Do Lawyers Matter? Evidence from Patents

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Abstract

We investigate the role of patent attorney capability in determining the economic and technological value of patents. First, we establish a positive correlation between attorneys' substantive expertise (success rate in obtaining patents) and the economic and technological value of patents. Also, we find no evidence that attorneys' process experience (number of patent applications filed) matters for patents. Then we identify the causal effect of patent attorney expertise by using two alternative approaches: changing to a more capable attorney and the openings of four new regional offices by the United States Patent and Trademark Office (USPTO) between 2012 and 2015. Overall, we find that successful patent attorneys matter as they increase both the economic and technological value of patents. Therefore, innovative firms that employ patent attorneys should closely monitor their success track record.

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 expertise and the economic and technological value of patents. Patent attorneys play a central role in drafting patent applications and negotiating with patent examiners (Reitzig, 2004). We argue that more capable patent attorneys can help firms secure more valuable patents.

American companies have spent $493 billion on research and development (R&D) in 2019 alone (Wolfe, 2021). 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 391,103 new patents granted in the United States in 2019 alone, an increase of 104% compared with 191,927 patents granted in 2009. The literature suggests that investors reward companies for obtaining patents (Kogan et al., 2017), which can boost firm growth (Farre-Mensa et al., 2020) and profitability (Pandit et al., 2011).

Previous studies have focused on studying the impact of patent examiners on patents (e.g., Lemley and Sampat, 2012; Shu et al., 2022). This paper differs from this literature by concentrating on patent attorneys, who can have a greater influence on patents than examiners. Moreover, by focusing on the process of obtaining patents from the patent office, this paper is different from the literature on patent litigation, which studies patent disputes between firms (e.g., Cohen et al., 2019; Mezzanotti, 2021).

The value implications of patent attorneys' expertise remain largely unexplored (de Rassenfosse et al., 2021). We address this gap by examining two types of value implications: *economic* and *technological*. We measure the economic value of patents using the market

[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 United States Patent and Trademark Office (USPTO).

reaction to patent grants and the technological value of patents using the number of citations received by a patent.

Should the capability of patent attorneys matter to shareholder wealth when it comes to their work on patents? The purpose of attorneys is to obtain valid, broad, and valuable patents for their clients. Their work requires both scientific and legal expertise. Patent attorneys often work closely with inventors, and they can recommend changes to an invention that would 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 of patent protection with relation to a technology. 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). Patent attorneys consider the probability of different legal scenarios and use their channels of influence to maximise the overall expected profits from obtaining patent protection for their clients (Reitzig, 2004).

The work of a patent attorney is comparable to the role of a conventional lawyer. Lawyers apply their knowledge of the law to construct legal arguments and negotiate on behalf of their clients. Lawyers 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 lawyers produce better outcomes for their clients (Miller et al., 2015; Szmer et al., 2007). Therefore, we argue that patent attorneys' legal expertise and the experience they gain in working with the USPTO should be reflected in the market valuation of patents that they have worked on. Moreover, the skill of patent attorneys should also affect the quality of their patents. Patent attorneys determine patent validity and the scope of patent rights (Yelderman, 2014), which can affect the number of citations received by a patent.[2]

Based on the *attorney capability theory* we distinguish between substantive legal expertise of patent attorneys and the procedural experience they gain as they repeatedly prosecute patent applications (Haire et al., 1999; Kritzer, 1998). Substantive legal expertise is captured by the percent of patent applications that a particular attorney worked on in the past that resulted in a granted patent, based on a rolling success measure. Procedural experience is captured by the cumulative number of patent applications filed by a patent attorney regardless of the application being successful or not. For robustness, we use alternative proxies of experience.

We examine the value of patent attorney capability by regressing the estimates of the economic value of patents on the measures of patent attorney expertise. Our results support the importance of legal expertise of patent attorneys. A one standard deviation increase in patent representative legal expertise is related to a 0.029% higher market reaction to a patent announcement. This effect accumulates to a 10.0% increase in market value for an average company in our sample, which obtained 346 patents between 2003-2019. Moreover, a one standard deviation increase in patent attorney legal expertise is associated with a 2% higher number of citations received by a patent.

It is plausible that firms choose to hire more capable attorneys to work on obtaining patents for inventions that are more important to them (de Rassenfosse et al., 2021). 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

[2] Forward citations are the most widely used proxy for patent quality (Hirschey and Richardson, 2004; Trajtenberg, 1990). One additional citation per patent is associated with a 3% higher firm value (Hall et al., 2005).

USPTO. Patent attorneys located in the states in which the new offices are opened should benefit from the change, because of an easier access to patent examiners with whom they can conduct in-person interviews to negotiate the grant of patents (Lemley and Sampat, 2010). Moreover, attorneys with a higher amount of expertise are likely to be more skilled negotiators (Karsten et al., 2021). Our results show that the importance of substantive expertise of patent attorneys for the economic value of patents increases for patent attorneys located in states in which new USPTO offices were opened, which suggests an existence of a causal relationship. However, the impact of attorney expertise on the technological value of patents was not affected by the opening of the new offices.

Second, we also consider whether a change in a firm's patent attorney impacts the economic and technological value of a company's patents. We compare patents represented by different attorneys that were granted to the same company in close succession. Patents obtained by the same company at a similar point in time are likely to protect similar technologies. 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.

Altogether, the results indicate that patent attorney capability is positively related to both economic and technological value of patents. However, the results are not explained by patent attorneys gaining experience purely by submitting more patent applications to the patent office. Contrary to the literature on conventional lawyer ability (Abrams and Yoon, 2007; McGuire, 1995), we find no evidence that process experience matters to economic and technological value of patents.

To our knowledge, this paper is the first to investigate the effect of patent attorney expertise on the economic and technological value of patents. We show that the legal expertise of patent attorneys is positively associated with the economic value of patents. Therefore, only capable patent attorneys create value for their clients , and consequently 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 forward citations. Finally, this paper 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., 2021; Gaudry, 2012; Somaya et al., 2007). This paper differs from this literature by using an objective measure of patent value, the market reaction to patent grants, and distinguishing between the process experience of patent attorneys and their substantive expertise.

2. Hypotheses development

Navigating the patent application process requires legal expertise (Lee, 2020). Applicants need to know how to write a valid patent application and what information must be disclosed with the patent office.[3] Also, applicants need to know how to negotiate with patent examiners. When an examiner receives a patent application, she initially rejects the patent application 86.5% of the time (Lemley and Sampat, 2010).[4] 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).

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[3] Applicants that fail to disclose information that is material to the invention's patentability risk the patent being held unenforceable (Hricik and Meyer, 2009).

[4] After an examiner first reviews a patent application, in 86.5% of the cases she sends 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).

The roles of a patent attorney and a conventional lawyer are similar. Applying one's knowledge of the law, constructing convincing arguments, and negotiating on behalf of their clients is required both of lawyers (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 (Miller et al., 2015). Attorneys gain procedural knowledge of the legal institutions they interact with, develop informal relationships with decision makers, build their credibility, and with time they can shape the law in their favour (Galanter, 1974; McGuire, 1995). Moreover, lawyers that possess expert legal knowledge should be more effective (Kritzer, 1998; Haire et al, 1999). The literature finds support for the attorney capability theory. Haire et al. (1999) find that inexperienced lawyers as well as lawyers not specialising in a relevant area of the law are less likely to succeed in litigation. Abrams and Yoon (2007) show that more experienced attorneys produce better outcomes for their clients. Therefore, we apply the attorney capability theory to test the importance of patent attorneys.

Lawyers 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 a lawyer's familiarity with a particular court and is commonly measured by counting the number of interactions between the lawyer 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 lawyer'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. 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. Patent attorneys need to consider the balance between breadth[5] and validity[6] of the claims. Broad claims are generally more valuable (Hegde et al., 2020; Lerner, 1994), but the benefit of broader scope is limited by the risk of a claim being found invalid (Yelderman, 2014). 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 inventions with a small amount of novelty (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,[7] and that they provide more citations for inventions that are more important to them. Furthermore, Kuhn et al. (2020) argue that some patents deliberately include an overwhelming number of citations. Applicants can benefit by hiding relevant information among dozens of immaterial citations, because the time-constraint examiners (Frakes and Wasserman, 2017) will not be able to review all of them (Kuhn et al., 2020). Moreover, patent applicants can impact which examiners are assigned to patent applications (Barber and Diestre, 2022), and which patents are cited by patent examiners (Doran and Webster, 2019). Overall, patent attorneys can influence how an invention is disclosed in a patent application, which can affect the number of citations it will receive. This leads to the second hypothesis:

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

[5] Patent breadth, 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).

[6] Validity determines the probability of the patent being found invalid in court. While 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).

[7] This suggests strategic behaviour, since it is unlikely that applicants are not aware of their own patents (Sampat, 2008).

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

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 10.3 million non-provisional 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). Moreover, we remove patents granted after 2019, because of the exceptional market circumstances created by the outbreak of COVID-19. This reduces the sample to 6.8 million patent applications. We drop all non-utility[8] patent applications, which leaves us with 6.4 million applications (Lerner et al., 2011; Mann, 2018; Appel et al., 2019). To study the market reaction to patent grants, we keep applications that were successful and

[8] 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.

resulted in granted patents. This leaves us with 3.9 million utility patents. The sample selection process is presented in Table 1.

/Table 1 here/

Market reaction to patent grants can only be measured for patents which belong to publicly listed companies. In order to identify these firms, we use the patent-CRSP link created by Stoffman et al. (2021), who matched 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., 2021). This leaves us with 1.4 million patents.[9] We obtain data on patent characteristics, including citations and claims from USPTO PatentsView (Stoffman et al., 2021).

For each company in our 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 drop all patent announcements which occur within two trading days of a firm's earnings or dividend announcements (Bowman, 1983; de Jong and Naumovska, 2016). This leaves us with 1.3 million patents granted to 3,727 firms during 2003-2019 (see Table A3 in the appendix). 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 4.2-4.5).

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

[9] Our 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 representative 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.

We capture process expertise using the cumulative number of patent applications (successful and unsuccessful) filed by patent attorneys. We take a 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 representatives.[10] Entities identified as patent representatives range from law firms, individual patent attorneys, or legal departments of companies. We clean the misspellings of patent representatives' names in the PatEx dataset before constructing the measures. The steps of the cleaning process are described in Table A1

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

in the appendix. Table 2 presents the list of top 25 patent representatives according to the total number of patent applications they filed between 1980 and 2019. Table 2 also illustrates the total success rate of each representative during the period, and it shows that even among the most popular representatives 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.[11] All variables are defined in Table A2 in the appendix. Panel A illustrates the characteristics of 3,727 public firms which obtained 1,291,239 patents in the sample. The average company has total assets of $28.7 billion, while the median company has total assets of $5.1 billion. With a debt to assets ratio of 0.51, the average company in our sample is highly leveraged in comparison to the average nonfinancial corporation headquartered in the US (Palazzo and Yang, 2019). The average firm in our sample has an R&D intensity of 9.1%. 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 1.2.[12] Moreover, the average patent contains 27.1 backward citations, and 1.1 independent claims.[13] The descriptive statistics of the measures of patent representative expertise are presented in Panel C. The average rolling success rate is 83.2%, with a standard deviation of 11.6%.[14] This is similar to Gaudry (2012), who reports that 65.2% of patent applications represented by patent

[11] 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.
[12] When counting the number of citations, we exclude citations that originated from patent examiners and citations by other patents of the same patent owner.
[13] 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.
[14] Given that the distribution of rolling success rate is skewed, we have rerun our analysis using a log-transformed rolling success rate. Our results are similar.

attorneys are successful, compared to 23.6% of applications represented by the inventors themselves.

/Table 3 here/

Table A3 in the appendix 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 33,973 in 2003 to 106,228 in 2019. Table A4 in the appendix 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.

Table A5 in the appendix 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 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:

$$AR_{i,t} = R_{i,t} - R_{m,t} \qquad (1)$$

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[15] on day t. Because many companies in our sample obtain patents every month or even every week, we use the market adjusted model in equation 1 (Kogan et al., 2017). 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 (MacKinlay, 1997; Brown and Warner, 1985).

We start with a graphical analysis. 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.[16] Graphical analysis suggests 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.[17]

/Figure 1 here/

We measure the patent announcement returns over a three-day event window (0,+2) (Kogan et al., 2017).[18] For robustness, we also measure the market response over alternative event windows and our results are similar. Table 4 shows the daily abnormal returns between day -1 and day +3 and the cumulative abnormal returns over the (0,+1), (0,+2), and (0,+3) event windows. Panel A shows that the market reacts positively to patent announcements. An average patent announcement has a CAR(0,+2) of 0.025%, which is statistically significant at the 1%

[15] The risk-free rate adjusted market return for North America is from Kenneth French's website.
[16] We define patent attorneys as more (less) capable when their rolling success rate is in the top (bottom) 40% of the distribution.
[17] 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.
[18] 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).

level. This is an economically significant result. The mean market capitalisation in our sample at the time of an average patent announcement is $29.7 billion (see Table 3). Given an average CAR(0,+2) of 0.025%, the mean patent announcement is associated with an increase in market value of $7.4 million (=0.025%*$29.7 bn). This is similar to Kogan et al. (2017), who find that a median patent owned by a publicly listed company is worth $3m, while 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, although they look at investor attention rather than the impact of patent attorneys.

/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.[19] Panel B of Table 2 shows that attorneys with high expertise are associated with a CAR(0,+2) of 0.070%, which is statistically significant at the 1% level. Similarly, panel C of Table 2 shows that announcements associated with attorneys with low expertise generate a CAR(0,+2) of -0.032%, significant at the 1% level. This suggests that using the services of more capable patent attorneys can increase the market valuation of patent announcements. To investigate the robustness of this result, and to test whether more capable patent attorneys affect the technological value of patents, we next turn to regression analysis.

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

We explore the relationship between patent representative expertise and the market valuation of patents in a multivariate OLS regression analysis. We estimate the following model:

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

[19] We define the expertise to be high (low) when the representatives' 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).[20] The independent variable of interest is *patent attorney expertise*, which is a proxy for a patent representative'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. In particular, we include *market capitalization*, 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., 2021) and *R&D*, as companies that invest more in R&D can be better innovators (Chen et al., 2018). Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects[21], 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 vary across technology fields (Carley et al., 2015; Hall et al., 2001).[22] Our 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 our analysis. Moreover, patent attorney fixed effects could be collinear with our main explanatory variable; rolling success rate, which captures patent attorney capability.

First, we use the rolling success rate of a patent representative 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

[20] In alternative specifications we use alternative event windows, and our results remain similar.
[21] We also test different combinations of fixed effects, including industry, art unit, and examiner fixed effects. Our results remain robust to the choice of fixed effects.
[22] 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. Our results are not sensitive to the way we compute the fixed effects. Moreover, our results are similar when we do not include patent class fixed effects in our model.

paribus, the positive and statistically significant coefficient on the rolling success rate indicates that the market valuation of a patent increases by 0.24% when the rolling success rate increases by 100%. The standard deviation of the rolling success rate is 12% (see Table 3). Therefore, a one-standard deviation increase in rolling success rate increases the market valuation by 0.029% (=12%*0.24%). This is economically significant. The average company in our sample has obtained 346 patents between 2003-2019 (see Table A3). 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 our sample by 10.0% (=346*0.029%).

/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 negatively predicts the market reaction to patent grants, which is consistent with prior literature (Chen et al., 2018; Chemmanur et al., 2021). Overall, the results support the first hypothesis (*H1a*). Although the R^2 is low, ranging from 2.7% to 2.8%, it is consistent with the literature on patent announcements (Chen et al., 2018; Boscaljon et al. 2006; Chemmanur et al., 2021).

Second, we proxy for patent representative 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. 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. Forward citations have been 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:

$$\begin{aligned} Forward\ citations_i = \alpha + \beta_1 * patent\ attorney\ expertise_{i,t} + \beta_2 * \\ \log(total\ assets)_{i,t-1} + \beta_3 * backward\ citations_i + \beta_4 * \\ independent\ claims_i + \gamma + \xi + \psi + u_{i,t} \end{aligned} \tag{3}$$

The dependent variable is *forward citations*, which is the truncation-adjusted number of citations received by a patent.[23] Using truncation-adjusted forward citations addresses the issue of older patents having had more time to receive citations than younger patents (Hall et al., 2001). Moreover, when counting citations, we exclude any citations that a patent receives from patent examiners and the 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 representative's rolling success rate. Our controls include *market capitalization,* which is a proxy for company size (Kogan et al., 2017) and patent quality control variables, which include *backward citations* and *independent claims.*[24] Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects,[25] respectively.

First, we study the relation between forward citations and patent attorney substantive expertise. The regression results are shown in Table 7. In column (1) of Table 7, we regress *forward 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

[23] 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.

[24] *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).

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

predictor of the technological value of patents. A one standard deviation increase in the rolling success rate is associated with 0.024 (12%*0.20) more truncation-adjusted forward citations. Given that the mean value of truncation adjusted citations is 1.2 (see Table 3), a one standard deviation higher rolling success rate increases forward citations by 2% (0.024/1.2). Therefore, patent attorneys with a higher degree of expertise are positively related to higher technological value of patents, which supports our 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 forward citations.

/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 Table A6 in the appendix. In column (1) of Table A6 we regress *forward citations* on the number of applications filed. The results suggest that the number of patent applications filed is negatively associated with the technological value of patents. A 20% increase in applications filed is associated with 0.002 (20%*0.01) lower number of truncation-adjusted forward 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

Next, 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 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:

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

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.[26] Control variables include *patent grants volume*, *market capitalization*, *firm age, return on assets*, *leverage*, and *R&D*. Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects, respectively.[27]

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

[26] A comparison of the descriptive statistics of the treatment and control groups is shown in Table A7 in the appendix.
[27] 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. Our results are not sensitive to the way we compute the fixed effects. Moreover, our results are similar when we do not include patent class fixed effects in our model.

effects. The coefficient on *new offices* equals 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%. Columns (2) and (3) of Table 8 add control variables and the results remain unchanged.

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

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

$CAR_{i,t}$ is the average cumulative abnormal return over a three-day window (0,+2).[28] *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 capitalization*, *firm age, return on assets*, *leverage*, and *R&D*. Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects, respectively.[29]

Regression results are shown in Table 9. 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. Our findings show that greater patent attorney substantive expertise increases the economic value of patents. Columns (4) and (5) of Table 9 add control variables, and our results remain unchanged.

/Table 9 here/

[28] In alternative specifications we use alternative event windows and our results remain similar.
[29] 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. Our results are not sensitive to the way we compute the fixed effects. Moreover, our results are similar when we do not include patent class fixed effects in our model.

To alleviate any concerns that the openings of the new offices impacted the firms located in the affected states and that this in turn drives our results, 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. 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. The regression results are shown in Table A8 in the appendix. Column (3) of Table A8 interacts *new offices (firm location)* with *rolling success rate*. The interaction is statistically insignificant, which suggests that patents filed by firms located in the states with the new USPTO offices were not affected by the change.

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

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

The dependent variable is *forward 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 capitalization*, *backward citations* and *independent claims.* Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects[30], respectively.

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 statistically insignificant, 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.

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

/Table 10 here/

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

Lastly, we investigate whether a change of a company's patent representative affects the economic and technological value of patents. We test whether the differences between the economic and technological value of patents that were granted to the same company one after the other 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 at a similar point in time. Patents that were obtained by the same firm in close succession are likely to be more similar than patents that were secured by a company years apart.

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

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

$\Delta CAR_{i,t}$ 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.[31] Restricting the analysis to single patent grants ensures that we are 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. Our 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

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

specific control variables, which includes *market capitalization*, *firm age, return on assets*, *leverage*, and *R&D.* Lastly, γ, ξ, and ψ denote year, firm, and patent technology class fixed effects, respectively.

Regression results are presented in Table 11. In panel A, we regress $\Delta CAR_{i,t}$ solely on *better patent attorney.* The coefficient on *better patent attorney* equals 0.08%, significant at the 10% level. This suggests that market valuation of a patent increases by 0.08% when a company switches to a more capable patent attorney. The effect seems small, but it will accumulate with each additional patent represented by the more capable patent attorney. The increase in shareholder wealth adds up to 27.7% (=346*0.08%) for an average company in our sample that obtained 346 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 representative 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 our new independent variable of interest in equation (6). 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 0.048% (=12*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:

$$\Delta\, forward\ citations_i = \alpha + \beta_1 * better/worse\ patent\ attorney_{\ i,t} + \beta_2 * market\ capitalization_{i,t-1} + \beta_3 * backward\ citations_i + \beta_4 * independent\ claims_i + \gamma + \xi + \psi + u_{i,t} \quad (8)$$

ΔForward citations$_i$ is the difference between the truncation-adjusted number of citations received by a single patent granted to a company and 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 capitalization* 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.

Regression results are presented in Table 12. In panel A we regress *Δ forward citations*$_i$ on *better patent attorney*. The coefficient on *better patent attorney* is positive and statistically significant at the 5% level. The results suggest that switching to a more capable patent attorney is associated with 0.06 more truncation-adjusted forward citations received by a patent. Given that the mean amount of truncation adjusted forward citations is 1.2 (see Table 3), this represents an increase of 5% (0.06/1.2). 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 forward citations by 0.07, significant at the 5% level. Lastly, in panel C, we regress *ΔForward 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 representative. Overall, changing to a better (worse) patent attorney is associated with both a higher (lower) economic and technological value of patents.

/Table 12 here/

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 but this time only using patent applications filed since 2001 instead of 1980. We repeat the same regressions from Table 5.[32] The results are presented in Table A9 in the appendix. Table A9 shows that the magnitude and the statistical significance of the rolling success rate remains unchanged. We further test the robustness of our measure by constructing it based on the customer id number[33] of a patent representative 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 Table A10 in the appendix. Our results remain unchanged. In addition, we also construct alternative measures of patent attorneys' process expertise[34] and substantive expertise[35]. Our results are similar and are available upon request.

As an additional robustness check, we estimate our 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 Table A11 in the appendix. 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). The results remain unchanged and are available upon request.

[32] We also repeat the same regressions from Table 8, and we obtain similar results.
[33] Customer id number uniquely identifies the patent representative (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 Table A8 in the appendix.
[34] In this paper 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.
[35] 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.

6. Conclusion

We examine the impact of patent attorney expertise 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 lawyers produce better outcomes. Contrary to the literature on lawyer 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 forward citations. Furthermore, we find evidence suggesting that changing to a better (worse) patent attorney increases (decreases) the economic and the technological value of patents. Lastly, 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. However, there was no effect of the change on the importance of patent attorney legal expertise for the technological value of patents.

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

Figure 1: Market Reaction to Patent Grants

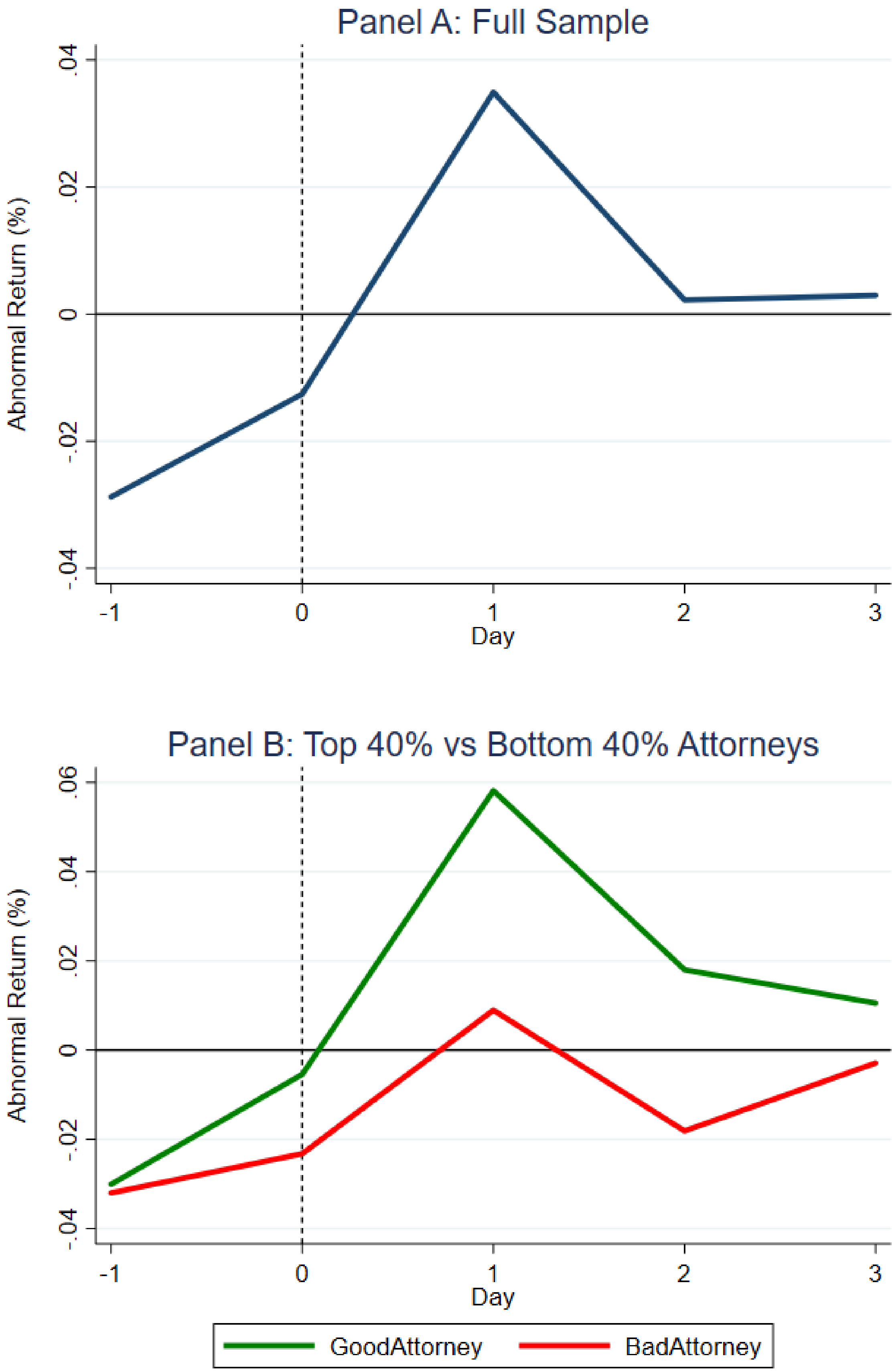

Table 1: Sample selection process

All non-provisional patent applications in the PatEx dataset	**10,339,559**	**100%**
Applications filed before 2001	-2,957,640	-28.6%
Patents granted after 2019	-487,353	-4.7%
Applications missing a filing date	-54,428	-0.5%
Non-utility applications	-446,496	-4.3%
Not granted applications	-2,493,959	-24.1%
Patents not matched to publicly listed companies	-2,408,826	-23.3%
Financial firms' patents	-18,119	-0.2%
Utility firms' patents	-622	-0.0%
Missing accounting data	-30,276	-0.3%
Missing stock return data	-22,079	-0.2%
Confounding events	-128,522	-1.2%
Total	**1,291,239**	**12.5%**

This table presents a breakdown of the sample selection process.

Table 2: Top 25 patent attorney firms by number of applications filed (1980-2019)

#	Name	Applications filed 1980-2019	Total success 1980-2019 %
1	Oblon McClelland Maier & Neustadt LLP	161,456	79%
2	IBM Corp	97,906	90%
3	Birch Stewart Kolasch & Birch LLP	95,533	75%
4	Sughrue Mion PLLC	89,439	68%
5	Oliff PLC	87,132	81%
6	Nixon & Vanderhye PC	85,853	72%
7	Venable LLP	76,314	88%
8	Knobbe Martens Olson & Bear LLP	74,806	70%
9	Foley & Lardner LLP	74,513	74%
10	Finnegan Henderson Farabow Garrett & Dunner LLP	66,858	72%
11	Microsoft Corp	58,247	80%
12	McDermott Will & Emery LLP	50,255	76%
13	Buchanan Ingersoll & Rooney PC	45,865	77%
14	Kilpatrick Townsend & Stockton LLP West Coast	45,041	71%
15	Wenderoth Lind & Ponack LLP	43,772	78%
16	Banner & Witcoff LTD	43,109	77%
17	Philips Intellectual Property & Standards	40,449	75%
18	Staas & Halsey LLP	39,166	70%
19	Sughrue Mion Zinn Macpeak & Seas	38,073	90%
20	Pillsbury Winthrop Shaw Pittman LLP	37,601	76%
21	Cantor Colburn LLP	34,561	69%
22	Harness Dickey Troy	33,322	73%
23	Antonelli Terry Stout & Kraus LLP	33,308	85%
24	Texas Instruments INC	32,861	85%
25	Sterne Kessler Goldstein & Fox PLLC	31,820	79%

This table lists the top 25 patent representatives 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 representatives 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	Patents
Panel A: Patent owner characteristics								
Total assets ($bn)	28.7	5.1	68.7	1.1	23.1	3,461	240,927	1,272,561
Market cap. ($bn)	29.7	6.7	63.8	1.4	27.5	3,460	240,866	1,272,488
Firm age	27.3	19.6	23.3	10.1	37.9	3,727	247,756	1,291,239
Return on assets (%)	9.1	12.1	17.5	7.2	16.9	3,459	240,823	1,272,424
Leverage (%)	51.2	51.2	23.8	34.7	65.8	3,459	240,172	1,270,271
R&D (%)	9.1	5.7	11.2	2.5	11.2	2,975	227,151	1,238,564
Tobin's Q	2.2	1.8	1.5	1.3	2.7	3,385	216,305	1,118,358
Institutional ownership (%)	58.0	68.8	30.7	37.4	81.9	3,559	219,167	1,152,518
Panel B: Patent characteristics								
Forward citations (truncation adjusted)	1.2	0.25	5.9	0.0	0.9	3,727	247,756	1,291,239
Backward citations	27.1	12.0	43.5	6.0	27.0	3,701	245,490	1,298,277
Independent claims	1.1	1.0	0.2	1.0	1.0	3,727	247,756	1,291,239
Panel C: Measures of patent representative expertise								
Rolling success rate (%)	83.2	84.4	11.6	75.3	92.5	3,724	247,756	1,291,064
Applications filed	4,380.9	1131.0	8551.2	249.0	4288.8	3,724	247,756	1,291,064

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 capitalization 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 representative expertise. Rolling success rate is in %, and applications filed is a simple count. See Table A2 in the appendix for variable definitions.

Table 4: Event study results

Mean AR (-1), %	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								
-0.029***	-0.013***	0.035***	0.002	0.003	0.022***	0.025***	0.027***	247,756
Panel B: Announcements with good attorneys								
-0.030***	-0.006	0.058***	0.018***	0.010	0.052***	0.070***	0.080***	99,203
Panel C: Announcements with bad attorneys								
-0.032***	-0.023***	0.009	-0.019***	-0.004	-0.014***	-0.032***	-0.036***	99,036

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 representatives with high, and low levels of substantive expertise, respectively. We define the expertise to be high (low) when the representatives' 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 patent representative expertise (rolling success rate)

	(1)	(2)	(3)
Rolling success rate	0.0024** (0.0010)	0.0025** (0.0010)	0.0030*** (0.0010)
Patent grants volume		-0.0002 (0.0001)	-0.0001 (0.0001)
Market capitalisation			-0.0015*** (0.0003)
Firm age			-0.0011** (0.0005)
Return on assets			-0.0004 (0.0016)
Leverage			-0.0007 (0.0009)
R&D			-0.0027 (0.0031)
Constant	-0.0018** (0.0008)	-0.0017** (0.0008)	0.0147*** (0.0033)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	247,020	247,020	237,167
R-squared	0.0281	0.0281	0.0275

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 Table A2 in the appendix for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

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

	(1)	(2)	(3)
Applications filed	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
Patent grants volume		-0.0002 (0.0001)	-0.0001 (0.0001)
Market capitalisation			-0.0015*** (0.0003)
Firm age			-0.0011** (0.0005)
Return on assets			-0.0004 (0.0016)
Leverage			-0.0007 (0.0009)
R&D			-0.0025 (0.0031)
Constant	0.0001 (0.0004)	0.0002 (0.0004)	0.0169*** (0.0032)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	247,020	247,020	237,167
R-squared	0.0280	0.0280	0.0275

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 Table A2 in the appendix for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

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

	(1)	(2)	(3)
Rolling success rate	0.20***	0.21***	0.19***
	(0.06)	(0.06)	(0.06)
Market capitalisation		-0.04	-0.05*
		(0.03)	(0.03)
Independent claims			0.02
			(0.02)
Backward citations			0.13***
			(0.01)
Constant	0.54***	0.99***	0.79***
	(0.05)	(0.30)	(0.30)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	1,288,975	1,257,722	1,172,721
R-squared	0.13	0.13	0.13

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 Table A2 in the appendix for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

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

	(1)	(2)	(3)
New offices	0.009** (0.004)	0.009** (0.004)	0.008** (0.004)
Patent grant volume		0.006*** (0.001)	0.006*** (0.001)
Market capitalisation			0.006** (0.002)
Firm age			-0.009** (0.004)
Return on assets			0.014 (0.010)
Leverage			0.003 (0.007)
R&D			0.051** (0.021)
Constant	0.831*** (0.000)	0.825*** (0.001)	0.794*** (0.023)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	247,054	247,054	237,209
R-squared	0.606	0.607	0.609

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 Table A2 in the appendix for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

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

	(1)	(2)	(3)	(4)	(5)
Rolling success rate	0.0025** (0.0010)		0.0022** (0.0010)	0.0023** (0.0010)	0.0027*** (0.0010)
New offices		0.0003 (0.0004)	-0.0060** (0.0029)	-0.0061** (0.0029)	-0.0056* (0.0029)
New offices x Rolling success rate			0.0078** (0.0035)	0.0079** (0.0037)	0.0078** (0.0035)
Patent grant volume				-0.0002 (0.0001)	-0.0000 (0.0001)
Market capitalisation					-0.0015*** (0.0003)
Firm age					-0.0011** (0.0005)
Return on assets					-0.0004 (0.0016)
Leverage					-0.0008 (0.0009)
R&D					-0.0028 (0.0031)
Constant	-0.0019** (0.0009)	0.0002 (0.0002)	-0.0016* (0.0009)	-0.0015* (0.0009)	0.0150*** (0.0033)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Patent class FE	YES	YES	YES	YES	YES
Observations	247,054	247,093	247,054	247,054	237,209
R-squared	0.0280	0.0280	0.0280	0.0280	0.0274

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 Table A2 in the appendix for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table 10: Forward citations and patent representative expertise (rolling success rate). Exploiting the openings of new USPTO offices.

	(1)	(2)	(3)	(4)	(5)
Rolling success rate	0.20*** (0.06)		0.20*** (0.06)	0.20*** (0.06)	0.18*** (0.07)
New offices		0.00 (0.04)	-0.08 (0.12)	-0.06 (0.12)	-0.05 (0.13)
New offices x Rolling success rate			0.10 (0.14)	0.09 (0.15)	0.09 (0.16)
Market capitalisation				-0.04 (0.03)	-0.05* (0.03)
Independent claims					0.02 (0.02)
Backward citations					0.13*** (0.01)
Constant	0.54*** (0.05)	0.71*** (0.00)	0.54*** (0.05)	0.99*** (0.30)	0.80*** (0.30)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Patent class FE	YES	YES	YES	YES	YES
Observations	1,290,093	1,290,447	1,290,093	1,258,819	1,173,745
R-squared	0.13	0.13	0.13	0.13	0.13

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 Table A2 in the appendix 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 representative change.

Panel A: Changed to a better attorney	(1)	(2)
Better patent attorney	0.0008* (0.0004)	0.0009** (0.0004)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	102,605	97,757
R-squared	0.0126	0.0125
Panel B: Changed to a worse attorney	**(3)**	**(4)**
Worse patent attorney	-0.0008* (0.0004)	-0.0008* (0.0004)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	102,605	97,757
R-squared	0.0126	0.0125

Table 11. Continued

Panel C: Difference in market reaction and the difference in patent attorney success rate	(5)	(6)
Difference in capability	0.0037** (0.0018)	0.0037** (0.0017)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	46,346	44,265
R-squared	0.0347	0.0348

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 Table A2 in the appendix for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

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

Panel A: Changed to a better attorney	(1)	(2)
Better patent attorney	0.06** (0.03)	0.06** (0.03)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	128,479	121,141
R-squared	0.01	0.02
Panel B: Changed to a worse attorney	**(3)**	**(4)**
Worse patent attorney	-0.07** (0.03)	-0.06** (0.03)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	128,479	121,141
R-squared	0.01	0.02

Table 12. Continued

Panel C: Difference in forward citations and the difference in patent attorney success rate	(5)	(6)
Difference in capability	0.39*** (0.13)	0.35*** (0.14)
Control variables	NO	YES
Firm FE	YES	YES
Year FE	YES	YES
Patent class FE	YES	YES
Observations	58,128	52,707
R-squared	0.03	0.04

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 Table A2 in the appendix for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Appendix

Table A1: Patent representative names' cleaning process

#	Step Name	Description
1	Capitalising all letters	We capitalise all letters in the string variable containing patent representatives' 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 representatives' 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 representatives' names from the Patent Examination Research Dataset.

Table A2: Variable definitions

Variable	Definition	Source
Applications filed	Applications filed is a natural logarithm of one plus the total number of patent applications filed by a particular patent representative. It is updated on a yearly basis.	Patent Examination Research Dataset
Backward citations	Backward citations is a simple count 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 the number of years since the firm first appearance in CRSP.	CRSP
Forward citations	Forward citations is the 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 simple count 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
Log of total assets	Log of total assets measures the size of a company. It is calculated as the logarithm of a firm's total assets (Compustat item: at) (Doidge and Dyck, 2015).	Compustat
Market cap. ($bn)	Market capitalization is the number of shares outstanding multiplied by the share price.	CRSP
New ethics code	New ethics code is a dummy variable equal to 1 if a patent was filed on or after 3 May 2013, and 0 otherwise.	Patent Examination Research Dataset
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

Table A2. Continued

Variable	Definition	Source
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 representative'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 representative by the total number of successful and abandoned applications filed by that representative. 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
Total assets	The total amount of assets.	Compustat
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

Table A3: 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	33,973	8,571	1,267	27
2004	46,446	11,712	1,364	34
2005	47,612	12,556	1,345	35
2006	61,049	14,091	1,467	42
2007	55,452	13,257	1,411	39
2008	57,440	13,100	1,330	43
2009	60,694	13,269	1,281	47
2010	77,349	15,063	1,301	59
2011	78,845	15,174	1,291	61
2012	84,545	15,137	1,308	65
2013	91,962	16,365	1,320	70
2014	100,987	17,317	1,361	74
2015	97,545	16,831	1,387	70
2016	98,392	16,532	1,392	71
2017	99,445	16,248	1,347	74
2018	93,275	15,623	1,333	70
2019	106,228	16,910	1,385	77
2003-2019	**1,291,239**	**247,756**	**3,727**	**346**

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.

Table A4: 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 our sample by patents obtained during 2003-2019.

Table A5: 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.

Table A6: Forward citations and patent representative expertise (applications filed)

	(1)	(2)	(3)
Applications filed	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
Market capitalisation		-0.02* (0.01)	-0.02* (0.01)
Independent claims			0.01 (0.01)
Backward citations			0.04*** (0.00)
Constant	0.35*** (0.01)	0.52*** (0.10)	0.45*** (0.10)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	1,288,975	1,257,722	1,172,721
R-squared	0.16	0.16	0.17

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 Table A2 in the appendix for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table A7: Control and Treatment groups summary statistics

	Mean	Median	SD	25^{th}	75^{th}	Firms	Total events	Patents
Panel A1: Treatment firms' characteristics								
Total assets ($bn)	36.0	5.4	80.3	1.6	25.1	575	9,723	58,980
Market cap. ($bn)	38.7	10.2	94.9	2.2	31.8	575	9,723	58,980
Firm age	25.9	21.2	21.6	8.8	33.7	626	10,055	60,388
Return on assets (%)	8.8	11.8	18.6	6.5	17.0	575	9,723	58,980
Leverage (%)	55.5	54.7	24.7	41.0	70.8	574	9,707	58,951
R&D (%)	10.3	6.8	11.4	3.2	12.9	507	9,132	57,412
Tobin's Q	2.7	2.0	2.0	1.4	3.2	544	8,620	49,889
Institutional ownership (%)	66.0	70.6	22.7	56.8	81.4	495	5,190	30,167
Panel A2: Treatment firms' patent characteristics								
Forward citations (truncation adjusted)	0.9	0.0	6.0	0.0	0.1	626	10,055	60,388
Backward citations	33.3	12.0	55.9	5.7	30.5	609	9,736	59,015
Independent claims	1.0	1.0	0.2	1.0	1.0	626	10,055	60,388
Panel A3: Treatment firms' patent attorney characteristics								
Rolling success rate (%)	82.6	83.4	11.5	73.3	92.0	626	10,055	60,388

Table A7. Continued

	Mean	Median	SD	25th	75th	Firms	Total events	Patents
Panel B1: Control firms' characteristics								
Total assets ($bn)	28.6	5.1	68.3	1.0	23.1	3,388	228,308	1,203,252
Market cap. ($bn)	29.5	6.6	62.5	1.4	27.5	3,387	228,250	1,203,182
Firm age	27.4	19.5	23.3	10.2	38.1	3,673	237,845	1,233,176
Return on assets (%)	9.1	12.1	17.5	7.3	16.9	3,386	228,221	1,203,138
Leverage (%)	51.1	51.0	23.7	34.5	65.6	3,386	227,572	1,200,993
R&D (%)	9.1	5.7	11.3	2.4	11.2	2,918	215,275	1,170,959
Tobin's Q	2.2	1.8	1.5	1.3	2.6	3,315	205,046	1,060,513
Institutional ownership (%)	58.0	68.9	30.9	37.1	82.1	3,480	210,933	1,111,293
Panel B2: Control firms' patent characteristics								
Forward citations (truncation adjusted)	1.2	0.3	5.9	0.0	0.9	3,673	237,845	1,233,176
Backward citations	27.1	12.0	43.2	6.0	27.0	3,648	232,795	1,215,182
Independent claims	1.1	1.0	0.2	1.0	1.0	3,673	237,845	1,233,176
Panel B3: Control firms' patent attorney characteristics								
Rolling success rate (%)	83.1	84.3	11.6	75.3	92.3	3,672	237,574	1,233,176

This table reports the summary statistics for the treatment and control groups used in the analysis presented in Tables 9 and 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 capitalization 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 Table A2 in the appendix for variable definitions.

Table A8: Market reaction (CAR 0,+2) and patent representative 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	0.0025** (0.0010)		0.0025** (0.0010)	0.0026** (0.0010)	0.0030*** (0.0010)
New offices (firm location)		0.0001 (0.0002)	-0.0080 (0.0073)	-0.0080 (0.0073)	-0.0080 (0.0073)
New offices (firm location) x Rolling success rate			0.0098 (0.0087)	0.0098 (0.0088)	0.0110 (0.0089)
Patent grant volume				-0.0001 (0.0001)	-0.0000 (0.0001)
Market capitalisation					-0.0014*** (0.0003)
Firm age					-0.0011** (0.0005)
Return on assets					-0.0004 (0.0015)
Leverage					-0.0008 (0.0009)
R&D					-0.0027 (0.0031)
Constant	-0.0019** (0.0009)	0.0002 (0.0002)	-0.0018** (0.0009)	-0.0018** (0.0009)	0.0146*** (0.0033)
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Patent class FE	YES	YES	YES	YES	YES
Observations	247,054	247,093	247,054	247,054	237,209
R-squared	0.0280	0.0280	0.0280	0.0280	0.0274

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 Table A2 in the appendix for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table A9: Robustness test I: Rolling success rate calculated from 2001 and the effect of patent representative expertise (success rate) on the market reaction (CAR 0,+2).

	(1)	(2)	(3)
Rolling success rate	0.0021*** (0.0008)	0.0022*** (0.0008)	0.0027*** (0.0008)
Patent grants volume		-0.0002 (0.0001)	-0.0001 (0.0001)
Market capitalisation			-0.0015*** (0.0003)
Firm age			-0.0011** (0.0005)
Return on assets			-0.0004 (0.0016)
Leverage			-0.0007 (0.0009)
R&D			-0.0027 (0.0031)
Constant	-0.0014** (0.0007)	-0.0013** (0.0007)	0.0152*** (0.0032)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	247,020	247,020	237,167
R-squared	0.0281	0.0281	0.0275

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 Table A2 in the appendix for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table A10: Robustness test II: Rolling success rate calculated based on customer id and the effect of patent representative expertise (success rate) on the market reaction (CAR 0,+2).

	(1)	(2)	(3)
Rolling success rate	0.0024*** (0.0009)	0.0025*** (0.0009)	0.0029*** (0.0009)
Patent grants volume		-0.0001 (0.0001)	-0.0000 (0.0001)
Market capitalisation			-0.0016*** (0.0003)
Firm age			-0.0011** (0.0005)
Return on assets			-0.0008 (0.0016)
Leverage			-0.0004 (0.0009)
R&D			-0.0019 (0.0031)
Constant	-0.0018** (0.0008)	-0.0017** (0.0008)	0.0151*** (0.0034)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	237,913	237,913	228,504
R-squared	0.0284	0.0284	0.0278

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 Table A2 in the appendix for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

Table A11: Robustness test III: Patent representative expertise (success rate) and the market reaction (CAR 0,+2) calculated using the Fama-French 5-Factor model

	(1)	(2)	(3)
Rolling success rate	0.0022** (0.0009)	0.0021** (0.0009)	0.0029*** (0.0010)
Patent grants volume		0.0001 (0.0001)	0.0002* (0.0001)
Market capitalisation			-0.0018*** (0.0003)
Firm age			-0.0004 (0.0004)
Return on assets			0.0008 (0.0016)
Leverage			-0.0033*** (0.0008)
R&D			-0.0027 (0.0029)
Constant	-0.0022*** (0.0008)	-0.0022*** (0.0008)	0.0156*** (0.0028)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Patent class FE	YES	YES	YES
Observations	245,276	245,276	236,581
R-squared	0.0256	0.0256	0.0254

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 Table A2 in the appendix for variable definitions. Significance at 10%, 5%, and 1% level is represented by *, **, and ***, respectively.

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