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Patent quality, firm value, and investor underreaction: Evidence from patent examiner busyness[☆]

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limited and inconclusive empirical evidence on how patent quality affects firm value.[2]

Using patent citations to measure patent quality, Hall et al. (2005) find that an extra citation per patent is associated with a three-percent increase in firm value. This novel finding, however, illustrates two major challenges to establishing a causal effect of patent quality on firm value. First, patent citations, the widely used measure of patent quality, are forward-looking and therefore not suitable for identifying the causal effect of patent quality on firm value. Second and more importantly, given the large literature on the determinants of a firm's patent quality, the observed positive relation between patent quality and firm value can be driven by omitted variables or reverse causality.

Recent works set to examine the relation between patent quality and future stock returns. Specifically, investors may underreact to complex information such as patent quality (e.g., Hirshleifer et al., 2009). Therefore, if patent quality positively affects firm value, then investor underreaction could cause a positive relation between patent quality and future stock returns. Consistent with this hypothesis, Hirshleifer et al. (2018) show that firms whose patents have higher innovation originality earn higher future stock returns, and Fitzgerald et al. (2021) document that exploitative patents positively predict firms' stock returns. Unlike patent citations, the measures of innovation originality and exploitation are based on historical information and therefore alleviate the concern about reverse causality. It is, however, still difficult to address the omitted variable concern, because these patent quality measures could correlate with unobserved firm fundamentals that affect firm value.

In this paper, we attempt to study the causal effect of patent quality on firm value in a unique setting, namely, the busyness of patent examiners working in the United States Patent and Trademark Office (USPTO). Patent examiners review patent applications and make sure patents allowed fulfill three criteria: "(i) it has to be novel in a legally defined sense; (ii) nonobvious, in that a skilled practitioner of the technology would not have known and (iii) it must be useful, meaning that it has potential commercial value." (Hall et al., 2005). Therefore, patent examiners can have a substantial impact on patent quality.

We study the busyness of patent examiners for two reasons. First, patent examiners are faced with tight time constraints. For example, among hundreds of USPTO employee reviews on Glassdoor—a major website for anonymous employee reviews, the two most representative "cons" are "… your ability to succeed… is seated in your ability to meet production requirements" and "Lots of stress to meet production."[3] If examiner busyness negatively affects patent quality, then conditional on issuance, patents approved by busy examiners should have lower quality and value than those issued by nonbusy examiners. If investors underreact to this effect of examiner busyness, then we expect firms with patents issued by busy examiners to have lower future stock returns than firms with patents issued by nonbusy examiners. Second, as discussed in detail in Section 1, patent examiner busyness is unlikely related to firm fundamentals because patent examiner assignments are determined by the USPTO rather than the firms. Therefore, the setting of patent examiners helps us address the concern about omitted variables.

Our empirical analyses use a large data set from the USPTO that covers all U.S. patents issued from 1981 to 2010, including 3.74 million patents allowed by over 11,000 examiners. We measure examiner busyness for a patent as the total number of patents issued by the patent's examiner during the year of focal patent issuance. Intuitively, the more patents allowed by an examiner during a period, the busier she is.[4] We find that the busyness measure is quite dispersed among examiners. The 90th percentile of examiner busyness in a year is generally above 100, but the 10th percentile is around 40.

Since the busyness measure is based on the number of issued patents, one concern is that it might be confounded by examiner leniency, i.e., the approval rate of the examiner.[5] To address this concern, we use a proprietary data set on examiner office actions, LexisNexis PatentAdvisor®, to construct a de facto busyness measure for a large subsample of patents. The de facto busyness measure for a patent is the number of patent applications for which the examiner takes office actions in the issuance year of the focal patent. Note that this busyness measure includes both the number of patents issued in the year (our busyness measure) and the number of patent applications rejected by the examiner in the year. We find that our busyness measure has a high correlation of 0.74 with this de facto measure. Furthermore, our results hold in the robustness tests that explicitly control for examiner leniency.

Another concern is that our measure captures examiner busyness in the year of patent issuance, rather than in the whole review process for the patent application. Alternatively, one could measure examiner busyness using the number of patents issued by the examiner during the whole review process for the focal patent, i.e., from application date to issuance date. This approach, however, is problematic because, as we show in the paper, busier examiners tend to approve an application significantly more quickly. Therefore, busier examiners could have lower values for the busyness measure under this alternative construction because of their shorter review periods. We ac-

[2] See, for example, Chemmanur and Fulghieri (2014), Kerr and Nanda (2015), and He and Tian (2018, 2020) for reviews of this literature. The effect of patent quality on firm value is part of a broader and underexplored topic on the real effects and stock market consequences of innovation.

[3] Legal studies have conducted event studies and found that examiner busyness negatively impacts the quality of issued patents (e.g., Lemley, 2001; Lemley and Sampat, 2012). Section 1 provides a comprehensive review of anecdotal and academic evidence of examiner busyness and its impact on patent quality. This pattern is also consistent with the finance literature that distracted economic agents are less effective at work. For example, busier directors and busier institutional investors tend to monitor their firms less effectively (e.g., Core, Holthausen, and Larcker, 1999; Fich and Shivdasani, 2006; Falato, Kadyrzhanova, and Lel, 2014; Kempf, Manconi, and Spalt, 2017; Hauser, 2018; Masulis and Zhang, 2019).

[4] This approach is in a similar vein as the finance literature that measures the busyness of a director using the number of her board positions.

[5] Frakes and Wasserman (2017a) show that busier examiners tend to be more lenient. Therefore, leniency and busyness can be positively correlated.

knowledge that a dramatic change in examiner busyness during the patent review period could introduce noise to our busyness measure. This noise, however, would bias against us finding any significant results.

We start our analysis by investigating the effect of examiner busyness on patent quality. To measure patent quality, we follow previous literature (e.g., Hall et al., 2001; Acemoglu et al., 2015; Hirshleifer et al., 2018) and construct a number of citation-based measures, including the number of future citations, the number of non-self future citations, a superstar dummy indicating whether the patent is invented by a "superstar" innovator, a tail innovation dummy indicating whether the patent receives extremely high future citations, a patent originality score, and a patent generality score. We require our sample firms to have at least one patent issued during the year of measure construction. To avoid the results being driven by microcap stocks, we drop stocks with prices below $5 or market capitalization below the NYSE 20-percent breakpoint following Fama and French (2008). Our baseline sample covers 4,176 unique U.S. public firms and 699,475 patents.

Patent-level regressions, which control for firm-year fixed effects and allow us to focus on the within-firm patent quality variation, show that examiner busyness is negatively associated with patent quality across several dimensions. Specifically, patents allowed by busy examiners receive a smaller number of future citations, both in terms of total and non-self citations. They are less likely to be invented by a superstar innovator, who ranks in the top 5% according to the average number of citations per patent in each year. Consistent with fewer future citations, a patent allowed by busy examiners is less likely to be a tail innovation, which is a patent ranking in the top 1% of the distribution of future citations. These patents have both lower originality scores as they cite patents in a narrower range of technology fields, and lower generality scores as they are cited by subsequent patents that belong to a narrower range of technology fields.

Besides citation-based quality measures, we use patent litigation to capture patent quality as well. Our test is motivated by the literature that firms launch patent infringement lawsuits only when their patents have sufficiently high quality to justify the expensive and complicated patent litigation.[6] We obtain the patent lawsuit data from the LexisNexis' Lex Machina database and focus on lawsuits in which patent owner firms are plaintiffs. We find that examiner busyness is negatively associated with both the probability and the number of future lawsuits. We also examine a smaller sample of 189 patent trials filed with the Patent Trial and Appeal Board (PTAB) of the USPTO for which final decisions are available in Lex Machina. In these PTAB trials, the patents are being challenged by parties other than patent owners. Despite the very small sample size, we find that examiner busyness is significantly positively related to patent invalidation. These two tests together provide strong evidence that examiner busyness negatively affects patent quality.

While examiner busyness is unlikely to be related to firm fundamentals and hence mitigates the endogeneity issue, we conduct two additional identification tests to examine the causal link between examiner busyness and patent quality. Firstly, we exploit time-series variations in examiner workload. Controlling for examiner fixed effects, we find that a large increase in an examiner's workload leads to deterioration of patent quality, captured by both citation- and litigation-based measures of patent quality. Second, we construct a proxy for examiner distractions based on the reallocation of examiner attention within an examiner's pool of patents and examine its effect on patent quality. Inspired by Kempf et al. (2017), we rely on large drops in the stock prices of patenting firms as attention-grabbing events, which create plausibly exogenous distractions to the patents that are under review by the same examiner but do not experience large stock price drops. We find that patents with examiner distractions have lower quality than those with examiner attention, and this result is robust across both citation- and litigation-based measures.

Having established the causal [illegible]m-iner busyness on patent qualit[illegible] effect of examiner busyne[illegible] value. We[illegible] ine both patent-holding f[illegible]ating and stock per[illegible]mance, with a focus on t[illegible] which directly measu[illegible] the impact on firm valu[illegible]nstruct a firm-level mea[illegible]sure of examiner busyness by taking the average of paten[illegible] level busyness of all patents issued to the firm during th[illegible] year. A higher value of the busyness measure for a fir[illegible] year indicates that the patents of the firm-year on ave[illegible] are issued by busier examiners. We first show that[illegible] with busy examiners and those with nonbusy e[illegible] are well balanced and similar in prior firm f[illegible]ls and stock market performances. We then [illegible] rela-tion between examiner busyness and f[illegible]e operat-ing performance. We find that firm[illegible]tents issued by busy examiners tend to have [illegible]y lower future return on assets (ROA) and pro[illegible]margins than firms whose patents are issued by [illegible] examiners.

Next, we examine the r[illegible]etween examiner busy-ness and future stock [illegible]nce. Specifically, we ex-amine whether investo[illegible] sociated with corporat[illegible] Hirshleifer et al., 2018[illegible]

[6] Lanjouw and Schankerman (2001) find that patents involved in litigation tend to have higher quality. And Bereskin, Hsu, Latham, and Wang (2021) find that firms involved in patent lawsuits experience significantly positive stock returns in the following year.

tonically decrease in examiner busyne[illegible]w returns, Fama-French three-factor alphas, C[illegible]factor alphas, and six-factor alphas using the Fa[illegible]five-factor model (Fama and French, 2018) wit[illegible]um factor. For example, the six-factor alpha is 0.[illegible]nth (t-stat 4.50) for the bottom quintile of ex[illegible]y-ness but −0.28% (t-stat −2.27) for the top qu[illegible] a spread of 0.90% per month (t-stat 4.44). Inter[illegible]-like most stock market anomalies, the majority[illegible] turn spread comes from the long portfolio rath[illegible] short portfolio. Since we exclude microcap stock[illegible] sample, our finding is not subject to the commo[illegible] that anomalies tend to be driven by small stocks.[illegible]

Besides the univariate analyses, we estimate[illegible] MacBeth regressions of stock returns on examine[illegible] ness that control for firm characteristics including[illegible] book-to-market ratio, momentum, short-term reversa[illegible] set growth, profitability, and industry fixed effects. We[illegible] control for a firm's total number of patents issued in[illegible] year to capture its overall patenting activity. Consist[illegible] with the sorting analysis, we find that the coefficient [illegible] timate of examiner busyness is negative and significant [illegible] the 1% level. In a panel regression, we also control for th[illegible] art unit fixed effects and our results continue to hold.

To address the concern that patent examiner

1. Examination of patent application and examiner assignment

In this section, we describe the review process for patent application by the USPTO, as well as the evidence on examiner busyness.

1.1. The examination process of patent application

Once a patent application has been filed with the USPTO, it is sent to one of the art units, with the specific unit selected based on the patent's technology field. An art unit has on average 8 to 15 examiners, including a supervisory patent examiner (SPE). The SPE then assigns the application to an examiner in the unit. It takes an average of 0.7 years from the application date to the date of examiner assignment. After reviewing the application, the examiner makes the first office action (OA). While examiners allow a small number of patent applications in the first round, they issue an initial rejection for the majority. The applicants generally respond to initial rejections by amending their applications. In this case, the examiner reviews the amendment, responds with a second OA, and decides whether to allow the application, issue another rejection, or issue a final rejection. On average, a final decision is reached three years after the application date (e.g., Lemley and Sampat, 2012).

The applicant has the right to file an appeal in the case of a final rejection, and the appeal is b The Board of Patent Appeals and Interferences (BPAI). If the appeal is rejected, the inventor can choose to take her appeal to the United States Court of Appeals for the Federal Circuit or file a civil action with the United States District Court. The Court will the records and either reverse or uphold the BPAI's decision.[11]

A unique feature of examiner assignment is that examiners are r assigned within an art unit. Although there are no explicit regulations regarding examiner assignments, a number of studies provide evidence based on surveys and interviews that examiner assignment within an art unit is r (e.g., Lemley and Sampat, 2012; Farre-Mensa et al., 2020). Specifically, the assignment is based on an examiner's current workload, the last digit of the application number, or the "first-in, first-out" principle by which the application with the earliest filing date is assigned to the first available examiner. Note that with any of these approaches, the selection of an examiner is beyond the applicant's control and unrelated to the quality of the patent application or firm fundamentals.[12]

While the examination process of patent applications takes three years on average, examiners on average spend only about 18 hours on any given patent application over the entire process (Allison and Lemley, 2000; Lemley, 2001; Frakes and Wasserman, 2017a). The review process often includes searching for prior art, writing a rejection, responding to an amendment with a second OA, conducting an interview, and fulfilling various format requirements. Criticisms of the U.S. patent system have risen in recent years, especially regarding the issuance of allegedly invalid patents that fail to meet patentability requirements. Invalid patents impede competition, impose large societal costs, and precipitate various issues including patent trolling by non-practicing entities (Frakes and Wasserman, 2015).

1.2. Busyness of patent examiners

An abundance of evidence suggests that patent examiners face tight time constraints during patent examinations. For example, Fig. 1 presents the webpage of the USPTO at Glassdoor, a major website for anonymous employee reviews; the two major issues raised (i.e., "cons") both focus on the stress of meeting production requirements. Several legal studies also show that the time constraints faced by examiners negatively affect patent quality (e.g., Lemley, 2001; Lemley and Sampat, 2012). For example, Frakes and Wasserman (2017a) find that a reduction in review time causes less stringent scrutiny and hence lower patent quality.[13] Frakes and Wasserman (2017b) show that nearly half of the first substantive reports (first-round decisions) by patent examiners are completed immediately prior to deadlines, and these reports are associated with a higher probability of "short-gun" rejection.[14]

The time pressure on patent examiners can also be exacerbated by their performance valuation scheme. The performance of patent examiners is evaluated according to four criteria: *Production* (35%), measured as the number of office actions; *Quality* (35%), measured by the quality of the examiners' major activities defined in the Performance Appraisal Plan; *Docket management* (20%), measured as compliance with the timeliness goals; *Stakeholder interaction* (10%), measured as the quality of customer service. Therefore, 55% of an examiner's performance evaluation, namely, production and docket management, could create time pressure for the examiner, while only 35% is based on the quality of work. Moreover, the quantity of an examiner's work is easy to observe and measure but the quality is not.

2. Sample selection and summary statistics

2.1. Sample selection

We obtain the data on patent applications and patent examiners from the USPTO, which includes all patent applications.[15] Each patent application has patent ID, examiner ID, application date, and a four-digit art unit code. An

[11] After a final rejection, the applicant can still file a continuation application, which is a new application that normally includes parts of the original application. The new application should focus on the content that deserves to be further explored as stated in the patent rejection notice.

[12] Our conversations with patent lawyers also confirm that examiners are randomly assigned within an art unit.

[13] Their measure of patent quality is based on whether the inventors of U.S. patents are able to have the same inventions patented in Europe or Japan.

[14] "Short-gun" rejection refers to cases in which patent examiners reject applications for "*questionable reasons… because of time pressure of work at the* [*Agency*]" (Pressman and Stim 2015).

[15] The data set is at https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-examination-research-dataset-public-pair. We use the 2015 version of the data set.

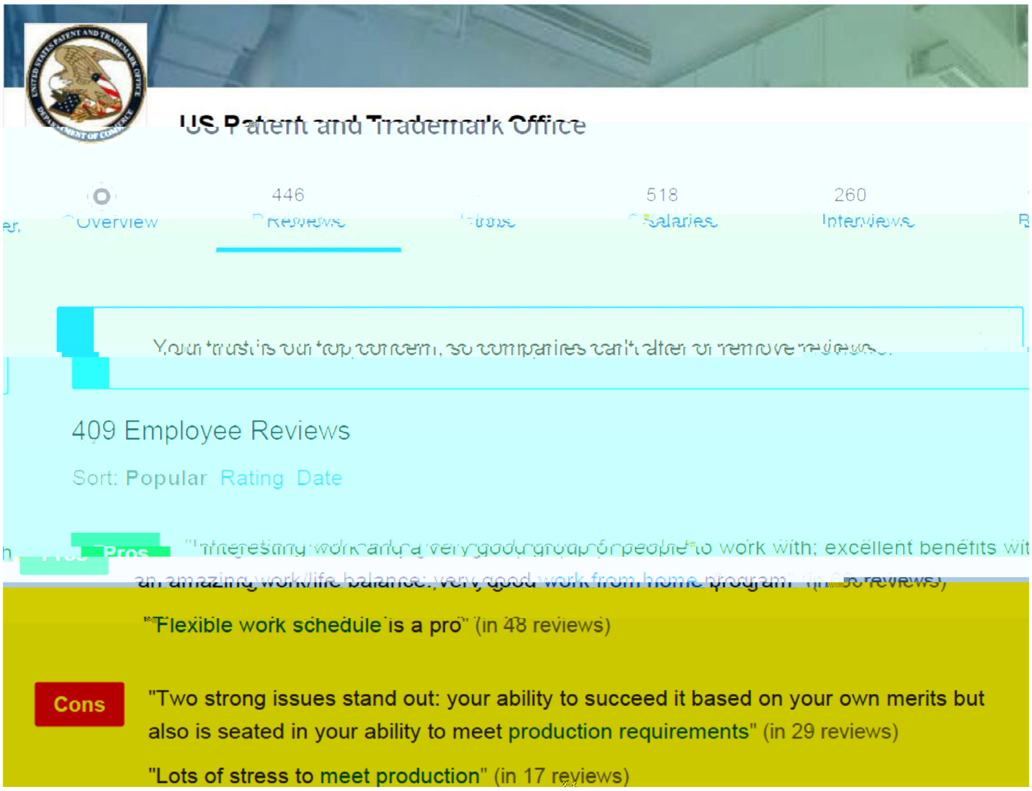

Fig. 1. Employee reviews by USPTO patent examiners at Glassdoor. This figure presents the webpage of employee reviews by patent examiners in the United States Patent and Trademark Office (USPTO) at Glassdoor, a major website for employees to anonymously review their companies. The page, which summarizes the most popular "Pros" and "Cons" from employee reviews, was downloaded on January 15, 2018.

approved patent application has information on the date of issuance. If an application does not have a date of issuance, then it is either under review or abandoned after rejection. Since this type of applications has no information on decisions, we do not know if they are still under review or have been abandoned after rejections (or if so when they are rejected or abandoned), and therefore we exclude them from our sample.

We use two samples of patents in our analysis. The first sample contains all issued patents from 1981 to 2010, including a total of 3,741,767 patents allowed by 11,215 unique examiners. We use it to construct the patent-level examiner busyness measure. The left panel of Table 1 presents the numbers of patents and examiners over time. The number of patents increases dramatically from 32,113 in 1981 to 245,153 in 2010. The number of unique examiners also increases by almost ten times, from 601 to 6,370.

The second sample is the patents

Table 1
Patents and examiner busyness over years. This table presents annual statistics for the number of patents, number of examiners, and patent- and firm-level busyness measures from 1981 to 2010. The left panel includes all patents issued by the USPTO, and the right panel includes patents for our sample public firms. We include only CRSP ordinary common shares, and drop penny stocks priced below $5 and microcap stocks (below NYSE 20 breakpoint). We require sample firms to have at least one patent issued in a given year to construct the firm-level busyness measure. The firm-level busyness measure for a firm-year is defined as the average of the patent-level examiner busyness measure for all patents issued to the firm in the year.

	All patents			Patents of sample firms		
Year	#Patents	#Examiners	Patent-Level Examiner Busyness	#Patents	#Firms	Firm-Level Examiner Busyness
1981	32,113	601	69.14	8,272	486	65.32
1982	39,599	632	88.62	9,916	517	75.75

1920

1962

1982

3 1 1 1972

1942

1962

,21(1)] TJ 0 Tc /F2 1 Tf 6.37619992 0 6.3761 19.171629 04.47368 Tm [( )] TJ 0.0138 Tc /F1 1 Tf 6.3761 0 0 6.3761 240117043 04.47368 Tm [(04..73)] TJ 0 Tc /F2 1 T

Panel A: Cuto

construct the adjusted number of non-self-citations by removing self-citations from the patenting firm. Second, we follow Acemoglu et al. (2015) and study whether a patent is invented by a "superstar innovator" or is a tail innovation. Specifically, a superstar innovator is defined as an inventor who ranks in the top 5% according to the average number of future citations of all the

Table 2

Summary statistics and correlations. Panel A reports the summary statistics for patent-level characteristics. *Busyness_Patent* is patent-level examiner busyness measured as the number of patents issued by the patent's examiner in the same year. *Citation* is the number of citations received by the patent, adjusted for truncation following Hall et al. (2001). *Non_Self_Citation* is the number of citations excluding self-citations received by the patent, adjusted for truncation following Hall et al. (2001). *Superstar* is a dummy variable that equals one if the patent has a superstar innovator, and zero otherwise. A superstar innovator is an inventor that ranks in the top 5% according to the average number of citations of all patents in which the inventor takes part in a given year. *Tail_Innovation* is a dummy variable that equals one if the number of citations received by the patent is above 99% of those received by patents granted in the same year, and zero otherwise. *Originality* is measured as number of unique technological classes (both primary and secondary classes) assigned to the patents cited by the focal patent, divided by 100. *Generality* is measured as the number of unique technological classes (both primary and secondary classes) assigned to the patents that cite the focal patent, divided by 100. Panel B reports summary statistics for firm-months in our sample from 1981 to 2010. We first calculate these statistics in each cross-section, and then report their time-series averages. *Busyness* is the firm-level measure of examiner busyness, calculated as the average of the patent-level examiner busyness measure of all patents issued to a firm in a year. We match *busyness* constructed in year *t-1* to the months from July of year *t* to June of year *t + 1*. *Stock return* the is monthly stock return for a firm-month. Ln*(ME)* is the natural log of a firm's market capitalization, measured at the end of the previous month. Ln*(BM)* is the natural log of the book-to-market ratio. *CRSP ME Percentile* and *CRSP BM Percentile* are the average percentile ranks of sample firms' market capitalization and book-to-market ratio in the CRSP universe, respectively. *Ret[−13, −2]* is buy-and-hold stock from month *t-13* to month *t-2*. *Asset Growth* is the change in total book assets scaled by lagged total book assets. *Gross margin* is defined as sales minus cost of goods sold, scaled by sales. *ROE* is return on equity, and *ROA* is return on assets. *R&D* is research and development expenses scaled by total assets. *Capex* is capital expenditure scaled by total assets. The accounting measures of the fiscal year ending in calendar year *t* is matched to the months from July of *t* to June of *t + 1*. The constructions of all the measures are described in Appendix A. Panel C reports time-series averages of cross-section Spearman correlations among firm characteristics.

Panel A: Summary statistics of patent characteristics

	Mean	STD	P10	P25	Median	P75	P90
Busyness_Patent	68.61	34.22	26.00	44.00	66.00	90.00	114.00
Citation	20.81	38.93	1.00	3.32	9.30	22.43	48.93
Non_Self_Citation	17.68	35.48	0.00	2.30	7.29	18.70	41.90
Superstar	0.04	0.20	0.00	0.00	0.00	0.00	0.00
Tail_Innovation	0.01	0.10	0.00	0.00	0.00	0.00	0.00
Originality	0.44	0.46	0.08	0.16	0.29	0.53	0.93
Generality	0.40	0.26	0.00	0.17	0.46	0.63	0.72

Panel B: Summary statistics of firm characteristics

	Mean	STD	P10	P25	Median	P75	P90
Busyness	70.29	20.86	43.35	57.82	70.91	82.38	95.15
Stock Return	0.02	0.10	−0.10	−0.04	0.01	0.07	0.14
ln(ME)	7.37	1.48	5.63	6.17	7.14	8.33	9.47
CRSP ME Percentile	0.86	0.10	0.70	0.77	0.88	0.95	0.98
ln(BM)	−0.85	0.67	−1.74	−1.27	−0.79	−0.38	−0.05
CRSP BM Percentile	0.37	0.22	0.10	0.19	0.34	0.52	0.70
Ret [−13, −2]	0.22	0.45	−0.22	−0.06	0.13	0.38	0.73
Asset Growth (%)	1.19	0.42	0.93	1.00	1.08	1.21	1.48
Gross Margin	0.33	0.56	0.16	0.26	0.38	0.54	0.69
ROE (Qtr.)	0.03	0.08	−0.02	0.01	0.03	0.05	0.08
ROA	0.14	0.11	0.03	0.10	0.15	0.20	0.25
R&D	0.07	0.07	0.01	0.02	0.04	0.09	0.16
Capex	0.06	0.04	0.02	0.03	0.05	0.08	0.11

Panel C: Correlations of firm characteristics

	Busyness	ln(ME)	ln(BM)	Ret [−13, −2]	Asset Growth	ROE	ROA	Gross Margin	R&D
ln(ME)	0.00								
ln(BM)	0.13	−0.14							
Ret [−13, −2]	−0.03	−0.08	−0.01						
Asset Growth	−0.06	−0.05	−0.22	−0.03					
ROE	−0.01	0.11	−0.17	−0.01	0.02				
ROA	0.04	0.19	−0.21	0.14	0.00	0.24			
Gross Margin	0.09	0.25	−0.19	−0.05	−0.03	0.49	0.42		
R&D	−0.22	−0.18	−0.35	0.09	0.10	−0.05	−0.16	−0.37	
Capex	0.03	0.08	−0.08	−0.04	0.05	0.08	0.02	0.20	0.05

granted by busy examiners are less likely to be tail innovations, indicating that they are less likely to attract extremely high future citations. Turning to patent originality and generality scores, Columns (5) and (6) present evidence that patents granted by busy examiners have significantly lower originality and generality scores.

Besides citation-based quality measures, patent quality could be captured by future patent litigation as well. Patent infringement lawsuits are both very complicated and expensive. For example, according to the American Intellectual Property Law Association, the average cost to litigate a patent infringement is $2.8 million. Therefore,

Table 3

The effects of examiner busyness on patent quality. The table presents patent-level regressions of patent quality measures on examiner busyness. Panel A reports the patent-level regressions of citation-based patent quality measures on examiner busyness. ln*(1+Citation)* is the natural logarithm of one plus citations received (adjusted for truncation, following Hall et al., 2001). ln*(1+Non_Self_Citation)* is the natural logarithm of one plus citations excluding self-citation (adjusted for truncation, following Hall et al., 2001). *Superstar* is a dummy variable which equals one if the patent has a superstar innovator, and zero otherwise. A superstar innovator is an inventor that ranks in the top 5% according to the average number of citations of all patents in which the inventor takes part in a given year. *Tail_Innovation* is a dummy variable that equals one if the number of citations received by the patent is above 99% of the number of citations received by patents granted in the same year, and zero otherwise. *Originality* is measured as the number of unique technological classes (both primary and secondary classes) assigned to the patents cited by the focal patent, divided by 100. *Generality* is measured as the number of unique technological classes (both primary and secondary classes) assigned to the patents that cite the focal patent, divided by 100. The main independent variable is *Busyness_Patent*, the patent-level examiner busyness measure, defined as the number of patents granted by the examiner in the same year as the focal patent. To exclude outliers and facilitate the evaluation of economic significance, we take the natural logarithm of the busyness measure. Panel B reports the patent-level regressions of future patent litigation on examiner busyness. *Litigation Dummy* is equal to one if a patent experiences patent litigation in the future, and zero otherwise. *#Cases* is the number of future lawsuits associated with a patent. The lawsuits include litigation and trial cases filed in federal district courts, and we require the patenting firms to be the plaintiffs. The constructions of all the measures are described in Appendix A. All models include firm-year fixed effects. *T*-statistics adjusted for heteroscedasticity and within firm-year clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Regressions of citation-based measures of patent quality on examiner busyness

	ln(1+ Citation)	ln(1+Non_Self_Citation)	Superstar	Tail Innovation	Originality	Generality
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Busyness_Patent)	−0.066***	−0.088***	−0.006***	−0.001***	−0.019***	−0.041***
	(−11.86)	(−16.44)	(−8.88)	(−4.22)	(−12.32)	(−19.57)
Firm-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.247	0.270	0.133	0.087	0.246	0.218
# Obs	690,323	690,323	692,572	690,323	650,906	623,459

Panel B: Regressions of patent litigation on examiner busyness

	Litigation Dummy	ln(1+#Cases)
	(1)	(2)
ln(Busyness_Patent)	−0.0004**	−0.0001
	(−2.16)	(−1.19)
Firm-year fixed effects	Yes	Yes
Adj. R^2	0.062	0.097
# Obs	695,539	692,248

a firm's decision to go to court to protect its patent is a positive signal of patent quality because the benefits of the lawsuit must overweigh the costs. Consistent with this intuition, Lanjouw and Schankerman (2001) find that patents involved in litigation have more citations and greater technological importance than their peers. Bereskin et al. (2021) document that firms with patent lawsuits experience abnormally positive future returns. Therefore, we expect that firms are less likely to file patent infringement lawsuits for their patents that are approved by busy examiners, if these patents tend to have lower patent quality and value.

We obtain patent lawsuits filed with the United States district courts from LexisNexis' Lex Machina database from 2000 to 2019. The database is regarded as the most comprehensive database of U.S. patent litigation and has been used by academic researchers (e.g., Akcigit et al., 2016; Allison et al., 2015, 2017; Cohen et al., 2016, 2019; Bereskin et al., 2021). We restrict the lawsuits to those with patent owners (innovating firms) as plaintiffs because they have an unambiguously positive implication for patent quality.

We estimate patent-level regressions of future patent litigation t l w o

d that equals one if the patent experiences litigation the zero otherwise. the

of future lawsuits involving the patent. The key of

We further examine the relation between examiner busyness and the probability of patent invalidation. The Lex Machina database includes an independent sample of patent trials filed in the Patent Trial and Appeal Board (PTAB) of the USPTO. In these trials, a petitioner challenges the validity of the claims in an issued patent. Unlike the lawsuits in our previous analysis that are filed in the courts, these trials are filed with the PTAB. The patent owner, as defendant, may respond to the petition, and the PTAB then determines whether or not to institute a trial. If the PTAB decides to institute a trial, then the petitioner and the patent owner gather evidence and conduct additional briefings to the PTAB. At the conclusion of the trial, the PTAB issues a final written decision that determines

Table 5

Examiner busyness and patent quality: Evidence from large increases of examiner workload. This table presents patent-level regressions of patent quality measures on large increases in examiner workload. The main independent variable, *Shock_Busyness*, is a dummy variable that equals one if the change in an examiner's busyness in year *t* is positive and in the top quartile of her tenure, and zero otherwise. The left panel presents regressions of citation-based patent quality measures. ln*(1+Citation)* is the natural logarithm of one plus citations received (adjusted for truncation, following Hall et al., 2001). ln*(1+Non_Self_Citation)* is the natural logarithm of one plus citations excluding self-citations (adjusted for truncation following Hall et al., 2001). *Superstar* is a dummy variable which equals one if the patent has a superstar innovator, and zero otherwise. A superstar innovator is an inventor that ranks top 5% according to the average number of citations of all patents in which the inventor takes part in a given year. *Tail_Innovation* is a dummy variable which equals one if the number of citations received by the patent is above 99% of the number of citations received by patents granted in the same year, and zero otherwise. *Originality* is measured as the number of unique technological classes (both primary and secondary classes) assigned to the patents cited by the focal patent, divided by 100. *Generality* is measured as the number of unique technological classes (both primary and secondary classes) assigned to the patents that cite the focal patent, divided by 100. The right panel presents patent-level regressions of patent litigation measures. *Litigation Dummy* is equal to one if a patent experiences patent litigation in the future, and zero otherwise. *#Cases* is the number of future lawsuits associated with a patent issued in year *t*. The lawsuits include litigation and trial cases filed in federal district courts, and we require the patenting firms to be the plaintiffs. We also control for firm characteristics. *Size* is the natural logarithm of total assets. *M/B* is defined as market value of equity divided by book value of equity. *R&D* is research and development expenditures scaled by total assets. *Capex* is capital expenditure scaled by total assets. The constructions of all the measures are described in Appendix A. All models include examiner and year fixed effects. *T*-statistics adjusted for heteroscedasticity and within firm-year clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Citation−based patent quality measures						Patent litigation	
	ln(1+Citation) (1)	ln(1+Non_Self_Citation) (2)	Superstar (3)	Tail Innovation (4)	Originality (5)	Generality (6)	Litigation Dummy (7)	ln(1+#Cases) (8)
Shock_Busyness	−0.008**	−0.012***	−0.000	−0.001**	−0.008***	−0.003*	−0.0003*	−0.0003*
	(−1.98)	(−3.01)	(−0.38)	(−2.19)	(−4.06)	(−1.87)	(−1.66)	(−1.74)
Size	−0.032***	−0.028***	−0.004***	−0.002***	−0.025***	−0.007***	−0.0018***	−0.0016***
	(−10.71)	(−9.49)	(−9.46)	(−9.37)	(−14.53)	(−5.65)	(−18.64)	(−16.25)
M/B	0.084***	0.058***	0.013***	0.005***	0.014***	0.032***	0.0016***	0.0016***
	(16.33)	(9.64)	(11.64)	(12.53)	(5.04)	(12.50)	(8.31)	(7.80)
R&D	−0.004	0.572***	−0.058***	−0.031***	−0.602***	0.141***	−0.0263***	−0.0225***
	(−0.04)	(3.87)	(−3.19)	(−5.25)	(−7.01)	(2.89)	(−7.11)	(−5.83)
Capex	−0.039	−0.442**	−0.012	0.025***	0.576***	0.088	−0.0002	0.0017
	(−0.28)	(−2.13)	(−0.48)	(3.26)	(3.14)	(1.51)	(−0.07)	(0.51)
ROA	−0.294***	−0.161*	−0.051***	−0.027***	−0.116*	−0.110***	−0.0065***	−0.0089***
	(−4.20)	(−1.79)	(−4.73)	(−6.60)	(−1.90)	(−3.93)	(−2.95)	(−3.73)
Examiner fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.264	0.295	0.094	0.045	0.203	0.230	0.020	0.027
# Obs	626,445	626,445	628,394	626,445	591,204	564,756	631,141	631,141

One empirical challenge for such quasi-natural experiment is that we cannot identify the exact time when an examiner is working on a particular patent. We therefore assume that, in the year before the issuance of the patents, the examiner devotes attention to the pool of patents. Hence, we identify attention-grabbing events in the year before the issuance. Specifically, we define an attention-grabbing event if a patent's applicant firm experiences a monthly stock return below −50% (i.e., the price drops by more than 50%) in any month of the year before patent issuance, and the patent as the attention-grabbing patent.[25]

Since our test exploits the attention shifting within an examiner's review pool caused by attention-grabbing events, we focus on examiner-year pools of patents that contain attention-grabbing patents (i.e., at least one applicant firm in the pool has large price drops). For each patent, we assign an *Examiner_Distraction* dummy, which equals one for those that are not attention grabbing patents (i.e., attention diverted to other patents), and zero for those that are attention-grabbing patents (i.e., attention attracted from other patents). If the effort of examiners matters for the review process and affects the quality of patents under review, we would expect the quality of patents with examiner distractions to be lower than patents with examiner attention. We then estimate patent-level regressions of patent quality measures on the *Examiner_Distraction* dummy that include firm-level controls, examiner fixed effects, and year fixed effects, and report the results in Table 6.

We find that, consistent with the negative effect of examiner busyness on patent quality, examiner distractions predict patent Columns (1) to (6) present the 5
regressions o citation-based patent quality measures, in which the coefficient estimates of the *Examiner_Distraction* dummy are negative and significant in all columns except for the specification in which *Tail_Innovation* is the dependent variable. Columns (7) and (8) present the regression results with litigation-based patent quality measures as the dependent variable. The coefficient estimates of the *Examiner_Distraction* dummy are significantly negative in both columns, which also suggest, that examiner distractions lead to

[25] The results are qualitatively similar if we instead use large price drops at daily or weekly frequency or use relative return performance to define the shock (e.g., monthly stock return in the bottom 1% of the stock universe).

Table 6

Examiner busyness and patent quality: Evidence from examiner distraction. This table presents patent-level regressions of patent quality measures on examiner distraction. The intuition is that, given the limited attention of an examiner, extreme price drops of other applicant firms in the examiner's review pool will divert attention to those firms and in turn cause distraction for the focal firm (Kempf et al., 2017). For a patent issued in year t, we first take all patents granted by the same examiner in year t where the applicants are public firms. We then define attention-grabbing patents as the thonse whose applicant firms in any month of year t-1 experienced a monthly stock return below −50%. *Examiner_Distraction* is a dummy variable that equals one for if the patent is not attention-grabbing but the examiner's portfolio contains attention-grabbing patents, and zero otherwise. We remove the examiner-year portfolios with no attention-grabbing patents (i.e., none of the applicant firms in the pool experience large price drops). ln(*1+Citation)* is the natural logarithm of one plus citations received (adjusted for truncation, following Hall et al., 2001). ln*(1+Non_Self_Citation)* is the natural logarithm of one plus citations, excluding self-citations (adjusted for

f

Table 7
Regressions of backward citations on examiner busyness. This table presents patent-level regressions of the number of backward citations on examiner busyness. *Back_cite* for a firm in year *t* is the number of U.S. patents cited by the patents issued in year *t*. The independent variable in Column (1) is *Busyness_Patent*, the patent-level examiner busyness measure of year *t*. To exclude outliers and facilitate the evaluation of economic significance and, we take the natural logarithm of the patent-level busyness measure and the backward citation measures. In Column (2), *Shock_Busyness* is a dummy variable that equals one for patents with examiners that experience a large increase in workload, and zero otherwise. In Column (3), *Examiner_Distraction* equals one for patents with examiners' attention distracted by other patents in the same review pool, and zero otherwise. The constructions of *Shock_Busyness* and *Examiner_Distraction* are described in the headers of Tables 5 and 6, respectively. *Size* is the natural logarithm of total assets. *M/B* is defined as the market value of equity divided by book value of equity. *R&D* is research and development expenditures scaled by total assets. *Capex* is capital expenditure scaled by total assets. *ROA* is return on asset. *T*-statistics adjusted for heteroscedasticity and within firm-year clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ln(Back_Cite)		
	(1)	(2)	(3)
ln(Busyness_Patent)	−0.032***		
	(−11.09)		
Shock_Busyness		−0.013***	
		(−3.91)	
Examiner_Distraction			−0.181***
			(−2.78)
Size		−0.055***	−0.078***
		(−16.75)	(−9.46)
M/B		0.024***	0.043***
		(4.83)	(4.29)
R&D		−1.908***	−2.439***
		(−12.93)	(−7.41)
Capex		0.864***	1.586***
		(3.09)	(2.70)
ROA		−0.322***	−0.752***
		(−3.15)	(−3.80)
Firm-year fixed effects	Yes	No	No
Examiner fixed effects	No	Yes	Yes
Year fixed effects	No	Yes	Yes
Adj. R^2	0.241	0.221	0.229
# Obs	679,124	616,116	28,034

unit are indeed random. We first calculated the firm-level measure of examiner busyness as the average of patent-level examiner busyness of the firm's patents in the year. Next, we identify the major art unit of a firm-year observation as the one that allows the most of the firm's patents in the year. Within each year and each art unit, we then classify firms into two groups according to firm-level examiner busyness and compare prior fundamental firm characteristics including size, market-to-book, R&D expenses, capital expenditure, ROA, gross margin, year-end monthly return, and annual stock return across the two groups of firms. Table 8

tw9(eeation)]] TJ 0 Tc /F2 1 Tf 6.3761 0 0 6.37 1 15166.416.3131578 Tm [( )] TJ 0.0005 Tc /F1 1 Tf 6.3761 0 0 6.342t

Table 9

Panel regressions of firm performance on examiner busyness. This table presents firm-level panel regressions of firm performance measures on examiner busyness. The dependent variables in models (1) and (2) are a firm's *ROA* of years *t + 1* and *t + 2*, respectively, where ROA is defined as income before extraordinary items scaled by total assets. The dependent variables in models (3) and (4) are a firm's gross profit margin (*GM*) of years *t + 1* and *t + 2*, respectively, where gross profit margin is defined as sales minus cost of goods sold, scaled by total sales. The main independent variable is *Busyness*, which is the firm-level examiner busyness measure of year *t*. To exclude outliers and facilitate the evaluation of economic significance, we take the natural logarithm of the firm-level busyness measure. *Size* is the natural logarithm of total assets. *M/B* is defined as the market value of equity divided by book value of equity. *R&D* is research and development expenditures scaled by total assets. *Capex* is capital expenditure scaled by total assets. We also control for ln*(#Patents)* in the same year as the busyness measure, where *#Patents* for a firm-year is the number of the patents issued to the firm in the year. All models include firm fixed effects and year fixed effects. We further include art unit fixed effects, where the art unit fixed effect for a firm in year *t* is based on the most common art unit of the firms' patents issued in year *t*. *T*-statistics adjusted for heteroscedasticity and within-firm clustering are reported in parentheses. *, **, and *** denote the statistical significance at 10%, 5%, and 1% level, respectively.

	ROA_{t+1} (%)	ROA_{t+2} (%)	GM_{t+1}(%)	GM_{t+2}(%)
	(1)	(2)	(3)	(4)
ln(Busyness)	−0.271	−0.703**	−3.979**	−4.227**
	(−0.89)	(−2.28)	(−2.00)	(−2.25)
Size	−0.659**	−1.529***	2.683*	2.920*
	(−2.15)	(−4.84)	(1.75)	(1.87)
M/B	1.550***	0.571***	2.956***	2.002**
	(13.36)	(4.76)	(4.00)	(2.50)
R&D	−25.845***	−9.281**	−69.697**	−68.583*
	(−5.95)	(−2.13)	(−2.21)	(−1.91)
Capex	3.604	3.222	32.928	29.815
	(1.12)	(0.97)	(1.44)	(1.15)
ln(#Patents)	−0.276**	−0.127	1.061	0.229
	(−2.10)	(−1.01)	(1.59)	(0.37)
Firm fixed effects	Yes	Yes	Yes	Yes
Art unit fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.731	0.721	0.696	0.691
# Obs	16,339	15,738	16,356	15,767

tively related to future outcomes associated with patent quality, specifically we examine the future operating performance of the innovating firms. We estimate firm-level panel regressions of the outcomes on examiner busyness in Table 9. The independent variable is the firm-level examiner busyness measure of year *t*. The dependent variables in Columns (1) and (2) are ROAs of years *t + 1* and *t + 2*, respectively, where ROA is defined as income before extraordinary items divided by total assets. The dependent variables in Columns (3) and (4) are gross profit margins of years *t + 1* and *t + 2*, respectively, where gross profit margin is defined as sales minus the cost of goods sold divided by total sales. We control for firm characteristics including firm size, the market-to-book ratio, R&D, and capital expendiJ -0.006859 Tm [((0.97))36.242 Tm [(and)] TJ 0 Tc846.2420 6.3761 71.0711 167.6251 Tm [( )] TJ /F6 1 Tf 7.9701 0 0.3761

Measurement

Jan. year *t-1* Dec. year *t-1* Jul. year *t* Jun. year *t+1* however, examines how, conditional on patent issuance, examiner leniency affects patent owner company's stock market performance. If examiner leniency negatively affects patent quality, then examiner leniency can potentially have a negative relation with future stock returns.

We follow Farre-Mensa et al. (2020) and construct a patent-level examiner leniency measure as the total number of patents issued by the examiner up to the end of the

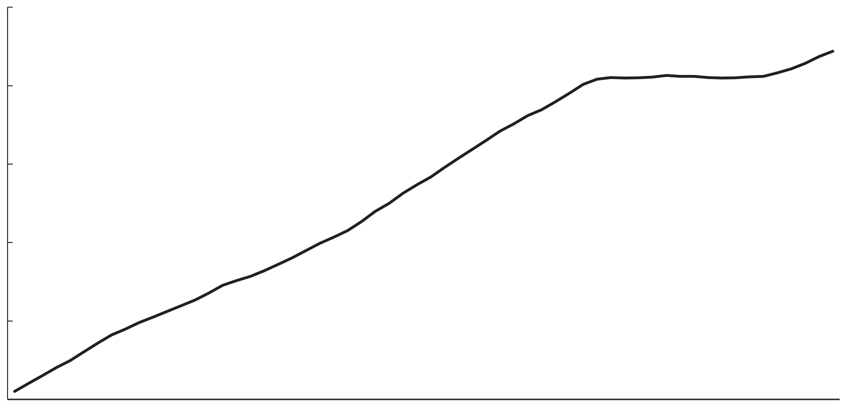

Table 11
Examiner busyness and examiner characteristics. Panel A presents patent-level regressions of examiner busyness on examiner characteristics. The dependent variable is *Busyness_Patent*, the patent-level examiner busyness measure. *Experience* for a patent is measured as the number of years from the first patent issued by the focal patent's examiner to the issuance of the focal patent. *Age* is proxied by the difference between patent issue year and the year of college entrance of an examiner plus 18. *Residual_Age* is the residual examiner age measure with respect to the examiner experience measure, which is constructed as the residual from the annual cross-sectional regression of the examiner-level age measure on the examiner-level experience measure. *Education* is a dummy variable that equals one if the highest degree an examiner obtains is a masters or above, and zero otherwise. *Generalist* is a dummy variable that equals one if the major of an examiner is not engineering or science, and zero otherwise. *HHI_TechClass* is the concentration (Herfindahl-Hirschman index) across technology class for patents allowed by an examiner in year *t-1. HHI_Industry* is the concentration (Herfindahl-Hirschman index) across two-digit SIC industry for patents allowed by an examiner in year *t-1. HHI_Location* is the concentration (Herfindahl-Hirschman index) across headquarter states of application firms for patents allowed by an examiner in year *t-1*. All models include firm-year fixed effects. *T*-statistics adjusted for heteroscedasticity and within firm-year clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Panel B presents the spreads of value-weighted six-factor alphas of portfolios simultaneously sorted on firm-level *examiner characteristics* and firm-level *examiner busyness* measure. Firm-level *examiner characteristics* are calculated as the average of corresponding patent-level examiner characteristics of all patents issued to the firm in the year. Technology complexity is equal to one for a patent in a technology class with above median review duration, where review duration for a patent is defined as the number of days for the patent application to be allowed by the examiner. Firm-level technology complexity is the average of patent-level technology complexity. At the beginning of each month from July of year *t* to June of year *t + 1*, stocks are sorted into two groups of firm-level experience measures and quintiles of busyness measures of the year *t-1*. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively. .

Panel A: Examiner characteristics and busyness

	Ln (Busyness_Patent)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Experience	0.039***						
	(55.54)						
Residual_Age		0.002					
		(1.23)					
Education			−0.028***				
			(−3.31)				
Generalist				−0.099***			
				(−10.19)			
HHI_TechClass					−1.472***		
					(−62.82)		
HHI_Industry						−0.591***	
						(−30.89)	
HHI_Location							−1.018***
							(−60.72)
Firm-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.*R2*	0.272	0.235	0.217	0.230	0.297	0.227	0.269
# Obs	695,539	44,645	69,528	62,132	670,783	656,055	656,055

Panel B: Return spread of examiner busyness across examiner characteristics

	Experience	Residual Age	Education	Generalist	HHI_TechClass	HHI_Industry	HHI_Location	TechComplexity
Low	−0.87***	−0.95***	−0.78**	−0.84***	−0.20	−0.55**	−0.50**	−0.57**
	(−3.94)	(−2.96)	(−2.35)	(−3.10)	(−0.64)	(−2.12)	(−2.31)	(−2.49)
High	0.33	−1.74***	−1.04***	−1.03***	−1.42***	−1.14***	−1.16***	−1.06***
	(0.74)	(−4.93)	(−3.38)	(−3.01)	(−5.42)	(−5.05)	(−4.82)	(−3.94)
H_L	1.19**	−0.79**	−0.26	−0.18	−1.22***	−0.59**	−0.66***	−0.49*
	(2.35)	(−2.10)	(−0.61)	(−0.47)	(−3.18)	(−2.22)	(−2.79)	(−1.73)

of busyness and further explore how these examiner characteristics interact with the busyness effect.

We first construct a measure of examiner experience as the number of years since the examiner's first patent review to the year before the focal patent issuance.[33] Frakes and Wasserman (2017a) document that more experienced patent examiners tend to be assigned more applications, and hence we expect examiner experience to be positively related to examiner busyness. We collect examiners' age and educational background by manually collecting examiner information from LinkedIn, including an examiner's year of entering college, levels of academic degrees, and areas of study. We are able to identify 2006 unique examiners in our sample who have a LinkedIn page. We define *Age* as the difference between patent issuance year and the year that an examiner enters college plus 18. As *Age* is positively correlated with experience, we define *Residual_Age* with respect to the examiner experience measure, which is constructed as the residual from annual cross-sectional regressions of the examiner-level age measure on the examiner-level experience measure. *Education* is a dummy variable that equals one if the examiner's highest degree is a masters and above, and zero otherwise. Using the information about an examiner's major of study, we define a generalist dummy that equals one for examiners with major that is not in engineering or science, and zero otherwise.[34]

[33] If the patent is the first one issued by the examiner, then the experience measure is set to zero. We use the patent data from 1926 for the construction of this measure.

[34] The current qualification requirement for becoming a patent examiner is "Minimum of a bachelor's degree in engineering or science." (see https://www.uspto.gov/jobs/become-patent-examiner).

We also study the concentration level of an examiner's review pool, which might have implications for examiner busyness. Specifically, we construct three concentration measures of patent pool granted by examiners in each year as the Herfindahl-Hirschman index (HHI) of an examiner's patent pool according to technology class (finest to the subclass), industry (two-digit SIC), and physical location (headquarters state).

We first conduct patent-level regressions of examiner busyness on examiner characteristics and report the results in Panel A of Table 11. Columns (1) to (4) present the relation between examiners' personal characteristics and their busyness. We find that experienced examiners tend to be busier. Older examiners are not significantly different from younger examiners in busyness after controlling for experience. Examiners with a masters degree or above and generalist examiners are less busy. Columns (5) to (7) demonstrate that examiners with more concentrated patent pools in terms of technology class, industry, and geography are less busy.

Finally, we investigate whether examiner characteristics could mitigate or exacerbate the negative effect of examiner busyness on stock returns. We construct firm-level examiner characteristics as the average patent-level examiner characteristics of all the patents issued to the firm in the year. We then independently sort firms into two-by-five portfolios based on examiner characteristic and examiner busyness, and calculate value-weighted six-factor alphas of the portfolios. We then report the return spread of examiner busyness (bottom minus top busyness quintile) for the two subgroups of examiner characteristics.

Panel B of Table 11 presents the results. In the first column, we divide firms into two groups according to whether the firm-level examiner experience is higher than ten years or not. If experience can help examiners conduct reviews more effectively and efficiently and therefore better deal with their time constraints, we expect the negative effect of examiner busyness on stock returns to be more pronounced for less experienced examiners. Consistent with this prediction, we find that the alpha spread of examiner busyness is negative and significant only among firms with less experienced examiners. Next, we examine the effect of examiners' age. We classify firms into two subgroups according to the residual age measure, and Column (2) shows that firms with older examiners are more affected by the negative effect of busyness on stock returns, possibly because older examiners have less energy to deal with attention and time constraints. Columns (3) and (4) show that examiners' education levels and specializations do not materially alter the negative effect of examiner busyness on stock returns.

Columns (5) to (7) examine how the concentration of examiners' patent pools alters the main results. We observe that the effect of busyness is stronger among firms with examiners whose patent pools are more concentrated. In untabulated results, we find that the portfolio of concentrated examiners outperforms that of diversified examiners among nonbusy subgroup, but busyness eliminates this difference and therefore causes a larger drop in performance for concentrated examiners. In Column (8), we study whether the effect of busyness is stronger when patents have more complex technologies and hence demand more attention from the examiners. We classify technology classes into two subgroups according to the average approval time of patents issued every year. A technology class that has above average approval time is defined as a more complex technology field and is assigned a value of one for the *TechComplexity* dummy. We then take the average of *TechComplexity* across a firm's granted patents in each year, and classify firms into two subgroups according to firm-level *TechComplexity*. We find that the negative effect of examiner busyness on future stock returns is stronger among firms with more complex patents, as these patents demand more effort from the examiners and in turn are affected more by examiner time constraints.

5. Conclusion

We study the effect of patent quality on firm value relying on the unique setting of patent examiner busyness. Using a large data set of 3 patents and examiners covering 4,176 unique U.S. firms from 1981 to 2010, s6.5571 Tm .0001 Tc [(

those with a less concentrated review pool. In addition, firms with more patents in complex technology classes, which

(*continued*)

Patent-level examiner residual age	The residual examiner age measure with respect to the examiner experience measure, which is constructed as the residual from annual cross-sectional regression of the examiner-level age measure on the examiner-level experience measure. Examiner age is the difference between patent issue year and the year of college entrance of a focal patent's examiner plus 18. Data source: USPTO application database and LinkedIn.
Firm-level examiner residual age	The average of patent-level examiner residual age of all patents issued to the firm in the year. Data source: USPTO application database and LinkedIn.
Patent-level examiner education	A dummy variable that equals one if the highest degree an examiner obtains is a masters or above, and zero otherwise. Data source: USPTO application database and LinkedIn.
Firm-level examiner education	The average of patent-level examiner education of all patents issued to the firm in the year. Data source: USPTO application database and LinkedIn.
Patent-level examiner generalist	A dummy variable that equals one if the major of an examiner is not engineering or science, and zero otherwise. Data source: USPTO application database and LinkedIn.
Firm-level examiner generalist	The average of patent-level examiner generalist dummy of all patents issued to the firm in the year. Data source: USPTO application database and LinkedIn.
Patent-level HHI_TechClass	The concentration level (Herfindahl-Hirschman index) across technology class for patents allowed by a patent's examiner in year *t-1*. Data source: USPTO application database.
Firm-level HHI_TechClass	The average of patent-level examiner HHI_TechClass (concentration across technology class) of all patents issued to the firm in the year. Data source: USPTO application database.
Patent-level HHI_Industry	The concentration level (Herfindahl-Hirschman index) across two-digit SIC industry for patents allowed by a patent's examiner in year *t-1*. Data source: USPTO application database.
Firm-level HHI_ Industry	The average of patent-level examiner HHI_Industry (concentration across industry) of all patents issued to the firm in the year. Data source: USPTO application database.
Patent-level HHI_ Location	The concentration level (Herfindahl-Hirschman index) across headquarter states of application firms for patents allowed by a patent's examiner in year *t-1*. Data source: USPTO application database.
Firm-level HHI_ Location	The average of patent-level examiner HHI_Location (concentration across location) of all patents issued to the firm in the year. Data source: USPTO application database.
Patent-level technology complexity	A dummy that equals one for a patent in a technology class with above median review duration in the year, where review duration for a patent is defined as the number of days for the patent application to be allowed by the examiner. Data source: USPTO application database.
Firm-level technology complexity	The average of patent-level technology complexity of all patents issued to the firm in the year. Data source: USPTO application database.

Appendix B. Additional tables

Table A1

Panel regressions of stock returns on examiner busyness. This table presents panel regressions of monthly stock returns on firm-level examiner busyness measures from 1981 to 2010. The dependent variable is raw return, industry adjusted return, or FF3-adjusted return. Industry adjusted return of a firm is calculated by subtracting the average return of the firm's Fama-French 48 industry from the firm's raw return. FF3-adjusted return is constructed as abnormal return calculated with out-of-sample betas estimated using the Fama-French three-factor model in the 36-month rolling window. The main independent variable is the natural logarithm of firm-level examiner busyness measure. The busyness measure of year *t-1* is matched to monthly returns from July of year *t* to June of year *t + 1*. We also control for firm characteristics. Ln*(ME)* is natural logarithm of market capitalization at the previous month-end. Ln*(BM)* is natural logarithm of book-to-market ratio. *Ret [−13, −2]* is the buy-and-hold return in the year up to month −2. *Ret [−1]* is the previous monthly return (reversal). *Assets growth* is annual change in total assets, scaled by lagged total assets. *ROE* is return to equity. We also control for ln*(#Patents)* in the same year as the busyness measure, where *#Patents* for a firm-year is the number of the patents issued to the firm in the year. The art unit fixed effect for a firm in year *t* is based on the most common art unit of the firms' patents issued in year *t*. Some models include two-digit SIC industry fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variables			
	Raw Return		Industry Adj. Ret.	FF3-Adj. Ret.
	(1)	(2)	(3)	(4)
ln(Busyness)	−0.314***	−0.334***	−0.283***	−0.296***
	(−3.04)	(−3.21)	(−2.99)	(−3.05)
Controls	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	No	Yes
Art unit fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.025	0.025	0.015	0.014
# Obs	182,322	182,210	181,329	179,045

Table A3

Returns of portfolios sorted on examiner busyness: Cross-sectional analyses based on R&D, competitive threats, and limited attention. Panel A presents value-weighted six-factor alphas of portfolios double sorted on the R&D and firm-level examiner busyness measure. At the beginning of each month from July of year *t* to June of year *t + 1*, stocks are simultaneously sorted into two groups of R&D expenses of fiscal year ending in calendar year *t-1* and quintiles of busyness measures of *t-1*. R&D is research and development expenditures scaled by total assets. We adjust the scaled R&D for firm size by estimating the cross-sectional regression of R&D on market capitalization each year and use the residual R&D for the sorting analysis. We calculate monthly value-weighted returns of these two-dimensional portfolios and then six-factor alphas using the Fama-French five-factors and a momentum factor. Panel B is similar to Panel A except that we sort on competitive threat rather than R&D. Competitive threats are measured by *Fluidity* of *t-1* (Horberg, Phillips, and Prabhala, 2014), where higher *Fluidity* indicates greater product market threats. The sample period is 1996–2010 due to the availability of the *Fluidity* measure. Panel C is similar to Panel A except that we sort on innovation distraction measures of *t-1* rather than R&D. Innovation distraction for a firm-year is the average of innovation distraction of all patents issued to the firm in the year, where innovation distraction for a patent is the number of patents in the same technology field announced on the same day as the focal patent. Robust Newey-West *t*-statistics that control for autocorrelations are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Subgroup analysis based on R&D

	Examiner busyness					
	Low	2	3	4	High	*H−L*
Low R&D	0.48	0.57	0.11	−0.05	−0.10	−0.58**
	(2.35)	(2.72)	(0.58)	(−0.29)	(−0.65)	(−2.56)
High R&D	1.02	0.49	−0.03	0.06	−0.32	−1.33***
	(4.50)	(2.88)	(−0.25)	(0.60)	(−1.72)	(−4.50)

Panel B: Subgroup analysis based on competitive threats

	Examiner busyness					
	Low	2	3	4	High	*H−L*
Low Competitive Threats	0.07	0.10	−0.14	−0.34	−0.52	−0.59
	(0.28)	(0.45)	(−0.77)	(−1.39)	(−1.99)	(−1.53)
High Competitive Threats	0.94	0.29	0.27	0.17	−0.43	−1.37***
	(2.59)	(0.83)	(1.12)	(0.97)	(−1.35)	(−2.69)

Panel C: Subgroup analysis based on limited attention

	Examiner busyness					
	Low	2	3	4	High	*H−L*
Low Innovation Distraction	0.02	0.08	0.08	−0.03	−0.28	−0.30*
	(0.16)	(0.52)	(0.63)	(−0.27)	(−1.95)	(−1.70)
High Innovation Distraction	0.73	0.51	−0.07	−0.10	−0.07	−0.80***
	(4.06)	(3.21)	(−0.60)	(−0.81)	(−0.44)	(−3.24)

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