Accessibility and materialization of firm innovation☆

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Strong patent protection is a pre-requisite for commercializing a new invention that allows firms to generate financial returns on their R&D investments, create a strong market position, and establish a positive firm image. Therefore, a well-devised corporate innovation strategy must include not only research and development (R&D) plans, but also patenting strategies for materializing and protecting innovation outputs. However, a first look at the National Bureau of Economic Research (NBER) Patent Citation database suggests that U.S. firms exhibit significant differences in the quantity of patents owned as well as the amount of time it takes for their inventions to be patented by the USPTO. The research question we are trying to understand in this study is, therefore, whether such inter-firm variation is attributed as least in part to heterogeneity in firms' accessibility to the USPTO.

As elaborated in the next section, we postulate that a firm's easy access to the USPTO, captured by distance between them, facilitates its patenting activities because of a few reasons. First, similar to other economic transactions, such as mergers and acquisitions (M&As), patent procurement is characterized by significant information asymmetry between patent filers and USPTO patent examiners. An emerging literature in accounting, economics, and finance has demonstrated that geographical proximity facilitates soft information production and reduces information asymmetry (e.g., Coval and Moskowitz, 1999; Ivkovic and Weisbenner, 2005; Bae et al., 2008; Baik et al., 2010; Tian, 2011; Cai et al., 2016). Second, firms near the USPTO headquarters (in Virginia) likely find it more convenient and less expensive to travel to the USPTO to learn about its services and patent process, and to attend examiner interviews to obtain interim feedback on their applications. As Manso (2011)'s model shows, timely feedback is conducive to innovation performance. Third, geographical proximity also likely lowers patent examiners' information gathering costs as they likely know more about local firms and can more easily acquire additional information (especially soft information) about local firm's research activities. Fourth, the USPTO may be part of an innovation ecosystem. Therefore, geographical proximity to the USPTO may also imply access to superior innovation resources, including innovation-intensive universities and their graduates who are innovation talent. Finally, there could be other benefits associated with geographical proximity. For example, there may be more patent attorneys near the USPTO who have easy access to patent examiners and knowledge of the patenting process. Firms closer to the USPTO may find it easier to hire former USPTO patent officers as their own employees to help handle patenting-related tasks. It is also plausible thatSusisibl8.6(it).5(h)-15o0e7d.5(ey16(ent0pl)23.3t04(o)1Ptr)23.68.5(D(e)15(e

2.2. Hypothesis development

We posit that geographical proximity to the USPTO facilitates patent procurement. Geographical proximity enhances the ease of collecting and transferring soft information that reduces information asymmetry between patent applicants and patent examiners. Similar to other business transactions, such as bank lending and M&As, patent procurement is plagued by significant information and knowledge gap between patent applicants and patent examiners (Wright, 1983; Cornelli and Schankerman, 1999; Scotchmer, 1999). Such gap arises from a few sources. First, patent applications that the USPTO receives cover a wide range of technologies. Although patent examiners have backgrounds related to the technology at hand, they are rarely experts on the precise details of the relevant invention. Patent examiners must acquaint themselves with a specific technology in a short time period to make a correct patentability decision, which can be difficult. Second, it is well recognized that knowledge pertaining to science and technology is localized. Such information is not widely disseminated and thus is likely to be known only to experts in the field (Wurman, 1990). This means information regarding relevant prior art for any patent claim is most likely to be known only to the inventor and her competitors. Hence, patent examiners are unlikely to be fully informed about the relevant prior art, creating a significant gap between inventor's information set and information possessed by the patent examiner when making decisions (Kesan, 2002). Third, patent applications are evaluated early in the life of a claimed technology, and thus at the time of patent examination there is typically no publicly available information about it. Worse, patent examiners cannot solicit credible outsider opinions, not only because for many technologies it is unclear at the early stages who the right experts might be, but also because patent evaluation is at least in part a confidential dialogue between applicants and examiners.

To bridge information and knowledge gap, patent filers are required to prepare and submit an application to the USPTO that provides relevant information in support of argument for patentability. Compressing information into a written application has certain benefits in that the information is concentrated and easily transmitted. However, Petersen (2004) notes that compression inevitably leads to a loss of information. More importantly, knowledge capital is intrinsically difficult to evaluate, and the tacit character of complex technology makes it difficult to quantify and transfer over a written document. As such, additional "soft" information about the claim – such as discussion of related technology and future commercialization plan, clarification the scope of claims and a demonstration of the invention – can be valuable input into patent decisions.

The literature on the economic implications of geographical proximity asserts that the ease of collecting soft information (e.g., Coval and Moskowitz, 1999; Taylor, 1975) and the effectiveness of knowledge transfer (e.g., Keller, 2002; Ambos and Ambos, 2009) are inversely related to geographical distance.[6] Another stream of literature studies technology diffusion and knowledge transfer (see for example, Adams and Jaffe, 1996; Keller, 2002) and points to an important role for geographical factors in determining the availability of technological knowledge across different countries or regions. A consensus finding is that knowledge transfer exhibits geographical decay effects where the intensity decreases with geographical distance. Based on these prior studies, we postulate that geographical proximity plays an important role in patent prosecution by facilitating the information flow (especially soft information) and knowledge transfer between patent applicants and USPTO patent examiners.

In addition to informational advantages, there may be other potential benefits associated with geographical proximity to the USPTO. For example, the USPTO is part of an innovation ecosystem. Therefore, geographical proximity to the USPTO could imply access to superior innovation resources, including innovation-intensive universities and their graduates who are innovation talent. Patent procurement could involve the service of external experts such as patent attorneys. There may be more patent attorneys near the USPTO who have easy access to patent examiners and are knowledge of the patenting process. Firms near the USPTO have superior access to these patent attorneys. It is also possible that firms closer to the USPTO may find it easier to hire former USPTO patent officers as their own employees to help handle patenting-related tasks. Those people may have long lived in the Virginia area and may be reluctant to relocate after resigning their positions from the USPTO, so firms closer to the USPTO may have better access to them and a higher chance of successfully recruiting them.

Taken all together, we expect that a firm's geographical proximity to the USPTO positively affects its patenting performance.

3. Sample selection and summary statistics

3.1. Sample selection

Our sample includes U.S. listed firms during the period of 1977–2005. We collect firm-year patent information from the latest version of the NBER Patent Citation database (see Hall et al., 2001 for details). We obtain a firm's headquarters location information from Compustat, financial statement items from Compustat Industrial Annual Files, and institutional holdings data from Thomson's CDA/Spectrum database (form 13F). Data on county level characteristics such as population and household income are obtained from the U.S. Census Bureau. We exclude firms that have never filed a single patent with the USPTO during our sample period. After excluding observations that do not have all available data for the baseline analysis, the final sample consists of 51,046 firm-year observations.

[6] For instance, Kedia and Rajgopal (2011) posit that geographic proximity allows the SEC to gather soft information about the firm when needed that enhances its monitoring ability. They find that firms residing closer to the SEC have a lower likelihood of engaging in fraudulent financial reporting. Chakrabarti and Mitchell (2016) argue that spatial constraints affect the extent of target-level knowledge that acquirers can access and assess and find that geographic distance has a significant impact on the likelihood of completing related acquisitions.

3.2. Variable measurement

3.2.1. Measuring patenting performance

We examine four variables related to patenting performance. The first variable, time-to-patent-grant, measures the speed of patent procurement. It is calculated as the number of years between patent application year and the approval year of a firm's patents filed (and eventually granted), averaged across all patents filed (and eventually granted). Duration of patent prosecution is an important patenting efficiency variable that has been investigated in a number of earlier studies (e.g., Johnson and Popp, 2003; Harhoff and Wagner, 2009).[7] Rivette and Kline (2000) and Gans et al. (2008) argue that the time to patent procurement is crucial for maximizing chances to commercialize a technology. For smaller companies, a faster examination process of patent applications could enhance their ability to attract financing and commercialize their inventions (Greenberg, 2013). To the extent that proximity to the USPTO helps advance patent prosecution, we expect to observe a shorter patent procurement time for geographically proximate firms.

The second variable that we examine is a firm's total number of patent applications filed in a given year that are eventually granted.[8] The number of patents obtained measures a firm's patenting productivity, and has also been extensively examined in earlier innovation studies (e.g., Fang et al., 2014; Chang et al., 2015). From a resource-based view of firms, if proximity to the USPTO enhances patenting efficiency, ceteris paribus, firms that reside closer to the USPTO likely possess a larger patent portfolio than their remote peers.

The last two outcome variables pertain to the type of patent activity. We define exploratory and exploitative patents according to the extent to which a firm's new patents use current versus new knowledge as proposed by Custodio et al. (2015). A firm's existing knowledge consists of its previous patent portfolio and the set of patents that have been cited by the firm's patents filed over the past five years. A patent is categorized as exploitative if at least 60% of its citations are based on current knowledge, and a patent is categorized as exploratory if at least 60% of its citations are based on new knowledge (i.e., citations not in the firm's existing knowledge base). We then calculate the intensity of exploitative patents for a given firm-year (*ExploitPat)* as the number of exploitative patents filed in a given year divided by the number of all patents filed by the firm in the same year. The intensity of exploratory patents for a given firm year (*ExplorePat)* is defined as the number of exploratory patents filed in a given year divided by the number of all patents filed by the firm in the same year.

Following the existing innovation literature, to account for the long-term nature of innovation process, our empirical tests relate firm characteristics in the current year to the above four patent-related variables three years ahead. We also adjust patent-related variables to address the truncation problems associated with the NBER patent database.[9] A first look at the distribution of the number of patents in the sample shows that the distribution is right skewed, that is, a significant number of firm-year observations have zero patents. To mitigate the right skewness problem, we use the natural logarithm of patent counts, *LnPatent,* and the natural logarithm of time to patent grant, *LnGrantTime*. To avoid losing firm-year observations with zero patents, we add one to the actual values when calculating the natural logarithm.

3.2.2. Measuring distance to the USPTO

During our sample period, the USPTO is located in Arlington, Virginia (zip code: 22202) with no other branch offices. Because the USPTO was established in 1790, far before the start of our sample period in 1977, and did not change its location during our sample period, it is reasonable to believe that the USPTO's location choice is exogenous to firm patenting during our sample period.[10]

We use a firm's headquarters when measuring its distance to the USPTO because innovation-intensive firms, i.e., firms that frequently apply for patents (especially large ones that constitute our sample), generally have in-house attorneys who handle patent filings and prosecution with the USPTO, and these attorneys mostly reside in the firm's headquarters that host legal and other administrative departments (Grupp and Schmoch, 1999; Hicks et al., 2001). Picci (2010) provide empirical evidence that multinational corporations generally file patents through their headquarters.[11] As prescribed by the USPTO, if a firm's in-house patent attorney is appointed to file patent applications, patent examiners will direct all correspondences to the designated attorney.

[7] Key advantages of an early patent grant include (1) obtaining some certainty regarding the state of one's own patent portfolio and (2) the option of early utilization of an injunction or other legal instrument for the prosecution of infringers, i.e., the full availability of legal recourse.

[8] The reason for using a patent's application year rather than its grant year is that previous studies (such as Griliches et al., 1988) have shown that the former is superior in capturing the actual time of innovation.

[9] The truncation problem arises because the patents appear in the NBER patent database only after they are granted. We observe a gradual decrease in the number of patent applications as we approach the last few years of our sample period. This observation is because the lag between a patent's application year and its grant year is significant (about two years on average) and many patent applications filed during these years were still under review and had not been granted by 2006. To adjust the truncation bias in patent counts, we supplement the NBER database with the Harvard Business School (HBS) patent database, which contains patents granted through 2010. To the extent that the patent application outcomes have been announced by 2010 for the patents filed by 2005 (the last year of our sample period), this approach largely mitigates the patent truncation concern. Neither the NBER nor the HBS patent database is likely to be affected by the survivorship bias. As long as a patent application is granted by the USPTO, it is attributed to the applying firm (i.e., the assignee) at the time of application even if the firm later gets acquired or goes bankrupt.

[10] On April 27, 2009, the USPTO (including the offices under Patents and the Chief Information Officer) moved to Randolph Square, a new building in Shirlington Village, Alexandria, Virginia.

[11] IBM, for example, headquartered in New York, has a dedicated Patent Center at its New York headquarters. Similarly, Google, Microsoft, Facebook all have general counsels for patents that reside at corporate headquarters.

Examiner interviews will also generally be conducted between patent examiners and the firm's in-house patent attorneys who then relay and communicate all relevant information within the firm.[12]

We retrieve headquarters address and zip code of each firm in our sample from Compustat.[13] For firms with missing business addresses and/or zip codes, we manually fill in this information by searching through the firm's website and other public sources. We obtain corresponding longitude and latitude information to calculate the distance between the firm and the USPTO using the great circle distance formula. In subsequent analyses, we use the natural logarithm of distance, *LnDistance*, as our main measure of distance to the USPTO.

3.2.3. Measuring control variables

Following the innovation literature, we control for a vector of firm and industry characteristics that may affect a firm's patenting activities. We provide detailed variable definitions in Table 1. We compute all variables for firm i over its fiscal year t. In the baseline regressions, our control variables include firm size (measured by the natural logarithm of total assets), profitability (measured by the return-on-assets ratio), investments in research and development (measured by R&D expenditures over total assets), asset tangibility (measured by net property, plants, and equipment scaled by total assets), leverage (measured by the total debt to total assets ratio), capital expenditures scaled by total assets, growth opportunities (measured by Tobin's q), financial constraints (measured by the Kaplan and Zingales, 1997 five-variable KZ index), industry concentration (measured by the Herfindahl index based on annual sales), and institutional ownership (measured by the percentage of institutional holdings).[14] To

Table 1
Variable definition.

Variable	Definition
Measures of innovation	
$LnGrantTime_{t\,+\,3}$	Natural logarithm of one plus the number of years between the patent application year and the approval year of firm *i*'s patents filed (and eventually granted) in year $t\,+\,3$, averaged across the number of patents filed (and eventually granted);
$LnPatent_{t\,+\,3}$	Natural logarithm of one plus firm *i*'s total number of patents filed (and eventually granted) in year $t\,+\,3$;
$ExplorePat_{t\,+\,3}$	Number of exploratory patents filed in year *t* divided by the number of all patents filed by the firm in the same year; a patent is classified as exploratory if at least 60% of its citations are based on new knowledge (i.e., citations not in the firm's existing knowledge base);
$ExploitPat_{t\,+\,3}$	Number of exploitative patents filed in year *t* divided by the number of all patents filed by the firm in the same year; a patent is classified as exploitative if at least 60% of its citations are based on current knowledge;
Measures of 991-259.6(citatij/F11T2m)-epaten339-1.3/F0TD( )169/F11Tf.61350TD-.0160234.1(in)-225.]TJ/control63(one)-v.5(De)]-262.3(8(usnd)-264.ear)]TJ.eaonLnPatent	

captures the number of patents that are filed in year $t + 3$. The main variable of interest is a firm's geographical distance to the USPTO, $LnDistance_{i,t}$. $Control_{i,t}$ is a vector of firm characteristics that could affect a firm's patent performance as discussed in Section 3.2.3. $County_{k,t}$ is a vector of county characteristics. $Year_t$ and $Industry_j$ capture year and industry fixed effects, respectively. Standard errors are clustered at the firm level.

Table 3 presents the regression results. In column (1) in which the dependent variable is *LnGrantTime*, the coefficient estimate on the key variable of interest, *LnDistance,* is 0.079 and significant at the 5% level. In column (2) in which the dependent variable is *LnPatent*, the coefficient estimate on *LnDistance,* is −0.111 and is significant at the 1% level. These findings are consistent with our conjecture that proximity to the USPTO helps advance patent prosecution, and is associated with a higher patenting efficiency and productivity. The economic effect is sizeable: increasing *LnDistance* by one standard deviation (1.144, i.e., 868.9 miles) is associated with a 9% (=0.079 ∗ 1.144) increase in patent procurement time (i.e., 72 days from the sample mean) and a 13% (=0.111 ∗ 1.144) decrease in the number of patents filed and granted (i.e., 2.2 patents from the sample mean). Control variables exhibit signs that are consistent with previous studies.

4.2. Exploration vs. exploitation

Next, we assess how distance to the USPTO affects different types of a firm's innovation activities and output, i.e., exploration vs. exploitation. We posit that distance likely matters more for exploratory innovation that entails higher informational and knowledge gap. We estimate the following model:

$$ExplorePat_{i,t+3}/ExploitPat_{i,t+3} = \alpha + \beta LnDistance_{i,j,k} + \lambda' Control_{i,t} + \delta' County_{k,t} + Year_t + Industry_j + \varepsilon_{i,t} \quad (2)$$

where *ExplorePat* and *ExploitPat* are exploratory and exploitative patent intensity, respectively. All other variables are the same as those in model (1).

Table 2
Summary statistics.
This table reports the sample distribution and summary statistics for variables used in the baseline analyses based on the sample of U.S. public firms from 1977 to 2005.

Panel A: Variable summary statistics

Variable	Median	Mean	S.D.	N
GrantTime	2.000	2.187	0.926	23,350
Patents	1.000	16.932	87.591	51,046
ExplorePat	1.000	0.745	0.370	27,165
ExploitPat	0.000	0.126	0.255	27,165
Distance	615.4	1006.6	868.9	51,046
Assets	4.461	4.563	2.034	51,046
ROA	0.035	−0.070	0.291	51,046
Leverage	0.157	0.201	0.209	51,046
Capex	0.045	0.059	0.053	51,046
R&DAssets	0.050	0.105	0.161	51,046
PPEAssets	0.409	0.469	0.316	51,046
KZ	−1.445	−7.181	23.642	51,046
HHI	0.197	0.249	0.182	51,046
TobinQ	1.572	2.748	4.353	51,046
InstOwn	0.002	0.199	0.279	51,046

Panel B: Sample distribution by industry

SIC code	Industry	Number of obs.	Percentage of sample	Cumulative percentage
38	Instruments & related products	8136	15.94%	15.94%
36	Electronic & other electric equipment	8100	15.87%	31.81%
28	Chemical & allied products	8038	15.75%	47.55%
35	Industrial machinery & equipment	7214	14.13%	61.69%
73	Business services	4713	9.23%	70.92%
37	Transportation equipment	1941	3.80%	74.72%
34	Fabricated metal products	1351	2.65%	77.37%
30	Rubber & miscellaneous plastics products	1026	2.01%	79.38%
20	Food & kindred products	773	1.51%	80.89%
33	Primary metal industries	767	1.50%	82.39%
	Others	8987	17.61%	100.00%
Total	–	51,046	–	–

Panel C: Sample distribution by state

State	Number of obs.	Percentage of sample	Average distance to USPTO (in miles)	Mean *GrantTime*	Mean *Patents*	Mean *ExplorePat*	Mean *ExploitPat*
CA	10,719	21.03%	2364.00	2.40	16.38	0.72	0.15
MA	4030	7.91%	387.78	2.35	11.33	0.74	0.13
NY	3917	7.69%	241.52	2.08	39.88	0.77	0.09
NJ	3050	5.98%	186.67	2.27	23.18	0.73	0.13
TX	2963	5.81%	1222.64	2.20	23.11	0.69	0.14
IL	2448	4.80%	616.54	2.04	27.21	0.77	0.11
PA	2342	4.60%	141.98	2.02	10.33	0.77	0.10
MN	2126	4.17%	935.24	2.35	9.24	0.76	0.11
OH	1922	3.77%	333.16	2.01	17.77	0.80	0.09
CT	1817	3.56%	272.29	2.06	21.83	0.76	0.10
FL	1515	2.97%	832.03	2.10	3.84	0.70	0.13
MI	1293	2.54%	451.57	2.01	39.99	0.78	0.11
CO	1115	2.19%	1495.80	2.13	3.29	0.77	0.11
WA	951	1.87%	2309.56	2.46	11.12	0.68	0.16
VA	933	1.83%	59.49	2.22	14.79	0.76	0.12
WI	932	1.83%	662.82	1.93	7.75	0.81	0.09
NC	847	1.66%	278.89	2.09	6.10	0.69	0.13
MD	825	1.62%	28.31	1.99	12.33	0.73	0.14
GA	754	1.48%	528.97	2.37	5.57	0.70	0.15
MO	741	1.45%	794.98	1.96	12.51	0.77	0.11
IN	591	1.16%	496.32	2.01	16.59	0.80	0.11
AZ	547	1.07%	1971.29	2.35	1.87	0.68	0.12
Others	4668	8.86%	–	–	–	–	–
Total	51,046	100.00%	–	–	–	–	–

Table 4 reports the regression results. The dependent variable in column (1) and (2) is *ExplorePat*. We use the ordinary least squares (OLS) method in column (1). Since *ExplorePat* is bounded between 0 and 1, we also estimate Eq. (2) using the Tobit model. In both cases, we find that the coefficient estimate on the key variable of interest, *LnDistance,* is negative and significant at the 5% level. In terms of the economic significance, we find that increasing *LnDistance* by one standard deviation (1.144,

Table 3
Regressions of patenting performance on distance to the USPTO.
This table reports regression estimates of patenting performance on firm's distance to the USPTO. Definitions of variables are provided in Table 1. Year and industry fixed effects are included in all regressions but the coefficients are not reported. Robust standard errors clustered by firm are displayed in parentheses.

Dependent variable	*LnGrantTime*	*LnPatent*
	(1)	(2)
LnDistance	0.079**	−0.111***
	(0.039)	(0.031)
Assets	0.002	0.551***
	(0.001)	(0.022)
ROA	0.007	0.319***
	(0.009)	(0.092)
Leverage	0.000	0.049
	(0.002)	(0.112)
Capex	0.180***	0.295
	(0.038)	(0.342)
R&DAssets	0.058**	0.791***
	(0.027)	(0.147)
PPEAssets	−0.082***	0.723***
	(0.008)	(0.110)
KZ	−0.000**	0.001***
	(0.000)	(0.000)
HHI	−0.037	−0.411
	(0.040)	(0.634)
HHISquare	0.049	0.777
	(0.047)	(0.755)
Tobin Q	0.002***	0.027***
	(0.000)	(0.004)
InstOwn	−0.026***	0.337**
	(0.009)	(0.138)
CountyPop	0.008	−0.186
	(0.041)	(0.219)
CountyIncome	−0.025	0.326
	(0.049)	(0.374)
CountyEdu	0.004*	−0.009
	(0.002)	(0.008)
CountyNumFirm	−0.015	0.240
	(0.041)	(0.220)
CountyRD	−0.001	0.070*
	(0.003)	(0.039)
Constant	−0.319	1.044
	(0.553)	(4.003)
Year and industry fixed effects	Included	Included
R^2	0.32	0.28
Observations	23,350	51,046

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

i.e., 868.9 miles) is associated with a 2.7% (=0.024 ∗ 1.144) decrease in exploratory patent intensity (i.e., 0.02 from the sample mean).

The dependent variable in column (3) and (4) is *ExploitPat*. In contrast to the significant results for *ExplorePat*, the coefficient estimate on *LnDistance* is statistically insignificant in both the OLS and Tobit models. Taken together, these results suggest that shorter distance to the USPTO is more important for the materialization of exploratory innovation which is characterized by new knowledge creation and a higher level of information asymmetry. However, distance to the USPTO does not appear to have a significant effect on the materialization of exploitative innovation that is characterized by existing knowledge usage and a lower level of information asymmetry.

4.3. Robustness tests

We conduct a rich set of robustness tests for our baseline results. First, in the baseline regressions, we follow the literature to set the patent counts to zero for firm-year observations without available patent information from the NBER or the HBS patent database.[15] To rule out the possibility that our results are driven by firm-year observations with zero patents, we restrict our

[15] *LnGrantTime* is treated as missing value for those firm-years in the baseline analysis.

analysis to a subsample of non-zero observations (i.e., firm-years with at least one patent) and re-run the regression for which the dependent variable is *LnPatent*. In the un-tabulated analysis, we find a significant coefficient estimate of -0.136 (p-value $= 0.003$) on *LnDistance*.

Second, since our dependent variable, the number of patents, is right skewed, we adopt the quantile regression model and find that our baseline results continue to hold in most cases. For example, when we use the quantile regression model at the 90th percentile, the coefficient estimate on *LnDistance* is -0.154 (p-value <0.001) when the dependent variable is

(1) Sub-period analysis

Our sample period is from 1977 to 2005. As noted by Lerner and Seru (2015), during this period there was a shift towards a more "pro-patent" policy that has been effected partially through legislation—e.g., the Computer Software Protection of Act of 1980 and the Semiconductor Chip Protection Act of 1984. To ensure our results are not affected by these policy changes, we partitioned our sample into two groups: one is from 1977 to 1979, the other one is from 1980 to 2005. We re-conduct the baseline analyses separately for these two groups of firms. The effect of distance to the USPTO on patenting performance is significant in both subsamples.

(2) Truncation problems

Truncation problem occurs if there is a delay in filing or issuing patents. As a robustness test we excluded the last 10 years of our sample to address the concern that we may not be able to observe pending patents towards the end of sample period. We continue to observe a significant effect of distance on time-to-patent-grant, patent quantity and exploration intensity.

(3) Technology classes

Firms in certain industries (e.g., computers and electronics) may experience a surge of patenting that may drive our results. To address this concern, we partition the sample into two groups based on industry composition: (1) electronic & other electric equipment (SIC 36); and (2) others industries. We re-conduct the main analyses separately for these two groups of firms, and find largely robust results.

(4) Regions

Some states (e.g., California, Massachusetts, and Delaware) may experience a surge in patenting during our sample period. We partition the sample into two subgroups: (1) firms in California, Massachusetts, and Delaware and (2) firms in other states. We continue to observe a significant effect of distance to the USPTO on patenting performance in both groups of firms.

(5) High market-to-book value

Lerner and Seru (2015) note that it is important to consider firms with features akin to those that experienced a surge in patenting (e.g., those with a high market-to-book value). Hence, we partition the sample into two groups based on the median value of the market-to-book ratio. We continue to observe a significant effect of distance on patenting performance in both groups of firms.

(6) Firm exits

The firm exit concern raised in Lerner and Seru (2015) stems from the truncation of patenting in the years prior to a firm is acquired or liquidated. To address this concern, we searched the SDC M&A database to identify firms that were acquired during our sample period and remove these observations from the analysis. We continue to observe a significant effect of distance on patenting after excluding these observations.

(7) Misleading assignment practices

This misleading assignment practice issue concerns the extent to which the firms under study may be engaging in misleading assignment practices, in order to disguise their technological strategy from competitors. Lerner and Seru (2015) note that such behavior may be more likely for firms operating in highly competitive industries in which innovation is more important to success. To address this concern, we partition the sample into two groups based on the intensity of product market competition in which the firm operates, where the intensity of competition is measured by the 4-digit SIC Herfindahl index. We continue to observe a significant effect of distance to the USPTO on patenting in both groups.

5. Endogeneity

A reasonable concern of our baseline results is that omitted variables correlated with both corporate location choice and patenting performance may bias the results. In addition, there is a potential reverse causality concern that innovative intensive firms may choose to locate closer to the USPTO. We attempt to address these concerns in this section. We first focus on a subsample of firms that have never changed their headquarters locations by removing from our sample those firms that experience at least one headquarters relocation during the sample period, and re-run the baseline regressions using non-moving firms only. Our baseline results continue to hold. While this test addresses reverse causality to some extent, i.e., firms relocate their headquarters locations to facilitate patenting activities, it does not help mitigate omitted variable concerns. To further address the endogeneity, we perform two additional tests below.

5.1. DiD approach – firm relocations

Our first identification attempt focuses on a sample of firms that relocate their headquarters away from the USPTO and compare their changes in patenting performance against a matched sample of firms whose headquarters locations do not change. While a firm's headquarters moving decision may arise from various strategic concerns such as tax avoidance and being closer to suppliers or customers, which may be correlated with a firm's innovation output, the decision to move *away* from the USPTO is likely to be based on reasons other than innovation and patenting concerns.

Table 5

DiD analysis of patenting performance and distance to the USPTO based on firm relocations.

This table reports diagnostics and results of the DiD tests on how changes in firm's distance to the USPTO due to firm relocation affects patenting performance. Panel A reports distribution of increase in distance to USPTO for moving-away firms. Panel B presents parameter estimates from the probit model used in estimating the propensity scores for the treatment and control groups. A one-to-four propensity matching method is used. The dependent variable is one if the firm-year belongs to the treatment group and zero otherwise. The "Pre-Match" column contains the parameter estimates of the probit model estimated using the sample prior to matching. These estimates are then used to generate the propensity scores for matching. The "Post-Match" column contains the parameter estimates of the probit model estimated using the subsample of matched treatment-control pairs after matching. Definitions of variables are listed in Table 1. Panel C reports the univariate comparisons between the treatment and control firms' characteristics and their corresponding t-statistics. Panel D reports the sub-sample DiD test results based on post-move firm distance. *GrantTime_3yr_avg* is firm i's average time to patent grant in the three-year window before or after the event year. *Patent_3yr_avg* is firm i's average number of patents in the three-year window before or after the event year. *Explore_3yr_avg* and *Exploit_3yr_avg* are firm i's average exploratory and exploitative patenting intensity, respectively, in the three-year window before or after the event year. Ordinary standard errors are given in parentheses below the mean differences in innovation outcomes and bootstrapped standard errors for the two-sample t-tests with unequal variance are given below the DiD t-stats.

Panel A: Distribution of increase in distance to USPTO for moving-away firms

(Number of Obs = 503)	Mean	Median	S.D.

Table 5 *(continued)*

Panel C: Differences in observables

	Treatment	Control	Differences	*t*-Statistics
Capex	0.062	0.060	0.002	0.213
R&DAssets	0.110	0.121	−0.011	−0.521
PPEAssets	0.415	0.406	0.009	0.274
KZ	−3.739	−3.776	0.037	0.033
HHI	0.252	0.254	−0.002	−0.045
HHISquare	0.109	0.110	−0.001	−0.049
Tobin Q	2.458	2.837	−0.379	−1.059
InstOwn	0.461	0.438	0.023	0.551

Panel D: DiD test results

	Mean treatment difference (after − before) (1)	Mean control difference (after − before) (2)	Mean DiD estimator (treat − control) (3)	*Z*-statistics for DiD estimator (4)
GrantTime_3yr_avg	−0.024	−0.127	0.103**	1.981
	(0.047)	(0.051)	(0.052)	
Patent_3yr_avg	3.071	4.754	−1.683**	−2.149
	(0.642)	(0.690)	(0.783)	
Explore_3yr_avg	−0.007	0.003	−0.010***	−3.333
	(0.002)	(0.002)	(0.003)	
Expoit_3yr_avg	0.006	0.004	0.002	0.400
	(0.004)	(0.003)	(0.005)	

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

A key advantage of this identification attempt is that there are multiple shocks (firms' moving away from the USPTO) that affect different firms at different time. Identification with multiple shocks avoids a common difficulty faced by studies with a single shock, namely, the existence of potential omitted variables coinciding with the shock that directly affect firm innovation performance. We conjecture that moving away from the USPTO would lead to a reduction in patenting efficiency and productivity, as well as a reduction in exploratory patent activity. But we do not expect to find significant changes in exploitative patent activity.

We collect a firm's headquarters relocation information from Compact Disclosure that publishes data on firm headquarters locations between 1990 and 2004. We identify moving firms as those firms whose headquarters city names change from one quarter to the next quarter in Compact Disclosure, and find 503 events where firms move away from the USPTO. As reported in Panel A of Table 5, firms' distance to the USPTO increases on average by 374.9 miles (with a standard deviation of 489.4 miles) following the relocation events of our sample firms.

To implement the DiD analysis, we need to first identify the treatment and control groups. For a firm to be classified into the treatment group, we need it to have non-missing matching variables (to be discussed below) for year −1 (one year before the moving year) and non-missing innovation variables (time-to-grant, the number of patents, exploratory patent activity, and exploitative patent activity) for at least three years before and after the relocation event (year −3, −2, −1, +1, +2, +3, respectively). Thus, we focus on relocation events that occur between 1980 and 2002 (given that our baseline sample is 1977–2005).[16]

We then proceed to construct a control group of firms that are matched to the treatment group on all important observable characteristics prior to the events but that do not experience a relocation of headquarters away from the USPTO. Our matching procedure relies on a nearest neighbor matching of propensity scores, originally developed by Rosenbaum and Rubin (1983) and also adopted in recent literature such as Lemmon and Roberts (2010).[17] We first run a probit regression of a dummy variable that equals one if a particular firm-year observation belongs to our treatment group (and zero otherwise) on a comprehensive list of observable characteristics, including all the independent variables in our baseline regression, as well as year dummies, 2-digit SIC industry dummies, and county dummies to capture any time-invariant, or industry-specific, or location-specific differences. Further, to ensure that the parallel trends assumption is satisfied, we also match firms on pre-event innovation growth variables (i.e., growth in time-to-grant *TimeGrowth*, the number of patents *PatGrowth*, exploratory patent intensity *ExploreGrowth*, and exploitative patent intensity *ExploitGrowth*, all computed over the three year period before the event).[18]

[16] The choice of a seven-year window (from year −3 to year +3) reflects a trade-off between relevance and accuracy. On the one hand, choosing a wide window may increase the accuracy of the estimation but introduce too much noise that is irrelevant to the events. On the other hand, choosing a narrow window reduces the sample size, reducing the power of our test. In addition, innovation involves long-term projects and any meaningful changes in patent productivity ensuing headquarters relocation may not be readily observed within a narrow window. Following the existing literature (He and Tian, 2013), we report results using a seven-year window, although our results are similar if we use a five-year window.

[17] See, e.g., Rosenbaum and Rubin (1983) and Lemmon and Roberts (2010), for a more detailed discussion of the matching method and cautionary notes.

[18] We match firms on the pre-event three-year averages of patent-related variables because many of these variables have values of zero, which makes it difficult to calculate meaningful percentage growth measures. Therefore, to satisfy the parallel trends assumption, we match firms on both the numerator and denominator of a hypothetical "percentage growth rate" for innovation output.

We report the probit model estimates in the first column of Panel B in Table 5, labeled “Pre-Match”. The results suggest that the specification has substantial explanatory power for the choice variable, as evidenced by a pseudo-R^2 of 21% and a very small *p*-value for a Chi-square test of the overall model fitness (well below 0.01). We then use the predicted probabilities, or propensity scores, from this probit estimation and perform a nearest-neighbor match with replacement. That is, for each treatment firm, we match it with four control firms with the closest propensity score.[19] Since we allow for replacement, a control firm may be matched to more than one treatment firm. This process results in 124 treatment firms and 438 control firms.[20]

The success of the DiD approach hinges on the satisfaction of the “parallel trends” assumption, which means that in the absence of treatment (or change in distance to the USPTO in our context), the observed DiD estimator is zero.[21] To check if the parallel trends assumption is satisfied, we conduct a number of diagnostic tests. In the first test, we re-run the probit model restricted to the matched sample and present the probit estimates in the second column of Table 5 Panel B, labeled “Post-Match”. None of the independent variables is statistically significant. In particular, the coefficient estimates of the four pre-shock patenting-related growth variables are not statistically significant, suggesting no observable different trends of patent procurement between the two groups of firms pre-event. Also, the coefficient estimates in the second column are much smaller in magnitude than the ones in the first column, suggesting that the results in the second column are not simply an artifact of a decline in degrees of freedom due to the drop in sample size. In addition, a Chi-square test for the overall model fitness shows that we cannot reject the null hypothesis that all of the coefficient estimates of independent variables are zero (with a *p*-value of 0.999).

As our second diagnostic test, we report in Table 5 Panel C the univariate comparisons between the treatment and control firms' characteristics and their corresponding *t*-statistics. As shown, none of the differences between the treatment and control firms' characteristics is statistically significant in the pre-relocation regime. In particular, the two groups of firms have similar levels of physical distance to the USPTO pre-relocations. Moreover, the univariate comparisons for patent growth variables are not significant either, suggesting that the parallel trends assumption is not violated.

In our third diagnostic test, we check the difference between the propensity scores of the treatment firms and the scores of their matched control firms. Untabulated results suggest that the difference is quite trivial. The maximum difference between the two matched firms' propensity scores is only 0.02, while the median difference is 0. In summary, the matching process has removed any meaningful observable differences from the two groups of firms.

Table 5 Panel D reports the results from the DiD analysis. We report the results beginning with the average difference between the pre-relocation period and the post-relocation period for the treatment and control firms. Column (1) shows that the average change in patent grant time *GrantTime_3yr_avg* for treatment firms is −0.024. We compute this estimate by first calculating the three-year average patent grant time (in years, without taking the natural logarithm) for the post-relocation era and then subtracting the three-year average patent grant time (in years, without taking the natural logarithm) for the pre-relocation era from it for each firm. This difference is then averaged over treatment firms. A similar procedure is conducted for the matched control firms. The average change in patent approval time for control firms *GrantTime_3yr_avg* is −0.127. We also report corresponding standard errors in parentheses. We conduct a similar procedure for the comparison of patent quantity, exploratory and exploitative patent intensity between treatment and control firms, where *Patent_3yr_avg* is the average change in the number of patents (without taking the natural logarithm) before and after the relocation; *Explore_3yr_avg* and *Exploit_3yr_avg* are the average change in exploratory and exploitative patent intensity before and after the relocation. We find that *Patent_3yr_avg* is 3.071 for treatment firms and 4.754 for control firms. *Explore_3yr_avg* is −0.007 for treatment firms and 0.003 for control firms. *Exploit_3yr_avg* is 0.006 for treatment firms and 0.004 for control firms.

In columns (3) and (4), we report the DiD estimates and the corresponding *t*-statistics of the null hypothesis that these estimates are zero, respectively, as well as bootstrapped standard errors for the DiD estimates. The DiD estimate for patent approval time is 0.103 and significant at the 5% level. The economic effect is sizable: the magnitude of the DiD estimate suggests that compared to firms that do not relocate their headquarters, firms that move away from the USPTO experience an average of 38 ($=0.103 * 365$) days increase in the length of patent procurement. The DiD estimate for the number of patents is −1.683 and significant at the 5% level, suggesting that firms moving away from the USPTO on average file approximately 1.7 fewer patents per year over three years after their headquarters relocation, compared to firms whose headquarters locations are unchanged. As for the type of patents, the DiD estimate for exploratory patent ratio is −0.01 and significant at the 1% level, suggesting that firms moving away from the USPTO on average incur a 0.01 reduction in the intensity of exploratory patents. In contrast, the DiD estimate for exploitative patent activity is −0.002 and insignificant, suggesting that relocating away from the USPTO does not affect a firm's exploitative patent activity.

[19] We also conducted one-to-one and one-to-three propensity score matching. Results remain qualitatively unchanged.

[20] The resulting matched sample is smaller than our baseline treatment sample (i.e., moving away companies) because we require treatment and control firms to have seven years of non-missing data on patent grant time surrounding the relocation event. So only firms that file for patents consecutively for seven years are retained in the DiD analysis, which is demanding on the data.

[21] To be precise, the parallel trends assumption does not require the level of outcome variables (patent variables in our setting) to be identical across the treatment and control firms or across the two regimes, because these distinctions are differenced out in the estimation. Instead, this assumption requires similar trends in the patent variables during the pre-relocation regime for both the treatment and control groups.

Taken together, the DiD analysis suggests that firms' moving away from the USPTO results in a reduction in the speed of patent procurement, patent quantity, and exploratory patent activity but not exploitative patents. This finding is consistent with our baseline results.[22]

To further strengthen our identification attempts, we conduct two "placebo tests" to corroborate the validity of our identification test based on firms' relocations. We discuss these placebo tests in more details and report the result in Internet Appendix.

5.2. DiD analysis – change in the number of direct flights

As an alternative measure of a firm's accessibility to the USPTO, we use the frequency of direct flights between them. The rationale behind this measure is that more frequent direct flights with no layovers make it more convenient for patent applicants to travel to the USPTO and thus reduce the "effective" distance between them. Specifically, we measure the number of direct flights as the natural logarithm of the number of direct flights each year (inbound and outbound) operated by all airlines between the airports closest to the firm and the USPTO. To avoid losing observations with zero direct flights, we add one to the actual values when calculating the natural logarithm.

For each firm in our sample, we manually search for its nearest commercial airport using the firm's zip code information. There are three major airports serving the DC area where the USPTO resides—Dulles International Airport (IAD), Reagan Washington National (DCA) and Baltimore Washington International (BWI). We obtain data on the frequency of direct flights from the U.S. Department of Transportation's Bureau of Transportation Statistics. Specifically, the "Airline On-Time Performance Data" section contains on-time arrival information for non-stop domestic flights by major commercial air carriers.[23] The dataset provides direct flight information since 1987. Table 6 Panel A reports the average number of direct flights each year (inbound plus outbound) between each state and the three airports near the USPTO during our sample period. We calculate *Ln(DirectFlights*) as the natural logarithm of the sum of direct flights (inbound plus outbound) between a firm's nearest airport and IAD, DCA, and BWI each year.

In our attempt to establish causality, we exploit plausibly exogenous variation in the frequency of direct flights due to airline restructuring events including bankruptcies, mergers and acquisitions, and strategic alliances. Prior studies show that an airline's decision to schedule and/or maintain direct flight routes between any city pair is primarily driven by the carrier's own strategic considerations, such as industry peer competition and dominance (Borenstein and Netz, 1999), choice between "point-to-point" network and "hub-and-spoke" network (Brueckner, 2004), and alliances with other airlines (Bamberger et al., 2004). City-pair direct service market structure is also restricted by local population and labor force composition (Pai, 2010), government regulation, airport and aircraft fleet characteristics (Evans and Kessides, 1993; Pai, 2010), and features of airlines' frequent flyer programs (Lederman, 2007). As such, it is reasonable to believe that airline restructuring activities are exogenous in that they are likely motivated by strategic considerations of the airlines themselves and are uncorrelated with a firm's patent activities. It is hence difficult to conceive a scenario in which a patent applicant is able to predict the occurrence of an airline restructuring event when choosing its location.

We manually search for information on airline restructuring events—bankruptcies, mergers and acquisitions, and strategic alliances — from Wikipedia and airlines' websites. We identified a total of 91 airline restructuring events, including 50 bankruptcies, 28 mergers and acquisitions, and 13 strategic alliances. Table 6 Panel B reports changes in the frequency of direct flights for our sample firms as a result of these restructuring events. We tabulate increase and decrease in the frequency of direct flights separately. Average increase in the frequency of direct flights between the firm's nearest airport and BWI (DCA and IAD) is 942 (1050 and 617). Average decrease in the frequency of direct flight between the firm's nearest airport and BWI (DCA and IAD) is −639 (−761 and −526).

As an attempt to identify the change in patent performance surrounding airline structuring events, we cI6saat

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Table 6

DiD analysis of patenting performance and distance to the USPTO based on the number of direct flights.

This table reports diagnostics and the results of the DiD tests on how exogenous shocks to the effective distance to the USPTO given changes in the frequency of direct flights between the firm and the USPTO due to airline restructuring events affects a firm's patenting performance. Panel A reports by state, the average number of annual direct flights (inbound + outbound) between a firm's nearest airport and the USPTO during our sample period. Panel B reports changes in annual direct flights (inbound + outbound) between a firm's nearest airport and the three airports closest to the USPTO. Panel C reports the univariate comparisons between the treatment and control firms' characteristics and their corresponding *t*-statistics. A one-to-four propensity score matching method is used. Panel D reports the distribution of estimated propensity scores for the treatment firm-years, control firm-years, and the difference in estimated propensity scores. Panels E and F report the subsample DiD test results based on increases and decreases in the number of direct flights, respectively. Ordinary standard errors are given in parentheses below the mean differences in innovation outcomes and bootstrapped standard errors for the two-sample *t*-tests with unequal variance are given below the DiD *t*-stats.

Panel A: Number of direct flights (inbound + outbound) between a firm's nearest airport and USPTO

State	Number of obs.	Percentage of sample	Average number of annual flights between the state and		
			BWI	DCA	IAD
CA	10,719	21.03%	3912	464	3213
MA	4030	7.91%	7383	15,033	5920
NY	3917	7.69%	11,487	4465	1739
NJ	3050	5.98%	3118	7157	1796
TX	2963	5.81%	9853	6359	3459
IL	2448	4.80%	12,571	13,022	3896
PA	2342	4.60%	5945	2824	1711
MN	2126	4.17%	2459	4635	1671
OH	1922	3.77%	10,142	3108	1961
CT	1817	3.56%	4100	2742	1894
FL	1515	2.97%	2253	2451	2158
MI	1293	2.54%	4389	5863	4204
CO	1115	2.19%	3065	1237	4873
WA	951	1.87%	0	1016	1689
VA	933	1.83%	5113	112	2279
WI	932	1.83%	1392	816	6517
NC	847	1.66%	9998	3741	2329
MD	825	1.62%	0	162	607
GA	754	1.48%	8886	10,452	4716
MO	741	1.45%	7024	3343	2369
IN	591	1.16%	1794	2099	1161
AZ	547	1.07%	4406	1425	952
Others	4668	8.86%	–	–	–
Total	51,046	100.00%	–	–	–

Panel B: Change in number of direct flights between a firm's nearest airport and USPTO

		BWI	DCA	IAD
Increase in direct flights	Mean	942	1050	617
	Median	702	660	235
	S.D	1125	1272	896
Decrease in direct flights	Mean	−639	−761	−526
	Median	−490	−472	−257
	S.D	745	882	695

Panel C: Differences in observables

	Increase in direct flights			
	Treatment	Control	Differences	*t*-Statistics
PatGrowth	3.678	3.009	0.669	0.931
TimeGrowth	−0.083	−0.078	−0.005	−0.109
ExploreGrowth	−0.003	0.018	−0.021	−1.292
ExploitGrowth	0.042	0.029	0.013	1.092
Ln(DirectFlights)	8.604	8.407	0.197	0.879
Assets	6.024	6.067	−0.043	−0.437
ROA	−0.067	−0.065	−0.002	−0.241
Leverage	0.184	0.192	−0.008	−0.888
Capex	0.055	0.054	0.001	0.547
R&DAssets	0.120	0.119	0.001	0.160
PPEAssets	0.485	0.480	0.005	0.318
KZ	−5.248	−5.151	−0.097	−0.163
HHI	0.231	0.231	0.000	0.000
HHISquare	0.086	0.084	0.002	0.127
Tobin Q	2.487	2.675	−0.188	−0.228
InstOwn	0.353	0.360	−0.007	−0.550

Table 6 (*continued*)

	Decrease in direct flights			
	Treatment	Control	Differences	*t*-Statistics
PatGrowth	1.742	1.016	0.726	0.889
TimeGrowth	0.079	0.081	−0.002	−0.027
ExploreGrowth	−0.063	−0.051	−0.012	−0.473
ExploitGrowth	0.074	0.045	0.029	0.548
Ln(DirectFlights)	8.907	8.855	0.052	0.571
Assets	6.117	6.137	−0.020	−0.122
ROA	−0.115	−0.096	−0.019	−0.893
Leverage	0.203	0.207	−0.004	−0.300
Capex	0.047	0.048	−0.001	−0.517
R&DAssets	0.130	0.115	0.015	1.179
PPEAssets	0.482	0.511	−0.029	−1.334
KZ	−4.744	−5.285	0.541	0.514
HHI	0.222	0.241	−0.019	−1.482
HHISquare	0.084	0.094	−0.010	−0.948
Tobin Q	2.375	2.534	−0.159	−0.964
InstOwn	0.353	0.350	0.003	0.172

Panel D: Estimated propensity score distributions

Propensity scores	*Increase in direct flights*				*Decrease in direct flights*			
	No. of obs.	Mean	SD	P50	No. of obs.	Mean	SD	P50
Treatment	1023	0.53	0.23	0.49	325	0.48	0.24	0.53
Control	1131	0.44	0.22	0.42	466	0.42	0.22	0.38
Difference		0.09	0.01	0.07		0.06	0.02	0.05

Panel E: DiD test results – increase in direct flights

Increase in direct flights	Mean treatment difference (after − before) (1)	Mean control difference (after − before) (2)	Mean DiD estimator (treat − control) (3)	*Z*-statistics for DiD estimator (4)
GrantTime_3yr_avg	−0.175	−0.032	−0.143***	−3.488
	(0.034)	(0.025)	(0.041)	
Patent_3yr_avg	6.323	0.932	5.391***	2.565
	(1.806)	(1.289)	(2.101)	
Explore_3yr_avg	−0.070	−0.090	0.020***	2.500
	(0.008)	(0.006)	(0.008)	
Expoit_3yr_avg	0.062	0.079	−0.017	−1.417
	(0.010)	(0.007)	(0.012)	

Panel F: DiD test results – decrease in direct flights

Decrease in direct flights	Mean treatment difference (after − before) (1)	Mean control difference (after − before) (2)	Mean DiD estimator (treat − control) (3)	*Z*-statistics for DiD estimator (4)
GrantTime_3yr_avg	0.227	0.042*	0.185**	2.372
	(0.065)	(0.058)	(0.078)	
Patent_3yr_avg	−3.328	4.333	−7.661**	−2.087
	(2.722)	(2.462)	(3.670)	
Explore_3yr_avg	−0.120	−0.090	−0.030***	−2.727
	(0.009)	(0.008)	(0.011)	
Expoit_3yr_avg	0.050	0.048	0.002	0.118
	(0.014)	(0.010)	(0.017)	

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

Table 6 Panel E reports the results of the DiD analysis based on treatment firms that experience an increase in the number of direct flights due to airline restructuring activities. The magnitude of the DiD estimate suggests that, compared to firms that do not experience an increase in the frequency of direct flights to the USPTO, firms that enjoy an increase in direct flights experience an average of 52 ($=0.143 * 365$) days reduction in the length of patent procurement process and obtain 5.4 more patents per year over three years after the increase in direct flights. In terms of innovation type, exploratory patent intensity increases significantly by 0.02 after the increase in direct flights, however, we do not find significant change in exploitative patent intensity.

Table 6 Panel F reports the DiD results using treatment firms that experience a decrease in the number of direct flights due to airline restructuring events. The results are opposite to those in Panel A. The magnitude of the DiD estimate suggest that, compared to firms that do not experience a decrease in the number of direct flights to the USPTO, firms that do experience a decrease incur an average of 68 ($=0.185 * 365$) days increase in the length of patent procurement process and obtain 7.6 fewer patents per year over three years after the decrease in direct flights. Exploratory patent intensity also decreases significantly by 0.03 while exploitative patent intensity shows no significant change.

Note that, while our identification tests suggest a likely causal effect of distance to the USPTO on a firm's patenting performance, an important caveat is that these identification attempts are not without limitations. For example, a firm's headquarters relocation decisions may be endogenous and is predominantly based on future path of the firm, which could be related to its innovation output. We acknowledge the limitations of our identification strategy. Caution needs to be exercised when interpreting or generalizing our results.

6. Additional analyses

In this section, we discuss additional test to further strengthen our identification attempts, address a few important concerns regarding our main findings, and answer a "bottom-line" question.

6.1. Cross-sectional analyses

We explore how the relation between accessibility to the USPTO and patenting performance varies in the cross section. We undertake three tests. First, we examine how a firm's past patenting experience affects our main results. We posit that accessibility to the USPTO could be more important for first-time applicants who lack relevant domain knowledge and are unfamiliar with the patenting process. To test this conjecture, we construct a dummy variable, $FirstTime_{i,t}$, that takes the value of one if firm i is a first time patent applicant (i.e., it has never filed a patent with the USPTO before year t), and zero otherwise. We then estimate the following model:

$$\begin{aligned} LnGrantTime_{i,t+3}\left(LnPatent_{i,t+3}/ExplorePat_{i,t+3}/ExploitPat_{i,t+3}\right) = {} & \alpha + \beta_1 LnDistance_{i,k} + \beta_2 LnDistance_{i,t} \times FirstTime_{i,t} \\ & + \beta_3 FirstTime_{i,t} + \lambda' Control_{i,t} + {}' County_{k,t} + Year_t \\ & + Industry_j + \varepsilon_{i,t} \end{aligned} \quad (3)$$

where i indexes firm, j indexes industry, k indexes county and t indexes time. *Control* and *County* are vectors of firm and county characteristics as in Eq. (1). Table 7 Panel A reports the results. We suppress the coefficient estimates of control variables for brevity. In all four columns, the coefficient estimate on *LnDistance* is consistent with our baseline results. More importantly, the coefficient estimates on the interaction term, $LnDistance \times FirstTime$, are significantly positive in column (1) and negative in column (2) and (3), suggesting that accessibility to the USPTO plays a more important role in improving the patenting performance of first-time filers.

Second, we examine a firm's overall information environment transparency. When a firm's information environment is opaque, outsiders (including the USPTO patent examiners) may possess less knowledge about the firm's operating and innovation activities. Reductions in information asymmetry associated with geographical proximity therefore become more important for these firms. We use a firm's earnings quality to capture firm transparency, which is commonly used in the accounting literature. Aboody et al. (2005), Francis et al. (2005) and Bhattacharya et al. (2012), among others, document a negative relation between earnings quality and information asymmetry. Earnings quality is operationalized using discretionary accruals (Dechow and Schrand, 2004) that are estimated using the modified Jones (1991) model by year and two-digit SIC codes, requiring at least 20 observations in each industry group. Because both positive and negative discretionary accruals indicate poor accruals/earnings quality, we define the main measure of earnings quality *(Ab_Acc)* as *Ln[abs(DiscretionaryAccruals)]*. A higher *Ab_Acc* indicates a lower firm transparency.

We use a similar model specification as in Eq. (3) except that the moderating factor is now *Ab_Acc*. Table 7 Panel B reports the regression results. The coefficient estimates on *LnDistance* are consistent with our prior results. More importantly, the coefficient estimates on the interaction term, $LnDistance \times Ab\_Acc$, are positive for *LnGrantTime* and negative for *LnPatent* and *ExplorePat*, suggesting that accessibility to the USPTO is more important for firms that are subject to a more opaque information environment.

Third, we examine how the introduction of electronic patent application filing system (EFS) affects our main results. On October 27, 2000, the USPTO initiated the EFS, which is perceived as a major step towards fully automating and improving the quality of patent application processing.[25] The EFS enables patent applicants to file an application for a new invention with the USPTO using the Internet. It saves time and offers the convenience of Internet filing 24 h a day, 7 days a week. The EFS assembles all application components, calculates fees, validates application content, and transmits the filing to the USPTO.

A stream of prior studies argues that developments in information technology (Internet, corporate intranet, video conferencing, among others) facilitate the ease of communication and information transmission between two distant parties. Consistent with this argument, Petersen and Rajan (2002) find that, owing to development in information technology, the distance between small business borrowers and their lenders has decreased over time. Based on this line of research, we conjecture that the intro-

Table 7
Heterogeneous effect of distance to the USPTO on patenting performance.
This table reports regression results on cross-sectional variation in the distance to the USPTO on a firm's patenting performance. In Panel A, *FirstTime* equals one if a firm files patents for the first time in a given year, and zero otherwise. In Panel B, *Dis_Acc* is the natural logarithm of discretionary accruals based on the modified Jones model. In Panel C, *Post-2000* is an indicator variable that equals one if the patent filing year is 2001 or after, and zero otherwise. Definitions of other variables are provided in Table 1. Year and industry fixed effects and control variables are included in all regressions but the coefficients are not reported. Robust standard errors clustered by firm are displayed in parentheses.

Panel A: First-time filing

Dependent variable	*LnGrantTime*	*LnPatent*	*ExplorePat*	*ExploitPat*
	(1)	(2)	(3)	(4)
LnDistance	0.074**	−0.044**	−0.017**	0.004
	(0.038)	(0.020)	(0.008)	(0.002)
FirstTime × *LnDistance*	0.019*	−0.021**	−0.001*	0.004
	(0.011)	(0.015)	(0.000)	(0.005)
FirstTime	−0.016	0.505***	−0.119	−0.013
	(0.052)	(0.035)	(0.086)	(0.034)
Constant	−0.771	−5.086*	0.500	0.018
	(0.909)	(2.674)	(0.418)	(0.271)
Controls	Included	Included	Included	Included
Year and industry fixed effects	Included	Included	Included	Included
R^2	0.32	0.27	0.16	0.16
Observations	23,350	51,046	27,165	27,165

Panel B: Firm information environment

Dependent variable	*LnGrantTime*	*LnPatent*	*ExplorePat*	*ExploitPat*
	(1)	(2)	(4)	(5)
LnDistance	0.104**	−0.108***	−0.015*	0.004
	(0.051)	(0.039)	(0.009)	(0.003)
DisAccruals × *LnDistance*	0.005*	−0.002*	−0.001*	0.002
	(0.003)	(0.001)	(0.000)	(0.002)
DisAccruals	−0.003	0.074	0.005	−0.010
	(0.002)	(0.251)	(0.017)	(0.011)
Constant	0.979	−0.209	0.121	0.246
	(1.401)	(4.687)	(0.536)	(0.351)
Controls	Included	Included	Included	Included
Year and industry fixed effects	Included	Included	Included	Included
R^2	0.36	0.26	0.17	0.18
Observations	15,532	31,173	16,833	16,833

Panel C: Electronic filing system

Dependent variable	*LnGrantTime*	*LnPatent*	*ExplorePat*	*ExploitPat*
	(1)	(2)	(4)	(5)
LnDistance	0.075**	−0.096***	−0.018***	0.002
	(0.037)	(0.022)	(0.006)	(0.002)
Post2000 × *LnDistance*	−0.007**	0.083***	0.003	0.004
	(0.003)	(0.019)	(0.004)	(0.002)
Post2000	−1.174***	−1.632***	0.146***	−0.038
	(0.024)	(0.135)	(0.046)	(−0.030)
Constant	0.477	−3.904	0.333	0.059
	(0.914)	(2.701)	(0.420)	(0.287)
Controls	Included	Included	Included	Included
Year and industry fixed effects	Included	Included	Included	Included
R^2	0.32	0.27	0.16	0.14
Observations	23,350	51,046	27,165	27,165

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

To test this conjecture, we construct a dummy variable, *Post2000*, that takes the value of one if firm *i*'s patent application year is 2001 or after and replace the key variable of interest in Eq. (3) with *Post2000*. Table 7 Panel C reports the results. Again, in all four columns, the coefficient estimate on *LnDistance* is consistent with our previous findings. The interaction term *LnDistance* × *Post2000* is negative and significant at 5% in column (1) where the dependent variable is *LnGrantTime*, and is positive and significant at the 1% level in column (2) where the dependent variable is patent quantity *LnPatent*. However, we do not find that the coefficient estimate on *LnDistance* × *Post2000* to be significant in columns (3) and (4) where the dependent variable is *ExplorePat* and *ExploitPat*, respectively. Taken together, these results suggest that while EFS may improve communication between patent applicants and USPTO examiners that lead to a more speedy patenting process and higher productivity, it does not completely displace the advantages associated with geographical proximity.

As we discussed before, a major concern of our main tests is that omitted variables that affect both distance to the USPTO and a firm's patenting activities drive our results. However, it is difficult to conceive an omitted variable that biases our results equally in firms that are first-time or repeated patent applicants, that have higher or lower earnings quality, and that file for patents both before and after year 2000. Our evidence on differential effects of distance t eh USPTO on patenting performance along these dimensions further helps alleviate he endogeneity concern to some extent and suggests that a causal effect may be at least partially in effect.

6.2. Oening of the Detroit of fice in 2012

Pursuant the 2011 Leahy-Smith America Invents Act, the USPTO opened the first regional office in Detroit in 2012, the second office in Denver in 2014 and another two offices in 2015 in Silicon Valley and Dallas, respectively. The opening of these regional offices reduces the geographical distance to the USPTO for many firms, which allows us to conduct additional analyses to further address the endogeneity concern.

Because patent procurement spans approximately two years and the latest available USPTO patent data that we have are in 2014, we focus on the opening of Detroit office in 2012 as our testent. This design choice ensures that patents obtained in 2014 are mostly filed after the event year. Our analysis involves comparing patenting performance in the post-event year (i.e., 2014) with pre-event year (i.e., 2010) for a sample of firms that experience a decrease in distance to the USPTO, against a sample of matched control firms.[26]

Table 9
Examiner interviews and patent performance.
This table reports the impact of accessibility to the USPTO on the likelihood of in-person examiner interview, and the impact of examiner interview on patent performance. Panel A reports the probit model of the relation between accessibility and the propensity of in-person examiner interview at the patent level. Panel B reports the impact of in-person examiner interview on patent performance, at the patent level. *Interview* is a dummy variable that equals one if the patent involved at least one interview, and zero otherwise.

Panel A: Geographical distance and the likelihood of in-person examiner interviews

Dependent variable	*In-person examiner interview*
	(1)
LnDistance	0.002**
	(0.001)
Firm size	0.001
	(0.004)
ROA	0.015**
	(0.007)
Citations	0.115**
	(0.059)
Originality	0.093**
	(0.042)
Constant	2.320***
	(0.511)
Year fixed effects	Included
Pseudo R^2	0.33
Observations	1000

Panel B: In-person examiner interviews and patent performance

Dependent variable	*LnGrantTime*	*ExplorePat*	*ExploitPat*
	(1)	(2)	(3)
Interview	−0.013**	0.048***	0.013
	(0.006)	(0.017)	(0.014)
LnDistance	0.073*	−0.005**	0.004
	(0.038)	(0.002)	(0.003)
Constant	−1.243***	0.331***	0.594**
	(0.268)	(0.031)	(0.288)
Controls	Included	Included	Included
Year and industry fixed effects	Included	Included	Included
R^2	0.29	0.26	0.16
Observations	1000	1000	1000

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

6.3. Advantages of being close to the USPTO

The main finding of this paper is that geographical proximity to the USPTO facilitates the materialization of innovation output. In this section we explore three underlying mechanisms. One plausible underlying mechanism is in-person examiner interviews that facilitate the gathering and transferring of (soft) information between patent applicants and patent examiners. The USPTO's PAIR system provides transaction-level data, including information on whether an interview was conducted, the date and the format of the interview, for each patent application filed after year 2001.[27] Given the large sample of data in our study, we randomly select 1000 patents between 2002 and 2005 (which is the ending year of our sample period). 8.2% of patents had at least one in-person examiner interview. In Table 9, Panel A, we show that firms residing closer to the USPTO are more likely to engage in in-person examiner interviews. In Table 9 Panel B, we test whether in-person examiner interviews are associated with superior patenting performance at the patent level. We use the same model as in baseline analysis with an added variable *Interview*, which is a dummy variable that equals one if the patent involves at least one in-person interview. Results suggest that examiner interviews indeed facilitate patenting performance and thus serve as plausible economic mechanism through which accessibility to the USPTO affects patent performance.

Another potential advantage associated with geographical proximity to the USPTO is access to superior innovation resources that include more innovation-intensive universities and skilled innovation labor and talent. Innovation-intensive universities play a critical role in corporate innovation by providing them highly skilled labor. In fact, the Organization for Economic Co-operation and Development (OECD)'s report highlights universities as an important source of highly skilled

[27] http://portal.uspto.gov/pair/PublicPair. Once a patent application number is entered, the transaction history can be retrieved from the tab "Patent Term Adjustments".

Table 10
Local skill channel.
This table reports the results of the local skill channel. Panel A reports the geographic distribution of top 20-innovation-intensive universities. Panel B reports the regional comparison of labor force. Panel C reports the results between local labor force skills and innovation performance. The dependent variables are the average innovation performance among firms in a given state. Robust standard errors clustered by firm are displayed in parentheses.

Panel A: Geographic distribution of top 20 innovation-intensive universities

	Number of innovative universities
East Coast regions	9
West Coast regions	4
Others	7
Total	20

Panel B: Labor force skill

	East Coast regions (1)	West Coast regions (2)	Others (3)	Difference (1) − (2)	Difference (1) − (3)
Occupation – professional (%)	37.14	33.08	32.12	4.06*	5.02***
Industry - information, scientific and management (%)	13.27	11.39	10.40	1.88	2.87***
Education – bachelor and above (%)	30.59	25.86	24.72	4.73**	5.87***
Class of worker - private wage and salary workers (%)	77.58	72.93	77.13	4.65*	0.45

Panel C: Labor force skill and innovation performance

Dependent variable =	*Average_LnGrantTime*	*Average_LnPatent*	*Average_Explore*	*Average_Exploit*
	(1)	(2)	(3)	(4)
Occupation	−0.724	8.391***	2.093***	−0.789**
	(0.450)	(1.977)	(0.493)	(0.382)
Industry	0.698	4.875***	2.366***	−1.566***
	(0.481)	(1.672)	(0.417)	(0.323)
Education	−0.286	0.296*	−0.004	0.000
	(1.950)	(0.156)	(0.004)	(0.003)
Class of worker	0.004	4.065***	0.814	0.375
	(0.004)	(0.856)	(0.214)	(0.165)
Constant	1.371***	−3.934***	−0.242	0.162
	(0.187)	(0.822)	(0.205)	(0.159)
R^2	0.15	0.45	0.50	0.36
Observations	50	50	50	50

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

labor and talent, which is one of the most powerful mechanisms for knowledge transfer to industry.[28] To test the local skill channel, we obtain data from the U.S. Census Bureau on industry, occupation, and class of workers for Americans in the labor force in different geographical areas. We report three pieces of evidence in Table 10: (1) As reported in Panel A, the east coast has more innovation-intensive universities than the West Coast and other states, respectively; (2) as reported in Panel B, east coast states on average have higher labor skills compared to other states.[29] In particular, these states have a higher percentage of professional workers, a higher percentage of workforce in information and scientific related areas, a higher percentage of workforce with higher education, as well as a higher percentage of private wage and salary workers. (3) As reported in Panel C, we examine the relation between local labor skills and local firms' innovation performance. We find that labor skills positively affect patent output and exploration intensity. Overall, the results in Table 10 are consistent with the local skill channel.

Another potential advantage associated with geographical proximity to the USPTO is access to more patent attorneys. We retrieve the location information of all patent attorneys in the U.S. from the USPTO's website (https://oedci.uspto.gov/OEDCI/). We find that the number of patent attorneys in East Coast states is approximately 10,002, which is much larger than that in the West Coast states (i.e., 5892). Hence, having access to more patent attorneys could be one advantage of being proximate to the USPTO.[30]

[28] https://www.oecd.org/innovation/research/37592074.pdf.
[29] Labor data offered by the U.S. Census Bureau are based on American community survey. The survey, however, is not conducted annually and aggregate data are available for 2000 and 2005 only. Hence, we take the average value of these two years.
[30] Note that that it is very possible that better personal connections with USPTO employees (due to the firms' proximity to the USPTO) could be an important advantage of being close to the USPTO and could explain our main findings. Due to data limitations, however, we cannot directly test this conjecture.

6.4. What explains the innovativeness of West Coast firms?

During our sample period, we observe an unprecedented innovation among firms in the West Coast despite their remoteness from the USPTO. A natural question is how to explain the innovativeness of these West Coast firms? In this section we explore two plausible actions that West Coast firms could undertake, which help explain these firms' high patent productivity despite being far from the USPTO.

First, West Coast firms could outsource innovation via corporate venture capital (CVC). Many innovation-intensive firms nowadays engage in CVCs to invest strategically in startups whose main businesses align closely with their own business directives. One of main goals of these firms' CVC investment is to acquire innovation talent and products/services. Ma (2016) shows that firms start CVC funds when their internal innovation deteriorates. Chemmanur et al. (2014) find that CVCs help their portfolio firms achieve a higher degree of innovation productivity. Dushnitsky and Lenox (2005, 2006) show that firms with CVC subsidiaries enjoy a significant increase in their own innovation productivity. Taken together, it appears that firms use CVCs to acquire innovation knowledge from startups. Hence, we posit that CVCs could explain the innovativeness of the West Coast companies despite being so far from USPTO. To explore this conjecture, we have followed Chemmanur et al. (2014) and identified 411 CVCs whose parent firms are in our sample and rank the total number of CVCs by state. For brevity, we report only the top 10 states in Panel A of Table 11. As one can observe, California ranks the very top with 126 CVCs, that is, approximately a quarter of CVCs affiliated with publicly traded parent firms in our sample reside in California. This observation suggests that firms in California enhance their innovation output, despite being far from the USPTO, through outsourcing innovation to startups via their CVC investment.

Second, an important way for firms to enhance their own innovation productivity is through the acquisition of innovation-intensive firms (Bena and Li, 2014; Sevilir and Tian, 2014). We conjecture that West Coast firms may engage in more acquisitions with target firms being more innovative (i.e., owning more patents). To test this conjecture, we have undertaken the following

Table 11
Innovativeness of West Coast firms.
This table reports the results of two analyses on the innovativeness of West Cost firms. Panel A reports the list of top ten states in terms of number of corporate venture capital. Panel B reports the results of a probit model of the likelihood of acquiring innovation-intensive targets. *InnovativeTarget* is a dummy variable that equals one if the target firm's average patent output in three years prior to the acquisition is above zero, and zero otherwise. *WestCoast* is a dummy variable that equals one if the firm is in a West Coast state (i.e., California, Washington, Oregon, and Alaska), and zero otherwise. Year and industry fixed effects are included in all regressions but the coefficients are not reported. Robust standard errors clustered by firm are displayed in parentheses.

Panel A: Top 10 states with most CVCs

State	Number of CVCs
CA	126
MA	24
NY	22
TX	22
IL	12
NJ	10
GA	9
WA	8
VA	7
MD	6

Panel B: Acquisitions of innovation-intensive firms

	Prob(InnovativeTarget)	
	(1)	(2)
WestCoast	0.146**	0.174***
	(0.067)	(0.058)
Size		0.133
		(0.125)
Lev		−0.415***
		(0.147)
ROA		1.095***
		(0.279)
Age		0.149***
		(0.025)
Constant	−2.752***	−3.320***
	(0.304)	(0.322)
Industry and year fixed effects	Included*	Included
R^2	0.10	0.13
Observations	43,235	43,235

***

analysis using the probit model:

$$Prob(InnovativeTarget)_{i,j} = \alpha + \beta WestCoast_{i,j} + \lambda^{'} Control_{i,t} + Year_t + Indu$$ [redacted]

where i indexes firm, j indexes industry, and t indexes time. The dependent [redacted] equals one if the target firm's average patent output in three years prior [redacted] *WestCoast* is a dummy variable that equals one if the firm is in a West Coast [redacted] ka), and zero otherwise. *Control* is a vector of firm characteristics including f[redacted] gression result in Panel B of Table 11. The coefficient estimate on *WestCoa*[redacted] supporting the conjecture that West Coast firms are more inclined to acquire [redacted] their own innovation performance, despite being far from the USPTO.

Overall, it appears that West Coast firms compensate for their distance t[redacted] through their CVC investment and by acquiring innovative target firms. It is [redacted] that the West Coast firms take other actions, such as using more corporate jet[redacted] ferencing tools earlier, to compensate their long distance to the USPTO. Du[redacted] conjectures.

6.5. How does the market value a firm's proximity to the USPTO?

Our paper so far has shown that a firm's proximity to the USPTO helps e[redacted] this section, we answer a "bottom-line" question on how the market value[redacted] two tests. First, we examine market reactions around the announcement of th[redacted] ent data are up to 2014, we examine the opening of Denver and Detroit office[redacted] actual opening of these regional offices from the USPTO's website. To gauge t[redacted] partition the sample into two groups based on whether a firm files for patents [redacted] the tests separately for high-patenting group (firms that filed for at least one [redacted] low-patenting group (firms that did not file for any patent in the year prior t[redacted] accessibility to the USPTO due to the opening of USPTO regional offices sho[redacted] participants firms with more patenting activities. In contrast, the opening of [redacted] with little patenting activities. Specifically, we estimate the following model: [redacted]

rpio58.5rst $$CAR_{i,t} = a + b_1 * ShorterDistance_{i,t} + Control_{i,t} + e_{i,t}$$

where *CAR* is the 3-day cumulative abnormal return, *ShorterDistance* is a du[redacted] regional office reduces a firm's geographical distance to the USPTO and zero [redacted] including firm size, leverage, age, and ROA. We report the results in Table 12[redacted] timate on *ShorterDistance* is positive and significantly only in the high-paten[redacted] perceive enhanced accessibility to the USPTO to be beneficial, but only for pa[redacted]

Second, we examine the value relevance of patents and the moderating ro[redacted] erature in accounting suggests that financial statements omit salient firm in[redacted] intangible assets to firm valuation (Cohen et al., 2012). Following this line of r[redacted] ity patents held by a firm increasingly defines its overall value. The stronger a[redacted] stock market. If geographical proximity is conducive to reducing information a[redacted] cess, we expect patents granted to firms located close to the USPTO to be of [redacted] benefits. Those patents should therefore be more value relevant, i.e., they sho[redacted] our conjecture, we follow the value relevance literature and use the Ohlso[redacted] tion:

$$MV_{i,t} = \alpha + \beta_1 BV_{i,t} + \beta_2 NI_{i,t} + \beta_3 PatentPerShare_{i,t} + \beta_4 LnDistance_i + \beta_5 F \ldots + \varepsilon_{i,t}$$ [redacted]

where i indexes firm, j indexes industry, and t MVdesha358pitte-1B)6Id/F21Tf76[redacted]

Table 12
Market reactions to the opening of USPTO regional offices.
This table reports market reactions to the opening of USPTO regional offices. *CAR* is three-cumulative abnormal return surrounding the announcement of the actual opening of each regional office. *ShorterDistance* is a dummy variable that equals one if the opening of the regional office reduces firm's distance to the USPTO and zero otherwise. High-Patenting Group includes firms that filed at least one patent in the year prior to the announcement. Low-Patenting Group includes firms that did not file any patent in the year prior to the announcement. Robust standard errors clustered by firm are displayed in parentheses.

	CAR [−1, 1] All firms	CAR [−1, 1] High-patenting group	CAR [−1, 1] Low-patenting group
	(1)	(2)	(3)
ShorterDistance	0.005	0.007*	0.005
	(0.003)	(0.004)	(0.004)
Assets	0.001	0.001	0.001
	(0.001)	(0.002)	(0.001)
ROA	0.016	−0.032*	0.040*
	(0.020)	(0.017)	(0.025)
Leverage	0.002	0.009	−0.001
	(0.011)	(0.018)	(0.012)
Age	−0.001	−0.009	0.005
	(0.010)	(0.015)	(0.015)
Constant	0.001	0.034	−0.033
	(0.040)	(0.059)**	(0.060)***
Industry fixed effects	Included	Included	Included
R^2	0.22	0.31	0.20
Observations	2651	623	2028

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

interaction effect by adding *LnDistance* and *PatentPerShare* × *LnDistance* into the model. In column (2), the coefficient estimate on the interaction term, *PatentPerShare* × *LnDistance,* is negative and significant at the 5% level, suggesting that, ceteris paribus, investors perceive patents held by firms located closer to the USPTO to have higher future economic value, and therefore assign them a larger valuation weight.

7. Conclusion

In this paper, we examine the effect of a firm's accessibility to the USPTO on its patenting performance. Our baseline results suggest that an easy access to the USPTO is negatively related to time-to-patent-procurement and is positively related to the number of patents owned. We also show that accessibility is important for exploratory, but not for exploitative, innovation activity. Accessibility is important for a firm's exploratory, but not for exploitative, innovation activity. The relation is more pronounced

Table 13
Patents, firm value, and distance to the USPTO.
This table reports regression results of the value relevance of patents. *MV* is share price at fiscal year end. *BV* is book value of equity per share. *NI* is earnings per share. *PatentPerShare* is the number of patents deflated by the number of shares outstanding. Year fixed effects and industry fixed effects are included in all regressions but the coefficients are not reported. Robust standard errors clustered by firm are displayed in parentheses.

Dependent variable	*MV*	
	(1)	(2)
BV	0.556***	0.553***
	(0.030)	(0.031)
NI	1.400***	1.396***
	(0.210)	(0.209)
PatentPerShare	6.439***	10.835***
	(0.467)	(2.391)
PatentPerShare × *LnDistance*		−0.706**
		(0.351)
LnDistance		−0.210
		(0.151)
Constant	10.515***	12.118***
	(1.670)	(2.026)
Year and industry fixed effects	Included	Included*
R^2	0.44	0.45
Observations	73,878	73,878

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

for first-time patent applicants, firms with a larger degree of information asymmetry, and before the launch of an electronic filing system. Finally, we show that market reacts positively to the opening of USPTO regional offices for innovation-intensive firms that enjoy a shorter distance to the USPTO, and that the contribution of a firm's patent portfolio to its equity value is larger when the firm is located closer to the USPTO. Our study demonstrates one strategy that firms can use to facilitate the materialization of their innovation outcomes, and highlights the importance of accessibility in fostering an effective innovation ecosystem.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcorpfin.2017.12.002.

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