

We find a very strong and robust relationship between examiner leniency and our preferred proxy for patent invalidity, the re-issuance of granted patents. Panel A of Table 8 reports this finding. The various rows of this panel correspond to separate univariate regressions. The first row of column 1 indicates that, conditional on year fixed effects, a one standard deviation increase in the examiner effect for the change in the number of words per claim (i.e., less leniency) leads to a 26 percent decline in the probability of re-issuance. Columns 2 and 3 show that the coefficient is very stable as art unit by year fixed effects and art unit by year by technology class fixed effects are introduced. Similarly strong and robust patterns are documented in the other rows of the tables for the grant rate and the linear predictor for PAE acquisition. Columns 4 to 6 show that the patterns are even stronger when we consider the re-issuance rate two years or more after grant, the delay beyond which a re-issuance request cannot petition for an increase in the scope of the claims. For instance, the coefficient for the change in the number of words per claim hovers between 55 percent and 61 percent across specifications. Since PAEs selectively assert patents granted by lenient examiner (more so than practicing firms), they are more likely to assert patents that are likely to contain mistakes, as reflected by the re-issuance rates.

Panel B of Table 8 shows that common proxies for patent invalidity based on court rulings cannot deliver conclusive results due to data limitations. For a small subsample of litigated patents, we observe rulings in which the courts may indicate that the patent is invalid (columns 1 to 3) or that an infringement is found (columns 4 to 6). The various regression coefficients reported in this panel show that with such proxies the research design is underpowered, regardless of the set of fixed effects. The points estimates switch signs across specifications and are very imprecisely estimated.

Panel C of Table 8 uses IPR occurrence and IPR institution as proxies for patent invalidity from the perspective of the Patent Office. Columns 1 to 3 of panel C of Table 8 document that examiner leniency is a very strong predictor of the occurrence of an IPR. For instance, the first row of column 2 indicates that a one standard deviation increase in examiner effects for the change in the number of words per claims (lower leniency) implies a 41 percent fall in the probability of an IPR. The regression coefficients are all large and very stable across specifications that include different sets of fixed effects. In contrast, columns 4 to 6 do not deliver conclusive results regarding IPR institution, because the selected sample of patents that go through an IPR is too small to provide adequate power.

In sum, Table 8 indicates that, when using suitable proxies for patent invalidity that do not suffer from small sample issues, there is strong and robust evidence that lenient examiners issue patents that are more likely to be invalid. These examiners account for a disproportionate share of patent litigation, in particular by PAEs. This finding indicates that examiner behavior during patent prosecution is a quantitatively important determinant of patent invalidity, suggesting that PAEs specialize in purchasing and asserting patents that should not have been issued as such in light of the standards set by current patent law.[52]

[52] This finding does not speak conclusively to the welfare effects of PAEs, because litigation of patents issued by lenient examiners could conceivably be socially valuable, even when these patents are deemed invalid by current patent law. The standards set by current patent law are often motivated by economic ideas of welfare maximization

Table 8—Examiner Behavior and Likelihood of Patent Invalidity

Leave-one-out examiner effects	Re-issuance rate			Re-issuance rate two years or more after grant		
(separate regressions)	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Re-issuance of granted patents						
Percent change in number of words per claim from app to grant	−0.26	−0.24	−0.25	−0.55	−0.57	−0.61
	(0.07)	(0.06)	(0.068)	(0.15)	(0.14)	(0.15)
Grant rate	0.29	0.27	0.28	0.54	0.53	0.54
	(0.06)	(0.06)	(0.061)	(0.13)	(0.13)	(0.13)
Linear predictor for PAE acquisition	0.139	0.136	0.142	0.24	0.26	0.27
	(0.038)	(0.035)	(0.036)	(0.079)	(0.075)	(0.078)
Fixed effects	Year	Year by art unit	Year by art unit by class	Year	Year by art unit	Year by art unit by class
Observations		274,464			273,839	

Leave-one-out examiner effects	Invalidity rate			Infringement rate		
(separate regressions)	(1)	(2)	(3)	(4)	(5)	(6)
Panel B. Court rulings						
Percent change in number of words per claim from app to grant	0.02	0.068	0.11	−0.01	−0.0001	−0.0002
	(0.06)	(0.29)	(0.32)	(0.06)	(0.24)	(0.28)
Grant rate	0.02	−0.039	−0.019	−0.03	0.06	−0.12
	(0.03)	(0.26)	(0.54)	(0.03)	(0.10)	(0.22)
Linear predictor for PAE acquisition	−0.057	−0.031	−0.069	0.01	−0.007	0.007
	(0.044)	(0.19)	(0.19)	(0.03)	(0.14)	(0.15)
Fixed effects	Year	Year by art unit	Year by art unit by class	Year	Year by art unit	Year by art unit by class
Observations		111			111	

Leave-one-out examiner effects	IPR rate			Institution rate of IPR		
(separate regressions)	(1)	(2)	(3)	(4)	(5)	(6)
Panel C. Trials at the patent office ("inter partes reviews")						
Percent change in number of words per claim from app to grant	−0.38	−0.43	−0.42	−0.03	−0.05	−0.23
	(0.098)	(0.094)	(0.087)	(0.057)	(0.27)	(0.29)
Grant rate	0.41	0.44	0.44	0.05	−0.03	−0.034
	(0.085)	(0.081)	(0.082)	(0.047)	(0.11)	(0.13)
Linear predictor for PAE acquisition	0.28	0.34	0.33	0.024	0.089	0.21
	(0.088)	(0.086)	(0.077)	(0.04)	(0.21)	(0.26)
Fixed effects	Year	Year by art unit	Year by art unit by class	Year	Year by art unit	Year by art unit by class
Observations		274,537			180	

Notes: The sample is restricted to IT patents. Regressors are standardized by their standard deviations, and coefficients are expressed as a fraction of the mean of the outcome. The linear predictor for PAE acquisition is given by specification (9) in Table 5. Standard errors are clustered by examiners.

D. *PAEs and the European Patent Office*

To further understand the nature of patents purchased by PAEs, we analyze grant decisions for patents that were simultaneously filed at both the EPO and USPTO. As discussed in the literature (e.g, Picard and Van Pottelsberghe 2011), the EPO has

(e.g., the recent Supreme Court decision in *Alice v. CLS Bank* cites economic literature on sequential innovation) but may not actually be socially optimal.

Table 9—Patent Acquisition by PAEs and Grant Decisions at the European Patent Office (EPO)

	Patent purchase by PAE	
	(1)	(2)
EPO grant	−0.211	−0.199
	(0.057)	(0.059)
Art unit by year fixed effects	Yes	Yes
Examiner fixed effects	No	Yes
Observations	218,867	217,491

Notes: This table examines whether PAEs selectively purchase higher quality patents, using patent grant decisions at the EPO as a proxy for patent quality (as in Lei and Wright 2017 and Picard and Van Pottelsberghe 2011). Regressors are standardized by their standard deviations, and regression coefficients are expressed as a fraction of the mean of the outcome. The sample includes all patents that were jointly filed at the USPTO and EPO, as described in Section IIID. Standard errors are clustered by examiners.

a stricter inventive step requirement for patentability.[53] We use the grant decision at the EPO as an indicator for the magnitude of the inventive step of the corresponding US patent. The methodology for building the joint-filing dataset is described in online Appendix C.[54]

We find that PAEs are much more likely to purchase patents that were rejected by the EPO, suggesting that PAEs target patents covering more incremental, less innovative technology. Table 9 reports the results. In column 1, we find that EPO grant is negatively correlated with patent purchase by PAEs, controlling for art unit by year fixed effects. In column 2, we add examiner fixed effects that control for factors such as specialization and other examiner behaviors that may affect the patent. The negative relationship remains: even within the portfolio of a given examiner, PAEs are more likely to purchase patents that are *rejected* at the EPO. This finding suggests that PAEs target more incremental, less innovative technologies. It is therefore plausible that patents purchased by PAEs are particularly productive for litigation, both because they are closer to existing intellectual property than average (given the small step size revealed by EPO rejections) and because their claims may be less well defined and harder to interpret than average (given the examiners who granted them).[55]

E. *Robustness Checks and Additional Results*

In the final part of this section, we discuss the robustness of our PAE results across samples, specifications, and PAE types. In addition, we use data on patent value and auction prices to shed further light on PAE behavior.

[53] Note that the EPO's patentability standards are not necessarily closer to the social optimum.

[54] We focus on non-continuation patent applications that were filed at both the EPO and USPTO within half a year. The sample covers about one-sixth of granted non-continuation patents in the United States.

[55] In additional breakdowns reported in online Appendix Table D12, we find that the relationship between EPO decisions and PAEs' purchase decisions is driven specifically by the set of patents granted by examiners with a large causal impact on PAE purchases.

Table 10—Heterogeneity in Examiner Causal Effects on Patent Acquisition by PAEs

	Signal standard deviation, percent of average	Average purchase rate (percent)
(A) Baseline	63.0	1.02
(B) Including assignee fixed effects	44.5	1.02
(C) Excluding Intellectual Ventures	82.7	0.55
(D) Intellectual Ventures only	82.0	0.47
(E) PAE list from Cotropia, Kesan, and Schwartz (2014)	67.8	0.60
(F) Small PAEs	40.7	0.07
(G) PAEs purchasing from small entities/unassigned patents	70.8	0.11

Notes: This table reports the signal standard deviation of examiner effects using different specifications and PAE outcomes, using the full sample. The Bayesian shrinkage methodology used to obtain these estimates is presented in Section IIA. Row (A) reports the baseline estimate from Table 2. In row (B), the specification includes assignee fixed effects. Row (C) uses purchase by a PAE other than Intellectual Ventures as the outcome. Row (D) considers purchases by Intellectual Ventures as the outcome. Row (E) uses the PAEs list from Cotropia, Kesan, and Schwartz (2014). Row (F) examines purchases by PAEs with a small patent portfolio, as identified by Cotropia, Kesan, and Schwartz (2014). Row (G) considers purchases by PAEs whose portfolios have more than 50 percent of patents that either were unassigned (i.e., the inventor is the owner) or that were assigned to a firm that the USPTO classifies as a small entity.

Robustness across Samples and Specifications.—Table 10 documents the robustness of the signal standard deviations of examiner effects for PAE purchases across alternative specifications and subsamples. Row A reports the baseline estimate in our main analysis sample, as in Table 2. Row B shows that the signal standard deviation remains similar when introducing assignee fixed effects in equation (1): PAEs selectively purchase patents coming from specific examiners even within the portfolio of a given assignee. Rows C to E show that the signal standard deviation is very similar across PAE lists. Row C reports similar estimates when excluding from the sample the patents purchased by the largest PAE, Intellectual Ventures. Conversely, row D shows that the results are comparable when considering only patents purchased by Intellectual Ventures.[56] The estimates also remain stable when using the list of PAEs defined by Cotropia, Kesan, and Schwartz (2014), as shown in row E.

Moreover, online Appendix Table D13 shows that the relationships between patent outcomes and examiner traits are similar when repeating the estimation using the "busyness instrument" methodology introduced in Section IIC.

Results by PAE Type.—Existing research has hypothesized that large and small PAEs may behave differently (Cotropia, Kesan, and Schwartz 2014). Row F of Table 10 shows that PAEs with a small portfolio of patents, as defined by Cotropia, Kesan, and Schwartz (2014), are as responsive to examiner effects as the average PAE. Another plausible hypothesis is that PAEs that primarily work with small firms or individual inventors may have a different behavior with respect to examiners, for instance because they may be focused on addressing frictions that specifically affect these firms

[56] The estimates reported in rows C and D do not average out to the estimate in row A, implying that there is not as much covariance between the two outcomes (purchase by Intellectual Ventures and purchase by a PAE other than Intellectual Ventures) as there is within outcomes. This result indicates that there is some segmentation of the market between PAEs, and that examiner effects are strong everywhere.

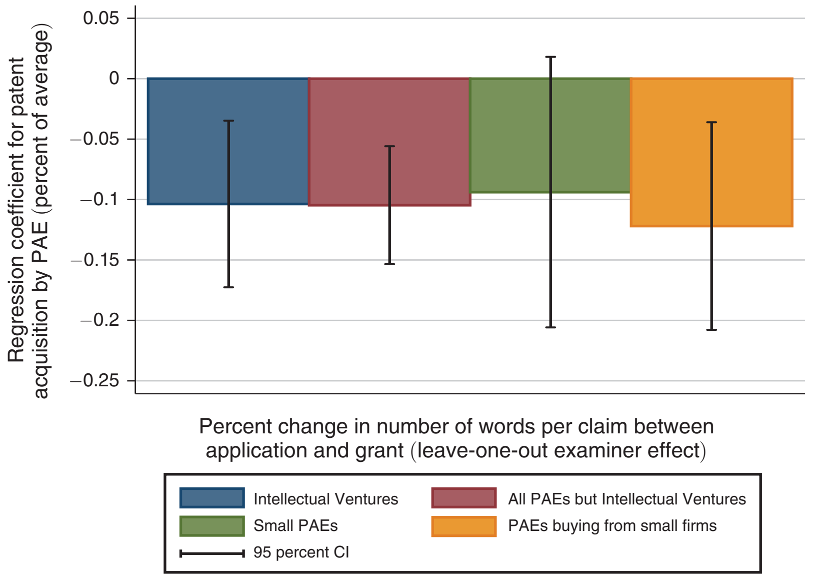

Figure 4. Heterogeneity in Patent Acquisition Behavior across Groups of PAEs

Notes: The sample is restricted to IT patents. The regression coefficients indicate the percentage change in the probability of PAE acquisition (relative to the baseline rate) for a one standard deviation increase in the examiner effect for the change in the number of words per claim during prosecution. The methodology is described in Section IIIB (see specification (8)). Regression coefficients are reported separately for four samples of PAEs: Intellectual Ventures, PAEs other than Intellectual Ventures, PAEs with a small patent portfolio according to the classification of Cotropia, Kesan, and Schwartz (2014), and PAEs that primarily buy patents from small entities (specifically, as described in the main text, they purchase more than half of their patents from small firms or individual inventors). The 95 percent confidence intervals are based on standard errors clustered by examiners.

and inventors. Row G considers a subset of PAEs that bought over 50 percent of their patents from small entities.[57] In this subsample as well, the signal standard deviation is very similar to the baseline.

Next, Figure 4 investigates whether different types of PAEs react differently to examiner leniency. Using specification (8), this figure reports the correlation between PAE purchase rates and the main proxy for examiner leniency from Section IIIB, the change in the number of words per claim between application and grant. We consider in turn Intellectual Ventures, all PAEs but Intellectual Ventures, small PAEs, and PAEs that purchased over 50 percent of their patents from small entities. We find that they all selectively purchase patents from more lenient examiners, with

[57] We define patents from small entities as patents that either were unassigned (i.e., the inventor is the owner) or that were assigned to a firm that the USPTO classifies as a "small entity" (if there is an assignee, each patent reports whether it was initially assigned to a small entity, i.e., a small firm). On average, PAEs purchase only 15.7 percent of their patents from small firms (19 percent when excluding continuation applications). Likewise, the share of unassigned patents in PAEs' purchases is low, ranging from 6.2 percent when including continuations to 10.7 percent without continuations. These low shares are difficult to reconcile with the view that the typical PAE is addressing frictions that specifically affect small firms or individual inventors.

relationships of very similar magnitudes across PAE groups.[58] The leniency bias of PAEs is therefore a very stable feature.

Patent Value and Transaction Prices.—Finally, to shed further light on the consequences of lenient examination, we consider data on the private value and transaction prices of the patents granted by lenient examiners.

First, we find that these examiners do not create greater private value for patent holders, suggesting a distinction between breadth and vagueness of claims. We might expect that lenient examiners are creating value for the applicant by approving the language that the applicant wanted. However, online Appendix Table D14 shows a small and statistically insignificant relationship between examiner PAE effect and examiner private value effect, as measured by stock market response.[59] This result suggests that these examiners are not simply granting patents with greater scope, which should create higher private value. A potential explanation is that the patents they grant contain less well-defined or vaguer language, which is consistent with the negative relationship between Section 112(b) blocking action usage and non-PAE litigation shown in panel B of Table D7.[60]

Second, we analyze patent transaction prices for a subset of patents where data is available. Having complete transaction price data would give us additional insight into the value of patents purchased by PAEs, but such data is generally not available. Here, we make use of data on a selected set of patents purchased in patent auctions. We find evidence that patents issued by more lenient examiners tend to sell at a lower price (online Appendix Figure D4).

IV. Conclusion

In this paper, we have shown that examiner effects have a large impact on several patent outcomes (conditional on grant), which suggests that significant heterogeneity in patent outcomes results from the process of creation of patent rights and is independent of technical merit. Our analysis leveraged the allocation of patent applications to examiners as a source of quasi-random variation in patent rights. To address identification concerns, we accounted for potential examiner specialization within narrow technology categories by developing new sources of quasi-experimental variation, based on assignment mechanisms at the patent office related to patent application serial numbers and examiner busyness. We also used flexible controls to address the potential concern that our results may be driven by selection effects stemming from the decision to grant a patent, rather than by patent crafting. These techniques could be used to investigate a host of issues related to the crafting of patent rights in future research.

[58] The results are similar with other proxies for examiner leniency, such as the grant rate, as well as when considering the full sample of patents instead of IT patents only (not reported).

[59] A caveat here is that the analysis only covers publicly traded firms, that is, the data is not informative about whether smaller firms benefit from examiner leniency.

[60] Section 112(b) is typically used to clarify indefinite claims language. Under a simple model, there would only be litigation in equilibrium if there is disagreement between parties, which would not happen if claims were broad but clear.

We have also shown that examiner effects are particularly important for understanding a central and much-debated feature of the US innovation system, the activities of PAEs. We found that PAEs selectively purchase and litigate patents issued by "lenient" examiners; these examiners tend to issue patents that are more likely to be litigated, but not purchased, by practicing firms. These patterns are quantitatively large and cannot be accounted for by standard PAE theories that describe PAEs either as intermediaries solving a generic friction in the patent market (such as transaction costs and illiquidity) or as perpetrators of frivolous lawsuits. Instead, we found that the activities of PAEs are best characterized as a response to a specific friction in the patent system that is caused by the way lenient examiners handle patent rights and affects litigation more broadly.

These findings imply that policies affecting the behaviors of patent examiners, and more specifically of lenient examiners, have the potential to greatly affect PAEs, but also litigation by practicing firms (for instance, in recent years patent litigation has been a major concern for smartphone manufacturers, including Apple and Samsung). Our results provide support for a recent policy effort at the USPTO aimed at improving examiner resources, tools, and training (the Enhanced Patent Quality Initiative was enacted in 2015). HR policies at the patent office have been the focus of an emerging academic literature (e.g., Frakes and Wasserman 2017 and Tabakovic and Wollmann 2018) and could serve as a useful complement to other recent policies that have started curbing PAEs' activities, including the introduction of inter partes reviews and recent Supreme Court rulings (e.g., *Alice v. CLS Bank*).

In future work, it would be instructive to investigate whether it is socially efficient to enforce patents issued by lenient examiners. Even if lenient examiners issue patents that are not socially valuable per se, there may still be potential spillovers to other patents from the enforcement activity. For example, PAEs' activities may deter infringement of all patents, not just patents of the types they choose to enforce directly. More broadly, our findings call for a greater focus on understanding the impact of the crafting of patent rights on innovation dynamics. This paper provides a set of tools to conduct such investigation and has shown the explanatory power and potential policy relevance of this line of inquiry in the context of the debate over PAEs.

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