Do Lawyers Matter? Evidence from Patents

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Abstract

We investigate the role of patent attorney capability in determining the value of patents. We establish a positive correlation between attorneys' substantive expertise (success rate in obtaining patents) and both the economic and technological value of patents. This finding holds irrespective of the number of patents obtained by patent attorneys to date (process experience). Then we identify the causal effect of patent attorney expertise on the value of patents by using two alternative approaches: patent attorney changes and the opening of four new regional offices by the United States Patent and Trademark Office (USPTO). Overall, we find that successful patent attorneys matter as they increase both the economic and technological value of patents. Therefore, tracking a patent attorney's success record can have significant implications.

JEL classifications: O31, C33, G14

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1. Introduction

We investigate whether patent attorneys[1] impact the value of firm innovation by examining the relation between patent attorney capability and the economic and technological value of patents. Patent attorneys play a central role in drafting patent applications and negotiating the scope of patent protection with patent examiners (Reitzig, 2004). We argue that more capable patent attorneys, those with more experience in filing patent applications and a higher success rate in obtaining patents, can help firms secure more economically- and technologically-valuable patents. The value implications of patent attorneys' capability remain largely unexplored. We address this gap by examining two types of value implications: *economic*, as measured by the market reaction to patent announcements, and *technological*, as measured by patent citations.[2]

Patents can create a financial motivation for innovation in return for the disclosure of the innovation to the public (Hall and Harhoff, 2012). Patents are valuable because they can protect firms' inventions from being practiced or commercialised by others. The number of patents is growing, with 388,900 new patents granted in the US in 2020, an increase of 103% compared with 191,927 patents granted in 2009. The market reacts positively to announcements of new patents (Kogan et al., 2017), which can boost firm growth (Farre-Mensa et al., 2020), profitability (Pandit et al., 2011), as well as survivability and access to capital (Hegde et al., 2022).

The purpose of patent attorneys is to obtain valid, broad, and both economically and technologically valuable patents for their clients. The USPTO advises inventors to hire patent attorneys to prepare and pursue patent applications on their behalf (USPTO, 2020). The work

[1] We use the term 'patent attorney' to refer to both patent attorneys and patent agents. Both attorneys and agents are qualified to represent their clients before the USPTO.
[2] Citations are the most widely used proxy for patent quality (Hirschey and Richardson, 2004; Trajtenberg, 1990) and are connected to firm value as Hall et al. (2005) find that one additional citation per patent is associated with a 3% higher firm value.

of patent attorneys requires both scientific and legal expertise. Patent attorneys consider the probability of different legal scenarios and use their expertise to draft patents and negotiate with patent examiners in a way that maximises the overall expected profits for their clients (Reitzig, 2004). Therefore, patent attorneys can have a significant influence on the value of patents, as measured by the market reaction to patent announcements and the number of citations received by patents.

Despite these patent-specific activities, the general work of a patent attorney is comparable to the role of a conventional attorney. Attorneys apply their knowledge of the law to construct legal arguments and negotiate on behalf of their clients. Attorneys have different levels of legal expertise (Posner and Yoon, 2011) and experience in representing their clients in courts (Abrams and Yoon, 2007). The *attorney capability theory* predicts that more capable attorneys produce better outcomes for their clients (Miller et al., 2015; Szmer et al., 2007). For example, more capable attorneys increase the probability of winning in the US Supreme Court (McGuire, 1995), obtain shorter sentences for the defendants they represent in felony cases (Abrams and Yoon, 2007), and secure higher monetary settlements for firms in corporate litigation (Ferrell et al., 2021). Therefore, we argue that patent attorneys' legal expertise and the experience they gain in working with the USPTO should be reflected in the economic and technological value of patents they have worked on. We distinguish between substantive legal expertise of patent attorneys and the process expertise they gain as they repeatedly pursue patent applications (Haire et al., 1999; Kritzer, 1998). We measure substantive legal expertise of attorneys using their success rate in obtaining patents from the patent office, and we capture their process expertise using the cumulative number of patent applications filed. For robustness, we also use alternative proxies of expertise, as discussed in section (5).

The results support the importance of legal expertise of patent attorneys. With regards to the economic value, a one standard deviation (11.6%) increase in legal expertise is related to a

0.035% higher market reaction to a patent announcement. This effect accumulates to a 13% (=373*0.035%) increase in market value for an average company in our sample which obtained 373 patents during 2003-2019. Moreover, we find that legal expertise of patent attorneys has a positive relation with the technological value of patents. A one standard deviation increase in legal expertise is associated with 3% more citations received by the patent. These results show that there is a positive correlation between patent attorney substantive expertise and the economic and technological value of patents. This suggests that successful attorneys are more skilled at pursuing patent applications.

We also test whether the experience accumulated by patent attorneys affects the value of patents. This helps us determine whether patent attorney firms that are simply larger or more popular, in terms of the number of applications filed, are associated with patents that are more valuable. Contrary to the literature on conventional attorney ability (Abrams and Yoon, 2007; McGuire, 1995), we find that the experience patent attorneys gain by submitting more patent applications is not related to the economic or technological value of patents. This suggests that the value of patents cannot be explained by the different popularity or the different process experience levels of patent attorneys.

Arguably, firms may choose to hire more capable attorneys to work on obtaining patents for inventions that are more important to them (de Rassenfosse et al., 2022). We address the potential selection issues arising from a non-random matching between the patent attorneys and the inventions in two different ways. First, we investigate whether patent attorney expertise has a causal effect on the economic and technological value of patents by exploiting the opening of new regional offices by the USPTO. Patent attorneys located in the states in which the new offices are opened can benefit due to an easier access to patent examiners with whom they can conduct in-person interviews to negotiate the grant of a patent (Lemley and Sampat, 2010). We find that the impact of substantive expertise of patent attorneys on the economic value of patents increased after the opening of the new USPTO offices. This only applies to patent attorneys located in the states in which new offices were opened, which suggests an existence of a causal relationship between patent attorney substantive expertise and the economic value of patents. We also find that the impact of the affected attorneys' expertise on the technological value of patents did not change after the new USPTO offices were opened. This is consistent with the fact that an examiner interview occurs at a late stage of the patent examination process, when the technological aspects of an invention have already been finalised (Lemley and Sampat, 2010).

Second, we study the changes in a firm's patent attorney. We compare patents represented by different attorneys that were granted to the same company in close succession. If patent attorneys matter, we expect a positive (negative) effect of a change to a more (less) capable attorney. We find that patents of companies that switch to a patent attorney with higher (lower) substantive expertise receive more (fewer) citations and experience a higher (lower) stock market reaction at grant. The magnitude of the effect increases as the capability gap between the new and the old patent attorney widens.

In the last part of this paper, we investigate whether more capable patent attorneys are recognised for their higher performance in the annual patent attorney law firm rankings published by the Legal500. We expect that the most successful patent attorneys are also among the highest ranked. We find that there is a simple negative (positive) correlation between top ranked patent attorney firms and their substantive (process) expertise. Moreover, we find that the top patent attorney firm rankings are not statistically related to higher economic or technological value of patents. This suggests that patent attorney rankings are not effective predictors of patent value, and that they perform poorly at identifying high-capability patent attorneys.

To our knowledge, this is the first study to investigate the effect of patent attorney capability on the economic and technological value of patents. We show that the legal expertise of patent attorneys increases the economic value of patents. Only capable patent attorneys create value for their clients. Therefore, innovating firms should closely monitor the attorneys' track record. Furthermore, we provide evidence that more capable patent attorneys are positively related to patents' technological value, as measured by patent citations. This study contributes to the literature studying the effect of patent attorneys on patents by examining their impact on the economic and technological value of patents (de Rassenfosse et al., 2022; Gaudry, 2012; Somaya et al., 2007; Klincewicz and Szumial, 2022). Finally, to our best knowledge, this is the first study to test the relation between patent attorney law firm rankings and the economic and technological value of patents.

2. Hypotheses development

Navigating the patent application process requires legal expertise (Lee, 2020). First, applicants need to know how to write a valid patent application and what information must be disclosed with the patent office. Applicants that fail to disclose information that is material to the invention's patentability risk the patent being held unenforceable (Hricik and Meyer, 2009). Second, applicants need to know how to negotiate with patent examiners. When an examiner receives a patent application, generally they initially reject it (Lemley and Sampat, 2010).[3] It takes on average 3 years to obtain a patent (Farre-Mensa et al., 2020). The USPTO recommends hiring a patent attorney because "the value of a patent is largely dependent upon skilled preparation and prosecution" (USPTO, 2020, p.2).

The capability of patent attorneys may affect the value of patents. Patent attorneys often work closely with inventors, and they can recommend changes to an invention that would

[3] After an examiner first reviews a patent application, in 86.5% of the cases they send the applicant a written notification that objects to one or more of the claims. In response, the applicant typically amends the claims and/or argues against the objections (Lu et al., 2017).

improve its commercial value and patentability before it is disclosed to the patent office (Chondrakis et al., 2021). Attorneys are often responsible for drafting patent claims, which determine the scope and validity of patent protection with relation to a technology (Yelderman, 2014). Also, attorneys often conduct prior art searches, prepare patent applications, and then negotiate the grant of patents with patent examiners (Gaudry, 2012; Lu et al., 2017).

The roles of a patent attorney and a conventional attorney are similar. Applying their knowledge of the law, constructing convincing arguments, and negotiating on behalf of their clients is required both of conventional attorneys (McGuire, 1995) and of patent attorneys (Chondrakis et al., 2021). The *attorney capability theory* posits that attorneys accrue valuable experience over time that helps them achieve better outcomes (McGuire, 1995; Miller et al., 2015). Therefore, we apply the *attorney capability theory* to test the importance of patent attorneys.

The origins of the theory can be traced back to Galanter (1974) who distinguishes between parties which only occasionally appear in courts and parties which are repeatedly engaged in litigation. The latter type accrues valuable experience over time that makes them more effective than infrequent litigators. McGuire (1995) modifies the party capability theory of Galanter (1974) and argues that attorneys themselves are repeat-players. Over time, judges develop trust in the arguments presented by experienced legal practitioners, who are expected to communicate truthful information to maintain their good reputation (McGuire, 1995; Szmer et al., 2007). McGuire (1995) shows that attorneys who frequently litigate in the US Supreme Court can increase their clients' probability of success by 8%. Szmer et al. (2007) find that attorneys' prior litigation experience and litigation team size are positively associated with the probability of winning in litigation. Haire et al. (1999) find that inexperienced attorneys as well as attorneys not specialising in a relevant area of the law are less likely to succeed in litigation. Miller et al. (2015) find that attorneys' past general and judge-specific success rates positively predict successful outcomes, while an attorney's workload negatively affects the probability of success (Miller et al., 2015). Overall, these studies show that attorney capability matters.

Attorneys differ in their levels of process expertise (McGuire, 1995); and substantive expertise (Haire et al., 1999; Posner and Yoon, 2011). Process expertise is defined as the level of an attorney's familiarity with a particular court and is commonly measured by counting the number of interactions between the attorney and the said court (Szmer et al., 2007). We capture process expertise by counting the number of patent applications filed by a patent attorney irrespective of whether they are successful or not. Substantive expertise refers to the attorney's specialist knowledge of law and the skill of applying relevant legal rules to situations at hand (Miller et al., 2015). Substantive expertise of patent attorneys is measured using the percent of patent applications filed by a patent attorney that resulted in a granted patent, based on a rolling success measure.

Overall, the literature finds support for the *attorney capability theory*. Attorneys with higher substantive expertise, and attorneys with higher process expertise produce superior results for their clients. Similarly, the different capability of patent attorneys may influence the value of patents that they worked on. This leads to the first hypothesis:

Hypothesis 1a: Patent attorney substantive expertise is positively related to the economic value of patents they represent.

Hypothesis 1b: Patent attorney process expertise is positively related to the economic value of patents they represent.

Patent attorneys can act strategically when drafting patent claims. They need to consider the balance between breadth and validity of the claims. Patent breadth, which is also known as patent scope, is largely determined by patent claims. Patents with a broader scope protect a larger number of competing products and processes (Merges and Nelson, 1990). Broad claims are generally more valuable (Hegde et al., 2022; Lerner, 1994), but the benefit of the broader scope is limited by the risk of a claim being found invalid (Yelderman, 2014). Validity determines the probability of the patent being found invalid in court.[4] Therefore, patent attorneys will try to increase the scope for inventions with a high degree of novelty and non-obviousness and will aim to decrease the scope for non-original inventions (Reitzig, 2004).

Moreover, patent applicants can act strategically when deciding what information to reveal to the patent office. Sampat (2010) finds that applicants often fail to disclose information about their own previous patents, and that they provide more citations for inventions that are more important to them. This suggests strategic behaviour, since it is unlikely that applicants are not aware of their own patents (Sampat, 2010). Furthermore, Kuhn et al. (2020) argue that some patents deliberately include a large number of citations. Applicants can benefit by hiding relevant information in this long list of immaterial citations, as examiners facing time constraints (Frakes and Wasserman, 2017) will not be able to review all of them (Kuhn et al., 2020). Moreover, Barber and Diestre (2022) find that patent attorneys can use patent citations to impact which examiners are assigned to patent applications. In turn, this can help them obtain patents more easily (Barber and Diestre, 2022). Overall, patent attorneys can influence how an invention is disclosed in a patent application, which can affect the number of patent citations that it ultimately receives. This leads to the second hypothesis:

Hypothesis 2a: Patent attorney substantive expertise is positively related to the technological value of patents they represent.

Hypothesis 2b: Patent attorney process expertise is positively related to the technological value of patents they represent.

The potential of patent attorneys to create value for firms is an understudied area. Only a few studies focus on the importance of patent attorneys for obtaining patents. Gaudry (2012)

[4] Although the USPTO is only supposed to grant valid patents, it has been criticised for awarding patents with low validity (Lemley and Shapiro, 2005; Farrell and Shapiro, 2008).

tests the effect of hiring a patent attorney by comparing patent examination histories of 250 randomly selected US patent applications, where an inventor represented herself, with 250 randomly selected US patent applications represented by a patent attorney. Gaudry (2012) finds that applications represented by the inventors themselves are abandoned 76.4% of the time, compared to 34.8% of applications represented by patent attorneys. Similarly, Klincewicz and Szumiał (2022) find that the involvement of patent attorneys in the process of pursuing patents increases the likelihood of obtaining patent protection in Poland. Somaya et al. (2007) use the total number of US patent attorneys working for a company in any given year as a proxy for patent expertise of a firm, and they find that it has a positive and statistically significant effect on patenting performance. Frietsch and Neufausler (2019) find that patent attorneys that represent individual inventors are less experienced than the ones representing large companies, and that patents represented by experienced attorneys have a lower probability of being opposed at the European Patent Office (EPO) after grant. In addition, they find no effect of patent attorney experience on the likelihood of patent grant. This is at odds with de Rassenfosse et al. (2019) who find evidence that a one standard deviation increase in patent attorney quality is associated with a 2% increase in the probability of a grant. The different findings might be explained by the fact that de Rassenfosse et al. (2019) used a sample of 1.2 million international patent applications instead of the 1.8 million EPO patent applications. Moreover, they measured patent attorney expertise using the conditional average patent grant success rate of each representative instead of the number of patent applications filed by an attorney.

The analysis presented in this paper differs from these studies in three main ways. First, we focus on how valuable patent attorney capability is to public companies by testing its effect on the economic and technological value of patents owned by the firms. Second, we draw on the *attorney capability theory* and we distinguish between the substantive legal expertise and the process expertise of patent attorneys. Lastly, we measure patent attorney capability using data on millions of US patent applications represented by different attorneys (see section 3.2). Arguably, the larger amount of data relative to the prior literature increases the power of the analysis.

3. Data and descriptive statistics

3.1 Data selection

We use the 2020 release of the USPTO's Patent Examination Research Dataset (PatEx). The dataset includes detailed information on 9.6 million utility[5] patent applications filed at the USPTO until 8 April 2021. This includes information on application number, application type, application filing date, and patent grant number along with its issue date (if the patent application was successful and it led to a grant of a patent). The primary advantage of using the PatEx dataset is that it also contains data on the patent applications' examination history, which includes the names and locations of patent attorneys or patent law firms representing the applications.

This type of data is only available for patent applications that are open to public inspection, and it does not cover non-public patent applications (Graham et al., 2015). The implementation of the American Inventors Protection Act (AIPA) on 29 November 2000 largely eliminated the selection bias in the dataset by requiring all patent applications to be published by default, 18 months after they were filed (Graham et al., 2015). Therefore, we restrict our sample to applications with a non-missing filing date that were filed from 2001 onwards (Farre-Mensa et al. 2020; Hegde et al., 2020). This reduces the sample to 6.9 million patent applications. To study the market reaction, we keep applications that were successful and resulted in granted patents (4.3 million utility patents). We remove patents granted after 2019, due to the

[5] Utility patents cover technological inventions (Durham, 2009). Over 90% of patents issued by the USPTO in 2019 were utility patents. The two other types of patents are design and plant patents. Design patents protect new and original artistic representations (Durham, 2009). Plant patents can be obtained on plants that are reproduced asexually.

exceptional market circumstances created by the outbreak of COVID-19, which leaves us with 3.9 million patents.

The market reaction to patent grants can only be measured for patents which belong to publicly listed companies. To identify these firms, we use the patent-CRSP link created by Stoffman et al. (2022), who match companies in CRSP to patents granted by the USPTO until 31 December 2020. We successfully match 1.5 million patents to publicly listed firms. We obtain security return data from CRSP and accounting data from Compustat. We remove observations with missing stock return or accounting data, and we exclude financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4949) (Kogan et al., 2017; Stoffman et al., 2022). This leaves 1.47 million patents.[6] We obtain data on patent characteristics, including citations and claims from USPTO PatentsView (Stoffman et al., 2022).

For each company in the sample, we obtain earnings announcement dates from CRSP and dividend declaration dates from Compustat. In order to avoid contamination of the patent events by other closely occurring events, we remove patent announcements which occur within two trading days of a firm's earnings or dividend announcements (Bowman, 1983; de Jong and Naumovska, 2016), resulting in 1.3 million patents granted to 3,461 firms during 2003-2019. This sample is used for conducting the event study of patent grants (section 4.1) and for testing the importance of patent attorney expertise (sections 4.2-4.6). The sample selection process is presented in Table 1.

/Table 1 here/

3.2 Measures of patent attorney expertise

We capture substantive expertise of patent attorneys with their rolling grant success rate. The success rate is calculated as the number of successful patent applications divided by the

[6] The sample size is similar to prior literature using US patent data. For example, Chemmanur et al. (2021) study a sample of 0.9 million US patents granted between 2000 and 2014. Kogan et al. (2017) use 1.8m patent grants between 1926 and 2010.

sum of successful and abandoned applications represented by an attorney. We update this measure on a yearly rolling basis. Measuring patent attorney expertise using their success rate captures how effective they are at obtaining patents for their clients. A rational individual will abandon a patent application when the costs of patent protection outweigh the potential benefits (Bessen, 2008; Lemley and Sampat, 2008). For example, a patent applicant might abandon an application when a patent examiner is only willing to allow the application if the patent applicant agrees to significantly narrow the claims (Lichtman et al., 2004). This, in turn, can deem the application as no longer worth of being pursued.

Process expertise is proxied by the cumulative number of patent applications (successful and unsuccessful) filed by patent attorneys. We use the natural logarithm of this number to account for the fact that filing of each additional patent application can have a plausibly decreasing marginal effect on process expertise (Frietsch and Neuhausler, 2019). We update this measure on a yearly rolling basis to include the filing of new patent applications.

We construct the expertise measures using data on all patent applications in the PatEx dataset, which includes patents filed by individual inventors, private firms, and public companies. We use all patent applications that were filed since 1980 in order to account for the fact that some patent attorneys have been gaining experience before the implementation of AIPA. Alternatively, we construct the measures using 29 November 2000 as the starting point for robustness.

We use the name of the entity with whom the USTPO is meant to correspond about the patent application to identify the patent attorneys.[7] Entities identified as patent attorneys include patent attorney firms, individual patent attorneys, and legal departments of companies. We clean the misspellings of patent attorneys' names in the PatEx dataset before constructing the measures. The steps of the cleaning process are described in Appendix A. Table 2 presents

[7] We use the "correspondence name" variable from the PatEx dataset (Graham et al., 2015).

the list of top 25 patent attorneys according to the total number of patent applications they filed between 1980 and 2019. Table 2 also illustrates the total success rate of each attorney during the period, and it shows that even among the most popular patent attorneys the success rate varies from 68% to 90%.

/Table 2 here/

3.3 Descriptive statistics

Table 3 shows the descriptive statistics, which are presented on a patent announcement day level.[8] All variables are defined in Appendix B. Panel A illustrates the characteristics of 3,461 publicly listed firms which obtained 1.3 million patents during 2003-2019. The average company has a market capitalisation of $27.7 billion, and the median company has a market capitalisation of $5.4 billion. With a debt to assets ratio of 0.52, the average company in the sample is highly leveraged in comparison to the average nonfinancial corporation headquartered in the US (Palazzo and Yang, 2019). The average firm in the sample has an R&D intensity of 9.3%. This is more than double the average R&D intensity of a typical US company of 4.1% (Wolfe, 2020). The characteristics of the patents granted to the companies are shown in Panel B. The average patent in the sample has a truncation adjusted amount of forward citations of 1.1.[9] Moreover, the average patent contains 29.6 backward citations, and 1.0 independent claims.[10] The descriptive statistics of the measures of patent attorney capability are presented in Panel C. The average rolling success rate is 83.8%, with a standard deviation of 11.6%.[11] This is similar to Gaudry (2012), who reports that 65.2% of patent applications represented by patent attorneys are successful, compared to 23.6% of applications represented

[8] New patents are announced by the USPTO every Tuesday. The USPTO can announce a grant of multiple patents to the same company on the same day, but since we observe one market reaction per announcement day, we treat each announcement as one observation.
[9] When counting the number of citations, we exclude citations that originated from patent examiners and citations by other patents of the same patent owner.
[10] Independent claims are complete sentences that stand on their own, without referring to other claims (Marco et al. 2019). Dependent claims refer to an independent claim and add a limitation to it.
[11] Given that the distribution of rolling success rate is skewed, we have rerun the analysis using a log-transformed rolling success rate. The results are similar.

by the inventors themselves. Lastly, 4.6% of patent announcements include a patent attorney firm which is ranked as a tier one firm by Legal500. Moreover, 18.9% of the announcements include a patent attorney firm that is listed in any of the five tiers in the Legal500 rankings (see section 4.6 for more details on the Legal 500 rankings).

/Table 3 here/

Appendix C presents a breakdown of the sample by year of patent grant along with the number of unique companies that obtained patents that year. The yearly number of patent grants increases from 33,983 in 2003 to 106,271 in 2019. Appendix D shows the top 25 firms by the number of patents obtained between 2003 and 2019. The top 25 patent owners are responsible for 42% of the patent grants.

Appendix E provides the sample statistics by industry. The top 5 industries, based on the Fama French 49 industry classification, are Electronic Equipment, Computer Software, Computer Hardware, Automobiles and Trucks, and Electrical Equipment, and they collectively account for 61% of patent grants. Lemley and Sampat (2008) report that the information technology industries are responsible for half of all patent applications. Building patent portfolios is important to technology companies (Burk and Lemley, 2009), because it can take multiple patents to protect a complex invention. This leads to fragmentation of patent rights. Ziedonis (2004) shows that semiconductor firms patent aggressively to secure the right to invest in new technologies and avoid being “fenced in” by other patent owners.

4. Methodology, analysis, and results

4.1 Event study of patent grants

We begin by using a standard event study approach to measure the market valuation of patent announcements. We estimate abnormal returns (ARs) based on the difference between the security’s return and the return on the market portfolio:

$$AR_{i,t} = R_{i,t} - R_{m,t} \tag{1}$$

where $AR_{i,t}$ is the abnormal return of a security i on day t, and $R_{i,t}$ is the actual return of a security i on day t. $R_{m,t}$ is the risk-free rate adjusted market return on day t.[12] As many companies in the sample obtain patents every month or even every week, we use the market adjusted model in equation (1), similar to Kogan et al. (2017).[13] This approach mitigates the potential measurement error that is introduced when estimating a company's stock market beta by using asset pricing models that rely on non-overlapping pre-event estimation periods (Brown and Warner, 1985; MacKinlay, 1997).

Panel A of Figure 1 illustrates the abnormal returns around the patent announcement. The daily abnormal return sharply increases on day 1, which suggests a delayed market response to patent announcements. In Panel B of Figure 1, we distinguish between the market reaction to patents represented by more capable versus less capable patent attorneys. We define patent attorneys as more (less) capable when their rolling success rate is in the top (bottom) 40% of the distribution. The graphs suggest that patents represented by patent attorneys with high substantive expertise experience a more favourable stock market reaction than patents represented by attorneys with low substantive expertise. When we define more (less) capable patent attorneys based on the total number of patent applications that they have filed, we see no difference in the share price reactions. This suggests that process expertise of patent attorneys does not matter.

We measure the patent announcement returns over a three-day event window (0,+2) as in Kogan et al. (2017).[14] For robustness, we also measure the market response over alternative event windows and the results are similar. Table 4 shows the daily abnormal returns between day 0 and day +3 and the cumulative abnormal returns over the (0,+1), (0,+2), and (0,+3) event

[12] The risk-free rate adjusted market return for North America is from Kenneth French's website.
[13] New patents are published by the USPTO every Tuesday. This is the first time that newly granted patents are announced by the patent office (Kogan et al., 2017).
[14] The share turnover increases during the (0,+2) window around a patent announcement, which suggests that this is when the market reacts to the announcement (Kogan et al., 2017).

windows. Panel A shows that the market reacts positively to patent announcements. An average patent announcement has a CAR(0,+2) of 0.029%, which is statistically significant at the 1% level. This is also economically significant. The mean market capitalisation in the sample at the time of an average patent announcement is $27.7 billion (see Table 3). Given an average CAR(0,+2) of 0.029%, the mean patent announcement is associated with an increase in market value of $8.0 million (=0.029%*$27.7 bn). This is similar to Kogan et al. (2017), who find that a median patent owned by a publicly listed company is worth $3m, and an average patent is valued at $10.3m. The results are also quantitively similar to those of Chemmanur et al. (2021), who report a market reaction of 0.010% based on 879,204 patent announcements.

/Table 4 here/

In panels B and C of Table 4, we distinguish between patent announcements associated with attorneys that have high and low substantive expertise, respectively.[15] Panel B of Table 4 shows that attorneys with high expertise are associated with a CAR(0,+2) of 0.074%, which is statistically significant at the 1% level. In contrast, panel C of Table 4 shows that announcements associated with attorneys with low substantive expertise generate a CAR(0,+2) of -0.032%, significant at the 1% level. This suggests that using the services of high-expertise patent attorneys can increase the market valuation of patent announcements.

4.2 The effect of patent attorney expertise on the economic value of patents

Next, to explore the relationship between patent attorney expertise and the value of patents in more detail, we conduct a multivariate OLS regression analysis. We estimate the following model:

$$CAR_{i,t} = \alpha + \beta_1 * patent\ attorney\ expertise_{i,t} + \beta_2 * patent\ grants\ volume_{i,t} + \beta_n * X_{i,t-1} + \gamma + \xi + \psi + u_{i,t} \quad (2)$$

[15] We define the expertise to be high (low) when the attorneys' rolling success rate is in the top (bottom) 40% of the distribution.

$CAR_{i,t}$ is the average cumulative abnormal return over a three-day window (0,+2).[16] The independent variable of interest is *patent attorney expertise*, which is a proxy for a patent attorney's level of competence. We include *patent grants volume* to control for the number of patents granted on the same day to the same firm since the market can react more positively to announcements of multiple patents. $X_{i,t-1}$ is a vector of firm specific control variables that includes *market capitalisation*, as larger firms may create more valuable innovation (Kogan et al., 2017); *firm age*, as younger firms can produce higher quality innovation (Balasubramanian and Lee, 2008), *return on assets*, as profitability is positively associated with patent quality (Pandit et al., 2011); *leverage*, as debt levels can impact firm innovation (Geelen et al., 2022) and *R&D*, as companies that invest more in R&D can be better innovators (Chen et al., 2018). γ, ξ, and ψ denote year, firm, and patent technology class fixed effects[17], respectively. We include patent technology class fixed effects because the value of patents can differ depending on the underlying technologies (Bessen, 2008), and to control for the fact that patent approval rates may vary across different technology fields (Carley et al., 2015; Hall et al., 2001).[18] the identifying assumption is that after controlling for the variables listed above, patent attorney expertise is exogenous. We do not use patent attorney fixed effects, because we are interested in studying the cross-sectional patent attorney-level variation in the analysis. Moreover, patent attorney fixed effects would be collinear with the main explanatory variable, rolling success rate, which captures patent attorney capability.

First, we use the rolling success rate of a patent attorney as a proxy for their substantive expertise. Regression results are shown in Table 5. In column (1), we regress CAR(0,+2) solely on the rolling success rate, and we include year, firm, and patent class fixed effects. Ceteris

[16] In alternative specifications we use alternative event windows, and the results remain similar.
[17] We also test different combinations of fixed effects, including industry, art unit, and examiner fixed effects. The results remain robust to the choice of fixed effects.
[18] If multiple patents are granted to the same firm on the same day, we use the dominant patent class on that day to compute the patent class fixed effects. The results are not sensitive to the way we compute the fixed effects. Moreover, the results are similar when we do not include patent class fixed effects in the model.

paribus, the positive and statistically significant coefficient (at the 1% level) on the rolling success rate indicates that the market valuation of a patent increases by 0.30% when the rolling success rate increases by 100%. The standard deviation of the rolling success rate is 11.6% (see Table 3). Therefore, a one-standard deviation increase in rolling success rate increases the market valuation by 0.035% (=11.6%*0.30%). This is economically significant. The average company in the sample has obtained 373 patents between 2003-2019 (see Appendix C). Hiring a competent law firm or a patent attorney to represent a firm's patent applications can increase the market value of an average company in the sample by 13.1% (=373*0.035%).

/Table 5 here/

Columns (2) and (3) in Table 5 add control variables and the main result remains unchanged. The coefficients on the control variables indicate that firm size and firm age negatively predicts the market reaction to patent grants, which is consistent with the results reported in prior literature (Chemmanur et al., 2021; Chen et al., 2018). Overall, the results support the first hypothesis (*H1a*). Although the R^2 is low, ranging from 2.8% to 2.9%, it is consistent with the literature on patent announcements (Boscaljon et al. 2006; Chen et al., 2018; Chemmanur et al., 2021).

Second, we proxy for patent attorney expertise using the number of patent applications that they have previously represented before the USPTO. We present the regression results in Table 6. The results show that across specifications, the number of applications filed to date do not have a statistically significant effect on the market valuation of patents. Similar to the results presented in Table 5, firm size and firm age are negatively correlated with the market reaction to patent grants. This finding suggests that patent attorneys do not gain valuable experience by simply submitting more patent applications to the USPTO, and the busiest patent attorneys are not necessarily the most capable. Therefore, the results do not support hypothesis *H1b*.

/Table 6 here/

4.3 The effect of patent attorney expertise on the technological value of patents

Next, we explore whether the expertise of a patent attorney, as measured by their rolling success rate, affects the number of citations that a patent receives. Patent citations are widely used as a proxy for patent quality (Hirschey and Richardson, 2004; Trajtenberg, 1990). Since patent attorneys influence the scope and validity of patents, we predict that the effect of patent attorney expertise will be reflected in the number of citations received by a patent. To test this, we estimate the following model:

$$Patent\ citations_i = \alpha + \beta_1 * patent\ attorney\ expertise_{i,t} + \beta_2 * \ln(market\ capitalisation)_{i,t-1} + \beta_3 * backward\ citations_i + \beta_4 * independent\ claims_i + \gamma + \xi + \psi + u_{i,t} \quad (3)$$

The dependent variable is *patent citations*, which is the truncation-adjusted number of citations received by a patent.[19] Using truncation-adjusted number of citations addresses the issue of older patents having had more time to accumulate citations than younger patents (Hall et al., 2001). Moreover, when counting citations, we exclude any citations that a patent receives from patent examiners and any citations it receives from the patent applicants themselves, because these citations are unlikely to reflect the technological value of a patent (Alcácer et al., 2009). The independent variable of interest is patent attorney's expertise, which we first proxy for using a patent attorney's rolling success rate. The controls include *market capitalisation*, which is a proxy for company size (Kogan et al., 2017) and patent quality control variables, which include *backward citations* and *independent claims.*[20] Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects,[21] respectively.

[19] We calculate the truncation-adjusted patent citations by dividing the number of citations received by a patent by the number of citations received by an average patent granted in the same year. For example, if a patent that was granted in 2005 has accumulated 6 citations, but the average patent granted in 2005 has so far received only 3 citations, the truncation-adjusted number of patent citations is equal to 2.

[20] *Independent claims* is a proxy for patent scope, which affects patent quality (Marco et al., 2019). Backward citations are correlated with patent importance (Jaffe and de Rassenfosse, 2019).

[21] The results remain robust to the choice of different fixed effects, including industry, art unit, and examiner fixed effects.

First, we study the relation between the number of patent citations and patent attorney substantive expertise. The regression results are shown in Table 7. In column (1) of Table 7, we regress *patent citations* on the rolling success rate in isolation and we include year, firm, and patent class fixed effects. The results suggest that patent attorney expertise is a statistically significant predictor of the technological value of patents, at the 1% level. A one standard deviation increase in the rolling success rate is associated with 0.032 (=11.6%*0.28) more truncation-adjusted patent citations. Given that the mean value of truncation adjusted citations is 1.1 (see Table 3), a one standard deviation higher rolling success rate increases citations by 3% (=0.032/1.1). Therefore, patent attorneys with a higher degree of expertise are positively related to higher technological value of patents, which supports the second hypothesis (*H2a*). We add control variables in columns (2) and (3) in Table 7 and rolling success rate remains a positive and statistically significant predictor of patent citations, at the 1% level. The coefficients on the control variables indicate that firm size is negatively correlated with the number of citations received by patents, which is consistent with prior literature (Plehn-Dujowich, 2009).

/Table 7 here/

Second, we measure patent attorney expertise using the number of patent applications handled by a patent attorney. We present the results in Appendix F, where we regress *patent citations* on the number of applications filed. The results suggest that the number of patent applications filed is statistically negatively associated with the technological value of patents, at the 5% level. A 20% increase in applications filed is associated with 0.002 (20%*0.01) lower number of truncation-adjusted citations. While the evidence of a negative correlation is surprising, the size of the effect is very close to zero. Therefore, we find no support for hypothesis *H2b*.

4.4 The effect of the openings of new USPTO offices on the economic and technological value of patents

Companies may choose to hire patent attorneys with higher capability to represent patent applications that are more valuable to them (de Rassenfosse et al., 2022). To address this potential selection issue, we exploit the effect of new openings of USPTO offices on the performance of patent attorneys. The USPTO is headquartered in the state of Virginia, which has been its only location for most of its history. This changed in July 2012, when the USPTO opened its first regional office in Detroit, Michigan. Not long after, the USPTO opened three additional regional offices. The second regional office opened in Denver, Colorado in June 2014. The third and the fourth regional offices opened in San Jose, California in October 2015, and in Dallas, Texas in November 2015 (USPTO, 2022).

We argue that the patent attorneys located in the states in which new USPTO offices has been opened should benefit from increased performance compared to patent attorneys located in other states. The job of a patent attorney requires negotiating the scope and the grant of patent rights with patent examiners (Gaudry, 2012; Lu et al., 2017). To facilitate the process, patent attorneys can request an in-person interview with a patent examiner at a patent office. Interviews can be an effective way to overcome examiners' objections about a patent application (Lemley and Sampat, 2010). Also, in contrast to written correspondence, the interviews are not recorded, which allows the patent attorneys to discuss the invention without creating a permanent record that could become a hinderance in any future patent litigation (Lemley and Sampat, 2010). Since negotiation is a skill, more capable patent attorneys should benefit more from the opening of the new regional offices.

First, to validate the shock, we examine whether the openings of new USPTO offices affected the performance of patent attorneys. We estimate the following model:

$$rolling\ success\ rate_{i,t} = \alpha + \beta_1 * new\ offices + \beta_2 * patent\ grants\ volume_{i,t} + \beta_n * X_{i,t-1} + \gamma + \xi + \psi + u_{i,t} \quad (4)$$

Rolling success rate$_{i,t}$ is a proxy for patent attorney substantive expertise. *New offices* is a dummy variable equal to 1 for patents filed by patent attorneys located in states in which the USPTO opened a new regional office, and 0 otherwise.[22] Control variables include *patent grants volume*, *market capitalisation*, *firm age*, *return on assets*, *leverage*, and *R&D*. Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects, respectively.[23]

The regression results are presented in Table 8. In column (1) of Table 8 we regress the *rolling success rate* solely on *new offices*, and we include firm, year, and patent class fixed effects. The coefficient on *new offices* is 0.9%, which is statistically significant at the 5% level. Therefore, the opening of new USPTO offices increased the rolling success rate of patent attorneys located in the affected states by 0.9%. The results remain similar and significant at the 10% level after adding control variables in columns (2) and (3) of Table 8. In terms of the control variables, the positive and statistically significant coefficient (at the 1% level) on the market capitalisation variable suggests that patent attorneys working for larger firms are on average more successful. Similarly, the positive and statistically significant coefficient (at the 5% level) on the R&D intensity variable suggests that patent attorneys employed by firms with a higher focus on R&D are more successful. This is intuitive, as larger firms can have more resources available to hire more successful patent attorneys.

/Table 8 here/

[22] A comparison of the descriptive statistics of the treatment and control groups is shown in Appendix G. The characteristics of the two groups are similar. For instance, the average return on assets in the treatment (control) group is 8.5% (8.2%). Similarly, the average R&D intensity in the treatment (control) group is 10.2% (9.2%). Importantly, the average success rates of the patent attorneys associated with the treatment and control groups are very similar at 83.8% and 83.0%, respectively.

[23] If multiple patents are granted to the same firm on the same day, we use the dominant patent class on that day to compute the patent class fixed effects. The results are not sensitive to the way we compute the fixed effects. Moreover, the results are similar when we do not include patent class fixed effects in the model.

Second, we test the effect of the openings of the new USPTO offices on the economic value of patents. We estimate the following model:

$$CAR_{i,t} = \alpha + \beta_1 * rolling\ success\ rate_{i,t} + \beta_2 * new\ offices + \beta_3 * new\ offices\ x\ rolling\ success\ rate_{i,t} + \beta_4 * patent\ grants\ volume_{i,t} + \beta_n * X_{i,t-1} + \gamma + \xi + \psi + u_{i,t} \quad (5)$$

$CAR_{i,t}$ is the average cumulative abnormal return over a three-day window (0,+2).[24] *Rolling success rate* is a proxy for patent attorney substantive expertise. *New offices* is a dummy variable equal to 1 for patents filed by patent attorneys located in states in which the USPTO opened a new regional office, and 0 otherwise. Control variables include *patent grants volume*, *market capitalisation*, *firm age, return on assets*, *leverage*, and *R&D*. Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects, respectively.[25]

The regression results are shown in Table 9. Column (1) of Table 9 includes only the rolling success rate, which has a positive and statistically significant (at the 1% level) coefficient of 0.30%, as previously shown in Table 5. Column (2) of Table 9 includes only the *new offices* dummy variable. The variable's coefficient is not statistically significant, which suggests that the opening of new offices did not have any effect on the economic value of patents represented by patent attorneys if their capability is ignored. Column (3) of Table 9 interacts *rolling success rate* with *new offices*. The interaction term is positive and statistically significant at the 5% level. This suggests that the importance of the expertise of patent attorneys located in the states in which the USPTO opened a new office increased after the new offices were opened. The findings show that higher patent attorney substantive expertise increases the economic value

[24] In alternative specifications we use alternative event windows and our results remain similar.
[25] If multiple patents are granted to the same firm on the same day, we use the dominant patent class on that day to compute the patent class fixed effects. The results are not sensitive to the way we compute the fixed effects. Moreover, the results are similar when we do not include patent class fixed effects in the model.

of patents. Columns (4) and (5) add control variables, and the result remains statistically significant at the 5% level.

/Table 9 here/

We want to ensure that any impact of the new offices on the economic value of patents is driven by the impact of the new offices on the patent attorneys and not by its impact on firms. Therefore, we rerun model (5) using a dummy variable *new offices (firm location)*, which is equal to 1 for patents filed by firms located in the affected states, and 0 otherwise. This approach can help alleviate concerns that the opening of new USPTO offices may have impacted the firms located in the affected states and the patents of these firms, and have not necessarily affected the patent attorneys located in the affected states. The regression results are shown in Appendix H. Column (3) of the table in Appendix H interacts *new offices (firm location)* with *rolling success rate*. The interaction is not statistically significant, which suggests that patents filed by firms located in the states with the new USPTO offices were not affected by the change. This suggests that the opening of new USPTO offices helped successful patent attorneys negotiate the grant of patents with higher economic value.

Third, we study the impact of the opening of the new offices on the technological value of patents. We estimate the following model:

$$\begin{aligned} Patent\ citations_i = {} & \alpha + \beta_1 * rolling\ success\ rate_{i,t} + \beta_2 * new\ offices + \\ & \beta_3 * new\ offices\ x\ rolling\ success\ rate_{i,t} + \beta_4 * \\ & \text{market capitalisation}_{i,t-1} + \beta_5 * backward\ citations_i + \beta_6 * \\ & independent\ claims_i + \gamma + \xi + \psi + u_{i,t} \end{aligned} \tag{6}$$

The dependent variable is *patent citations*, which is the truncation-adjusted number of citations received by a patent that excludes examiner and self-citations. The independent variable of interest is *rolling success rate*. *New offices* is a dummy variable equal to 1 for patents filed by patent attorneys located in states in which the USPTO opened a new regional office, and 0 otherwise. The control variables include *market capitalisation*, *backward citations* and *independent claims*. Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects[26], respectively.

The regression results are shown in Table 10. Column (3) of Table 10 interacts *rolling success rate* with *new offices*. The coefficient on the interaction term is not statistically significant, which suggests that the impact of patent attorney expertise on the technological value of patents was not affected by the opening of new USPTO offices. This is not a surprising result. The main benefit to patent attorneys from the opening of the new offices is the fact that they have an easier access to the patent examiners with whom they can conduct in-person interviews when negotiating the grant of a patent. These negotiations occur at an advanced stage of the patent examination process, after a patent attorney has already finished writing a patent application and sent it to the patent office. Therefore, the technological specification and the contents of a patent application have already been largely determined (Lemley and Sampat, 2012). This likely limits the extent to which a better access to an examiner affects the number of citations received by a patent.

/Table 10 here/

4.5 The impact of a patent attorney change on the economic and technological value of patents

In this section, we investigate whether a change of a company's patent attorney affects the economic and technological value of patents. We test whether the differences between the economic and technological value of patents that were consecutively granted to the same company can be explained by the fact that a different patent attorney was employed by the company. This approach helps isolate the effect of a patent attorney on patent value, because we focus on patents obtained by the same firms in a close time proximity. These patents are

[26] The results remain robust to the choice of different fixed effects, including industry, art unit, and examiner fixed effects.

likely to be more similar than patents that were secured by a company with a significant time delay. Given that the state of technology can rapidly evolve (Taub et al., 2007; Ebert, 2018), a patent granted to a computer hardware company in 2006 may protect a different technology than one granted to the same company in 2007.

First, we study the effect of patent attorney change on the economic value of patents. We use the following model:

$$\Delta CAR_{i,t} = \alpha + \beta_1 * better/worse\ patent\ attorney_{\ i,t} + \beta_n * X_{i,t-1} + \gamma + \xi + \psi + u_{i,t} \quad (7)$$

ΔCAR$_{i,t}$ is the difference between the market valuation of an announcement of a single patent and the market reaction to the preceding announcement of a single patent that was granted to the same company.[27] Restricting the analysis to single patent grants ensures that we am comparing similar patent announcements. Including grants of multiple patents would confound the analysis, because multiple patents granted on the same day to the same company share a single market valuation, but they can be associated with different patent attorneys. The independent variable of interest is *better/worse patent attorney*, which is a dummy variable equal to 1 if the same company changed to a different patent attorney with a higher/lower rolling success rate than the previous attorney, and 0 otherwise. $X_{i,t-1}$ is a vector of firm specific control variables, which includes *market capitalisation*, *firm age, return on assets*, *leverage*, and *R&D.* Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects, respectively.

The results in Table 11 show that the coefficient on *better patent attorney* is positive and statistically significant at the 10% level. The results suggest that the market valuation of a patent increases by 0.08% when a company switches to a more capable patent attorney.

[27] The sample size decreases to 102,605, because we only keep announcements of single patents to the same company.

Although seemingly a small effect, it has a considerable effect since it can accumulate with each additional patent represented by the more capable patent attorney. For example, the increase in shareholder wealth can add up to 29.8% (=373*0.08%) for an average company in the sample that obtained 373 patents between 2003-2019. In panel B of Table 11, we regress $\Delta CAR_{i,t}$ on *worse patent attorney* and we find consistent evidence. Changing to a less capable patent attorney is associated with a 0.08% lower shareholder wealth, which is significant at the 10% level. In panel C of Table 11, we test whether the effect is larger when the capability difference between the new and the old patent attorney widens. We calculate *difference in capability* by subtracting the rolling success rate of a new patent attorney from the rolling success rate of the previous patent attorney. We use *difference in capability* as the new independent variable of interest in equation (7). The coefficient on difference in capability is equal to 0.37%, which is statistically significant at the 5% level. Therefore, a 1% increase in *difference in capability* is associated with a 0.004% (0.37% / 100) higher market valuation, and a patent attorney that is one standard deviation more capable increases shareholder wealth by 0.046% (=11.6*0.004%).

/Table 11 here/

Next, we study the effect of patent attorney change on the technological value of patents. We use the following model:

$$\begin{aligned}\Delta \text{ patent } citations_i = \alpha + \beta_1 * better/worse\ patent\ attorney_{\ i,t} + \beta_2 * \\ market\ capitalization_{i,t-1} + \beta_3 * backward\ citations_i + \beta_4 * \\ independent\ claims_i + \gamma + \xi + \psi + u_{i,t}\end{aligned} \tag{8}$$

Δ patent citations$_i$ is the difference between the truncation-adjusted number of citations received by a single patent granted to a company and the number of citations received by the previous single patent that was granted to the same company. The independent variable of interest is *better/worse patent attorney*, which is a dummy variable equal to 1 if a company changed to an attorney with a higher/lower rolling success rate, and 0 otherwise. We include *market capitalisation* to control for firm size, and *backward citations* and *independent claims* to control for patent quality. Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects, respectively.

The results in Table 12 show that the coefficient on *better patent attorney* is positive and statistically significant at the 1% level. The results suggest that switching to a more capable patent attorney is associated with 0.09 more truncation-adjusted citations received by a patent. Given that the mean amount of truncation adjusted forward citations is 1.1 (see Table 3), this represents an increase of 8% (0.09/1.1). Similarly, the results in panel B of Table 12 suggest that the opposite is also true, with a change to a less capable patent attorney decreasing the number of truncation adjusted citations by 0.06, significant at the 5% level. Lastly, in panel C, we regress Δ *patent citations*$_i$ on *difference in capability*, and we find that the strength of this effect increases depending on the difference in capabilities between the old and new patent attorney. Overall, changing to a better (worse) patent attorney is associated with both a higher (lower) economic and technological value of patents.

/Table 12 here/

4.6 The relation between patent attorney expertise and patent attorney rankings

The results so far suggest that attorneys with higher substantive expertise, as measured by their rolling success rate, obtain patents with higher economic and technological value. Moreover, the process expertise of patent attorneys does not matter for patents. In this section, we investigate whether successful patent attorneys are recognised in the law firm rankings for their superior performance. If successful patent attorneys are also the highest ranked, then using patent attorney ranking tables can be a quicker way of identifying more capable patent attorneys than calculating their historical success rates.

Legal500 is one of the leading providers of law firms rankings in the US across a broad range of practice areas (Ferrell et al., 2021). The company publishes the rankings based on the information provided by law firms, interviews conducted with the law firms' lawyers, and feedback provided by law firms' clients (Ferrell et al., 2021). The rankings are frequently used in the literature to identify the highest-performing law firms (Segal-Horn and Dean, 2009; Paolella and Durand, 2016; Romano and Sanga, 2017). Moreover, to our best knowledge, Legal500 is the only company that ranks legal firms in the patent prosecution practice area in the US.[28] Therefore, we use the Legal500 rankings to identify the top patent attorney firms.

We hand-collect the Legal500 rankings data in the Patent Prosecution category by visiting the historical snapshots of the Legal500 website through the Wayback Machine. The firm started ranking law firms in this category in 2007. Hence, our ranking data covers the period from 2007 to 2019. Every year, Legal500 provides a list of the top patent prosecution firms. The list is divided into five different groups called tiers, with tier one being the highest. Moreover, within tiers, the firms are listed alphabetically. On average, each tier recognises six different law firms, for a total of 30 patent attorney firms ranked every year.

To test whether the patent attorney firms recognised in the rankings are also the most capable, we first calculate the correlation between the substantive and process expertise of a patent attorney firm and their Legal500 ranking. Specifically, we define a dummy variable *top tier attorney* which is equal to 1 if a patent attorney firm has been recognised as a tier one firm by the Legal500 and 0 otherwise. For robustness, we also create a dummy variable *any tier attorney*, which is equal to 1 if a patent attorney firm has been listed in any of the five tiers, and 0 otherwise. We drop in-house[29] patent attorneys before calculating the correlations and

[28] The main competitors of Legal500 are Chambers and Partners, and The American Lawyer. However, only the Legal500 publishes rankings of patent prosecution firms.

[29] We identify in-house attorneys based on their name structure, following the literature (Moeen et al., 2013; Chondrakis et al., 2021). For example, names ending in "Associates", "LLP", and "Law Firm" are coded as external patent attorneys, while names ending in "Corporation", "Technologies", and "Laboratories" are coded as internal patent attorneys (Chondrakis et al., 2021). For robustness, we alternatively identify in-house attorneys as

conducting subsequent analysis because Legal500 only ranks external law firms, as opposed to the internal patent law departments of companies.[30] Not removing the in-house patent attorneys would make it harder to detect the relation between rankings and the patent outcome variables because it is not possible for an in-house patent attorney to be ranked. Nonetheless, the results are not sensitive to how we identify in-house patent attorneys, and they are similar if we keep both in-house and external patent attorneys in the analysis.

The correlations between substantive expertise and the one- and two-year lags of the ranking variables are presented in Table 13.[31] The first row of Table 13 shows that there is a negative correlation of -0.05 between the *rolling success rate* and *top tier attorney*, and a negative correlation of -0.08 between the *rolling success rate* and *any tier attorney*. Moreover, the second row of Table 13 shows that there is a positive correlation of 0.13 between *applications filed* and *top tier attorney*, and a positive correlation of 0.29 between *applications filed* and *any tier attorney*. The results suggest that the most capable patent attorneys, as measured by their success rate, are not recognised in the rankings. In contrast, the rankings more frequently consist of attorneys with higher process expertise, as measured by the number of applications filed. Given that *rolling success rate* (*applications filed*) is (is not) positively related to the economic and technological value of patents, this suggests that the Legal500 rankings are not a reliable way of identifying the most capable patent attorneys.

/Table 13 here/

It is possible that the Legal500 rankings represent a different side of patent attorney capability which is not captured by the rolling success measure. Therefore, we test whether the

ones that only represented patent applications of a single company in their career, as in de Rassenfosse et al. (2022).

[30] Companies may use in-house patent attorneys to prepare patent applications and negotiate their grant with patent examiners. Two example of such firms are the IBM Corporation and the Microsoft Corporation (see Table 2).

[31] We lag the ranking variables by one and two years to capture the ranking of a patent attorney as of the patent examination process, which takes on average 3 years. The results are similar if we use the third lag of the ranking variable or if we use the concurrent value.

top ranked patent attorney firms are associated with higher economic and technological value of patents. First, we investigate the relation between rankings and the economic value of patents, and we use the following model:

$$CAR_{i,t} = \alpha + \beta_1 * top\ tier\ attorney_{i,t-1} + \beta_2 * patent\ grants\ volume_{i,t} + \beta_n * X_{i,t-1} + \gamma + \xi + \psi + u_{i,t} \quad (9)$$

$CAR_{i,t}$ is the average cumulative abnormal return over a three-day window (0,+2). *Top tier attorney* is a dummy variable equal to 1 if a patent attorney firms if a patent announcement includes a patent attorney ranked as tier one, and 0 otherwise.[32] [33] Control variables include *patent grants volume*, *market capitalisation*, *firm age*, *return on assets*, *leverage*, and *R&D*. Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects, respectively. We drop in-house patent attorneys before running the model, but the results are similar if we keep in-house patent attorneys in the analysis.

The results are presented in Table 14. In column (1), we regress CAR(0,+2) solely on the *top tier attorney*, and we include year, firm, and patent class fixed effects. The coefficient on the dummy variable is not statistically significant, and it remains not statistically significant after the control variables are added in columns (2) and (3). The results suggest that, compared with the lower-ranked and unranked patent attorneys, tier one patent attorneys do not obtain patents that are more valuable. Moreover, the results are similar if we limit the comparison group to other ranked attorneys only and remove the unranked patent attorneys from the analysis.

/Table 14 here/

[32] We use the one year lag of the ranking variable in the model. However, the results are similar if we use a two- or a three- year lag of the variable instead. The results are also similar if we use the concurrent value of the ranking variable or its one-, two-, or three- year forward values.

[33] The results are similar if we use the dummy variable *any tier attorney* instead. Moreover, the results hold regardless of which lag or forward value of the variable we use.

Next, we explore whether patent attorneys that are recognised in the Legal500 rankings are associated with a higher technological value of patents. We estimate the following model:

$$\begin{aligned}&Patent\ citations_i = \alpha + \beta_1 * top\ tier\ attorney_{i,t-1} + \beta_2 * \\ &\quad \ln(market\ capitalisation)_{i,t-1} + \beta_3 * backward\ citations_i + \beta_4 * \\ &\quad independent\ claims_i + \gamma + \xi + \psi + u_{i,t}\end{aligned} \tag{10}$$

The dependent variable is *patent citations*, which is the truncation-adjusted number of citations received by a patent. The independent variable of interest is *top tier attorney,* which is a dummy variable equal to 1 for tier one patent attorney firms, and 0 otherwise.[34] [35] The controls include *market capitalisation, backward citations* and *independent claims.* Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects, respectively. We remove in-house patent attorneys before running the model, but the results are similar if we keep in-house patent attorneys in the analysis.

The regression results are shown in Table 15. In column (1) of Table 15, we regress *patent citations* on *top tier attorney* in isolation and we include year, firm, and patent class fixed effects. The coefficients on the dummy variable are not statistically significant. This holds regardless of whether or not control variables are included, as shown in columns (2) and (3) of Table 15. The results suggest that the top ranked patent attorneys are not associated with higher technological value of patents. The results remain similar regardless of whether we compare top ranked attorneys with all other attorneys or if we use only the lower ranked patent attorneys as the comparison group.

/Table 15 here/

[34] We use the one year lag of the ranking variable in the model. However, the results are similar if we use a two- or a three- year lag of the variable instead. The results are also similar if we use the concurrent value of the ranking variable or its one-, two-, or three- year forward values.

[35] The results are similar if we use the dummy variable *any tier attorney* instead. Moreover, the results hold regardless of which lag or forward value of the variable we use.

Overall, we find that rankings of patent attorney firms are not a good predictor of the economic or technological value of patents obtained by the attorneys. Therefore, patent attorney firm rankings do not seem to matter for patent value. The findings are consistent with Hanretty (2016) who finds that having a higher ranked legal representation does not matter for the probability of winning in conventional litigation. The author argues that law firm rankings are not a good measure of attorney skill. The findings are also similar to Griffin et al. (2014) who find that securities produced by high-ranked banks do not perform better than the structured products issued by their less reputable peers. The authors argue that high-ranked underwriters may produce securities of lower quality than other underwriters which is similar to our finding of a negative correlation between rankings and the patent attorney success rate. A higher ranking may help a patent attorney firm attract more clients, as suggested by its positive correlation with number of applications filed, but we find no evidence that higher ranking is associated with better outcomes for the clients.

5. Robustness checks

In order to rule out whether the results are driven by the time scale over which we constructed the rolling success measure, we formulate the measure again and this time only using patent applications filed since 2001 instead of 1980. We repeat the same regressions from Table 5.[36] The results are presented Appendix I. Appendix I shows that the magnitude and the statistical significance of the rolling success rate remains unchanged. We further test the robustness of the measure by constructing it based on the customer id number[37] of a patent attorney instead of using the string variable containing their name. We obtain the customer id number from the PatEx dataset. We rerun the regressions and present the results in Appendix J. The results remain unchanged. Furthermore, to rule out the possibility that the results are

[36] We also repeat the same regressions from Table 8, and we obtain similar results.
[37] Customer id number uniquely identifies the patent attorney who represents the application (Graham et al., 2015). However, the variable has a larger number of missing values than the patent representative name variable. This is reflected by the lower number of observations in the table shown in Appendix J.

affected by potential differences in patent allowance rates across different technologies, we also construct the rolling success measure while distinguishing between the six main patent technology groups[38] (Carley et al., 2015). We rerun the regressions and present the results in Appendix K. We find that the results are similar. In addition, we also construct alternative measures of patent attorneys' process expertise[39] and substantive expertise[40] and the results are very similar.

As an additional robustness check, we estimate the dependent variable, CAR (0,+2), using the Fama-French 5 factor model (Fama and French, 2015) instead of the market-adjusted model. We obtain data on the risk-free rate and the five factors in North America from Kenneth French's website. We estimate the α and β coefficients using a 250-day estimation window (with a minimum of 200 valid daily returns) ending 50 days before the respective patent announcement. The main regression results are statistically significant and quantitatively similar and are shown in Appendix L. Similarly, we have also rerun the regression analysis using CARs (0,+2) estimated using the market model and the Fama-French 3-factor model (Fama and French, 1993) and the results remain unchanged.

6. Conclusion

We examine the impact of patent attorney capability on both the economic and technological value of patents. We draw on the *attorney capability theory* which distinguishes between two types of expertise: process expertise and substantive expertise. According to the *attorney capability theory*, more experienced attorneys produce better outcomes. Contrary to the

[38] The six main patent technology groups are Chemical, Computers and Communications, Drugs and Medical Devices, Electrical and Electronic, and Mechanical.
[39] In this study we use the number of patent applications filed by a patent attorney to measure their process expertise. We obtain similar results when we use a range of alternative measures of process expertise including the number of patents obtained, number of applications filed or patents obtained by patent technology class, and the number of applications filed, or patents obtained by art unit.
[40] We use a patent attorney's rolling success rate to proxy for their substantive expertise. We obtain similar results when we use their total success rate calculated over 1980-2019 instead. We also arrive at similar results when we use a yearly success rate measure.

literature on attorney expertise (Abrams and Yoon, 2007; McGuire, 1995), we find that patent attorney process expertise has no effect on the economic value of patents as captured by the market valuation of patent grants. However, a patent attorney's success rate (substantive expertise) is positively associated with the economic value of patents. This suggests that only successful patent attorneys matter. We also show that higher patent attorney expertise is positively related to the technological value of a patent, as captured by the number of citations received by a patent. Furthermore, the importance of legal expertise of patent attorneys on the economic value of patents has increased for attorneys located in states in which the USPTO opened new regional offices between 2012 and 2015, which implies an existence of a causal relationship. Moreover, the change did not affect the importance of patent attorney substantive expertise for the technological value of patents. Furthermore, we find evidence suggesting that changing to a better (worse) patent attorney increases (decreases) the economic and the technological value of patents. Lastly, we show that patent attorney law firm rankings are not positively correlated with patent attorney capability, and that they are not a good predictor of the economic and technological value of patents.

In sum, the implications of the findings are twofold. First, it is the capability of patent attorneys that matters, and not simple process expertise. Second, successful patent attorneys have a positive association with both the economic and technological value of a patent. Therefore, companies should pay close attention to the track records of patent attorneys that they consider hiring and pay little attention to patent attorney law firm rankings.

Figure 1: Market Reaction to Patent Grants

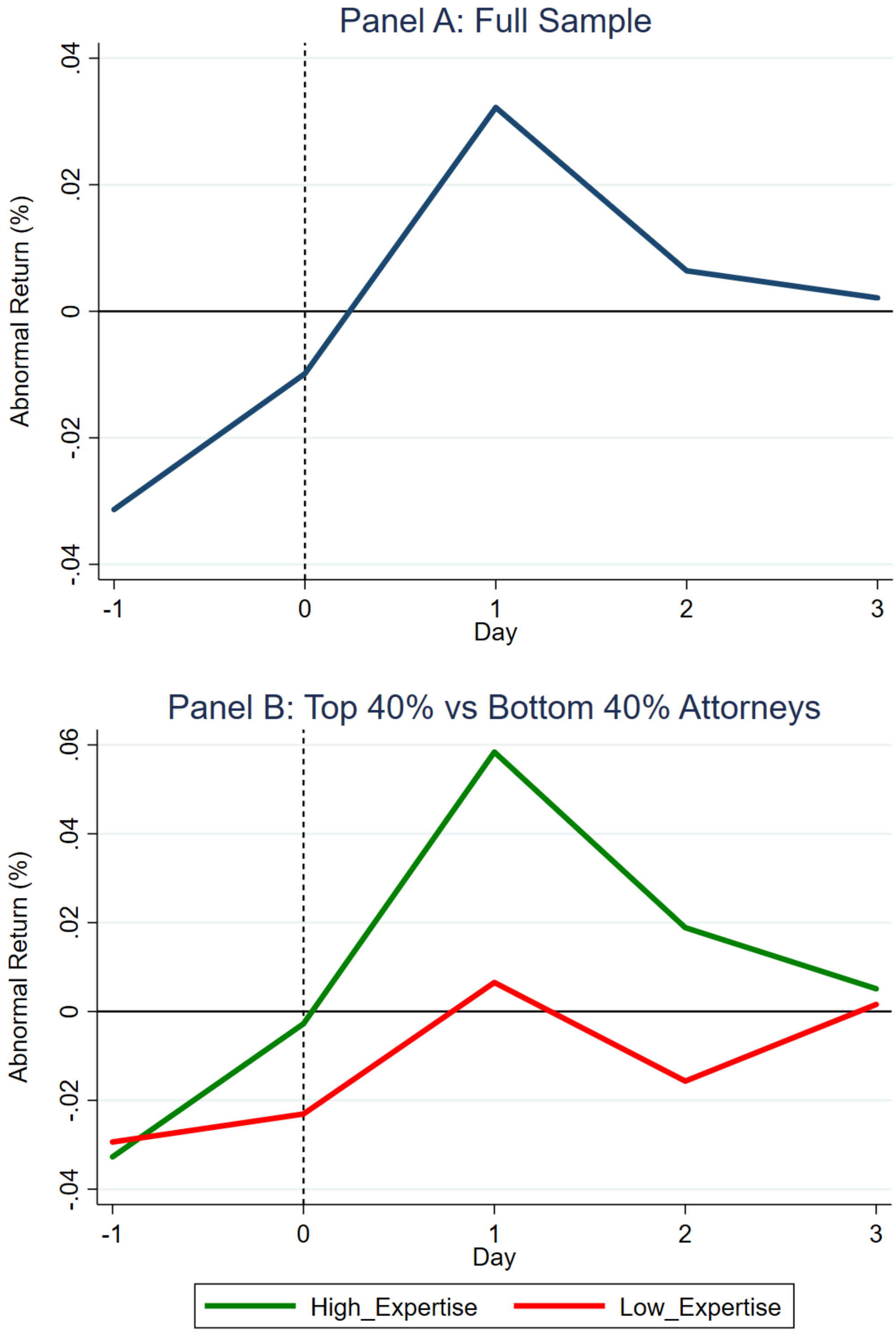

Table 1: Sample selection process

All utility patent applications in the PatEx dataset	9,616,956	100%
Applications filed before 2001	-2,738,734	-28.5%
Applications with missing application date	-52,958	-0.6%
Not granted patent applications	-2,483,187	-25.8%
Patents granted after 2019	-442,397	-4.6%
Patents not matched to publicly listed companies	-2,408,825	-25.0%
Patents matched to financial firms	-18,119	-0.2%
Patents matched to utility firms	-622	-0.0%
Missing stock return data	-25,525	-0.3%
Confounded patent announcements	-155,259	-1.6%
Total	**1,291,330**	**13.4%**

This table presents a breakdown of the sample selection process.

Table 2: Top 25 patent attorney firms by number of patents (2003-2019)

#	Name	Applications filed 1980-2019	Total success 1980-2019 %
1	Oblon McClelland Maier & Neustadt LLP	163,510	79%
2	IBM Corp	101,901	90%
3	Birch Stewart Kolasch & Birch LLP	97,048	75%
4	Sughrue Mion PLLC	91,004	68%
5	Oliff PLC	88,247	81%
6	Nixon & Vanderhye PC	86,629	72%
7	Knobbe Martens Olson & Bear LLP	77,414	70%
8	Foley & Lardner LLP	76,866	74%
9	Venable LLP	76,670	88%
10	Finnegan Henderson Farabow Garrett & Dunner LLP	67,514	72%
11	Microsoft Corp	59,560	80%
12	McDermott Will & Emery LLP	50,704	76%
13	Buchanan Ingersoll & Rooney PC	46,335	77%
14	Kilpatrick Townsend & Stockton LLP West Coast	45,844	71%
15	Banner & Witcoff LTD	44,868	77%
16	Wenderoth Lind & Ponack LLP	44,226	78%
17	Philips Intellectual Property & Standards	40,852	75%
18	Staas & Halsey LLP	39,302	70%
19	Sughrue Mion Zinn Macpeak & Seas	38,076	70%
20	Pillsbury Winthrop Shaw Pittman LLP	37,823	76%
21	Cantor Colburn LLP	35,518	88%
22	Harness Dickey Troy	33,857	73%
23	Texas Instruments Inc	33,745	85%
24	Antonelli Terry Stout & Kraus LLP	33,311	85%
25	Sterne Kessler Goldstein & Fox PLLC	32,931	79%

This table lists the top 25 patent attorney firms between 1980-2019 by the total number of patent applications filed. Along with the number of patent applications, this table also shows the total success rate of the patent attorney firms during 1980-2019 which is calculated as the total number of successful patent applications divided by the sum of successful and unsuccessful (abandoned) patent applications.

Table 3: Descriptive statistics (patent announcement-level)

	Mean	Median	SD	25^{th}	75^{th}	Firms	Total events
Panel A: Patent owner characteristics							
Market cap. ($bn)	27.7	5.4	65.7	1.2	22.0	3,184	214,307
Firm age	28.8	20.5	24.5	10.5	41.1	3,461	223,205
Return on assets (%)	8.3	12.1	22.4	7.0	17.0	3,184	214,307
Leverage (%)	51.7	51.2	27.5	33.6	66.2	3,184	214,307
R&D (%)	9.3	5.5	14.0	2.1	11.2	3,184	214,307
Tobin's Q	2.1	1.7	1.8	1.2	2.6	3,184	214,307
Institutional ownership (%)	66.3%	72.7%	23.8%	57.0%	83.4%	3,038	191,213
Panel B: Patent characteristics							
Forward citations (truncation adjusted)	1.1	0.3	2.0	0.0	1.0	3,461	223,205
Backward citations	29.6	14.0	43.1	7.0	30.3	3,439	218,835
Independent claims	1.0	1.0	0.1	1.0	1.0	3,461	223,205
Panel C: Measures of patent attorney expertise							
Rolling success rate (%)	83.8%	85.2%	11.6%	75.8%	93.1%	3,459	222,964
Applications filed	3589.8	915.5	7484.1	217.0	3407.0	3,459	222,964
Top tier attorney (%)	4.6	0.0	21.0	0.0	0.0	3,153	192,100
Any tier attorney (%)	18.9	0.0	39.1	0.0	0.0	3,153	192,100

This table reports the summary statistics for the full sample of 1,291,239 of patents issued during 2003-2019. Panel A shows patent owner characteristics. Total assets and market capitalisation are displayed in $billion, and the rest of the firm variables are expressed in %. Panel B reports patent characteristics variables, all of which are expressed as a simple count. Lastly, Panel C shows the created measures of patent attorney expertise. Rolling success rate is in %, and applications filed is a simple count. See Appendix B for variable definitions.

Table 4: Event study results

	Mean AR (0), %	Mean AR (+1), %	Mean AR (+2), %	Mean AR (+3), %	Mean CAR (0,+1), %	Mean CAR (0,+2), %	Mean CAR (0,+3), %	Events
Panel A: All patent announcements								
All events	-0.0099**	0.0322***	0.0064	0.0021	0.0224***	0.0288***	0.0309***	223,205
Panel B: Announcements with high-expertise attorneys								
High-expertise events	-0.0028	0.0584***	0.0189***	0.0051	0.0556***	0.0745***	0.0796***	89,426
Panel C: Announcements with low-expertise attorneys								
Low-expertise events	-0.0231***	0.0065	-0.0157**	0.0016	-0.0166*	-0.0322***	-0.0306**	89,187

This table presents the event study results computed using the market-adjusted model. All results are in %. Panel A presents full sample results. Panels B and C show patent announcements that are accompanied by patent attorneys with high, and low levels of substantive expertise, respectively. We define the expertise to be high (low) when the attorneys' rolling success rate is in the top (bottom) 40% of the distribution. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 5: Market reaction (CAR 0,+2) and attorney expertise (rolling success rate)

	(1)	(2)	(3)
Rolling success rate	0.0030***	0.0030***	0.0034***
	(0.0010)	(0.0010)	(0.0010)
Patent grants volume		-0.0001	0.0000
		(0.0001)	(0.0001)
Market capitalisation			-0.0015***
			(0.0004)
Firm age			-0.0023***
			(0.0007)
Return on assets			-0.0017
			(0.0020)
Leverage			-0.0010
			(0.0010)
R&D			0.0031
			(0.0038)
Constant	-0.0022**	-0.0022**	0.0174***
	(0.0009)	(0.0009)	(0.0038)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	222,431	222,431	213,608
R-squared	0.0292	0.0292	0.0285

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 6: Market reaction (CAR 0,+2) and attorney expertise (applications filed)

	(1)	(2)	(3)
Applications filed	-0.0000	-0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)
Patent grants volume		-0.0001	0.0000
		(0.0001)	(0.0001)
Market capitalisation			-0.0015***
			(0.0004)
Firm age			-0.0023***
			(0.0007)
Return on assets			-0.0017
			(0.0020)
Leverage			-0.0010
			(0.0010)
R&D			0.0034
			(0.0038)
Constant	0.0004	0.0004	0.0201***
	(0.0004)	(0.0004)	(0.0037)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	222,431	222,431	213,608
R-squared	0.0291	0.0291	0.0285

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 7: Forward citations and attorney expertise (rolling success rate)

	(1)	(2)	(3)
Rolling success rate	0.2756***	0.2924***	0.2758***
	(0.0678)	(0.0691)	(0.0712)
Market capitalisation		-0.0703**	-0.0738**
		(0.0347)	(0.0345)
Independent claims			-0.0063
			(0.0240)
Backward citations			0.1422***
			(0.0112)
Constant	0.5081***	1.2142***	0.9585***
	(0.0574)	(0.3634)	(0.3602)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	1,287,963	1,256,800	1,172,856
R-squared	0.1270	0.1242	0.1310

The dependent variable is the truncation-adjusted number of forward citations, which has been corrected for the presence of examiner and self-citations. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. All patent quality control variables are winsorized at the 1% and 99% tails. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 8: Patent attorney expertise (rolling success rate) and the openings of new USPTO offices.

	(1)	(2)	(3)
New offices	0.0093**	0.0089**	0.0080*
	(0.0043)	(0.0042)	(0.0042)
Patent grant volume		0.0064***	0.0061***
		(0.0013)	(0.0012)
Market capitalisation			0.0074***
			(0.0027)
Firm age			-0.0141**
			(0.0063)
Return on assets			0.0181
			(0.0142)
Leverage			0.0066
			(0.0074)
R&D			0.0722**
			(0.0303)
Constant	0.8322***	0.8264***	0.7941***
	(0.0002)	(0.0011)	(0.0303)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	258,770	258,770	248,687
R-squared	0.6077	0.6086	0.6100

The dependent variable is rolling success rate. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 9: Market reaction (CAR 0,+2), patent attorney expertise (rolling success rate), and the opening of new USPTO offices.

	(1)	(2)	(3)	(4)	(5)
Rolling success rate	0.0030**		0.0027***	0.0027***	0.0031***
	(0.0010)		(0.0010)	(0.0010)	(0.0011)
New offices		0.0000	-0.0060**	-0.0061**	-0.0054*
		(0.0004)	(0.0028)	(0.0028)	(0.0029)
New offices x			0.0073**	0.0073**	0.0069**
Rolling success rate			(0.0034)	(0.0034)	(0.0034)
Patent grant volume				-0.0001	-0.0000
				(0.0001)	(0.0001)
Market capitalisation					-0.0015**
					(0.0004)
Firm age					-0.0023***
					(0.0007)
Return on assets					-0.0018
					(0.0020)
Leverage					-0.0010
					(0.0010)
R&D					0.0030
					(0.0038)
Constant	-0.0022**	0.0003	-0.0020**	-0.0019**	0.0177***
	(0.0009)	(0.0002)	(0.0009)	(0.0009)	(0.0038)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Patent class FE	YES	YES	YES	YES	YES
Observations	222,431	222,472	222,431	222,431	213,608
R-squared	0.0292	0.0291	0.0292	0.0292	0.0286

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 10: Forward citations and patent attorney expertise (rolling success rate), and the opening of new USPTO offices.

	(1)	(2)	(3)	(4)	(5)
Rolling success rate	0.2756***		0.2838***	0.2991***	0.2832***
	(0.0678)		(0.0713)	(0.0728)	(0.0754)
New offices		0.0221	0.1106	0.0947	0.1127
		(0.0423)	(0.1254)	(0.1236)	(0.1287)
New offices x Rolling success rate			-0.1024	-0.0750	-0.0852
			(0.1453)	(0.1444)	(0.1508)
Market capitalisation				-0.0710**	-0.0746**
				(0.0349)	(0.0348)
Independent claims					-0.0063
					(0.0240)
Backward citations					0.1422***
					(0.0112)
Constant	0.5081***	0.7404***	0.5001***	1.2140***	0.9593***
	(0.0574)	(0.0022)	(0.0609)	(0.3651)	(0.3626)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Patent class FE	YES	YES	YES	YES	YES
Observations	1,287,963	1,288,371	1,287,963	1,256,800	1,171,856
R-squared	0.1270	0.1269	0.1279	0.1243	0.1311

The dependent variable is the truncation-adjusted number of forward citations, which has been corrected for the presence of examiner and self-citations. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 11: Difference in market reaction (CAR 0,+2) and the patent attorney change.

Panel A: Changed to a better attorney	(1)	(2)
Better patent attorney	0.0008**	0.0008*
	(0.0004)	(0.0004)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	109,026	104,068
R-squared	0.0090	0.0087
Panel B: Changed to a worse attorney	(3)	(4)
Worse patent attorney	-0.0008**	-0.0008*
	(0.0004)	(0.0004)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	109,026	104,068
R-squared	0.0126	0.0125
Panel C: Difference in market reaction and the difference in patent attorney success rate	(5)	(6)
Difference in capability	0.0037**	0.0036**
	(0.0017)	(0.0017)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	48,428	46,358
R-squared	0.0301	0.0295

The dependent variable in panels A, B, and C is the difference in CARs(0,+2) of two consecutive announcements of single patents granted to the same company. We use the same control variables as in Table 5. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at 1% and 99% tails. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 12: Difference in forward citations and the patent attorney change.

Panel A: Changed to a better attorney	(1)	(2)
Better patent attorney	0.0868*** (0.0316)	0.0875*** (0.0323)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	114,796	109,975
R-squared	0.0119	0.0166
Panel B: Changed to a worse attorney	(3)	(4)
Worse patent attorney	-0.0713** (0.0291)	-0.0642** (0.0296)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	120,183	109,975
R-squared	0.0119	0.0165
Panel C: Difference in forward citations and the difference in patent attorney success rate	(5)	(6)
Difference in capability	0.5072*** (0.1491)	0.4779*** (0.1526)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	55,004	50,428
R-squared	0.0277	0.0357

The dependent variable in panels A, B, and C is the difference in the truncation-adjusted number of forward citations received by patents that were granted to the same company in two consecutive announcements of single patents. We use the same control variables as in Table 7. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at 1% and 99% tails. All patent quality control variables are winsorized at 1% and 99% tails. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 13: Correlations between attorney capability and Legal 500 ranking

Expertise/Ranking	Top tier attorney (lag 1)	Top tier attorney (lag 2)	Any tier attorney (lag 1)	Any tier attorney (lag 2)
Rolling success rate	-0.0568	-0.0546	-0.0824	-0.0792
Applications filed	0.1324	0.1273	0.2966	0.2883

This table shows the pairwise correlations between substantive expertise (rolling success rate), process expertise (applications filed) and dummy variables identifying top ranked patent attorneys.

Table 14: Market reaction (CAR 0,+2) and Legal 500 ranking

	(1)	(2)	(3)
Top tier attorney (lag 1)	0.0004	0.0004	0.0001
	(0.0005)	(0.0005)	(0.0005)
Patent grants volume		0.0001	0.0001
		(0.0002)	(0.0002)
Market capitalisation			-0.0014***
			(0.0005)
Firm age			-0.0034***
			(0.0010)
Return on assets			-0.0047*
			(0.0027)
Leverage			0.0004
			(0.0012)
R&D			0.0039
			(0.0049)
Constant	0.0002	0.0001	0.0217***
	(0.0003)	(0.0003)	(0.0050)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	127,707	127,707	121,982
R-squared	0.0403	0.0403	0.0391

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 15: Forward citations and Legal 500 ranking

	(1)	(2)	(3)
Top tier attorney (lag 1)	-0.0216	-0.0254	-0.0272
	(0.0247)	(0.0251)	(0.0239)
Market capitalisation		-0.0937**	-0.0954**
		(0.0468)	(0.0461)
Independent claims			-0.0058
			(0.0372)
Backward citations			0.1487***
			(0.0128)
Constant	0.7542***	1.7079***	1.4112***
	(0.0015)	(0.4783)	(0.4669)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	728,589	709,425	651,737
R-squared	0.1400	0.1363	0.1443

The dependent variable is the truncation-adjusted number of forward citations, which has been corrected for the presence of examiner and self-citations. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. All patent quality control variables are winsorized at the 1% and 99% tails. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix

Appendix A: Patent attorneys names’ cleaning process

#	Step Name	Description
1	Capitalising all letters	We capitalise all letters in the string variable containing patent attorneys’ names (Bessen, 2009; Autor et al., 2020).
2	Standardizing words for “and”	We recode all common words for “and” to “&”. This includes “+”, “ET”, “UND”, “AND” (Bessen, 2009).
3	Removing punctuation characters	We remove characters such as “;”, “<”, “%”, “#”, “/”, “-“, “(“, “!”, etc. from the string variable (Bessen, 2009; Autor et al., 2020). We do not remove “&”.
4	Deleting addresses	In some cases, the name variable mistakenly contains an address instead of patent attorneys’ name. We drop observations that contain words such as “STREET”, “ROAD”, “BOULEVARD”, etc.
5	Standardizing commonly used words	We standardize commonly used words. For example, we change “CORPORATION” to “CORP”, “CHEMICAL” to “CHEM”, “LABORATORIES” to “LABS”, “TECHNOLOGY” to “TECH”, “LIMITED” to “LTD”, etc. (Autor et al., 2020; Bessen, 2009). This helps in cleaning the names of companies that use their own law departments to file the patent applications. An example of a business that does that is the IBM Corporation.
6	Removing redundant phrases	We remove words that do not convey useful information. These include “LAW OFFICE OF”, “DEPARTMENT OF”, “ATTORNEY AT LAW”, “INTELLECTUAL PROPERTY LAW DEPARTMENT”. For example, this step allows us to identify “DEBORAH A GADOR” and “DEBORAH A GADOR ATTORNEY AT LAW” as the same patent attorney.
7	Manual cleaning	We conduct an extensive manual cleaning of the name variable. For example, we change “ADRIENNE B NAUMANNLAW” and “ADRIENNE B NAUMANN8210” to “ADRIENNE B NAUMANN”. We also correct “SKJERVENMORRILLMACPHERSON” and “"SKJERVEN MORRILL MCPHERSON” to “SKJERVEN MORRILL MACPHERSON”, etc.

This table describes the cleaning process of patent attorneys’ names from the Patent Examination Research Dataset.

Appendix B: Variable definitions

Variable	Definition	Source
Any tier attorney	This is a dummy variable which is equal to 1 if a patent attorney firm has been listed by the Legal500 in any of the five ranking tiers, and 0 otherwise.	Legal500
Applications filed	Applications filed is a natural logarithm of one plus the total number of patent applications filed by a particular patent attorney. It is updated on a yearly basis.	Patent Examination Research Dataset
Backward citations	Backward citations is a natural logarithm of the number of prior art references that a patent makes to other patents (Fung, 2003).	PatentsView
Better patent attorney	Better patent attorney is a dummy variable equal to 1 if the same company changed to a different patent attorney with a higher rolling success rate than the previous attorney, and 0 otherwise.	Patent Examination Research Dataset
Difference in capability	Difference in capability is calculated by subtracting the rolling success rate of a new patent attorney from the rolling success rate of the previous patent attorney.	Patent Examination Research Dataset
Firm age	Firm age is natural logarithm of the number of years since the firm first appearance in CRSP.	CRSP
Forward citations	Forward citations is the truncation-adjusted number of citations received by a patent, excluding examiner citations and self-citations, divided by the number of citations received by an average patent granted in the same year.	PatentsView
Independent claims	Independent claims is a natural logarithm of the number of independent claims of a patent (Marco et al., 2019).	PatentsView
Institutional ownership (%)	Institutional ownership is the proportion of a company's shares owned by institutional investors.	Ghaly et al. (2020)
Leverage	Leverage is defined as total liabilities (Compustat item: lt) divided by total assets (Fang et al., 2014).	Compustat
Market cap. ($bn)	Market capitalisation is the natural logarithm of the number of shares outstanding multiplied by the share price.	CRSP
New offices	New offices is a dummy variable equal to 1 for patents filed by patent attorneys located in states in which the USPTO opened a new regional office, and 0 otherwise.	N/A
Patent grants volume	Patent grants volume is a logarithm of one plus the number of patents that a particular company obtained from the USPTO on the same trading day.	Patent Examination Research Dataset
R&D	R&D is defined as research and development expense (Compustat item: xrd) divided by total assets (Hirshleifer et al., 2012).	Compustat
Return on assets	Return on assets is defined as operating income before depreciation (Compustat item: oibdp) divided by total assets (Fang et al., 2014),	Compustat
Rolling success rate	Rolling success rate measures a patent attorney's effectiveness in obtaining patent protection. It takes a value between 0 and 1. It is calculated by dividing the number of successful patent applications of a particular patent attorney by the total number of successful and abandoned applications filed by that patent attorney. This measure is updated yearly.	Patent Examination Research Dataset
Tobin's Q	Tobin's Q is the ratio of market value to book value of assets (Hirshleifer et al., 2012).	Compustat and CRSP
Top tier attorney	This is a dummy variable which is equal to 1 if a patent attorney firm has been listed by the Legal500 in any of the five ranking tiers, and 0 otherwise.	Legal500

Worse patent attorney	Worse patent attorney is a dummy variable equal to 1 if the same company changed to a different patent attorney with a lower rolling success rate than the previous attorney, and 0 otherwise.	Patent Examination Research Dataset

Appendix C: Patents granted by year, and yearly grants to unique firms (2003-2019)

Year	Patents granted	Number of announcements	Unique firms	Patents per unique firm this year(s)
2003	33,983	8,897	1,267	27
2004	46,443	10,895	1,364	34
2005	47,616	11,313	1,346	35
2006	61,045	12,521	1,467	42
2007	55,448	11,538	1,411	39
2008	57,435	11,536	1,330	43
2009	60,705	11,703	1,281	47
2010	77,365	13,327	1,301	59
2011	78,846	13,477	1,291	61
2012	84,559	13,431	1,308	65
2013	91,974	14,701	1,320	70
2014	100,990	15,635	1,360	74
2015	97,544	15,099	1,387	70
2016	98,387	14,878	1,392	71
2017	99,433	14,707	1,347	74
2018	93,286	14,142	1,334	70
2019	106,271	15,405	1,385	77
2003-2019	**1,291,330**	**223,205**	**3,461**	**373**

This table breaks the sample down by year. Grants per unique firm this year is calculated by dividing patent grants by the number of unique firms that obtained patents that year.

Appendix D: Top 25 patent owners by the number of patents obtained (2003-2019)

#	Patent owner name	Grants per firm	% of sample	Cumulative %
1	IBM Corp	80,278	6.2%	6.2%
2	Canon Inc	43,314	3.4%	9.6%
3	Sony Group Corp	33,738	2.6%	12.2%
4	Intel Corp	29,367	2.3%	14.5%
5	Microsoft Corp	29,231	2.3%	16.7%
6	General Electric Co	26,514	2.1%	18.8%
7	Panasonic Corp	21,259	1.6%	20.4%
8	Hitachi Ltd	19,931	1.5%	22.0%
9	Alphabet Inc	19,795	1.5%	23.5%
10	Qualcomm Inc	19,735	1.5%	25.0%
11	Toyota Motor Corp	18,566	1.4%	26.5%
12	Micron Technology Inc	17,633	1.4%	27.8%
13	Xerox Holdings Corp	16,923	1.3%	29.1%
14	Apple Inc	16,408	1.3%	30.4%
15	HP Inc	16,251	1.3%	31.7%
16	Taiwan Semiconductor Manufacturing Co	16,057	1.2%	32.9%
17	AT&T Inc	14,583	1.1%	34.0%
18	Honeywell International Inc	14,392	1.1%	35.2%
19	Honda Motor Co Ltd	14,244	1.1%	36.3%
20	Telefonaktiebolaget Lm Ericsson	13,845	1.1%	37.3%
21	Koninklijke Philips Nv	13,059	1.0%	38.3%
22	Ford Motor Co	12,616	1.0%	39.3%
23	Siemens Ag	12,276	1.0%	40.3%
24	Texas Instruments Inc	11,534	0.9%	41.2%
25	Nokia Corp	11,437	0.9%	42.1%

This table shows the top 25 patent owners in the sample by patents obtained during 2003-2019.

Appendix E: Top 25 of Fama and French industries (49) by patent grants during 2003-2019

	Industry	Patent grants	% of sample	Cumulative %
1	Electronic Equipment	299,834	23.2	23.2
2	Computer Software	205,277	15.9	39.1
3	Computer Hardware	138,442	10.7	49.8
4	Automobiles and Trucks	77,936	6.0	55.9
5	Electrical Equipment	65,492	5.1	60.9
6	Medical Equipment	60,422	4.7	65.6
7	Pharmaceutical Products	58,015	4.5	70.1
8	Machinery	44,835	3.5	73.6
9	Communication	39,958	3.1	76.7
10	Petroleum and Natural Gas	33,174	2.6	79.3
11	Chemicals	27,312	2.1	81.4
12	Aircraft	26,785	2.1	83.4
13	Measuring and Control Equipment	21,537	1.7	85.1
14	Consumer Goods	20,267	1.6	86.7
15	Business Supplies	12,989	1.0	87.7
16	Retail	12,811	1.0	88.7
17	Defense	5,586	0.4	89.1
18	Business Services	4,930	0.4	89.5
19	Recreation	4,195	0.3	89.8
20	Agriculture	4,114	0.3	90.1
21	Construction Materials	3,825	0.3	90.4
22	Apparel	3,276	0.3	90.7
23	Entertainment	2,868	0.2	90.9
24	Wholesale	2,695	0.2	91.1
25	Healthcare	1,741	0.1	91.3

This table breaks the sample down by 49 Fama and French industries. Only the top 25 industries are shown.

Appendix F: Forward citations and patent attorney expertise (applications filed)

	(1)	(2)	(3)
Applications filed	-0.0094** (0.0044)	-0.0099** (0.0044)	-0.0092** (0.0044)
Market capitalisation		-0.0677* (0.0350)	-0.0714** (0.0348)
Independent claims			-0.0069 (0.0239)
Backward citations			0.1425*** (0.0112)
Constant	0.8120*** (0.0329)	1.5094*** (0.3691)	1.2368*** (0.3691)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	1,287,963	1,256,800	1,171,856
R-squared	0.1270	0.1242	0.1310

The dependent variable is the truncation-adjusted number of forward citations, which has been corrected for the presence of examiner and self-citations. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. All patent quality control variables are winsorized at the 1% and 99% tails. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix G: Control and Treatment groups summary statistics

Panel A1: Treatment firms' characteristics

	Mean	Median	SD	25th	75th	Firms	Total events
Market cap. ($bn)	36.5	9.9	93.5	2.2	31.3	533	9,448
Firm age	26.4	21.7	21.9	8.8	34.6	583	9,767
Return on assets (%)	8.5%	12.0%	24.1%	6.7%	17.2%	533	9,448
Leverage (%)	56.6%	55.3%	28.9%	41.0%	71.2%	533	9,448
R&D (%)	10.2%	6.3%	14.9%	3.0%	12.4%	533	9,448
Tobin's Q	2.4	1.8	2.3	1.2	3.0	533	9,448
Institutional ownership (%)	68.5%	72.0%	20.3%	59.0%	82.8%	451	5,012

Panel A2: Treatment firms' patent characteristics

Forward citations (truncation adjusted)	0.6	0.0	1.8	0.0	0.1	583	9,767
Backward citations	34.4	12.5	53.0	6.0	33.0	568	9,471
Independent claims	1.0	1.0	0.1	1.0	1.0	583	9,767

Panel A3: Treatment firms' patent attorney characteristics

Rolling success rate (%)	83.0%	83.9%	11.5%	73.9%	92.5%	583	9,767

Panel B1: Control firms' characteristics

	Mean	Median	SD	25th	75th	Firms	Total events
Market cap. ($bn)	27.3	5.2	64.1	1.2	21.7	3,151	204,859
Firm age	28.9	20.5	24.6	10.5	41.5	3,410	213,438
Return on assets (%)	8.2%	12.1%	22.3%	7.0%	16.9%	3,151	204,859
Leverage (%)	51.5%	50.9%	27.4%	33.4%	66.1%	3,151	204,859
R&D (%)	9.2%	5.5%	13.9%	2.1%	11.2%	3,151	204,859
Tobin's Q	2.1	1.7	1.8	1.2	2.6	3,151	204,859
Institutional ownership (%)	66.0%	73.0%	24.0%	57.0%	83.0%	3,214	186,201

Panel B2: Control firms' patent characteristics

Forward citations (truncation adjusted)	1.1	0.3	2.0	0.0	1.1	3,410	213,438
Backward citations	29.4	14.0	42.6	7.0	30.0	3,387	209,364
Independent claims	1.0	1.0	0.1	1.0	1.0	3,410	213,438

Panel B3: Control firms' patent attorney characteristics

Rolling success rate (%)	83.8%	85.2%	11.6%	75.8%	93.1%	3,408	213,197

This table reports the summary statistics for the treatment and control groups used in the analysis presented in Table 9 and Table 10. Panels A1, A2, and A3 show the characteristics of firms, patents, and patent attorneys associated with patent applications that were filed by patent attorneys located in states in which the USPTO opened a new office. Panels B1, B2, and B3 show the same set of characteristics for the control group. Total assets and market capitalisation are displayed in $billion, and the rest of the firm variables are expressed in %. Rolling success rate is in %, and applications filed is a simple count. See Appendix B for variable definitions.

Appendix H: Market reaction (CAR 0,+2) and attorney expertise (rolling success rate). Exploiting the openings of new USPTO offices. Robustness test using firms located in the states where new offices were opened.

	(1)	(2)	(3)	(4)	(5)
Rolling success rate	0.0030*** (0.0010)		0.0030*** (0.0010)	0.0030*** (0.0010)	0.0034*** (0.0010)
New offices (firm location)		0.0002 (0.0005)	-0.0065 (0.0069)	-0.0065 (0.0069)	-0.0069 (0.0070)
New offices (firm location) x Rolling success rate			0.0082 (0.0083)	0.0081 (0.0083)	0.0089 (0.0085)
Patent grant volume				-0.0001 (0.0001)	0.0000 (0.0001)
Market capitalisation					-0.0015*** (0.0004)
Firm age					-0.0023*** (0.0007)
Return on assets					-0.0017 (0.0020)
Leverage					-0.0010 (0.0010)
R&D					0.0031 (0.0038)
Constant	-0.0022** (0.0009)	0.0003 (0.0002)	-0.0022** (0.0009)	-0.0021** (0.0009)	0.0174*** (0.0038)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Patent class FE	YES	YES	YES	YES	YES
Observations	222,431	222,472	222,431	222,431	213,608
R-squared	0.0292	0.0291	0.0292	0.0292	0.0285

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix I: Robustness test I: Rolling success rate calculated from 2001 and the effect of patent attorney expertise (success rate) on the market reaction (CAR 0,+2).

	(1)	(2)	(3)
Rolling success rate	0.0025*** (0.0008)	0.0025*** (0.0008)	0.0029*** (0.0009)
Patent grants volume		-0.0001 (0.0001)	-0.0000 (0.0001)
Market capitalisation			-0.0015*** (0.0004)
Firm age			-0.0023*** (0.0007)
Return on assets			-0.0017 (0.0020)
Leverage			-0.0010 (0.0010)
R&D			0.0031 (0.0037)
Constant	-0.0017** (0.0007)	-0.0016** (0.0007)	0.0181*** (0.0037)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	222,431	222,431	213,608
R-squared	0.0292	0.0292	0.0285

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix J: Robustness test II: Rolling success rate calculated based on customer id and the effect of patent attorney expertise (success rate) on the market reaction (CAR 0,+2).

	(1)	(2)	(3)
Rolling success rate	0.0029*** (0.0009)	0.0030*** (0.0009)	0.0034*** (0.0009)
Patent grants volume		-0.0001 (0.0001)	0.0000 (0.0002)
Market capitalisation			-0.0015*** (0.0004)
Firm age			-0.0023** (0.0007)
Return on assets			-0.0022 (0.0021)
Leverage			-0.0005 (0.0010)
R&D			0.0033 (0.0038)
Constant	-0.0022** (0.0008)	-0.0021** (0.0008)	0.0174*** (0.0039)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	213,688	213,688	205,245
R-squared	0.0295	0.0295	0.0289

The dependent variable is CAR (0,+2) calculated using the market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix K: Robustness test III: Rolling success rate calculated based on different patent technology groups and the effect of patent attorney expertise (success rate) on the market reaction (CAR 0,+2).

	(1)	(2)	(3)
Rolling success rate	0.0019** (0.0009)	0.0019** (0.0009)	0.0019*** (0.0009)
Patent grants volume		-0.0001 (0.0001)	0.0000 (0.0001)
Market capitalisation			-0.0014*** (0.0004)
Firm age			-0.0022*** (0.0007)
Return on assets			-0.0016 (0.0020)
Leverage			-0.0038*** (0.0009)
R&D			0.0015 (0.0035)
Constant	-0.0012 (0.0008)	-0.0012 (0.0008)	0.0185*** (0.0030)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	220,412	220,412	213,589
R-squared	0.0291	0.0291	0.0285

The dependent variable is CAR (0,+2) calculated using market-adjusted model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix L: Robustness test IV: Patent attorney expertise (success rate) and the market reaction (CAR 0,+2) calculated using the Fama-French 5-Factor model

	(1)	(2)	(3)
Rolling success rate	0.0027*** (0.0010)	0.0026*** (0.0010)	0.0032*** (0.0010)
Patent grants volume		0.0002 (0.0001)	0.0003*** (0.0001)
Market capitalisation			-0.0018*** (0.0003)
Firm age			-0.0007 (0.0005)
Return on assets			0.0007 (0.0019)
Leverage			-0.0038*** (0.0009)
R&D			0.0015 (0.0035)
Constant	-0.0026*** (0.0008)	-0.0027*** (0.0008)	0.0157** (0.0030)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	220,755	220,755	213,024
R-squared	0.0269	0.0269	0.0266

The dependent variable is CAR (0,+2) calculated using the Fama-French 5-factor model. Standard errors are clustered at firm and grant date-level and are reported in parentheses. All firm control variables are lagged by one year and winsorized at the 1% and 99% tails. Observations is the total number of patent announcements which have been adjusted to correct for multiple patents granted to the same firm on the same day. See Appendix B for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

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