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

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A B S T R A C T

This paper attempts to study the causal effect of examiner busyness on patent quality and firm value. Using a broad set of patent quality measures, we find strong evidence that patents allowed by busy examiners exhibit significantly lower quality. Further, examiner busyness of firms' patents negatively predicts the firms' future stock returns, which is consistent with investor underreaction to examiner busyness. Examiners' experience helps attenuate the negative effect of examiner busyness.

As one examiner in [Technology Center] 1700 explained, "When you add it up it's not enough time to do a proper job on a case." A junior examiner expressed a similar sentiment, stating that, "Rather than doing what I feel is ultimately right, I'm essentially fighting for my life." … Examiners consistently expressed the need for additional time. This was stated mostly in concern to not being able to do a highly-quality examination and to avoid taking short-cuts."

—Manhattan Strategy Group, August 2010 report commissioned by the U.S. Patent and Trademark Office[1]

Patents vary substantially in their qualities, from major breakthroughs to negligible improvements. While a large strand of literature has examined various drivers of the quality of corporate innovation, to this date, we have only

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[1] See https://www.washingtonpost.com/news/the-switch/wp/2014/07/31/inside-the-stressed-out-time-crunched-patent-examiner-workforce/?utm_term=.869367685670.

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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 effect of patent examiner busyness on patent quality, we turn to exploring the effect of examiner busyness on firm value. We examine both patent-holding firms' operating and stock performance, with a focus on the latter, which directly measures the impact on firm value. We construct a firm-level measure of examiner busyness by taking the average of patent-level busyness of all patents issued to the firm during the year. A higher value of the busyness measure for a firm-year indicates that the patents of the firm-year on average are issued by busier examiners. We first show that firms with busy examiners and those with nonbusy examiners are well balanced and similar in prior firm fundamentals and stock market performances. We then study the relation between examiner busyness and firms' future operating performance. We find that firms with patents issued by busy examiners tend to have significantly lower future return on assets (ROA) and profitability margins than firms whose patents are issued by nonbusy examiners.

Next, we examine the relation between examiner busyness and future stock performance. Specifically, we examine whether investor underreaction to information associated with corporate innovation (Cohen et al., 2013; Hirshleifer et al., 2018; Fitzgerald et al., 2021) causes a negative relation between examiner busyness and future stock returns. At the beginning of each month from July of year *t* to June of year *t + 1*, we sort sample firms into quintiles according to their examiner busyness measures of year *t-1*, and calculate time-series averages of value-weighted portfolio returns. We follow the literature and allow a six-month interval between the measurements of examiner busyness and stock returns to ensure that the information is widely disseminated before the return measurement window.[7] We find that portfolio returns mono-

[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.

[7] Note that the busyness measure of year *t-1* is publicly available from the end of year *t-1*, since the USPTO announces patent issuances in the

tonically decrease in examiner busyness using raw returns, Fama-French three-factor alphas, Carhart four-factor alphas, and six-factor alphas using the Fama-French five-factor model (Fama and French, 2018) with a momentum factor. For example, the six-factor alpha is 0.63% per month (t-stat 4.50) for the bottom quintile of examiner busyness but −0.28% (t-stat −2.27) for the top quintile, with a spread of 0.90% per month (t-stat 4.44). Interestingly, unlike most stock market anomalies, the majority of the return spread comes from the long portfolio rather than the short portfolio. Since we exclude microcap stocks from our sample, our finding is not subject to the common critique that anomalies tend to be driven by small stocks.[8]

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

To address the concern that patent examiner busyness might be related to examiner leniency, which could drive our results, we conduct a robustness test that controls for examiner leniency. We construct a measure of examiner leniency following Farre-Mensa et al. (2020) and find some evidence that examiner leniency negatively predicts future stock returns, but this effect is smaller than that of examiner busyness. We further construct a residual busyness measure as the residual from the cross-sectional regression of examiner busyness on examiner leniency, and find that this residual measure, which is orthogonal to examiner leniency, continues to significantly negatively predict stock returns. These results show that our findings on examiner busyness are not driven by examiner leniency.

Next, we explore the heterogeneity of our main results by conducting cross-sectional analyses. We find that the negative relation between examiner busyness and future stock returns is much stronger among firms for which innovation and patents are more important as measured by higher R&D expenditure or greater product market threats. The negative relation is also much stronger when investors are subject to limited attention to patent issuance. In addition, we examine long-term returns and find that the negative relation between examiner busyness and future stock returns persists for three years without a subsequent reversal. These results support our hypothesis that investor underreaction to patent quality causes the observed negative relation between examiner busyness and future returns.

Finally, we try to understand whether some examiner characteristics can mitigate or exacerbate the negative effect of examiner busyness. Specifically, we examine returns of portfolios two dimensionally sorted on examiner busyness and examine characteristics. We first study examiner experience, age, and education by manually collecting data of patent examiners from the LinkedIn webpage. Interestingly, the negative effect of examiner busyness on future stock returns is mitigated as examiners become more experienced, but exacerbated as examiners become older. In addition, the level or the major of examiner education does not appear to have material impacts on the busyness effect. Next, we find that the busyness effect is stronger among examiners with more concentrated review pools in terms of industry, technology, or geographic locations.[9] Moreover, the negative effect of examiner busyness is stronger for patents with more complex technologies, which is consistent with the notion that patent applications with complex technologies demand greater examiner effort (Frakes and Wasserman, 2017a).

Our paper provides new evidence on the causal effect of examiner busyness on patent quality, which, in turn, affects firm value. This is an important yet underexplored research question in the literature of corporate innovation. Our results show that patent examiner busyness has a negative causal effect on patent quality and could negatively predict stock returns, which suggests that patent quality is an important driver of firm value. Our findings also support the rationale that investors underreact to information associated with corporate innovation (Cohen et al., 2013; Hirshleifer et al., 2018; Fitzgerald et al., 2021).

Our results also show that patent examiners, who are largely underexplored by the existing literature, could have substantial influence on corporate innovation. Our paper extends a small strand of literature on patent examiners.[10] Farre-Mensa et al. (2020) find that start-ups whose patent applications are reviewed by more lenient patent examiners are more likely to have patents issued and experience higher subsequent growth. Feng and Jaravel (2020) find that, conditional on patent issuance, patent examiner fixed effects can help explain patent citations and lawsuits. We differ from these two studies not only in that we find examiner busyness to be an important driver of innovation outcomes, but also in that we use the setting of patent examiner busyness to investigate the effect of patent quality on firm value.

The remainder of the paper is organized as follows: Section 1 provides institutional background on patent application and examiner assignment. Section 2 describes our data and sample construction. Section 3 presents the results regarding the effect of examiner busyness on patent quality. Section 4 discusses the results regarding the effect of examiner busyness on stock returns. Section 5 concludes.

weekly *Official Gazette of the United States Patent and Trademark Office*, and the announcement includes the examiner information.

8 The sample firms' average market capitalization is at the 86th percentile of the CRSP universe.

9 Further analysis shows that concentrated examiners outperform diversified examiners when they are not busy, but busyness eliminates such advantage and causes a larger performance drop for concentrated examiners than for diversified examiners.

10 Jia and Tian (2018) document that firms that are geographically closer to the USPTO have shorter patent review processes and more patents granted.

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 reviewed by 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 review the records and either reverse or uphold the BPAI's decision.[11]

A unique feature of examiner assignment is that examiners are randomly 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 random (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.

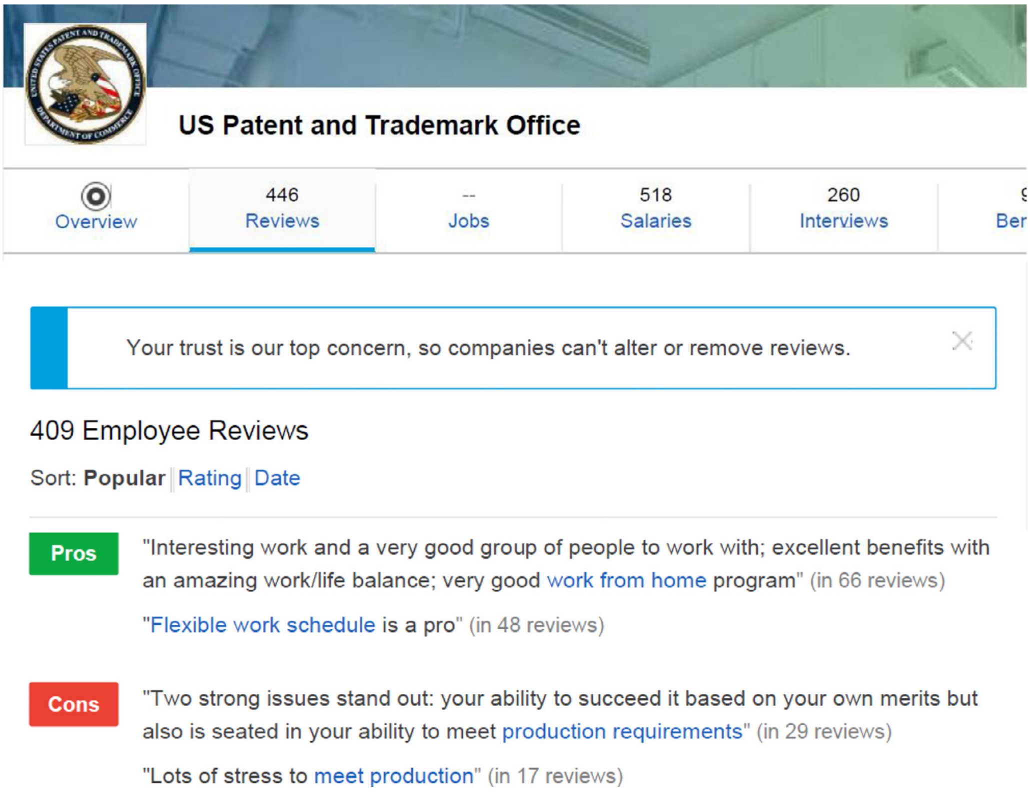


Fig. 1. Employee reviews by USPTO patent examiners at Glassdoor. This figure presents the webpage of employee reviews by patent examiners in the United States Patent and Trademark Office (USPTO) at Glassdoor, a major website for employees to anonymously review their companies. The page, which summarizes 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 granted to U.S. publicly listed firms. We match the patent data from the first sample to public firms using the linkages constructed by Kogan et al. (2017).[16] We require our sample firms to have at least one patent during the measurement year of the examiner busyness measure. We include only firms with ordinary common shares and available return data from CRSP, and drop penny stocks with prices below $5. To avoid our results being driven by microcap stocks, following Fama and French (2008), we drop the stocks with market capitalizations below the NYSE 20% breakpoint. Our sample includes 4,176 unique firms, or 18,957 firm-years, from 1981 to 2010. These firms account for 699,475 patents allowed by 9,967 examiners during this period, which is about one-fifth of all the patents issued. The right panel of Table 1 presents summary statistics for this sample. The number of sample firms gradually increases from 486 in 1981 to 911 in 1998, and then declines to 572 in 2010, a pattern consistent with the well-documented decline in the number of U.S. public firms since the early 2000s (e.g., Gao et al., 2013).

2.2. The constructions of examiner busyness and patent quality measures

We construct the patent-level busyness measure for each issued patent as the total number of patents issued by the focal patent's examiner in the year of patent issuance. The intuition is that the more patents that are issued by an examiner during a year, the busier the examiner is during that year. We use the full sample of issued patents to construct this measure.[17] The left panel

[16] We thank Professor Noah Stoffman for making the data available at https://iu.app.box.com/v/patents.

[17] Ideally, we would also incorporate the applications rejected by the examiner into the construction, but as discussed in Section 2.1, for the applications that are not approved, we do not know if they are rejected,

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
1983	40,235	717	85.54	10,435	515	71.07
1984	46,877	781	90.08	11,603	527	75.80
1985	49,756	841	87.63	11,550	488	77.33
1986	50,993	874	86.72	10,674	492	73.75
1987	62,897	937	100.96	12,290	531	85.33
1988	62,152	1,042	96.09	11,471	511	78.13
1989	80,169	1,211	104.75	14,398	557	91.45
1990	84,934	1,431	96.59	14,826	573	82.39
1991	97,997	1,732	93.15	17,282	567	77.46
1992	105,223	1,873	87.95	19,125	600	73.79
1993	108,884	2,027	91.98	20,145	674	72.40
1994	112,743	2,046	91.78	21,095	750	71.89
1995	113,137	2,164	89.87	20,642	732	68.33
1996	121,247	2,306	87.50	22,876	761	71.44
1997	124,070	2,435	84.71	23,183	749	66.39
1998	163,408	2,691	107.21	30,254	911	82.01
1999	169,340	3,235	98.68	30,728	876	76.39
2000	176,331	3,464	100.81	30,911	783	70.18
2001	184,298	3,442	101.02	31,554	687	71.78
2002	184,640	3,604	93.21	33,688	689	68.99
2003	187,248	3,806	89.20	34,740	631	62.71
2004	181,492	3,857	85.67	35,056	648	60.64
2005	157,954	4,079	72.13	32,722	608	54.52
2006	196,854	4,763	92.91	38,699	655	61.74
2007	183,393	5,003	88.47	33,987	637	55.94
2008	185,825	5,395	90.78	34,028	615	54.92
2009	192,805	5,956	79.32	36,065	615	50.46
2010	245,153	6,370	77.53	37,260	572	57.11

of Table 1 shows that the average patent-level examiner busyness measure increases from 69.14 in 1981 to the peak of 107.21 in 1998, and then decreases to 77.53 in 2010.

Next, we construct a firm-level measure of examiner busyness for a firm-year as the average of the patent-level busyness measure of all patents issued to the firm in the year. A higher value of the busyness measure for a firm-year indicates that the firm's patents are issued by busier examiners on average. The right panel of Table 1 presents the average of the firm-level measure of examiner busyness across years. The firm-level busyness measure starts from 65.32 in 1981, peaks at 91.45 in 1989, and then decreases to 57.11 in 2010.

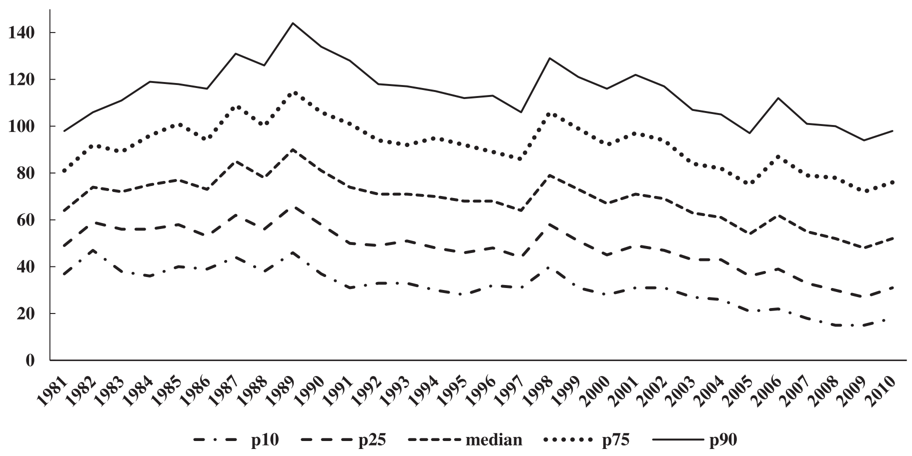
We plot the 10th, 25th, 50th, 75th, and 90th percentiles for the busyness measures in Fig. 2. Panel A plots the patent-level busyness measure and Panel B plots the firm-level busyness measure. Both measures have high cross-sectional dispersions throughout our sample period. For example, Panel B shows that the 90th percentile of the firm-level busyness measure is generally around 100, much higher than the 10th percentile of around 40.

One concern of our measure of examiner busyness is that it could be affected by examiner leniency because a generous examiner could issue more patents than a strict examiner, even if they review the same number of applications. To check the impact of this issue, we use the LexisNexis PatentAdvisor® database, which contains office actions for the patent applications reviewed by most of the examiners after 2000.[18] This data set includes the dates of all office actions for the patent applications including the rejected/abandoned ones. LexisNexis PatentAdvisor® is a proprietary data set and therefore is not suitable for stock return analysis because it is private information that may not be available to investors. However, it can help us assess the validity of our examiner busyness measure. We construct a de facto busyness measure for a patent as the number of patent applications for which the examiner takes office actions in the issuance year of the focal patent. This de facto measure not only captures the number of patents issued in the year (i.e., our busyness measure) but also the number of patent applications rejected by the examiner in the year. We find that the de

abandoned, or still under review. There is no information about action dates either.

[18] The examiners who are missing in this data set are mainly very senior examiners.

Panel A: Cutoff points of patent-level busyness measure over years



Panel B: Cutoff points of firm-level busyness measure over years

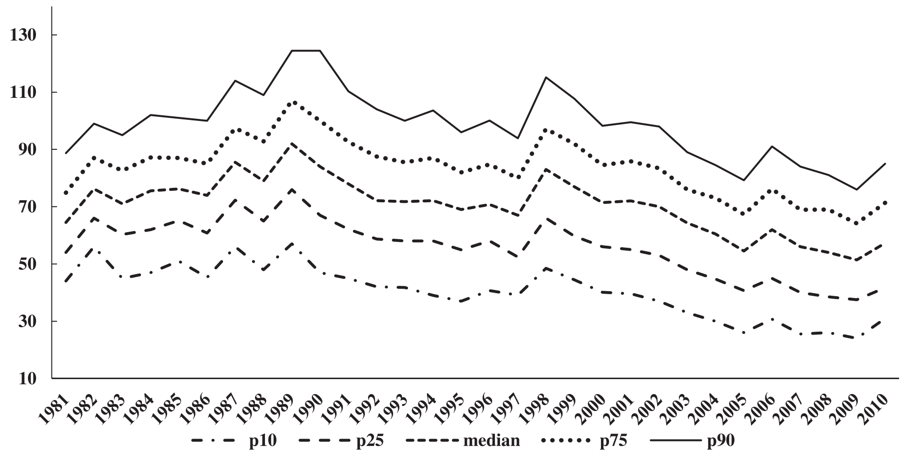


Fig. 2. Cutoff points of examiner busyness: 1981–2010. Panel A plots the 90th, 75th, 50th, 25th, and 10th cutoff points of the patent-level busyness measure for each year during our sample period, 1981 to 2010. The patent-level busyness measure is defined as the number of patents allowed by the patent's examiner during the year of patent issuance. Panel B plots the cutoff points of the firm-level busyness measure, which is calculated for a firm-year as the average of patent-level busyness across the patents issued to the firm in the year.

facto measure of examiner busyness has a very high correlation of 0.74 with our measure of examiner busyness. Therefore, our construction approach does a good job capturing the busyness of examiners. As discussed later in Section 4.4, we nevertheless conduct a robustness test that controls for the examiner leniency measure proposed by Farre-Mensa et al. (2020) and find that our results are not driven by examiner leniency.

Another concern is that our busyness measure captures only the busyness of an examiner in the year of patent issuance rather than the busyness during the entire review period. An alternative approach is to measure the number of patents issued by the patent's examiner during the entire review process of the focal patent rather than just the issuance year of the focal patent. There are, however, two issues with this approach. First, it is unclear when an examiner works on the application during the review process. For example, as discussed earlier, it takes an average of 0.7 years for an application to be assigned to the examiner and it can take several more months before the examiner starts to work on the application. Second and more importantly, in an unreported test, we find that busier examiners tend to have a shorter review time on average. Compared with nonbusy examiners whose review time is longer, busy examiners could have worked on fewer rather than more patents during the review process for a particular patent application. We acknowledge that if an examiner's busyness changes dramatically during the patent review period, then our measure can be noisy. This issue, however, will bias against us finding any significant results.

We follow the literature and construct a number of citation-based patent quality measures. First, we measure the number of future citations received by a patent following Hall et al. (2001), who address the issues of citation truncation by adjusting the number of future citations based on the lagged citation distribution. We also 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 investor's patents in a given year. We then define the superstar dummy that equals one if a patent is invented by at least one superstar innovator, and zero otherwise. We also define the dummy of tail innovation that equals one if a patent's number of future citations is in the top 1% of the patents granted in the same year, and zero otherwise. Third, we define patent originality and generality scores. The patent originality score 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 (Hirshleifer et al., 2018). The patent generality score 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.[19] Patents that cite a wider array of technology classes of patents are viewed as having greater originality, while patents being cited by a wider array of technology classes of patents are viewed as having great generality. Both patent originality and generality reflect the fundamental importance of the innovation being patented.

2.3. Summary statistics

Panel A of Table 2 presents summary statistics of patent-level examiner busyness and patent quality measures, including the number of citations, the number of non-self-citations, the superstar dummy, the tail innovation dummy, originality scores, and generality scores. Panel B of Table 2 presents the firm-level busyness measure, which shows that, consistent with Fig. 2, the busyness measure is quite dispersed over the sample period. Panel B also reports firm characteristics and stock metrics, including market capitalization, the book-to-market ratio, the monthly stock return, momentum, asset growth, gross margin, ROE, ROA, R&D, and capital expenditures. The definitions of these variables are described in detail in Appendix A. The sample firms are much larger than an average firm in the CRSP universe, as the average market capitalization of sample firms is at the 86th percentile of the CRSP universe. This is because we exclude microcap stocks and require sample firms to have patents. Additionally, our sample firms' book-to-market ratio is at the 37th percentile of the CRSP universe, consistent with growth firms having more innovation activities.

Panel C of Table 2 reports correlations for the firm-level variables. We find that the busyness measure has very low correlations with most of the firm characteristics, including the market capitalization (0.00), momentum (−0.03), asset growth (−0.06), ROE (−0.01), ROA (0.04), and capital expenditures (0.03). The busyness measure has mild correlations with the book-to-market ratio (0.13), gross margin (0.09), and R&D (−0.22). We control for all these firm characteristics in multivariate regressions. The correlations among firm characteristics are consistent with the existing literature.

3. Examiner busyness and patent quality

In this section, we examine the relations between examiner busyness and patent quality measures, and then attempt to establish the causal link between them using two different approaches.

3.1. Examiner busyness and patent quality

We start our investigation of the relation between examiner busyness and patent quality using citation-based patent quality measures, which are frequently used in the literature (e.g., Hall et al., 2005; Acemoglu et al., 2015; Hirshleifer et al., 2018). We estimate patent-level regressions of patent quality on examiner busyness. The dependent variables are the citation-based patent quality measures discussed in Section 2. To control for unobserved heterogeneity across patenting firms and across years, we include firm-year fixed effects in the regressions. This empirical specification allows us to identify whether patent examiner busyness has a significant effect on patent quality within a firm's patent portfolio in a given year. We also report robust standard errors adjusted for heteroscedasticity and within firm-year clustering. We expect significantly negative coefficient estimates of the examiner busyness measure.

Panel A of Table 3 confirms our conjecture and shows that examiner busyness negatively affects patent quality across different citation-based measures of patent quality. For example, the coefficient estimate of the busyness measure is −0.066 in Column (1), suggesting that a one standard deviation increase in the patent-level busyness measure from the mean is associated with a 3.3% reduction in the number of future citations.[20] The effect of busyness on the number of non-self citations is even stronger with a coefficient estimate of −0.088 as reported in Column (2), significant at the 1% level. Busy examiners are less likely to grant patents with superstar innovators. The coefficient estimate of the busyness measure is −0.006 in Column (3), suggesting that a one standard deviation increase in the patent-level busyness measure from the mean is associated with a 7.5% reduction in the likelihood of having superstar innovators.[21] Consistently, we find that the patents

[19] Our results hold if we follow Hall, Jaffe, and Trajtenberg (2001) and define the originality score as one minus the Herfindahl index of the citations made by the focal patent based on two-digit technological classes, and the generality score as one minus the Herfindahl index of the citations received by the patent based on two-digit technological classes.

[20] A one standard deviation increase in busyness at the mean represents an increase of 49.88% (34.22/68.61) in busyness, which corresponds to an unconditional effect on adjusted citation of −3.29% (−49.88%*0.066).

[21] A one standard deviation increase in busyness at the mean represents an increase of 49.88% (34.22/68.61) in busyness, which corresponds to an unconditional effect on likelihood of superstar innovation of −0.30% (−49.88%*0.006). Since the average value of the patent-level superstar dummy is 4%, this change corresponds to a 7.48% decrease in superstar dummy (−0.30/4).

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) (1)	ln(1+Non_Self_Citation) (2)	Superstar (3)	Tail Innovation (4)	Originality (5)	Generality (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 (1)	ln(1+#Cases) (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 on examiner busyness using two litigation-based dependent variables. The first is the future litigation dummy that equals one if the patent experiences litigation in the future, and zero otherwise. The second is the number of future lawsuits involving the patent. The key variable of interest is the patent-level examiner busyness measure. We again control for firm-year fixed effects to pin down the impact of examiner busyness, and report robust standard errors adjusted for heteroscedasticity and within firm-year clustering.

Panel B of Table 3 shows the regression results: Columns (1) and (2) present the regressions with the litigation dummy and the number of lawsuits as the dependent variable, respectively. The coefficient estimates of examiner busyness are negative in both columns, and are significant at the 5% level in Column (1) where the dependent variable is the litigation dummy. The result is also economically significant. For example, the coefficient estimate of examiner busyness in Column (1) suggests that a one standard deviation increase in the busyness measure from the mean is associated with a 2.6% reduction in future litigation probability.[22] These results are consistent with examiner busyness having a negative effect on patent quality.

[22] A one standard deviation increase in busyness at the mean represents an increase of 49.88% (34.22/68.61), which corresponds to an unconditional effect on future litigation dummy of −0.02% (−49.88%*0.0004). Since the average value of the patent-level litigation dummy is 0.78%, this change corresponds to a 2.56% decrease in litigation probability (−0.02/0.78).

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 whether the challenged claims are unpatentable.

The Lex Machina database includes information on final decisions for a small number of PTAB trials, which allows us to examine the relation between examiner busyness and trial outcome. If examiner busyness negatively affects patent quality, then conditional on a trial, we would expect that examiner busyness is positively related to the probability of a patent being invalidated. We define *Unpatentable* for a PTAB trial as a dummy variable that equals one if the outcome is either "all claims unpatentable" or "patent owner disclaimed", and zero otherwise. We then conduct patent-level regressions of *Unpatentable* on the patent-level examiner busyness measure.[23] As shown in Table 4, we find that, despite the very small sample (189 observations), examiner busyness is positively and significantly associated with unpatentable outcomes, which is consistent with the conjecture that examiner busyness negatively affects patent quality.

Table 4
Regressions of unpatentable trial outcomes on examiner busyness. This table presents trial-level regressions of patent trial outcomes on examiner busyness. The sample includes the patent trial cases filed with The Patent Trial and Appeal Board (PTAB) of the USPTO with available data for trial outcomes. *Unpatentable Dummy* is equal to one if a PTAB trial case has "all claims unpatentable" or "patent owner disclaimed" as the final trial outcome. The main independent variable is the patent-level busyness measure, *Busyness_Patent*, 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. *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. *ROA* is return on asset. The constructions of all the measures are described in the Appendix A. We include two-digit SIC industry fixed effects and year fixed effects in Column (2). *T*-statistics adjusted for heteroscedasticity and within-firm clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: Unpatentable Dummy	
	(1)	(2)
ln(Busyness_Patent)	0.099**	0.139*
	(1.98)	(1.83)
Size	−0.007	0.006
	(−0.30)	(0.20)
M/B	0.009	0.002
	(0.37)	(0.06)
R&D	0.840	1.684*
	(1.16)	(1.70)
Capex	1.093	1.337
	(1.35)	(1.11)
ROA	0.204	0.319
	(0.59)	(0.68)
Industry fixed effects	No	Yes
Year fixed effects	No	Yes
Adj. R^2	0.021	0.046
# Obs	189	189

3.2. Further identification attempts

Although the setting of examiner busyness alleviates the endogeneity concern because examiner busyness is unlikely related to firm fundamentals, in this section, we further attempt to establish the causal link between examiner busyness and patent quality using two different tests.

Our first test employs time-series variations in the workload of examiners. A large increase in an examiner's workload represents a shock to examiner busyness, which should negatively affect patent quality if our argument is supported. We first calculate annual changes in an examiner's busyness measure over her tenure, and then identify large workload increases as the positive changes that are above the 75% of the changes during her tenure.[24] Patents granted by the examiner in the year with a large workload increase are the ones that are affected and therefore are assigned with a *Shock_Busyness* dummy that equals one. We then estimate patent-level regressions of patent quality measures on the *Shock_Busyness* dummy. We control for examiner and year fixed effects, and report robust standard errors adjusted for heteroscedasticity and within firm-year clustering. We also control for firm-level variables including size, market to book, R&D expenses, capital expenditure, and ROA in the regressions.

Columns (1) to (6) of Table 5 report the regression results with the citation-based patent quality measures as the dependent variable. The coefficient estimates of *Shock_Busyness* are negative in all columns and statistically significant except in the regression, in which the superstar dummy is the dependent variable. Columns (7) and (8) report the regression results with future patent litigation likelihood and the number of lawsuits as the dependent variable, respectively. The coefficient estimates of *Shock_Busyness* are negative and statistically significant in both regressions. Overall, consistent with our baseline results, a large increase in the examiner's workload leads to a lower quality of granted patents using both citation-based and litigation-based measures.

Our second identification test uses plausibly exogenous reallocation of an examiner's attention within the pool of patents she reviews. In the spirit of Kempf et al. (2017), we consider large drops in stock prices of patent applicant firms as attention-grabbing events that exogenous distractions to the patent applications that are under review by the same examiner, but without large stock price drops.

[23] Due to the small sample and limited variation in the cross section, for this regression, we control for industry fixed effects rather than firm-year fixed effects.

[24] Our results are largely consistent if we use other cutoff points, for example 60%, 67% (two-third), or 80%.

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 lower patent quality. Columns (1) to (6) present the regressions of 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 lower patent quality.

3.3. Examiner busyness and backward citations

To further validate our examiner busyness measure and show that busy examiners indeed spend less effort on the

[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 truncation, following Hall et al., 2001). *Superstar* is a dummy variable that equals one if a patent has a superstar innovator, and zero otherwise. *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. *Litigation Dummy* is equal to one if a patent issued in year *t* 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 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. 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)
Examiner_Distraction	−0.150***	−0.181***	−0.018***	−0.004	−0.089**	−0.055***	−0.010***	−0.007**
	(−2.86)	(−2.83)	(−2.62)	(−1.29)	(−2.48)	(−2.60)	(−2.93)	(−2.34)
Size	−0.058***	−0.046***	−0.005***	−0.002***	−0.042***	−0.018***	−0.003***	−0.003***
	(−7.88)	(−5.72)	(−4.02)	(−3.41)	(−10.00)	(−5.90)	(−4.01)	(−3.17)
M/B	0.082***	0.057***	0.012***	0.004***	0.018***	0.028***	0.001***	0.001*
	(8.57)	(6.05)	(5.27)	(5.21)	(3.01)	(5.46)	(2.60)	(1.90)
R&D	−0.944***	−0.447	−0.110***	−0.059***	−0.948***	−0.146	−0.037**	−0.032**
	(−3.70)	(−1.51)	(−2.94)	(−3.55)	(−5.00)	(−1.49)	(−2.36)	(−2.24)
Capex	−0.396	−1.655***	−0.106**	0.005	1.032***	−0.104	−0.036*	−0.037*
	(−1.20)	(−2.86)	(−1.97)	(0.18)	(3.16)	(−0.69)	(−1.92)	(−1.78)
ROA	−0.446***	−0.229	−0.086***	−0.028**	−0.293***	−0.065	0.010	0.013
	(−3.02)	(−1.39)	(−3.37)	(−2.55)	(−2.84)	(−1.08)	(1.02)	(1.14)
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	0.289	0.312	0.135	0.052	0.189	0.245	0.030	0.029
# Obs	29,174	29,174	29,340	29,174	27,126	26,288	29,417	29,417

patents they review, we investigate the relation between examiner busyness and backward citations of the issued patents. An important part of a patent examiner's work is to search "prior art", i.e., previously issued patents that are relevant to the application, and require the applicant to cite these patents if they are missing from the application. Therefore, if the busyness of examiners leads to a lack of effort during the review process, we would expect that examiner busyness is negatively related to the number of backward citations in the issued patents. We first conduct a patent-level regression analysis of backward citations on examiner busyness and report the results in Column (1) of Table 7. The coefficient estimate of examiner busyness is negative and significant at the 1% level. We then use the two identification approaches in the previous section to examine backward citations and report the results in Columns (2) and (3). We find a significant reduction in the number of backward citations in both models. These results provide additional evidence that busier examiners spend less effort in the review process, and hence reduce the quality of granted patents.

If busy examiners spend less effort in the review process, then they could choose to quickly wrap up a patent review without spending enough time. We examine this possibility by constructing a measure of review duration for a patent as the number of days from the application date to the issuance date. We then repeat the regression analysis in Table 7 and replace the dependent variable with review duration. In untabulated results, we find largely consistent evidence that review duration significantly decreases in examiner busyness, which is consistent with busy examiners spending less time on patent review.

4. Examiner busyness, operating performance, and future stock returns

In this section, we study the relations of examiner busyness with future operating performance and stock market performance of innovating firms, with a focus on the stock market performance, which directly measures the impact on firm value.

4.1. Balance tests

Before we investigate the effect of firm-level examiner busyness on firm performance, we conduct balance tests to check whether the firms with busy examiners and those with nonbusy examiners are fundamentally different from each other before patent issuance. This test can provide evidence as to whether examiners' assignments within an art

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 shows that none of the differences in firm characteristics across the two groups are statistically significant, which confirms that firms with busy examiners and those with nonbusy examiners are well balanced and similar in firm characteristics before patent issuance. Such tests lend additional support to the random examiner assignment and allow us to explore the causal link between examiner busyness and firm value.

4.2. Examiner busyness and future performance of innovating firms

If examiner busyness negatively affects patent quality, then we expect the examiner busyness to be nega-

Table 8
Balance tests. This table presents balance tests across firms with busy patent examiners and those with nonbusy patent examiners. For each year and each art unit, we classify firms into busy and nonbusy groups according to the firm-level examiner busyness measure, where the art unit for a firm in year *t* is based on the most common art unit of the firms' patents issued in year *t*. Firm-level examiner busyness in a year is calculated as the average of the patent-level examiner busyness measure using all patents of the examiner-year. Then we compare the lagged firm fundamental difference between the two groups of firms. *Size* is 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. *GM* is gross profit margin defined as sales minus cost of goods sold, scaled by total sales. *Monthly return* is the year-end monthly stock return. *Annual return* is the annual stock return.

	Busy	Nonbusy	Difference	*t*-statistics
Size	6.984	6.966	0.018	0.63
M/B	2.291	2.334	−0.043	−1.49
R&D	0.078	0.080	−0.002	−1.10
Capex	0.053	0.053	0.000	0.20
ROA	0.120	0.122	−0.002	−1.09
GM	0.294	0.300	−0.006	−0.53
Monthly Return	0.020	0.020	−0.000	−0.18
Annual Return	0.290	0.292	−0.002	0.23

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} (%) (1)	ROA_{t+2} (%) (2)	GM_{t+1}(%) (3)	GM_{t+2}(%) (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 expenditure. We also control for a firm's overall patenting activities, measured as the number of patents issued to the firm in year *t*. All models include firm fixed effects, art unit fixed effects, and year fixed effects, and we report robust standard errors with within-firm clustering.

Table 9 shows that examiner busyness is negatively related to future firm performance. Though the coefficient estimate of the busyness measure is insignificant in Column (1), the sign is negative. The coefficient estimate becomes significantly negative in Column (2), suggesting that examiner busyness is negatively related to the firm's ROA two years after the patent issuance. The coefficient estimate of the examiner busyness measure is also negative and significant in Columns (3) and (4), in which the dependent variables are the gross profit margins of years *t + 1* and *t + 2*, respectively. Overall, the results in Table 9 support the conjecture that the lower patent quality caused by busy examiners has a negative impact on future firm operating performance.

4.3. Examiner busyness and future stock returns

In this subsection, we examine the relation between examiner busyness and future stock returns. We expect that examiner busyness negatively predicts future stock returns if investors underreact to the information associated with patents (Cohen et al., 2013; Hirshleifer et al., 2018; Fitzgerald et al., 2021).

We first examine returns of stock portfolios sorted on examiner busyness. As shown by the timeline in Fig. 3, we sort sample firms into quintiles at the beginning of each month from July of year *t* to June of year *t + 1* according to the firm-level measure of examiner busyness in year *t-1*, and report monthly value-weighted portfolio returns. The busyness measure of year *t-1* is publicly available at the end of year *t-1*, since the USPTO discloses patent issuance in the weekly *Official Gazette of the United States Patent and Trademark Office*, and the disclosure includes examiner information. We allow a six-month window before the return measurement to be consistent with the existing literature and to ensure that the information has been widely disseminated to investors. We calculate monthly value-weighted portfolio returns and then report time-series averages with *t*-statistics using the Newey-West robust standard errors.

The first row in Panel A of Table 10 shows that raw returns of portfolios monotonically decrease in examiner busyness, from 1.34% per month for the bottom quintile to 0.83% for the top quintile. The spread is 0.52% per month, both economically and statistically significant (*t*-stat 2.39). We also report alphas of the Fama-French three-factor model, the Carhart four-factor model that includes the three Fama-French factors and a momentum factor, and the six-factor model based on five Fama-French factors (Fama and French, 2018) and a momentum factor.[26] The return spreads in terms of alphas remain large and significant for all these models. For example, the six-factor alpha is 0.63% (*t*-stat 4.50) for the bottom quintile and −0.28% (t-stat −2.27) for the top quintile, with a spread of 0.90% (*t*-stat 4.44).[27] It is worth noting that the negative return of the top quintile does not necessarily indicate that patents

[26] We thank Professor Kenneth French for making the factor returns available in his data library.

[27] For robustness, we also calculate alphas of the q-factor model (Hou, Xue, and Zhang, 2015), and the untabulated results show that the portfolio returns also monotonically decrease from 0.68% for the bottom busyness quintile to the −0.22% for the top busyness quintile, with a spread of 0.90% (*t*-stat 3.65).

Table 10
Examiner busyness and future stock returns. This table examines the relation between examiner busyness and future stock return. Panel A presents value-weighted returns of portfolios sorted on firm-level examiner busyness measures from 1981 to 2010. The examiner busyness measure for a firm-year is calculated as the average of patent-level examiner busyness of the patents issued to the firm in the year, where patent-level examiner busyness for a patent is the number of patents issued by the patent's examiner in the same year. At the beginning of each month from July of year *t* to June of *t + 1*, stocks are sorted into quintiles of the firm-level busyness measure of *t-1*. We calculate monthly returns of these quintile portfolios and then report time-series averages and t-statistics. In addition to raw returns, we report three-factor alphas based on the Fama-French three-factor model, four-factor alphas based on the Carhart four-factor model that includes the three Fama-French factors and a momentum factor, and six-factor alphas based on the Fama-French five-factor model and a momentum factor. Robust Newey-West *t*-statistics that control for serial correlations are reported in parentheses. Panel B presents Fama-MacBeth 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. The industry-adjusted return of a firm is calculated by subtracting 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 Fama-French three-factor model in the 36-month rolling window. The main independent variable is the natural logarithm of the 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 the 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. Some models include two-digit SIC industry fixed effects. Robust Newey-West *t*-statistics that control for serial correlations are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Returns of stock portfolios sorted on examiner busyness

	Firm-level measure of examiner busyness					
	Low	2	3	4	High	H − L
Raw Return	1.34	1.11	1.09	1.08	0.83	−0.52**
	(3.82)	(4.00)	(4.63)	(4.55)	(2.84)	(−2.39)
3-factor Alpha	0.42	0.18	0.15	0.11	−0.27	−0.68***
	(2.95)	(1.72)	(2.14)	(1.29)	(−2.25)	(−3.42)
4-factor Alpha	0.43	0.29	0.11	0.06	−0.22	−0.65***
	(3.37)	(2.37)	(1.56)	(0.72)	(−1.86)	(−3.47)
FF5+MOM Alpha	0.63	0.42	−0.01	−0.09	−0.28	−0.90***
	(4.50)	(2.88)	(−0.12)	(−1.10)	(−2.27)	(−4.44)

Panel B: Fama-MacBeth regressions of stock returns on examiner busyness

	Dependent variables			
	Raw Return		Industry Adj. Ret.	FF3-Adj. Ret.
	(1)	(2)	(3)	(4)
ln(Busyness)	−0.536***	−0.464***	−0.490***	−0.416***
	(−3.82)	(−3.72)	(−4.22)	(−3.64)
ln(ME)	−0.551***	−0.590***	−0.523***	−0.515***
	(−7.48)	(−8.84)	(−8.60)	(−11.28)
ln(BM)	0.044	0.089	0.066	−0.066
	(0.39)	(0.90)	(0.82)	(−0.86)
Ret [−13,−2]	0.193	0.11	0.117	−0.029
	(0.76)	(−0.46)	(0.57)	(−0.13)
Ret [−1]	−3.466***	−4.138***	−4.103***	−5.291***
	(−5.17)	(−6.43)	(−7.02)	(−8.64)
Assets Growth	−0.114	−0.136	−0.086	−0.215*
	(−0.92)	(−1.18)	(−0.79)	(−1.95)
ROE	2.712**	2.989**	3.083***	3.105***
	(2.08)	(2.37)	(2.67)	(2.83)
ln(#Patents)	0.152***	0.177***	0.137***	0.132***
	(4.47)	(5.98)	(5.05)	(4.60)
Industry fixed effects	No	Yes	No	Yes
Adj. R^2	0.094	0.204	0.067	0.172
# Obs	182,323	182,211	181,331	179,046

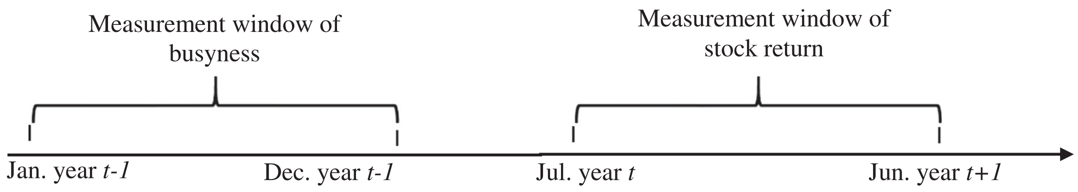


Fig. 3. Timeline of stock return analysis. This table plots the measurement windows for the firm-level busyness measure and stock returns. We first construct the busyness measure for a firm in year *t-1*, and then match it to the firm's monthly stock returns from July of year *t* to June of year *t + 1*.

issued by busiest examiners cause net losses to the firms. Instead, the negative returns indicate that investors underreact to the negative effect of examiner busyness on patent quality, causing overpricing for these firms. Overall, these results are consistent with a negative effect of examiner busyness on firm value.

In addition to the sorting analysis, we conduct Fama-MacBeth regression analysis of stock returns. The dependent variable is the monthly stock return from July of year t to June of year $t + 1$, and the independent variable is the firm-level busyness measure of year $t-1$. We control for firm characteristics including size, book-to-market, momentum, and short-term reversal, as well as asset growth and ROE, the two characteristics associated with the investment anomaly and the profitability anomaly. We also control for the overall patenting activity of a firm, measured by the number of patents issued to the firm in the year. We report t-statistics using Newey-West robust standard errors. Column (1) of Table 10 Panel B presents the regression result: the coefficient estimate of examiner busyness is negative and significant at the 1% level (t-stat −3.82). Column (2) further includes industry fixed effects and the results are similar.[28]

For robustness, we use industry-adjusted return and the Fama-French three-factor adjusted (FF3-adjusted) return as the dependent variables in Columns (3) and (4), respectively. The industry-adjusted return is constructed using the Fama-French 48-industry classifications, and the FF3-adjusted return is estimated using factor loadings of the Fama-French three-factor model in the previous 60-month rolling window (Brennan et al., 1998). The coefficient estimates of the busyness measure remain negative and significant at the 1% level in both alternative models. These results support the sorting analysis that examiner busyness significantly negatively predicts future stock returns. Regarding control variables, the coefficient estimates are significantly positive for ROE, and significantly negative for market cap and lagged monthly return, which is consistent with the literature on profitability anomaly, the size effect, and the short-term reversal. The coefficient estimates of book-to-market and momentum become insignificant, which is consistent with the literature that value premium and return momentum weaken among large cap firms.

While the regression analyses in the previous section control for the art unit fixed effects, this approach is not applicable to the Fama-MacBeth return regressions. Specifically, there are several hundred firms in each cross-section, so including a large number of art unit fixed effects in the cross-sectional regressions would cause overfitting. We therefore conduct a robustness test by estimating panel regressions of stock returns which have enough observations to include the art unit fixed effects. Table A1 of Appendix B presents the panel regressions of returns on examiner busyness that include the industry fixed effects, art unit fixed effects, and year fixed effects, and the coefficient estimates of examiner busyness remain negative and significant at the 1% level in all models (t-stats from −2.99 to −3.21).

Kogan et al. (2017) propose a novel measure of patent value based on stock price response upon patent issuance (henceforth, the KPSS measure). We examine the relation between our examiner busyness measure and the KPSS measure and find that the two have a very low correlation (i.e., −0.0987).[29] This finding is consistent with investor underreaction to examiner busyness, so investors' response to patent issuance does not correctly incorporate the information about examiner busyness. For robustness, we include the KPSS measure into the return regressions, and the untabulated results show that the magnitude and significance level of the coefficient estimates of patent examiner busyness remain similar.

4.4. Examiner leniency and future stock returns

The measure of examiner busyness is based on the number of patents issued by an examiner and therefore can be affected by examiner leniency. As discussed in Section 2.2, this concern is alleviated because our busyness measure has a high correlation of 0.74 with the de facto measure of examiner busyness that considers both issued and rejected patent applications. In this subsection, we examine whether the observed negative relation between examiner busyness and future returns can be explained by examiner leniency.

We first investigate the relation between examiner leniency and future stock returns. Farre-Mensa et al. (2020) find that start-up firms whose patent applications are reviewed by lenient examiners are more likely to have their patents issued and in turn experience greater future growth. Feng and Jaravel (2020) find that, conditional on patent issuance, patents issued by lenient examiners have higher invalidity rates. Neither study,

[28] The industry fixed effects are based on two-digit SIC classifications. The results are similar when we use the finest four-digit SIC industry fixed effects.

[29] The low correlation holds whether we use the raw value of the KPSS measure (dollar value of a patent) or scale it by the firm's market capitalization.

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 focal patent's issuance year divided by the total number of patent applications reviewed by the examiner up to the end of the focal patent's issuance year. We then construct the leniency measure for a firm-year as the average patent-level leniency of all patents issued to the firm in the year. We first conduct the sorting analysis using the examiner leniency measure and report the results in Table A2 of Appendix B. Panel A shows that the spread of raw returns, three-factor alphas, or four-factor alphas is statistically insignificant between the top and bottom leniency portfolios (*t*-stat from 0.78 to 1.54). The six-factor alpha of the bottom leniency quintile, however, is much higher than the top leniency quintile, with a significant difference of 0.56% (*t*-stat 3.03). This spread is smaller than the corresponding spread for examiner busyness in Panel A of Table 10 (0.90%, *t*-stat 4.44). Therefore, these results provide some evidence that examiner leniency could negatively affect future stock performance as well, but the effect is smaller than that of examiner busyness.

Next, we investigate whether our finding of the negative relation between examiner busyness and future returns can be explained by examiner leniency. We construct a residual busyness measure, which is the residual from annual cross-sectional regression of the examiner busyness measure on the examiner leniency measure and then is aggregated to the firm level. This residual busyness measure is orthogonal to examiner leniency by construction. Panel B of Table A2 reports the sorting analysis using the residual busyness measure, in which the spreads of all return measures are significant. For example, the spread of six-factor alpha is 0.63% (*t*-stat 3.56). Note that since examiner busyness has been shown to cause examiner leniency, the residual examiner busyness measure in fact removes the component of examiner busyness that is associated with examiner leniency and therefore tends to underestimate the effect of examiner busyness. Despite this issue, the alpha spread of 0.63% in Panel B is still over two-thirds of the baseline result of 0.90% (Panel A of Table 10). Overall, the results in Table A2 show that the observed negative relation between examiner busyness and future returns cannot be explained by examiner leniency.

4.5. Cross-sectional heterogeneity

To better understand the underlying channels through which examiner busyness affects future stock returns, we conduct several cross-sectional analyses in this subsection based on innovation intensity, competitive threats, and limited investor attention.

4.5.1. Innovation intensity

If examiner busyness affects patent quality and in turn firm value, then we expect the relation between examiner busyness and future stock returns to be stronger for more innovation-intensive firms, because patent quality matters more to these firms. We measure a firm's innovation intensity using its R&D expenditure, scaled by total assets. We follow the literature and match R&D expenditure of the fiscal year ending in year *t-1* to monthly stock returns from July of year *t* to June of year *t + 1*.[30] As R&D expenditure is negatively correlated with firm size (Table 2), we construct a residual R&D measure by estimating the regressions of R&D expenditure on market capitalization in each cross-section and taking the residuals.[31]

We simultaneously sort stocks into high and low R&D groups and quintiles of examiner busyness, and calculate the value-weighted returns of these two-dimensional portfolios. Since the results are similar across different return measures, for brevity we focus on six-factor alphas using the Fama-French five-factor model and a momentum factor. In Table A3 of Appendix B, Panel A shows that, consistent with our prediction, the effect of examiner busyness is much stronger in high-R&D firms. Specifically, the spread of six-factor alphas between bottom and top quintiles of examiner busyness is 1.33% (*t*-stat 4.50) for high R&D firms, but only 0.58% (*t*-stat 2.56) for low-R&D firms.

4.4.2. Product market threats

The effect of patent quality on a firm's value also depends on the firm's competitive landscape. For firms facing greater product market threats, the marginal value of patent quality should be larger because high-quality patents help these firms enhance competitive advantages and survive the fierce competition. In contrast, a firm that is not subject to competitive pressure has more "cushion" and therefore its value is less sensitive to patent quality. Thus, we expect the relation between examiner busyness and future returns to be stronger among firms with greater product market threats.

We measure product market threats using the product market *Fluidity* measure proposed by Hoberg et al. (2014). The product market *Fluidity* measures the similarity between changes in a firm's and its rivals' products. Greater *Fluidity* for a firm indicates that rivals have a greater ability to enter the firm's product space and therefore cause larger competitive threats. We match *Fluidity* of the fiscal year ending in year *t-1* to monthly stock returns from July of year *t* to June of year *t + 1*.[32] We sort stocks into two-dimensional portfolios according to *Fluidity* and examiner busyness, and report value-weighted six-factor alphas of the portfolios in Panel B of Table A3. Consistent with our expectation, the effect of patent quality is concentrated among firms with greater competitive threats. For example, the spread of six-factor alphas between the bottom and the top quintiles of examiner busyness is 1.37% (*t*-stat

[30] We follow the conservative approach and drop the firms with missing R&D values, rather than replacing the missing values with zeros.

[31] The results are similar if we directly use the scaled R&D expenditure for this analysis.

[32] We thank Professor Gerard Hoberg for providing the data of product market fluidity. Since *Fluidity* is available from 1996, the monthly stock returns start from June 1997.

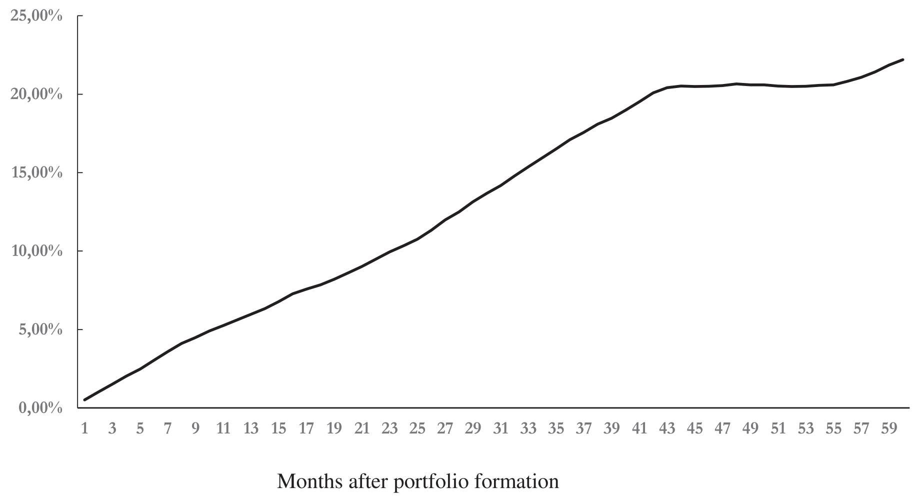


Fig. 4. The spread of long-term buy-and-hold returns between the bottom and top quintile portfolios of examiner busyness. This figure plots the spread of buy-and-hold returns between the bottom and top quintile portfolio of examiner busyness over the 60-month period after portfolio formation. At the beginning of each month from July of year t to June of year $t + 1$, stocks are sorted into quintiles of the firm-level busyness measure of year t-1. We then hold each quintile portfolio for 60 months after the portfolio formation. To calculate the buy-and-hold portfolio return for the k^{th} (k takes a value from 1 to 60) month after portfolio formation, we first calculate the buy-and-hold portfolio returns until the k^{th} month for each stock in the portfolio, and then calculate the value-weighted average across all stocks in the portfolio. We then calculate the time-series average of the k^{th} month buy-and-hold portfolio return for the top and bottom quintiles. Finally, we calculate the spread for k^{th} month as the difference between the bottom and top quintiles.

2.69) for high-*Fluidity* firms, but only 0.59% (t-stat 1.53) for low-*Fluidity* firms.

4.4.3. Limited investor attention to patents

A fundamental assumption of our return analysis is that investor underreaction to patent quality causes a negative relation between examiner busyness and future stock returns. We therefore examine whether our results are stronger when there are more investor distractions, which cause investor underreaction (Hirshleifer and Teoh, 2003; Hirshleifer et al., 2009).

We construct a unique measure of limited investor attention to patents by following the intuition of Hirshleifer et al. (2009), who find greater underreaction to earnings news when a larger number of earnings announcements are made at the same time. The USPTO announces patent issuance in its *Official Gazette of the United States Patent and Trademark Office* every Tuesday. Limited investor attention to any given patent announcement is likely if a large number of other patents in the same technology field are also announced on the same day. We construct a patent-level measure of innovation distraction as the total number of patents in the same technology field issued on the same day as the focal patent. We then construct the firm-level innovation distraction measure as the average of the patent-level innovation distraction of all patents issued to the firm in the year.

We conduct the two-dimensional sorting analysis using the innovation distraction measure, and report the results in Panel C of Table A3. We find that the spread of six-factor alphas is 0.80% (t-stat 3.24) for stocks with high innovation-distraction measures (limited attention to patents), which is much larger than the spread of 0.30% (t-stat 1.70) for stocks with low innovation distraction measures. These results are consistent with investor underreaction causing a negative relation between examiner busyness and future stock returns.

4.6. Examiner busyness and long-term returns

If the relation between examiner busyness and future returns is due to investor underreaction, then we should observe no long-term reversal after the abnormal returns. We conduct analysis of long-term returns in this subsection. At the beginning of each month from July of year t to June of year $t + 1$, we sort stocks into quintiles of the firm-level busyness measure of year t-1. We then hold each quintile portfolio for 60 months after the portfolio formation. To calculate the buy-and-hold portfolio return until the k^{th} month (k takes a value from 1 to 60) after portfolio formation, we first calculate the buy-and-hold portfolio returns until the k^{th} month for each stock in the portfolio, and then calculate the value-weighted average across all stocks in the portfolio. We then calculate the time-series average of the k^{th} month buy-and-hold portfolio returns for each quintile. Fig. 4 plots the buy-and-hold return spread between the bottom and top quintiles of examiner busyness in the five-year period after portfolio formation. We find that the buy-and-hold return spread gradually increases after portfolio formation and becomes flat after about three and a half years without a reversal. This result is consistent with the conjecture that the negative relation between examiner busyness and future returns is driven by investor underreaction.

4.7. Examiner busyness and examiner characteristics

Given our findings on examiner busyness so far, a natural question is which factors drive the busyness of a patent examiner. In this section, we examine several dimensions of examiner characteristics to understand the determinants

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 patents and examiners covering 4,176 unique U.S. firms from 1981 to 2010, we first construct a patent-level measure of examiner busyness and find that examiner busyness negatively affects both citation- and litigation-based patent quality measures after controlling for unobserved heterogeneity across firms and years. We address identification issues by exploiting the time-series variations in an examiner's workload and by using plausible exogenous shocks to an examiner's attention allocation within the pool of patents under review.

Next, we study the effect of busyness on future firm operating performance and find that firms whose patents are granted by busier examiners underperform in accounting performance. Motivated by the existing literature on investor underreaction to patent quality, we examine the relation between examiner busyness and future stock returns, and find that stocks in the top quintile of busyness underperform stocks in the bottom quintile by 0.90% per month in terms of six-factor alphas based on Fama-French five-factor model with a momentum factor. This result is robust to the use of alternative measures of stock returns and the Fama-MacBeth return regressions.

We conduct cross-sectional analyses to understand the negative relation between examiner busyness and future returns, and find that such negative realtion is much stronger for firms that have greater innovation intensity, firms that are faced with stronger product market threats, and firms that are subject to limited investor attention to patent issuance. We also find that the abnormal returns associated with examiner busyness last for more than three years without a long-term reversal. These results together suggest that investors have limited attention or cognitive processing power in the context of corporate innovation.

Finally, we examine interactions between examiner characteristics and the busyness effect. We find that examiner experience helps attenuate the negative effects of examiner busyness on firm value but examiner age exacerbates the busyness effect. Examiners with more concentrated review pool in terms of industry, technology, or geographical location are affected more by busyness, which eliminates these examiners' advantages over the those with a less concentrated review pool. In addition, firms with more patents in complex technology classes, which demand more attention and efforts from examiners, suffer more from examiner busyness.

Our results provide new evidence on the effect of patent quality on firm value and, more broadly, on the underexplored question of the stock market consequences of corporate innovation. Our findings also extend the existing literature that shows investor underreaction to the complex information about innovation. Finally, our findings have policy implications for the U.S. patent review system, which has been increasingly criticized for issuance of invalid patents by providing new evidence that alleviating patent examiners' tight time constraints could help improve patent quality. For patent approvals, quantity is immediately visible, but quality takes a long time to be realized. Given this contrast, it is important to evaluate the review process and design optimal mechanisms to balance quantity and quality.

Appendix A. Variable definition

Busyness_Patent	Patent-level examiner busyness, defined as the number of patents issued by the patent's examiner in the same year. Data source: USPTO application database.
Busyness	Firm-level examiner busyness, defined as the average of patent-level examiner busyness of all issued to the firm in the year.
Citation	Number of citations received by the patent, adjusted for truncation, following Hall et al. (2001). Data source: USPTO application database.
Non_Self_Citation	Number of citations excluding self-citations received by the patent, adjusted for truncation, following Hall et al. (2001). Data source: USPTO application database.
Superstar	A dummy variable that 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. Data source: USPTO application database.
Tail_Innovation	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. Data source: USPTO application database.
Originality	Number of unique technological classes (both primary and secondary classes) assigned to the patents cited by the focal patent, divided by 100, following Hirshleifer et al. (2018). Data source: USPTO application database.
Generality	Number of unique technological classes (both primary and secondary classes) assigned to the patents that cite the focal patent, divided by 100. Data source: USPTO application database.
Litigation Dummy	A dummy that is equal to one if the patent experiences patent litigation in the future in which patent holder is plaintiff, and zero otherwise. Data source: LexisNexis' Lex Machina.
#Case	The number of future lawsuits associated with the patent in which patent holder is plaintiff. Data source: LexisNexis' Lex Machina.
Unpatentable Dummy	A dummy that is equal to one if a PTAB trial case has "all claims unpatentable" or "patent owner disclaimed" as the final trial outcome. Data source: LexisNexis' Lex Machina.
Backward Citations	The average number of U.S. patents cited by the focal patent. Data source: USPTO application database.
#Patents	Number of patents issued to the firm in the year. Data source: Patent data, Prof. Noah Stoffman's personal website: https://iu.app.box.com/v/patents.
ln(ME)	Natural logarithm of market capitalization. Data source: CSRP.
ln(BM)	Natural logarithm of book-to-market ratio as defined in Fama and French (1992). Data source: CRSP and Compustat.
Ret[−13, −2]	Buy-and-hold return from month −13 to month −2. Data source: CRSP.
Ret [−1]	Stock return in the last month. Data source: CRSP.
Size	Natural logarithm of total assets. Data source: Compustat.
M/B	Market value of equity divided by book value of equity. Data source: Compustat.
Capex	Capital expenditure scaled by total assets. Data source: Compustat.
R&D	Research and development expenditures scaled by total assets. Data source: Compustat.
ROA	Operating income before extraordinary items divided by total assets. Data source: Compustat.
Gross Margin	Operating profitability (sales−cost of goods sold) divided by sales. Data source: Compustat.
Assets Growth (%)	Change in total assets scaled by lagged total assets in percentage. Data source: Compustat.
ROE	Quarterly return on equity, defined as quarterly income before extraordinary items divided by lagged quarterly book equity. Data source: Compustat.
Art unit	The art unit to which a patent application was assigned. Data source: USPTO application database.
Patent-level examiner leniency	The total number of patents issued by the focal patent's examiner up to the end of the year of focal patent issuance divided by the total number of patents assigned to the examiner up to the end of the year of focal patent issuance. Data source: USPTO application database.
Firm-level examiner leniency	The average of patent-level examiner leniency of all patents issued to the firm in the year. Data source: USPTO application database.
Patent-level examiner experience	The number of years from the first patent issued by the focal patent's examiner to the issuance of the focal patent. Data source: USPTO application database.
Firm-level examiner experience	The average of patent-level examiner experience of all patents issued to the firm in the year. Data source: USPTO application database.

(*continued on next page*)

(*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 A2

Examiner busyness and stock returns: Controlling for examiner leniency. This table examines the relation between examiner busyness and future stock returns after controlling for examiner leniency. Panel A presents value-weighted returns of portfolios sorted on the firm-level examiner leniency measures from 1981 to 2010. We first calculate the patent-level examiner leniency measure as the total number of patents issued by the focal patent's examiner up to the end of the year of focal patent issuance divided by the total number of patents assigned to the examiner up to the end of the year of focal patent issuance, and then calculate the firm-level examiner leniency measure as the average of patent-level examiner leniency of all patents issued to the firm in the year. At the beginning of each month from July of year *t* to June of year *t + 1*, stocks are sorted into quintiles of the firm-level leniency measure of year *t-1*. We then calculate monthly value-weighted returns of these quintile portfolios and report time-series averages. In addition to raw returns, we report three-factor alphas based on the Fama-French three-factor model; four-factor alphas based on the Carhart four-factor model which includes the three Fama-French factors and a momentum factor; and six-factor alphas based on Fama-French five-factor model and a momentum factor. Panel B is similar to Panel A except that we sort stocks on firm-level residual examiner busyness measure with respect to the examiner leniency measure, which is constructed as the residual from annual cross-sectional regression of the examiner-level busyness measure on the examiner-level leniency measure and then is aggregated to the firm-level. Robust Newey-West *t*-statistics that control for serial correlations are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Returns of portfolios sorted on examiner leniency						
	Low	2	3	4	High	H – L
Raw Return	1.06	1.20	1.11	1.00	0.89	−0.17
	(3.06)	(4.06)	(4.76)	(4.14)	(3.46)	(−0.78)
3-factor Alpha	0.14	0.22	0.14	0.04	−0.13	−0.27
	(1.03)	(1.87)	(1.94)	(0.40)	(−1.32)	(−1.41)
4-factor Alpha	0.17	0.35	0.11	0.01	−0.11	−0.28
	(1.32)	(2.79)	(1.45)	(0.13)	(−1.15)	(−1.54)
FF5+MOM Alpha	0.43	0.44	−0.04	−0.21	−0.13	−0.56***
	(3.19)	(3.36)	(−0.55)	(−2.17)	(−1.32)	(−3.03)
Panel B: Returns of portfolios sorted on residual examiner busyness with respect to examiner leniency						
	Low	2	3	4	High	H – L
Raw Return	1.30	1.10	1.03	1.03	0.96	−0.33**
	(4.17)	(4.13)	(4.11)	(4.10)	(3.46)	(−2.04)
3-factor Alpha	0.30	0.21	0.11	0.06	−0.13	−0.44***
	(2.79)	(2.13)	(1.37)	(0.76)	(−1.24)	(−2.87)
4-factor Alpha	0.30	0.27	0.12	0.02	−0.14	−0.44***
	(2.64)	(2.64)	(1.51)	(0.27)	(−1.36)	(−2.90)
FF5+MOM Alpha	0.41	0.26	0.10	−0.01	−0.22	−0.63***
	(3.21)	(2.46)	(1.25)	(−0.11)	(−1.89)	(−3.56)

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)

References

Acemoglu, D., Akcigit, U., Celik, M.A., 2015. Young, restless and creative: openness to disruption and creative innovations. Unpublished working paper. Nat. Bur. Econ. Res..

Akcigit, U., Celik, M.A., Greenwood, J., 2016. Buy, keep, or sell: economic growth and the market for ideas. Econometrica 84, 943–984.

Allison, J.R., Lemley, M.A., 2000. Who's patenting what? An empirical exploration of patent prosecution. Vanderbilt Law Rev. 53, 2099–2174.

Allison, J.R., Lemley, M.A., Schwartz, D.L., 2015. Our divided patent system. Univ. Chic. Law Rev. 82, 1073–1154.

Allison, J.R., Lemley, M.A., Schwartz, D.L., 2017. How often do non-practicing entities win patent suits? Berkeley Technol. Law J. 32, 237–310.

Bereskin, F.L., Hsu, P., Latham, W.R., Wang, H., 2021. So sue me! Stock market reactions to alleged patent infringers. Unplublished Working Paper. University of Missouri.

Brennan, M.J., Chordia, T., Subrahmanyam, A., 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. J. Financ. Econ. 49, 345–373.

Chemmanur, T.J., Fughlieri, P., 2014. Entrepreneurial finance and innovation: an introduction and agenda for future research. Rev. Financ Stud. 27, 1–19.

Cohen, L., Diether, K., Malloy, C., 2013. Misvaluing innovation. Rev. Financ Stud. 26, 635–666.

Cohen, L., Gurun, U.G., Kominers, S.D., 2016. The growing problem of patent trolling. Science 352, 521–522.

Cohen, L., Gurun, U.G., Kominers, S.D., 2019. Patent trolls: evidence from targeted firms. Manag. Sci. 65, 5461–5486.

Core, J.E., Holthausen, R.W., Larcker, D.F., 1999. Corporate governance, chief executive officer compensation, and firm performance. J. Financ. Econ. 51, 371–406.

Falato, A., Kadyrzhanova, D., Lel, U., 2014. Distracted directors: does board busyness hurt shareholder value? J. Financ. Econ. 113, 404–426.

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. J. Financ. 47, 427–465.

Fama, E.F., French, K.R., 2008. Dissecting anomalies. J. Financ. 63, 1653–1678.

Fama, E.F., French, K.R., 2018. Choosing factors. J. Financ. Econ. 128, 234–252.

Farre-Mensa, J., Hegde, D., Ljungqvist, A., 2020. What is a patent worth? Evidence from the U.S. patent "lottery. J. Financ. 75, 639–682.

Feng, J., Jaravel, X., 2020. Crafting intellectual property rights: implications for patent assertion entities, litigation, and innovation. Am. Econ. J.: Appl. Econ. 12, 140–181.

Fich, E.M., Shivdasani, A., 2006. Are busy boards effective monitors? J. Financ. 61, 689–724.

Fitzgerald, T., Balsmeier, B., Fleming, L., Manso, G., et al., 2021. Innovation search strategy and predictable returns. Manag. Sci. 67, 1109–1137.

Frakes, M.D., Wasserman, M.F., 2015. Does the U.S. patent and trademark office grant too many bad patents? Evidence from a quasi-experiment. Stanf. Law Rev. 67, 613–676.

Frakes, M.D., Wasserman, M.F., 2017a. Is the time allocated to review patent applications inducing examiners to grant invalid patents? Evidence from microlevel application data. Rev. Econ. Stat. 99, 550–563.

Frakes, M.D., Wasserman, M.F., 2017b. Procrastination in the workplace: evidence from the U.S. Patent Office. Unpublished working paper. Nat. Bur. Econ. Res..

Gao, X., Ritter, J.R., Zhu, Z., 2013. Where have all the IPOs gone? J. Financ.Quant. Anal. 48, 1663–1692.

Hall, B.H., Jaffe, A.B., Trajtenberg, M., 2001. The NBER patent citations data file: lessons, insights and methodological tools. Unpublished working paper. Nat. Bur. Econ. Res..

Hall, B.H., Jaffe, A.B., Trajtenberg, M., 2005. Market value and patent citations. RAND J. Econ. 36, 16–38.

Hauser, R., 2018. Busy directors and firm performance: evidence from mergers. J. Financ. Econ. 128, 16–37.

He, J., Tian, X., 2018. Finance and corporate innovation: a survey. Asian Pac. J. Financ. Stud. 47, 165–212.

He, J., Tian, X., 2020. Institutions and Innovation: a review of recent literature. Annual Rev. Financ. Econ. Forthcoming.

Hirshleifer, D., Hsu, P., Li, D., 2018. Innovative originality, profitability, and stock returns. Rev. Financ. Stud. 31, 2553–2605.

Hirshleifer, D., Lim, S., Teoh, S., 2009. Driven to distraction: extraneous events and under-reaction to earnings news. J. Financ. 64, 2289–2325.

Hirshleifer, D., Teoh, S., 2003. Limited attention, information disclosure, and financial reporting. J. Account. Econ. 36, 337–386.

Hoberg, G., Phillips, G., Prabhala, N., 2014. Product market threats, payouts, and financial flexibility. J. Financ. 69, 293–324.

Hou, K.i, Xue, C., Zhang, L., 2015. Digesting anomalies: an investment approach. Rev. Financ. Stud. 28, 650–705.

Jia, N., Tian, X., 2018. Accessibility and materialization of firm innovation. J. Corp. Financ. 48, 515–541.

Kempf, E., Manconi, A., Spalt, O., 2017. Distracted shareholders and corporate actions. Rev. Financ. Stud. 30, 1660–1695.

Kerr, W.R., Nanda, R., 2015. Financing innovation. Annu. Rev. Financ. Econ. 7, 445–462.

Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation and growth. Q. J. Econ. 132, 665–712.

Lanjouw, J.O., Schankerman, M., 2001. Characteristics of patent litigation: a window on competition. RAND J. Econ. 32, 129–151.

Lemley, M.A., 2001. Rational ignorance at the patent office. Northwest Univ. Law Rev. 95, 1495–1532.

Lemley, M.A., Sampat, B., 2012. Examiner characteristics and patent office outcomes. Rev. Econ. Stat. 94, 817–827.

Masulis, R.W., Zhang, J., 2019. How valuable are independent directors? Evidence from external distractions. J. Financ. Econ. 132, 226–256.

Pressman, D., Stim, R., 2015. Nolo's Patents for Beginners, 8th Edition Nolo, Berkeley, CA.