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

Josh Feng and Xavier Jaravel

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A Examiner Effect Estimation Methods

In this appendix, we report additional steps involved in the research designs described in Section II to recover the causal effect of examiner on patent outcomes, namely (1) the baseline research design with the Bayesian shrinkage correction, (2) the design using applications' last digits as a source of variation, (3) the design using examiners' busyness as a source of variation, and (4) the baseline research design with the Beta-Binomial count model for binary outcomes.

1. Bayesian shrinkage. In what follows, we describe the two steps we take to estimate the shrunk examiner effects introduced in Section II.A. These two steps help increase the precision of the Empirical Bayes posterior estimate of each examiner effect in equation (4).

In the first step, we amend the statistical model to allow for an examiner-by-year shock θ_{jt}, i.e.

$$Y_i = a_{ut(i)} + v_{ij},$$
$$v_{ij} = \mu_j + \theta_{jt(i)} + \epsilon_i,$$

where i indexes the patent, j the examiner, u the art unit and t the year. We compute $\bar{v_{jt}}$ using (2), $\widehat{\sigma_\mu}$ using (3), as well as $\widehat{\sigma_\epsilon}^2 = Var(v_{ij} - \bar{v_{jt}})$ and $\widehat{\sigma_\theta}^2 = Var(v_{ij}) - \widehat{\sigma_\mu}^2 - \widehat{\sigma_\epsilon}^2$.

In the second step, for each examiner we compute a weighted average of the yearly average residuals $\{\bar{v_{jt}}\}$ that has the property of being a minimum variance unbiased estimate of μ_j. This average uses weights such that years in which the examiner granted more patents are given a higher weight:

$$\bar{v}_j = \sum_t w_{jt} \bar{v}_{jt},$$

where

$$w_{jt} = \frac{h_{jt}}{\sum h_{jt}}$$
$$h_{jt} = \frac{1}{\widehat{\sigma_\theta}^2 + \frac{\widehat{\sigma_\epsilon}^2}{n_{jt}}}$$

We then compute the Empirical Bayes posterior estimate of each examiner as in (4):

$$\widehat{\mu_j} = \frac{\widehat{\sigma_\mu}^2}{Var(\bar{v}_j)} \cdot \bar{v}_j,$$

with

$$Var(\bar{v}_j) = \widehat{\sigma_\mu}^2 + \left(\sum h_{jt}\right)^{-1}.$$

The shrinkage factor is the ratio of the signal variance to the total variance and varies across examiners depending on the total number of patents they granted.

The shrunk examiner effects $\{\widehat{\mu_j}\}$ have two noteworthy properties. First, under the assumption that $\mu_j \sim N(0, \sigma_\mu^2)$, $\theta_{jt} \sim N(0, \sigma_\theta^2)$ and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$, the shrunk examiner effect is the optimal Bayesian posterior expectation of an examiner's effect given the history of patent outcomes up to the current period. The derivation is a standard application of Bayes' rule. Intuitively, since there is no drift in examiner effects, we can use the average patent outcome in all years prior to the current year as a sufficient statistic to form the posterior distribution of examiner effects. Second, the shrunk examiner effects also have a frequentist interpretation. The shrinkage factor is the regression coefficient in the hypothetical regression of the true (unobserved) μ_j on $\bar{v}_j$. The regression coefficient is naturally the ratio of the covariance of μ_j and v_j (given by $\widehat{\sigma_\mu}^2$ because the other components of $\bar{v}_j$ are noise) to the variance of $\bar{v}_j$.

2. Allocation of applications to examiners using the last digit of applications' serial numbers. To identify art units assigning applications based on the last digit of their serial numbers, we use the USPTO patent examination database and follow three steps.

First, we prepare the data. We exclude continuation applications, since these applications are almost always assigned to the examiner who processed the parent application. For each patent application we record the "docket date", which is the date on which the application was assigned to the relevant art unit. After an application is filed, the USPTO assigns the application to a specific art unit according to its technological features, which takes some time; therefore the docket date is typically different from the filing date and is the relevant point in time when examiner assignment occurs within the art unit.

Second, we compute the key statistics of interest. We count the number of applications falling in each last-digit-by-examiner-by-art-unit-by-docket-year cell; we denote the application count in each cell by n_{djut}, where d indexes the last digit of the application's serial number (ranging from 0 to 9), j the examiner, u the art unit and t the docket year. In addition, for each examiner we record the total number of applications they were assigned in each art unit in each docket year, denoted by n_{jut}.

Third, for each art unit in each year, we implement a statistical test of the null hypothesis that examiner assignment does not depend on last digits. If last digits are not used, the expected number of application with last digit d assigned to examiner j is simply one tenth of the total number of application assigned to this examiner in this art unit and docket year, which we denote by $n^E_{djut} = \frac{n_{jut}}{10}$. To assess whether the data rejects the null in a given art unit and docket year, we compute the following Pearson's Chi-squared statistic:

$$\chi^2_{ut} \equiv \sum_{j \in ut} \sum_{d=0}^{9} \frac{(n_{djut} - n^E_{djut})^2}{n^E_{djut}}.$$

Intuitively, we compare the *actual* number of applications with last digit d assigned to examiner j in art unit u in docket year t (n_{djut}) to the *expected* number (n^E_{djut}). If the actual assignment patterns are "too concentrated" relative to what may happen simply by chance, we reject the null. Formally, under the null that art unit u did not use last digits for examiner assignment in docket year t, χ^2_{ut} has a Chi-squared distribution with $9 \cdot (J_{ut} - 1)$ degrees of freedom, where J_{ut} is the number of examiners in art unit u in docket year t. The degrees of freedom follow from the fact that there are ten possible last digits per examiner, minus the constraints for the total number of applications within each examiner and for the total number of applications by last digit cells. Accordingly, we compute the p-value for the null by comparing the value we obtain in the data for χ^2_{ut} with a Chi-squared distribution with $9 \cdot (J_{ut} - 1)$ degrees of freedom.[61]

Fourth, we draw the list of art units for which we reject the null that last digits are not used for assignment at the 1% level, i.e. with a p-value of the Chi-squared test below 0.01. We draw this list by docket years, i.e. based on statistics $\{\chi^2_{ut}\}$ that are specific to both art units and docket years, so that each art unit is allowed to change its assignment mechanism over time. To make it simple for

[61] Our Chi-squared test is similar in spirit to the divergence statistics used by Righi and Simcoe (2017) to provide evidence of examiner specialization based on the dispersion of patent technology classes across examiners working in the same art unit. The exact formulas for their divergence tests differ from ours because they allow for technology-specific patterns of specialization within an art unit (i.e., within a given art unit, it could be that only a subset of all technology classes feature examiner specialization); we use a similar but technically different test for assignment by last digits, because it seems implausible that only a subset of last digits would be used for examiner assignment.

other researchers to use this source of variation in future work, we make publicly available on our websites the list of art units by docket years for which we rejected the null at the 1% level (direct link).

Online Appendix Figure A1 presents the results. Panel A shows the distribution of the p-values of the Chi-square tests across art units. There is a large number of art units with a p-value below 1%, indicating that these art units use application last digit to assign patents. The test only rejects the null that last digits are *not* used and it can of course not guarantee that in art units with a p-value below 1% all applications are assigned to examiners solely based on last digits. To address this limitation, we use a split-sample procedure to quantify the extent to which examiners get consistently assigned the same last digits. We split our main sample into two 50% samples at random. For each of the two subsamples, we compute the share of each last digit in an examiner's pool of assigned applications. We then test whether the shares computed in the first subsample are predictive of those in the second subsample (comparing assigned shares for the same examiner in the same year in the two samples). Panel B of Figure A1 presents the results. For the art units that use last digits to allocate applications according to the Chi-square test (p-value < 0.01), we find a strong correlation between the last digit shares that were independently estimated in the two subsamples, with a slope close to one. This result indicates that the use of last digits for allocation of patents is quantitatively important (i.e. the Chi-square tests are not identifying statistically significant but quantitatively small rejections of the null that last digits are not used for application assignment). In contrast, in the art units for which we cannot reject that last digits are not used for application assignment (p-value > 0.01), there is no relationship between the last digit shares across the two samples. The two panels of Figure A1 thus establish that there is a large number of art units that use last digits for application assignment and that they do so in a quantitatively important way.

Busyness instrument. We describe below our methodology to recover the application-specific examiner assignment probabilities p_{ij} used in equations (5) and (6) in Section II.C. Our approach delivers variation in examiner assignment solely from changes in examiner busyness over time, which is useful to validate the baseline estimates of examiner effects.

We start by preparing the data. We aggregate total disposals (grants plus abandonments) for examiners in each two-week period in a given year. As before, we exclude continuation applications because they tend to be assigned to the examiner who handled the parent application. For each incoming application, we create the list of all examiners that it could have been assigned to, which is given by the set of examiners who processed at least one application in that art unit and in that year. As a proxy for how an examiner's busyness changes over time, we compute the number of patent application cases closed by the examiner in each two-week period. Intuitively, an examiner may be assigned more applications as they become less busy, i.e. in periods when they just finished working on other applications.

Next, we estimate the following linear probability model by OLS:

$$Y_{ij} = \beta D_{jt} + \delta_i + \gamma_j + \epsilon_{ijt}, \tag{A1}$$

where i indexes the application, j the examiner and t the two-week period. Y_{ij} is an indicator variable for the assignment of application i to examiner j; D_{jt} is the number of patent application cases closed by the examiner during the relevant two-week period; δ_i is an application fixed effect which captures the fact that a larger or smaller number of examiners may be available when a given application arrives; and γ_j is an examiner fixed effect which accounts for the possibility that some examiners might be systematically assigned a large of smaller number of applications (e..g, due to seniority). The coefficient β estimates the extent to which an examiner is more likely to be assigned an application (relative to the baseline captured by the fixed effects) in a period when they just finished working on other applications.

Finally, we use the estimates from (A1) to compute the predicted assignment probabilities $p_{ij} \equiv \widehat{Y_{ij}}$, which are used in equations (5) and (6) in Section II.C. If the estimate of β were zero, there would be no variation in the application-specific examiner assignment probabilities$\{p_{ij}\}$ across applications received in the same art unit in the same year and the research design would have now power. In fact, we estimate $\beta > 0$ and obtain sufficient variation in examiner assignment probabilities to implement the busyness research design presented in Section II.C.

Beta-Binomial count model. In what follows, we derive the integrated likelihood for the Beta-Binomial count model used in Section II.C. As a reminder, we aggregate data for each examiner j in year t and art unit u into the form (n_{jau}, r_{jut}), where n denotes the total number of granted patents for a given examiner and r the total number of patents purchased by PAEs (or some other binary outcome) for this examiner. We then model the data generating process with a binomial likelihood on each examiner for each art unit and year: each examiner has some true probability p_{jut} of patent purchase by a PAE (conditional on grant). We drop the ut subscripts below for brevity.

For each art unit in each year, we specify a flexible Beta prior distribution on examiner effects:

$p \sim Beta(\alpha, \beta)$. We then compute the integrated likelihood:

$$\begin{aligned} L(r|n,\alpha,\beta) &= \int_{p=0}^{1} \binom{n}{r} p^r(1-p)\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}p^{\alpha-1}(1-p)^{\beta-1}dp \\ &= \binom{n}{r}\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\int_{p=0}^{1} p^r(1-p)p^{\alpha-1}(1-p)^{\beta-1}dp \\ &= \binom{n}{r}\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\frac{\Gamma(r+\alpha)\Gamma(n-r+\beta)}{\Gamma(n+\alpha+\beta)}, \end{aligned}$$

where the second step conjugates the inside to integrate to one based on the probability density function of the Beta distribution. Using this expression, we estimate the hyperparameters α and β by maximum likelihood.

Finally, we compute the shrunk examiner effect for each examiner. A shrunk examiner effect is simply a posterior mean: we start from the prior, which is governed by the estimates for α and β for each art unit and year, and apply Bayesian updating with the examiner's data in that art unit and year according to equation (7). We then aggregate these shrunk effects across years within each examiner by taking a weighted average (weighting by number of cases) to obtain the overall shrunk effect for each examiner.

B Building the Patent Portfolios of Patent Assertion Entities

In this appendix, we describe the procedure to we use to build the patent portfolio of Patent Assertion Entities. We proceed in four steps:

1. We start with the list of PAE names from RPX for our main sample and from Cotropia et al. (2014) for robustness checks. We exclude universities (e.g. Wisconsin Alumni Research Foundation) and academic hospitals (Children's Medical Center Corporation). For the Cotropia et al. (2014) list, we only include entities in categories 3 (Large aggregator) and 5 (Patent holding company). This excludes failed companies and technology development companies.

2. We normalize entity names from both the PAE list and the USPTO Assignment Database from Marco et al. (2015). We do so by capitalizing all names, removing punctuation, and removing the following standard entity terms: INC, CO, COMPANY, COMPANIES, CORP, CORPORATIONS, DIV, GMBH, LLC, LC, INCORPORATED, KG, LIMITED, LIMITED PARTNERSHIP, LP, LTD, NV, PLC, SA, SARL, SNC, SPA, SRL, TRUST USA, CENTER, BV, AG, AB, GROUP, FOUNDATION, INSTITUTE, and TECHNOLOGIES.

3. We collect the identifiers of patent transactions in the USPTO Assignment Database ("Reel/Frame IDs" in the USPTO assignment data, which corresponds to one transaction) that have a normalized entity name matching the normalized name of a PAE in Step 2.

4. Using the patent transaction identifier from Step 3, we know from the USPTO Assignment Database whether the patent was assigned to the employer of the inventor(s). We only keep transactions that are non-employer assignments, to mitigate any PAE classification errors that might cause us to include patents filed by failed companies and technology development companies. We exclude transactions such as securitization, mergers, and name changes. We end up with a list of patents that were sold to PAEs on the patent market.

C Building the EPO Analysis Dataset

In this appendix, we describe our procedure for constructing the sample used for the EPO analysis in Section III.D:

1. We start from the full dataset of patent applications filed at the USPTO and EPO from 2001-2014, available from PATSTAT

2. For both the USPTO and EPO samples, we restrict the sample to documents that are the first in the family in each jurisdiction, based on the family ID ("docdb_family_id") assigned by PATSTAT

3. We then merge USPTO applications to EPO applications by family ID (this is a one-to-one match given data processing in step 2).

4. Finally, we only keep matched pairs for which the filing date difference was strictly less than 180 days. We then restrict our analysis to patents granted in the US, as we do throughout Section III.

D Online Appendix Tables and Figures

Table A1: Distribution of Number of Applications Assigned to an Examiner in a Given Filing Year

Percentile	# of Apps Examiner-Year
5	1
10	1
25	5
50	19
75	46
90	75
95	94

Notes: This table reports the distribution of the number of applications assigned to an examiner in a given year, using the sample of non-continuation applications. This is a breakdown of the summary statistics reported in Panel C of Table 1.

Table A2: Raw Standard Deviations of Patent Outcomes across Examiners

	Raw S.D.	
	% of Average (1)	Level (2)
Patent value from Kogan et al. (2017), $M	106.14	8.65
4th-year fee payment rate	11.44	0.0996
8th-year fee payment rate	18.05	0.1101
12th-year fee payment rate	34.57	0.0722
Log total patent citation	42.71	0.20
Log patent citations by same assignee	92.37	0.19
Log patent citations by other assignees	46.43	0.09
Rate of patent acquisition by non-PAEs	68.41	0.1344
Rate of patent acquisition by PAEs	286.88	0.0292
Rate of patent litigation by non-PAEs	439.17	0.0285
Rate of patent litigation by PAEs	1359.17	0.0055

Notes: This table reports the raw standard deviations of examiner effects as a percentage of the mean (Column 1) and in level (Column 2). The raw standard deviations refer to the standard deviations of the average residuals (defined by equation (2)) across examiners. The raw standard deviations account for art unit by year fixed effects but not for excess variance from noise. The results in this table are directly comparable to those of Table 2, which account for excess variance. See Section I.A for details on the sample and variable definitions.

Table A3: Signal Standard Deviations of Examiner Causal Effects by Technology Categories

	Signal S.D., % of Average			
	Patent value from Kogan et al. (2017)	Log total patent citation	Non-PAE purchase	Change in number of words per claim
	(1)	(2)	(2)	(3)
(A) Biotechnology and organic chemistry	25.33	30.58	15.39	18.55
(B) Chemical and materials engineering	74.89	24.85	23.11	19.30
(C) Computer architecture, software and information security	9.00	24.69	6.43	25.60
(D) Computer networks, multiplex communication, video distribution, and security	11.80	31.80	6.10	18.06
(E) Communications	24.39	20.78	11.68	30.97
(F) Semiconductors, electrical and optical systems and components	30.83	17.59	12.08	26.47
(G) Transportation, construction, electronic commerce, agriculture, national security, and license and review	21.95	21.42	12.77	19.15
(H) Mechanical engineering, manufacturing	29.78	23.08	19.41	19.73

Notes: This table reports the signal standard deviations of examiner effects (as a percentage of the mean) for four patent outcomes across the eight technology centers of the USPTO. The means are re-computed within each technology center. The table shows that examiner effects are substantial in all technology centers. We have studied heterogeneity in signal standard deviations for the other outcomes reported in Table 2 and did not find large differences across technology centers, except for patent acquisitions by PAEs, which occur primarily in computers, software and communications (not reported). The Bayesian shrinkage methodology used to obtain these estimates is presented in Section II.

Table A4: Signal Standard Deviations of Examiner Prosecution Behaviors

	Signal S.D.		S.D. of Shrunk
	% of Average	Level	Effects, % of Average
	(1)	(2)	(3)
Change in number of words per claim, % (average over all claims)	23.37	13.39	17.47
Change in number of claims, %	136.83	4.99	82.43
Use of Section 101 - Lack of utility or eligibility	60.43	0.032	52.44
Use of Section 102(a) - Prior art exists	108.69	0.018	75.65
Use of Section 103(a) - Obvious invention	25.27	0.105	19.61
Use of Section 112(b) - Vague claims	47.72	0.088	39.09
Patent citations added by examiner, %	14.53	7.95	11.52
Citations to non-patent literature added by examiner, %	39.70	5.73	32.09

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 II. See Section I.A for details on the sample and variable definitions.

Table A5: PAE Patent Portfolios and Litigated Patents across Technology Categories

Panel A: Patents Owned by PAEs

Technology Category	Number of Patents
Chemical	1,669
Computers & Communications	27,156
Drugs & Medical	1,312
Electrical & Electronic	10,660
Mechanical	2,709
Others	1,453

Panel B: Patents Litigated by Non-PAEs

Technology Category	Number of Patents
Chemical	1,626
Computers & Communications	4,175
Drugs & Medical	2,609
Electrical & Electronic	2,497
Mechanical	2,859
Others	4,611

Notes: This table reports the number of patents owned by PAEs (Panel A) and the number of litigated patents by non-PAEs (Panel B) across technology categories. The technology categories are based on the primary USPTO technology class for each patent, following Hall et al. (2001). These panels show that PAEs tend to be most active in technology areas related to computers, communications and electronics, where patent litigation by non-PAEs is also frequent.

Table A6: Patent Acquisition and Examiner Behavior, Full Sample

Panel A: Patent Acquisition by PAEs

Leave-one-out Examiner Effects	Patent Purchase by PAE								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Change in Number of Word per	-0.076***								-0.062**
Claim from Application to Grant	(0.0177)								(0.026)
% Change in Number of Claims		0.064***							0.057**
from Application to Grant		(0.021)							(0.023)
Grant Rate			0.064***						-0.01
			(0.015)						(0.02)
Use of Section 101				-0.059*				-0.057*	-0.052
- Lack of utility or eligibility				(0.033)				(0.0342)	(0.036)
Use of Section 102(a) -					0.027			0.0343	0.033
- Prior art exists					(0.022)			(0.0214)	(0.022)
Use of Section 103(a)						-0.033**		-0.031**	-0.015
- Obvious invention						(0.016)		(0.015)	(0.019)
Use of Section 112(b)							-0.020	-0.0025	0.01
- Vague claims							(0.019)	(0.018)	(0.02)
Fixed Effects	Year by Art Unit								
N	1,109,882	1,110,522	1,270,027	1,269,751	1,269,751	1,269,751	1,269,751	1,269,751	1,109,882

Panel B: Patent Acquisition by Practicing Firms

Leave-one-out Examiner Effects	Patent Purchase by Practicing Firm								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Change in Number of Word per	0.0022								-0.003
Claim from Application to Grant	(0.005)								(0.006)
% Change in Number of Claims		0.0005							-0.0005
from Application to Grant		(0.005)							(0.0058)
Grant Rate			0.001						0.0014
			(0.005)						(0.008)
Use of Section 101				0.0136***				0.012**	0.013**
- Lack of utility or eligibility				(0.0052)				(0.005)	(0.005)
Use of Section 102(a) -					0.006			0.005	0.005
-Prior art exists					(0.004)			(0.004)	(0.004)
Use of Section 103(a)						0.0045		0.003	0.004
-Obvious invention						(0.004)		(0.004)	(0.005)
Use of Section 112(b)							0.004	0.0002	0.001
-Vague claims							(0.004)	(0.004)	(0.004)
Fixed Effects	Year by Art Unit								
N	1,109,882	1,110,522	1,270,027	1,269,751	1,269,751	1,269,751	1,269,751	1,269,751	1,109,882

Notes: Regressors are standardized by their standard deviations and coefficients are expressed as a fraction of the mean of the outcome. Results are similar with patent-level controls and assignee fixed effects (not reported). Standard errors are clustered by examiners. $*p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Patent Litigation and Examiner Behavior, Full Sample

Panel A: Patent Litigation by PAEs

Leave-one-out Examiner Effects	Patent Litigation by PAE								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Change in Number of Word per	-0.27***								-0.17**
Claim from Application to Grant	(0.06)								(0.08)
% Change in Number of Claims		0.16***							0.11**
from Application to Grant		(0.04)							(0.05)
Grant Rate			0.28***						0.09
			(0.06)						(0.09)
Use of Section 101				-0.17				-0.15	-0.055
- Lack of utility or eligibility				(0.08)				(0.091)	(0.095)
Use of Section 102(a) -					-0.014			0.0051	0.022
- Prior art exists					(0.055)			(0.055)	(0.055)
Use of Section 103(a)						-0.077		-0.054	0.005
- Obvious invention						(0.051)		(0.053)	(0.062)
Use of Section 112(b)							-0.077	-0.032	-0.0203
- Vague claims							(0.048)	(0.049)	(0.049)
N	1,109,882	1,110,522	1,270,027	1,269,751	1,269,751	1,269,751	1,269,751	1,269,751	1,109,882
Fixed Effects	Year by Art Unit								

Panel B: Patent Litigation by Practicing Firms

Leave-one-out Examiner Effects	Patent Litigation by Practicing Firm								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Change in Number of Word per	-0.066***								-0.07**
Claim from Application to Grant	(0.022)								(0.035)
% Change in Number of Claims		0.029*							0.016
from Application to Grant		(0.017)							(0.017)
Grant Rate			0.073**						0.002
			(0.028)						(0.038)
Use of Section 101				-0.069***				-0.068***	-0.050**
- Lack of utility or eligibility				(0.022)				(0.023)	(0.021)
Use of Section 102(a) -					-0.0016			0.004	-0.0009
- Prior art exists					(0.0158)			(0.016)	(0.016)
Use of Section 103(a)						-0.021		-0.018	0.022
- Obvious invention						(0.016)		(0.017)	(0.018)
Use of Section 112(b)							-0.012	0.005	0.004
- Vague claims							(0.017)	(0.019)	(0.019)
N	1,109,882	1,1105,22	1,270,027	1,269,751	1,269,751	1,269,751	1,269,751	1,269,751	1,109,882
Fixed Effects	Year by Art Unit								

Notes: Regressors are standardized by their standard deviations and coefficients are expressed as a fraction of the mean of the outcome. Results are similar with patent-level controls and assignee fixed effects (not reported). Standard errors are clustered by examiners. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Examiner Behavior and Likelihood of Patent Invalidity, Full Sample

Panel A: Reissuance of Granted Patents

	Leave-one-out Examiner Effects (separate regressions)	Reissuance Rate (1)	(2)	(3)	Reissuance Rate Two Years or More after Grant (4)	(5)	(6)
(A)	% Change in Number of Word per Claim from Application to Grant	-0.12***	-0.10***	-0.12***	-0.19***	-0.20***	-0.20***
		(0.031)	(0.029)	(0.03)	(0.069)	(0.066)	(0.069)
(B)	Grant Rate	0.13***	0.11***	0.16***	0.26***	0.25***	0.29***
		(0.03)	(0.02)	(0.031)	(0.067)	(0.063)	(0.069)
	Fixed Effects	Year	Year by Art Unit	Year by Art Unit by Class	Year	Year by Art Unit	Year by Art Unit by Class
	N		1,109,882			1,107,565	

Panel B: Court Rulings

	Leave-one-out Examiner Effects (separate regressions)	Invalidity Rate (1)	(2)	(3)	Infringement Rate (4)	(5)	(6)
(A)	% Change in Number of Word per Claim from Application to Grant	0.019	0.11	0.17	0.046	0.117	0.082
		(0.028)	(0.11)	(0.179)	(0.032)	(0.119)	(0.163)
(B)	Grant Rate	0.005	-0.025	-0.097	-0.010	-0.027	-0.024
		(0.02)	(0.09)	(0.16)	(0.027)	(0.102)	(0.165)
	Fixed Effects	Year	Year by Art Unit	Year by Art Unit by Class	Year	Year by Art Unit	Year by Art Unit by Class
	N		479			479	

Panel C: Trials at the Patent Office ("Inter Partes Reviews")

	Leave-one-out Examiner Effects (separate regressions)	IPR Rate (1)	(2)	(3)	Institution Rate of IPR (4)	(5)	(6)
(A)	% Change in Number of Word per Claim from Application to Grant	-0.288***	-0.283***	-0.27***	-0.042	-0.027	-0.08
		(0.067)	(0.063)	(0.06)	(0.032)	(0.158)	(0.209)
(B)	Grant Rate	0.286***	0.2613***	0.28***	0.046	-0.045	-0.109
		(0.061)	(0.058)	(0.06)	(0.0309)	(0.123)	(0.151)
	Fixed Effects	Year	Year by Art Unit	Year by Art Unit by Class	Year	Year by Art Unit	Year by Art Unit by Class
	N		1,109,882			523	

Notes: 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 A7. Results are similar with patent-level controls and assignee fixed effects (not reported). Standard errors are clustered by examiners. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Patent Acquisition and Examiner Behavior, IT and Random Digit

Panel A: Patent Acquisition by PAEs

Leave-one-out Examiner Effects	Patent Purchase by PAE								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Change in Number of Word per	-0.136**								-0.056
Claim from Application to Grant	(0.059)								(0.090)
% Change in Number of Claims		-0.063							-0.118**
from Application to Grant		(0.055)							(0.051)
Grant Rate			0.140***						0.100
			(0.043)						(0.069)
Use of Section 101				-0.006				-0.009	-0.004
- Lack of utility or eligibility				(0.025)				(0.029)	(0.026)
Use of Section 102(a) -					-0.011			-0.005	-0.030
- Prior art exists					(0.036)			(0.031)	(0.032)
Use of Section 103(a)						-0.058		-0.044	0.013
- Obvious invention						(0.046)		(0.054)	(0.062)
Use of Section 112(b)							-0.029	0.072	0.092
- Vague claims							(0.036)	(0.057)	(0.058)
Fixed Effects	Year by Art Unit								
N	92,335	92,335	93,100	92,335	92,335	92,335	92,335	92,335	92,335

Panel B: Patent Acquisition by Practicing Firms

Leave-one-out Examiner Effects	Patent Purchase by Practicing Firm								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Change in Number of Word per	0.012								0.028
Claim from Application to Grant	(0.016)								(0.026)
% Change in Number of Claims		0.011							-0.015
from Application to Grant		(0.020)							(0.019)
Grant Rate			0.001						0.014
			(0.012)						(0.020)
Use of Section 101				0.014**				0.010	0.007
- Lack of utility or eligibility				(0.007)				(0.011)	(0.010)
Use of Section 102(a) -					0.005			0.014	-0.001
-Prior art exists					(0.011)			(0.011)	(0.012)
Use of Section 103(a)						-0.007		-0.008	-0.012
-Obvious invention						(0.010)		(0.016)	(0.018)
Use of Section 112(b)							-0.008	-0.030	-0.031
-Vague claims							(0.009)	(0.019)	(0.020)
Fixed Effects	Year by Art Unit								
N	92,335	92,335	93,100	92,335	92,335	92,335	92,335	92,335	92,335

Notes: Results calculated for all IT patents, using examiner effects computed on the sample of patents in the random digit sample. Patents for which the examiner is never part of the random digit sample are excluded from the analysis. Regressors are standardized by their standard deviations and coefficients are expressed as a fraction of the mean of the outcome. Results are similar with patent-level controls and assignee fixed effects (not reported). Standard errors are clustered by examiners. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Patent Litigation and Examiner Behavior, IT and Random Digit

Panel A: Patent Litigation by PAEs

Leave-one-out Examiner Effects	Patent Litigation by PAE								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Change in Number of Word per	-0.631***								-0.352
Claim from Application to Grant	(0.173)								(0.257)
% Change in Number of Claims		-0.060							-0.216
from Application to Grant		(0.284)							(0.278)
Grant Rate			0.709***						0.539*
			(0.146)						(0.296)
Use of Section 101				-0.040				-0.035	-0.009
- Lack of utility or eligibility				(0.059)				(0.076)	(0.080)
Use of Section 102(a) -					-0.230			-0.013	-0.134
- Prior art exists					(0.174)			(0.117)	(0.130)
Use of Section 103(a)						-0.085		-0.073	0.172
- Obvious invention						(0.127)		(0.231)	(0.244)
Use of Section 112(b)							-0.079	0.085	0.193
- Vague claims							(0.121)	(0.235)	(0.239)
N	92,335	92,335	93,100	92,335	92,335	92,335	92,335	92,335	92,335
Fixed Effects	Year by Art Unit								

Panel B: Patent Litigation by Practicing Firms

Leave-one-out Examiner Effects	Patent Litigation by Practicing Firm								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Change in Number of Word per	-0.092								0.029
Claim from Application to Grant	(0.081)								(0.148)
% Change in Number of Claims		-0.032							-0.196*
from Application to Grant		(0.092)							(0.103)
Grant Rate			0.100						0.081
			(0.075)						(0.130)
Use of Section 101				0.022				0.013	0.009
- Lack of utility or eligibility				(0.029)				(0.038)	(0.038)
Use of Section 102(a) -					0.045			0.062	0.014
- Prior art exists					(0.056)			(0.052)	(0.042)
Use of Section 103(a)						-0.034		0.062	0.102
- Obvious invention						(0.053)		(0.084)	(0.091)
Use of Section 112(b)							-0.142***	-0.257***	-0.247**
- Vague claims							(0.046)	(0.096)	(0.096)
N	92,335	92,335	93,100	92,335	92,335	92,335	92,335	92,335	92,335
Fixed Effects	Year by Art Unit								

Notes: Results calculated for all IT patents, using examiner effects computed on the sample of patents in the random digit sample. Patents for which the examiner is never part of the random digit sample are excluded from the analysis. Regressors are standardized by their standard deviations and coefficients are expressed as a fraction of the mean of the outcome. Results are similar with patent-level controls and assignee fixed effects (not reported). Standard errors are clustered by examiners. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Correlation between Patent Grant Rate and Other Examiner Effects

Examiner Effect	Correlation with Examiner Effect for Grant
% Change in Number of Word per Claim from Application to Grant	-0.73
% Change in Number of Claims from Application to Grant	0.24
Use of Section 101 - Lack of utility or eligibility	-0.25
Use of Section 102(a) - - Prior art exists	-0.08
Use of Section 103(a) - Obvious invention	-0.43
Use of Section 112(b) - Vague claims	-0.32

Notes: This table reports the correlation between the examiner effect for patent grant and all other examiner effects used to characterize examiner behavior in Section III. See Table 5 for a description of the sample.

Table A12: Patent Acquisition by PAEs and Grant Decisions at the European Patent Office (EPO) - Subsample Analysis

	Patent Acquisition by PAE		Patent Acquisition by Practicing Firm		Patent Litigation by Practicing Firm	
	(1)	(2)	(3)	(4)	(5)	(6)
EPO Grant	-0.2144**	0.0819	0.0037	-0.0052	-0.0831	0.0196
	(0.1001)	(0.0702)	(0.0133)	(0.0126)	(0.1074)	(0.0921)
Subsample of examiners with PAE purchase effect above median only	Yes		Yes		Yes	
Subsample of examiners with PAE purchase effect below median only		Yes		Yes		Yes
Art unit by year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Examiner Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Assignee Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	109,383	109,484	109,383	109,484	109,383	109,484

Notes: This table provides a further breakdown for our results in Table 10. Regressors are standardized by their standard deviations and regression coefficients are expressed as a fraction of the mean of the outcome. Columns (1) and (2) show that PAEs selectively purchase patents that were rejected by the EPO *only* in the patent portfolios of examiners who have a relatively large causal impact on PAE purchases (specifically, their PAE purchase effect is above median; the examiner-specific PAE purchase effects were estimated using equation (4)). These patterns suggest that PAEs selectively purchase patents with two features: (i) these patents are close to existing intellectual property because they bear on incremental technologies (hence their higher likelihood of rejection at EPO); (ii) these patents were issued by specific (lenient) examiners at the USPTO, and their claims may be less well-defined are harder to interpret than average. Given these two features, it is plausible that these patents are particularly productive for litigation, as they offer many potential litigation targets. The effect in Column (1) is quantitatively large: the probability of a purchase by a PAE decreases by 21% if the patent is granted by the EPO. As shown in Columns (3) to (6), there is no such effect for patent acquisition by practicing firms (for which we obtain precisely estimated zeros) or for non-PAE litigation. The results all account for art unit by year, examiner and assignee fixed effects; the results are similar when removing the fixed effects or changing the cutoff for the examiner PAE effects (not reported). Standard errors are clustered by examiners. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Patent Outcomes and Examiner Behavior, Busyness Variation

	PAE Purchase	Non-PAE Purchase	PAE Litigated	Non-PAE Litigated
% Change in Number of Word per Claim from Application to Grant (weighted)	-0.184***	-0.007	-0.465***	-0.219***
	(0.025)	(0.007)	(0.115)	(0.049)
Art unit by year Fixed Effects	Yes	Yes	Yes	Yes
N	309,008	309,008	309,008	309,008

Notes: This table uses variation in busyness to show that the relationship between outcomes and examiner effects is robust (IT sample). We calculate a weighted examiner effect using assignment probabilities predicted by the busyness model described in Equation A1, and then predict the outcome using the weighted examiner effect. Again, we report the change in the baseline rate of the outcome per standard deviation of the predictor. As noted in Section II.C, these estimates should not be interpreted through the lens of instrumental variables, but instead represent a check that the predictive regression coefficients remain similar in sign and magnitude when accounting for potential violations of random assignment. Standard errors are clustered by examiners. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Examiner Behavior and Other Patent Outcomes

Panel A: Patent Value from Kogan et al. (2017)

Leave-one-out Examiner Effects	Patent Value								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Purchase by PAE	0.012								
	(0.016)								
% Change in Number of Word per		-0.0033							0.019
Claim from Application to Grant		(0.008)							(0.017)
% Change in Number of Claims			-0.0026						-0.005
from Application to Grant			(0.0226)						(0.023)
Grant Rate				0.0398***					0.054**
				(0.0149)					(0.024)
Use of Section 101					0.0308**				0.035**
- Lack of utility or eligibility					(0.0150)				(0.015)
Use of Section 102(a) -						-0.0071			-0.005
- Prior art exists						(0.013)			(0.013)
Use of Section 103(a)							-0.011		-0.002
- Obvious invention							(0.007)		(0.013)
Use of Section 112(b)								-0.008	-0.004
- Vague claims								(0.011)	(0.013)
Fixed Effects	Year by Art Unit								
N	356,250	310,264	310,332	356,318	356,250	356,250	356,250	356,250	310,332

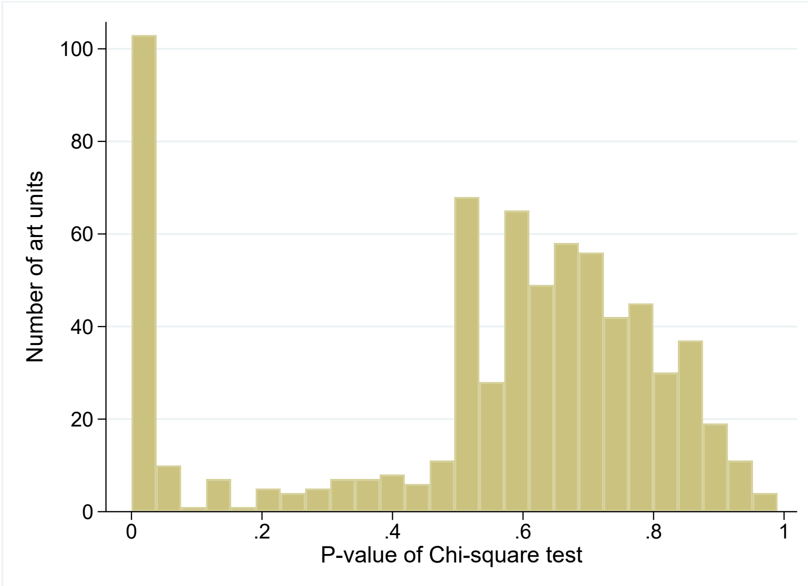
Panel B: Patent Citations

Leave-one-out Examiner Effects	Log Total Patent Citations								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Purchase by PAE	0.015**								
	(0.006)								
% Change in Number of Word per		-0.065***							0.002
Claim from Application to Grant		0.006							(0.008)
% Change in Number of Claims			0.010						-0.001
from Application to Grant			(0.010)						(0.01)
Grant Rate				0.111***					0.091***
				(0.007)					(0.013)
Use of Section 101					-0.03***				-0.0128**
- Lack of utility or eligibility					(0.004)				(0.0049)
Use of Section 102(a) -						0.001			0.0099*
- Prior art exists						(0.006)			(0.0057)
Use of Section 103(a)							-0.054***		-0.023***
- Obvious invention							(0.005)		(0.006)
Use of Section 112(b)								-0.027***	0.0041
- Vague claims								(0.006)	(0.006)
Fixed Effects	Year by Art Unit								
N	988,249	848,162	848,527	988,432	988,249	988,249	988,249	988,249	848,162

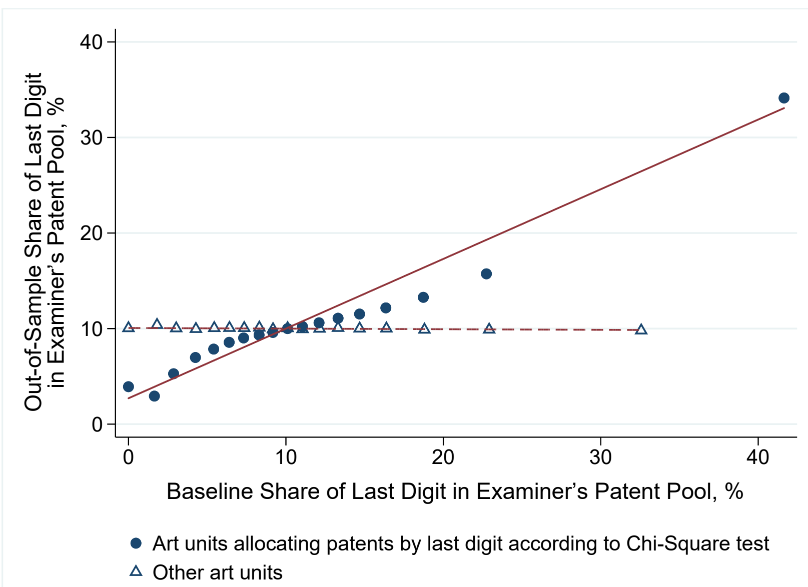
Notes: Regressors are standardized by their standard deviations and regression coefficients are expressed as a fraction of the mean of the outcome. The sample includes all technology categories. Standard errors are clustered by examiners. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: The Allocation of Patent Applications to Examiners by Application's Last Digit

Panel A: Distribution of p-values of Chi-square tests



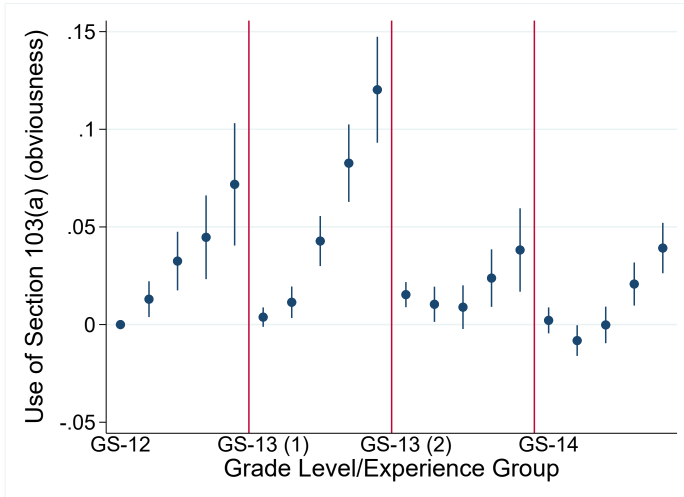
Panel B: Graphical Evidence on Allocation by Application's Last Digit



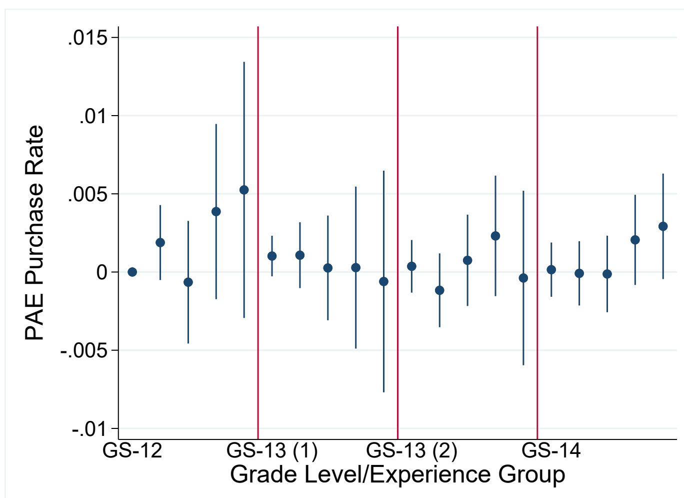
Notes: In Panel A, the level of observation is an art unit. This panel reports the distribution of the p-values of the Chi-square tests described in the main text; a p-value below 0.01 indicates excess concentration of patent applications across examiners by application's last digit. In Panel B, the level of observation is an examiner-by-application's last digit cell. Two binned scatter plots are reported with the corresponding best fit lines; each cell is weighed by the total number of applications processed by the examiner.

Figure A2: Examiner Career Effects

Panel A: Prosecution Behavior

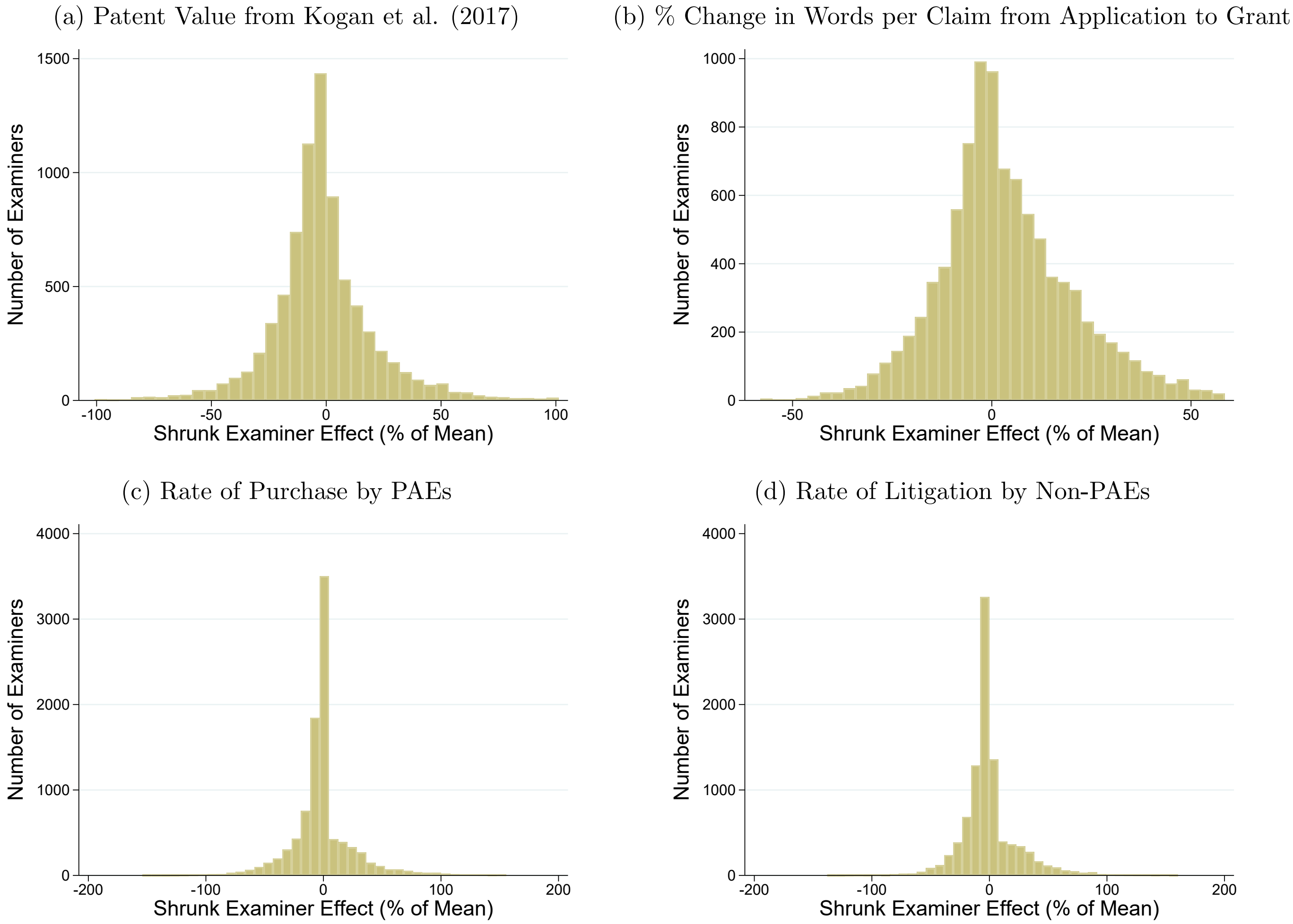


Panel B: Patent Acquisition by PAEs



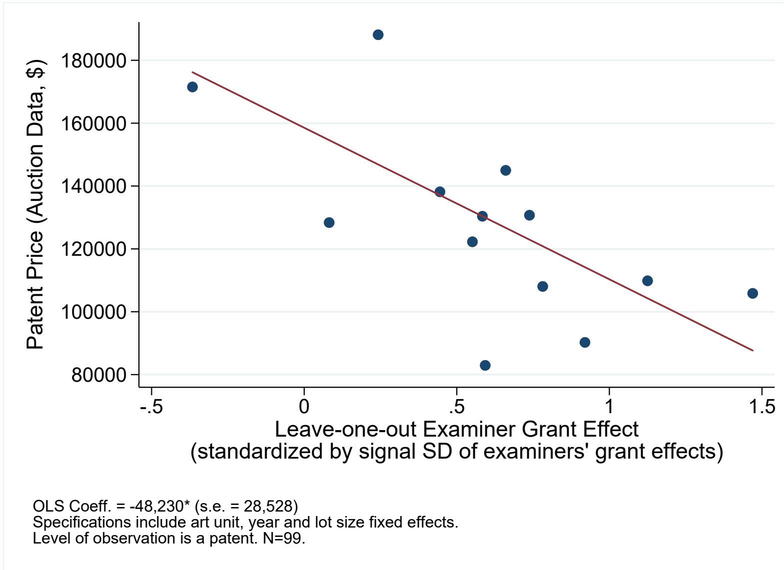
Notes: Following Frakes and Wasserman (2017), this figure examines the behavior of individual examiners over the course of various promotions (indicated by red bars on the figure) that carry with them reductions in examination time allocations. In each panel, we regress the outcome on a series of dummy variables reflecting examiners' experience within a grade level. For each grade level — GS-level 12, GS-level 13 without signatory authority, GS-level 13 with signatory authority, and GS-level 13 —, we track examiners for 1-2, 3-4, 5-6, 7-8, and over 9 years of experience. Specifications include examiner and year fixed effects, and standard errors are clustered by examiners. Panel A shows that after being promoted (and having less time for examination), examiners tend to make fewer demands on the applicant during the prosecution process, as evidenced by the reduction in the issuance of 103(a) blocking action (which is consistent with the findings on grant rates in Frakes and Wasserman (2017)). In contrast, Panel B reports that the rate of purchase by PAEs does not vary significantly around promotion events. This result indicates that examiner career effects have a second-order impact on PAE purchase, relative to the examiner fixed effects estimated in Section II.

Figure A3: Distributions of Shrunk Examiners Effects



Notes: This figure reports histograms of the shrunk examiner effects for four patent outcomes. The shrunk examiner effects are computed according to equation (4). In each panel, the shrunk examiner effects are expressed as a percentage of the mean of the outcome and the histogram is reported for shrunk effects that are within 2.5 signal standard deviations of the mean. This figure shows that there is substantial variation in shrunk examiner effects, i.e. the data delivers very different Bayesian posterior expectations across examiners. The distribution is more concentrated towards zero for rare outcomes like purchase by a PAE or litigation, because the shrinkage factors are higher for such outcomes.

Figure A4: Examiner Prosecution Behavior and Patent Prices



Notes: This figure reports the relationship between the (leave-one-out) examiner grant effect and the patent price in an auction. The examiner grant effects (on the x-axis) are computed as in Section II and are standardized by their signal standard deviation. The auction price (on the y-axis) is from Ocean Tomo data provided by Ryan Lampe and Carlos Serrano. Each dot on the figure represents 5% of the underlying data and the OLS best-fit line is reported. Since patents are sometimes auctioned as a group rather than individually, we include fixed effects for lot size. The specification also includes art unit and year fixed effects. The negative slope shows that more lenient examiners (with a higher grant rate) issue patents that sell for less in the patent market. A patent issued by an examiner with a grant rate one signal standard deviation above the mean is sold for $48,000 less on average.