Inorganic growth in innovative firms: evidence from patent acquisitions

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Abstract:

Startup firms are better suited to exploration (radical breakthrough) than exploitation (incremental improvements). Nonetheless, I find that approximately 10% of VC-backed companies acquire external patents while still private. They are neither low-quality firms nor firms with low patent output, lending little support to the hypothesis that patent acquisition is a response to low productivity. Rather, patent litigation risk appears to play an important role. Startup firms are significantly more likely to buy external patents when they are sued for patent infringement or exposed to a high threat of litigation. Using a difference-in-differences design around the Supreme Court decision *Alice Corp. vs. CLS Bank*, I show that firms whose patent litigation risks are reduced the most become significantly less likely to buy patents. Consistent with these findings and with the litigation risk preventing firms from reaching their full potential, firms buying patents are significantly more likely to be acquired rather than to go public.

Keywords: Entrepreneurial finance, venture capital, intellectual property rights

JEL classification: L26, G24, O34

1. Introduction

Startup firms are distinct from mature firms along key dimensions. Unlike incumbents, startup firms generally have more limited resources and weaker market power. However, as suggested by Pavitt and Wald (1971) and Acs and Audretsch (1987), their small size allows flexibility, which in turn provides relative advantages in new industries. Rapidly evolving product designs in these industries make mature firms' advantages of economies of scale and scope less valuable (Vernon, 1966). In addition, unlike mature firms, who are better suited to exploitation due to their established routines and structures (Levinthal and March, 1993; Arora, Fosfuri, and Gambardella, 2001), startup firms are incentivized to pursue exploration. These considerations suggest that startup firms' core value comes from innovation. Consistent with this view, the quality of internal innovation is higher before firms go public (Bernstein, 2015), and investors are more likely to fund entrepreneurs who have obtained patents (Farre-Mensa, Hegde, and Ljungqvist, 2017), a widely used measure of innovation.

Although innovation represents the key value driver of these firms, a nontrivial fraction of entrepreneurial firms buy at least a portion of their patents, rather than achieving them through in-house innovation, in early stages of their lifecycle. Across 27,870 startup firms with initial VC rounds between 1980 and 2013, approximately 10% of firms acquired external patents while still private. When Facebook was preparing its IPO, it had approximately 1,400 patents, of which 90% were acquired rather than developed in-house.[1]

The paper focuses on understanding what motivates these firms to buy external patents. While firms may pursue inorganic (i.e. external) growth for reasons such as synergy and market power, under the neoclassical theory of economics, these motives can be summarized into one rationale: firms rely on external patents when they find it less efficient, or more costly, to develop patents on their own. Based on this framework, I propose the productivity hypothesis and the litigation hypothesis, which focus on the internal and external factors that can contribute to firms' patent acquisition decisions, respectively.

The productivity hypothesis posits that patent acquisition is a response to weak internal innovation capabilities or low internal productivity. Prior literature documents that firms experiencing declines in internal productivity or deteriorations of internal innovation engage in

[1] https://techcrunch.com/2012/04/27/facebook-google-patents/

outsourcing-type acquisitions to replenish their research pipelines (Higgins and Rodriguez, 2006) or launch corporate venture capital (CVC) programs to acquire innovation knowledge (Ma, 2016). In this regard, firms that have fundamentally low internal innovation capabilities, or firms whose patent grants are delayed, may consider buying external patents to obtain necessary intellectual property rights. This argument is in line with the recent work by Akcigit, Celik, and Greenwood (2016) who develop an endogenous growth model in which a firm can buy an idea if it fails to innovate.

Contrary to the productivity hypothesis, the results suggest that startup firms buying external patents are neither low-quality firms nor firms with low innovation output. Startup firms that ultimately buy external patents receive investments from more experienced VCs and VCs with better investment performance. Moreover, in subsequent years, these firms advance to later stages of development and produce higher quality patents. Regression analyses indicate that a 10% increase in the number of internal patent applications is associated with a 0.3%–0.6% higher probability of buying external patents (17%–33% of the baseline probability). Similarly, a 10% increase in patent quality, measured by forward citations, is associated with a 0.2%–0.4% higher probability of buying patents (11%–22% of the baseline probability). Overall, these findings suggest that external patents complement, rather than substitute, firms' internal innovation.[2]

The litigation hypothesis posits that patent acquisition represents a response to the threats stemming from firms' intellectual property (IP) environment. Firms often do not have proprietary control over all the essential complementary components of the technologies they are developing (Cohen, Nelson, and Walsh, 2000). Failing to secure proper IP protection can be particularly detrimental to startup firms because they may not possess sufficient financial and legal resources to handle disputes. If sued, patent litigation imposes significant burdens on defendants through both direct legal costs and indirect costs such as management distraction and loss of market share, as discussed by Bessen and Meurer (2008b) and Feldman (2013).[3] In this vein, acquiring external patents can help startup firms to preempt potential lawsuits or to have better bargaining power in

[2] In a related work, Bowen III (2016) examines public firms and finds that patent acquirers subsequently increase R&D and internal patenting. He similarly concludes that patent acquisition is motivated by the pursuit of investment synergies rather than innovation substitution.

[3] According to the 2015 Report of the Economic Survey by American Intellectual Property Law Association (AIPLA), the median costs of patent litigation ranges from $0.6 million to $5 million, depending on amount at risk.

the case of lawsuits by strengthening their patent portfolios. This is because (1) existing patents are subject to fewer prior art, meaning that they are easier to defend against patent lawsuits (Atkinson, Marco, and Turner, 2009; Miller, 2013), and (2) firms can save time and remove uncertainty associated with patent application outcomes by acquiring readily available patents.[4] Based on these considerations, I predict that firms facing a high threat of patent litigation will be more likely to acquire external patents.

Empirical results strongly support the litigation hypothesis. Startup firms sued for patent infringement are 4.3% more likely than their counterparts to buy patents in the following year. In terms of magnitude, this equates to 2.5 times the unconditional probability of patent acquisition. Importantly, the decision to buy external patents appears to depend not only on *realized* lawsuits but also on the *potential* threat of litigation. Because public firms are one of the major plaintiffs suing startup firms (37% of cases have at least one public firm as a plaintiff), the litigation hypothesis further predicts that startup firms' patent acquisition behavior should be responsive to their public competitors' patenting behavior. Consistent with this reasoning, I find that startup firms whose public competitors own broad patents, which are difficult to invent around and thus increase the threat of litigation, are more likely to rely on external patents.

Firms facing a high threat of patent litigation are unlikely to be randomly distributed. If the firm characteristics associated with the probability of being targeted in patent lawsuits (e.g., stages of development) are also correlated with the decision to buy patents, the observed relation between the threat of litigation and the decision to buy patents is potentially affected by endogeneity. To address the selection bias, I exploit the Supreme Court decision *Alice Corp*. vs. *CLS Bank*, which created a plausibly exogenous variation in patent litigation risk for a subset of firms. As described in Srinivasan (2018), the decision invalidated four business method patents on electronic methods and computer programs for financial-trading systems, based upon the rationale that an abstract idea itself cannot be patented unless it transforms the abstract idea into a patent-eligible invention. Because the ruling also raised the patent eligibility standards for business method patents in general, it led to a sudden reduction in the threat of litigation for firms whose technologies rely on business method patents. The difference-in-differences estimates show that firms whose

[4] Farre-Mensa, Hegde, and Ljungqvist (2017) document that the final accept/reject decision generally takes about 3.2 years from the patent application date. They also find that about 36% of patent application are not approved.

technologies are likely to rely on business method patents are 3% more likely to reduce patent acquisitions after the ruling compared to their counterparts. In terms of magnitude, this equates to 1.9 times the unconditional probability of patent acquisition.

If patent litigation risk is a critical determinant for startup firms' decisions to buy external patents, an important follow-on question is the extent to which patent acquisition can help firms to counterbalance the litigation risk. To answer this question, I first look at the behavior of startup firms' investors. If the treatment effect of patent acquisition is sufficiently strong, investors will react positively (at least neutrally) when firms buy patents. On the other hand, if the treatment effect is not strong enough to counterbalance the litigation risk, investors will react negatively when firms buy patents. Examination of financing round characteristics provides suggestive evidence that acquiring external patents counterbalances the litigation risk at least in the short run: firms neither experience drops in valuations nor fail to secure new investors after patent acquisition. However, there is a strong evidence that patent applications are perceived by informed investors as a much better signal than patent acquisitions: while the follow-on rounds receive higher valuations and secure higher-quality VCs when startup firms *apply* for patents, this is not the case when firms *buy* patents.

In the long run, firms buying patents exhibit similar probability of exit/failure compared to their counterparts but there is a stark contrast in exit channels. Firms buying patents are 3.1% *less* likely to exit via IPO, which corresponds to a 40% decrease relative to the baseline probability. On the other hand, firms buying patents are 5% *more* likely to be acquired, which equates to a 20% increase relative to the baseline probability. To the extent that IPO is an exit option mainly available for higher-quality companies (see, e.g., Chemmanur et al., 2018), the results indicate that firms buying patents exhibit less successful exit performance in general. I interpret this as the treatment effect of acquiring external patents not fully offsetting the negative selection effect of high patent litigation risk in the long run.

Finally, I also explore alternative mechanisms that might incentivize startup firms to buy patents. To the extent that one of the key advantages of inorganic growth is speed and efficiency, it is possible that patent acquisition is a strategy for startup firms to grow fast and achieve competitive advantages over their rivals (Gao, Ritter, and Zhu, 2013; Inderst and Mueller, 2009). If this conjecture were true, firms in competitive industries should be more likely to acquire patents. Alternatively, patent acquisition could be motivated by investors' contractual horizon. Due to the fixed lifespan of fund structure, VC funds with a shorter remaining horizon are pressured to exit their investments faster (Masulis and Nahata, 2011; Bhattacharya and Ince, 2015). Therefore, older VC funds may encourage their companies to rely on external patents as a way to build their patent portfolios more quickly. This suggests that firms funded by older VC funds would be more likely to acquire patents. However, I find no evidence to support either of these explanations.

This paper makes several contributions to the literature. Broadly, the findings shed light on the inorganic growth behaviors of young firms. Prior literature finds that young firms' reliance on inorganic growth increases after the IPO for reasons related to the infusion of capital (Celikyurt, Sevilir, and Shivdasani, 2010) and managerial career concerns (Bernstein, 2015). This study contributes to the literature by showing that IP rights is an important determinant for young firms' decisions to rely on inorganic growth. In recent work, Caskurlu (2019) finds that public firms who lose a patent infringement lawsuit sharply increase M&As to acquire substitute patents. The findings in this paper shows that VC-backed private firms acquire the majority of patents in the secondary market rather than through mergers, consistent with startup firms' limited resources.

Second, this study relates to the literature on the secondary patent market, or more generally, on the market for technology. Recent studies document that startup firms' patents are used as collateral for loans (Hochberg, Serrano, and Ziedonis, 2018), and are sold quickly when startups fail (Serrano and Ziedonis, 2018). These studies focus on the utilization and transfer of patents that are internally developed by startup firms. In contrast, the findings in this study highlight startup firms' role as patent buyers, which is in line with the argument that markets for technology may be critical for high-tech startup firms, as they have to acquire the complementary assets in order to commercialize their own innovation (Arora, Fosfuri, and Gambardella, 2001).

Finally, this paper adds to the literature on the relation between patent rights and industrial structure. Gilbert and Newbery (1982) show theoretically that a firm with monopoly power has an incentive to maintain its monopoly power by patenting new technologies before potential competitors, which can lead to patents that are neither used nor licensed to others. In addition, Bessen and Maskin (2009) show that patent protection is not as useful for encouraging follow-on innovation as in a static setting when innovation is sequential and complementary. In line with these arguments, Cockburn and MacGarvie (2011) show empirically that patent rights reduce the rate of entry in product markets. The finding in this paper—that firms buying patents are more likely to be acquired rather than to go public, even though they are high-quality firms to begin with—indicates that patent litigation risk imposes substantial burdens on these firms. Furthermore, it suggests that patent rights can shape industry concentration by affecting entrepreneurial firms' exit channels.

2. Data

The main data in this study consist of information on VC-backed private firms, patent grants, and patent assignments. This section describes the construction of the dataset, including data sources and matching procedures, and it provides summary statistics.

2.1. Private firm sample

The primary sample consists of 27,870 US-based private companies with initial venture capital financing between 1980 and 2013. I focus on VC-backed firms, as a way to identify entrepreneurial ventures that are willing to work on disruptive ideas characterized by high risk and high potential returns (information technology, biotechnology, etc.).[5]

I use Thomson Reuters Private Equity (formerly known as VentureXpert) to identify VC-backed companies. Thomson Reuters began collecting venture capital investments in 1961, and it has more complete coverage of investments than other databases (Kaplan and Lerner, 2016).

To track innovative firms from the early stage, I require firms to be in "seed", "early", or "expansion" stage in their initial VC round (i.e., if firms raise their first venture capital financing in "later stage" or "buyout stage", then they are excluded from the sample). I also require firms to receive investments from at least one fund with the investment type "venture capital" or fund type "independent private partnership", thus excluding firms whose financing is solely from real estate, mezzanine finance, or private equity.[6]

[5] Puri and Zarutskie (2012) find that the key firm characteristics on which VC focuses is scale or potential for scale, rather than short-term profitability.

[6] The investment type includes venture capital, buyout, generalist private equity, mezzanine, fund of fund, other private equity, real estate, and other investor (non-private equity). The fund type includes independent private partnership, corporate PE/venture fund, other banking/financial institution, investment bank, SBIC, government, evergreen, fund of funds, etc.

Using the SDC New Issues database and the SDC VC-backed M&A database, I identify whether firms went public (IPO) or were acquired (M&A).[7] Firms are tracked up to the earliest of (exit date (IPO or M&A), last financing round date + 365*4, or 12/31/2017). If a firm neither exits nor raises a financing round in the last four years prior to the end of the sample period (12/31/2017), the firm is classified as failed (defunct). Financing rounds that (1) occur after firms' exit dates or (2) are classified as "public" by Thomson Reuters are dropped from the analysis.

Table 1 provides summary statistics on these 27,870 VC-backed firms. The first set of rows shows the stage level of startup firms, measured at the initial VC round. About 77% of firms are in either seed (29%) or early stage (47.7%), meaning that the majority of firms in this study represent young startup firms. The second set of rows shows the industry distribution of these firms. Consistent with VCs' preference for high growth sectors, industries are concentrated in information technology (computer software, internet), followed by medical/health and biotechnology. The third set of rows shows the geographic location of these firms. Firms are concentrated in California (36.0%), Massachusetts (9.6%), and New York (7.0%), with these three states making up more than half of all firms raising VC capital. The fourth set of rows shows financing characteristics, measured as of the last round prior to exit or leaving the sample. An average firm received 3.3 rounds, had 3.5 VCs, and raised $23.5 million. Finally, the fifth set of rows shows the status of firms as of 12/31/2017. Overall, 32.6% of firms have exited private status (7.6% via IPO and 25% via M&A), 57.6% of firms have failed, and the remaining 9.8% firms are still active.

2.2. Patent data

Patent grant data is obtained from the United States Patent and Trademark Office (USPTO). Using a Python script, I download and extract all patents granted since 1976.[8] For each patent, I obtain the patent number (grant number), grant date, application number, application date,

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[7] I match these databases both on CUSIP and name. Appendix A.2. describes the details for the name-matching procedure.

[8] This process greatly benefitted from Douglas Hanley's Python scripts: https://github.com/iamlemec/patents. Appendix Figure A1 shows the number of utility patents in the NBER-HBS patent database (which includes patents granted up to 2010) and the number of utility patents I extracted from the USPTO. Comparison of the two datasets during the period 1976–2010 shows that the numbers are consistent.

technology class, assignee name, assignee city, assignee state, and assignee country.[9] Following the literature, I focus on utility patents, which, according to the USPTO, may be granted for new inventions or discoveries.

Since there is no common identifier between the USPTO patent database and Thomson Reuters, I name match the two databases using the procedure described in Appendix A.2. Patent grants are similarly tracked up to the earliest of (exit date, last financing round date + 365*4, or 12/31/2017). Finally, I correct for the patent application and citation truncation biases using the fixed-effects approach employed by Hall, Jaffe, and Trajtenberg (2001) and Bernstein (2015), among others. Specifically, for patent counts, I divide each patent application by the average number of patent applications by VC-backed private firms in the same year and technology class. For patent citations, I divide the number of citations by the average number of citations received by all patents granted in the same year and technology class.

Patent assignment data is also obtained from the USPTO. This dataset is created under the leadership of the Office of Chief Economist of the USPTO (see Marco, Myers, Graham, Agostino, and Apple, 2015), and contains roughly 8 million assignments and other transactions recorded during the period 1970–2017. It includes identities of the assignors and assignees, transaction dates, related patent numbers, and the conveyance types.[10] An earlier version of this dataset was used by Serrano (2006, 2010), Hochberg et al. (2018), and Ma (2016), among others.

While patent transactions are not required to be disclosed, they must be filed with the USPTO to be legally binding (Serrano, 2010). Hence, patent assignees (buyers) have a strong incentive to record the transaction.[11]

I name-match the private firm sample with the USPTO patent assignment database using the procedure described in Appendix A.2. One critical step is handling false positives. The

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[9] Technology class is based on the International Patent Classification (IPC), established by the Strasbourg Agreement 1971. The IPC divides technology into eight sections with approximately 70,000 subdivisions. The eight sections are A (Human necessities); B (Performing operations; Transporting); C (Chemistry; Metallurgy); D (Textiles; Paper); E (Fixed constructions); F (Mechanical engineering; Lighting; Heating; Weapons; Blasting); G (Physics); and H (Electricity). See https://www.wipo.int/classifications/ipc/en/ for details.

[10] Conveyance types include assignment, correct, employee assignment, government interest, merger, name change, release, security interest, and other. I use this information to identify patent acquisitions.

[11] Specifically, 35 U.S. Code § 261 states that "*An interest that constitutes an assignment, grant or conveyance shall be void as against any subsequent purchaser or mortgagee for a valuable consideration, without notice, unless it is recorded in the Patent and Trademark Office within three months from its date or prior to the date of such subsequent purchase or mortgage*."

majority of recorded assignments represent the first within-firm transfer from inventing employees to their employer assignees. This is because for all applications filed before September 16, 2012, the patent must issue to a human inventor, requiring a legal assignment to an employer-owner. To exclude such within-firm transactions (false positives), I drop transactions that are classified as "employer assignment" by the USPTO before performing the matching procedure.

Next, I perform additional data cleansing using the method similar to Ma (2016) and Bowen III (2016). First, I check if patents that appear to be assigned to firms overlap with the patents granted to those firms. If there is an overlap, I do not count such cases as patent transactions. Second, I check if the patent assignor (seller) and the patent assignee (buyer) are the same. I use the name-matching procedure described in Appendix A.2. to identify such potential matches. If the patent assignor matches the patent assignee, the transaction is not classified as a patent transaction. Third, for each firm (buyer)-patent number-assignor (seller)-transaction date tuple, I list firm's inventor names that applied for at least one patent prior to the transaction date.[12] If the patent assignor (seller) matches one of the existing inventor names, the transaction is not classified as a patent transaction. After these steps, I keep transactions that are recorded as "assignment".[13] Analogous to patent grants, patent transactions are tracked up to the earliest of (exit date, last financing round date + 365*4, or 12/31/2017).

Figure 1 presents the time-series evolution of patent acquisitions by startup firms. Panel A highlights the steady increase in the fraction of startup firms buying external patents, from about 5% in the 1980s to 15% in the 2000s. In comparison, the fraction of firms applying for patents was already about 25% in the 1980s, increasing to 38% in the 2000s. Interestingly, the fraction of firms applying for patents and buying patents both started to decline in later years, starting from the mid 2000s.[14]

Panel B shows the number of patents acquired by startup firms, plotted against the transaction year. Patents acquired through mergers are also included for comparison. It clearly shows that the majority of patents are obtained through the secondary market, rather than via M&A.

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[12] Inventor names are obtained from the HBS Dataverse (https://dataverse.harvard.edu/dataverse/patent), which is an updated version of the original NBER patent data project. See Li et al. (2014) for details.

[13] For Panel B of Figure 1, I also keep transactions that are recorded as "mergers".

[14] Since the years in Panel A of Figure 1 does not correspond to the actual transaction years, one should interpret the figure with caution.

This finding is consistent with the fact that acquiring patents in the secondary market is a much more viable option than acquiring an entire company, given startup firms' limited financial resources. Anecdotal evidence suggests that the median asking price for a patent is about $200,000–$250,000, compared to a typical M&A transaction size of $130 million.[15] As a benchmark, the average VC round size for early stage (later stage) deals in the sample is approximately $5 million ($10 million) during the period 1980–2017. Therefore, the asking price for a patent corresponds to about 2%–5% of a typical VC round. The overall pattern in Panel B is similar to that in Panel A: the number of patents acquired by startup firms shows an increasing trend up to the late 2000s, then decreases afterwards.

Panel C restricts the sample to the 9,178 firms that either applied for or acquired at least one patent and plots the composition of the patent portfolio[16]. The composition is defined by (# Patents acquired) / (# Patents applied + # Patents acquired), calculated within each firm.[17] The figure shows the averages of these compositions, plotted against the initial VC round year. For example, a typical company that raised its initial VC financing in 1998 obtained about 30% of its patents from the secondary market. Again, the pattern in Panel C coincides with the patterns in Panels A and B.

Figure 2 shows the timings of patent acquisitions. Panel A shows that, while some firms buy patents before raising capital from VCs, the majority of transactions occur after the VC investment, with 44.9% concentrated within the first five years. Panel B plots the distribution of the timings of patent acquisitions against the number of years from the exit date, where the exit date can be either an IPO date or an acquired date (M&A). The figure indicates that about 67% of transactions are concentrated within the three years prior to the exit event.

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[15] See, for example, http://www.ipwatchdog.com/2017/04/18/2016-patent-prices-key-diligence-data/id=81708/ and https://ipcloseup.com/2017/03/20/patent-transactions-are-flat-u-s-asking-prices-firm-at-250k-per/. The average M&A transaction size of $130 mil is calculated based on Table 4 in Netter, Stegemoller, and Wintoki (2011). The sample covers acquisitions between 1992–2009 done by U.S. acquirers (including public acquirers).

[16] Patents acquired via M&A are excluded. The results are insensitive to the inclusion of patents acquired via M&A.

[17] The results are not driven by the truncation bias in patent data. Defining the composition as (# Patents acquired) / (# Patents granted + # Patents acquired) generates similar results.

3. Do startup firms buy patents because they fail to innovate?

In this section, I test the productivity hypothesis, which postulates that firms buy patents because they fail to innovate, or because their innovation is delayed. Under this hypothesis, firms with weak internal innovation capabilities or firms with low innovation output should be more likely to buy external patents.

3.1. Internal innovation capabilities

Panel A of Table 2 provides descriptive evidence on the productivity hypothesis by comparing startup firms along several dimensions. The first column focuses on the 2,918 VC-backed firms that acquired at least one patent prior to exit or leaving the sample. The second column focuses on the remaining 24,952 firms that did not acquire any patent.

Looking at the first set of rows, startup firms that ultimately buy patents raise investments from more experienced venture capitalists at the time of initial financing round. On average, VC firms are 1.6 years older (14.42 vs. 12.85) and have made investments in 2 more companies (26.48 vs. 24.47). In addition, these VCs have better investment performance: they have exited 0.8 more companies via IPO (3.70 vs. 2.95) and 1.1 more companies via M&A (5.50 vs. 4.42). Looking at the second set of rows, firms acquiring patents also achieve later stages of development. Firms buying patents raise 1.5 more financing rounds (4.69 vs. 3.19), receive investments from more VCs (4.85 vs. 3.31), and raise more capital ($46.62 million vs. $20.84 million) from VCs.[18] Finally, looking at the third set of rows, firms acquiring patents are more likely to apply for patents (68% vs. 25%) and apply for more patents (4.66 vs. 0.79). Moreover, the patents they are granted are more highly cited (1.03 vs. 0.28).

Considering that (1) more experienced VCs invest in better companies (Sørensen, 2007); (2) firms with higher innovation capabilities are more likely to achieve later stages of development; and (3) a patent application is one of the widely used measures of innovation output, the univariate results shown in Panel A of Table 2 are not consistent with the productivity hypothesis. The next section tests the productivity hypothesis in a more systematic manner using a regression framework.

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[18] These firms also raise larger financing round at the initial round ($5.78 million vs. $4.29 million)

3.2. Innovation output

Panel B of Table 2 examines the relation between startup firms' internal innovation output and the decision to buy external patents using a firm-year panel. Analogous to the firm-level data, firms are tracked from the initial financing year to the earliest of (exit year – 1, last financing year + 4, or 2017).[19] Following Dass, Nanda, and Xiao (2017), firm-years 2014–2017 are dropped to minimize the truncation bias in patent data.

Looking at column 1, the dependent variable equals one if a firm buys at least one patent in year *t*, and zero otherwise. All independent variables are measured as of year $t - 1$. Building on prior literature (see Lanjouw, Pakes, and Putnam (1998) and Hall, Jaffe, and Trajtenberg (2001), among others), I use the number of patent applications as a proxy for firm's internal innovation output. The main independent variable of interest is the natural logarithm of one plus the number of patents applied in year $t - 1$. Variables capturing firms' financing conditions, firm size, and VC investors' experience and quality are included as control variables. Location dummies for California, Massachusetts, and New York are included to control for both the geographic concentration of venture capital investments and differences in growth opportunities. Stage dummies are also included to control for differences in the stages of development. Industry fixed effects are included to capture heterogeneity in the importance of patents across industries. Finally, year fixed effects are included to absorb aggregate shocks that might influence firms' patent acquisition decisions.

If patent acquisition is a response to firms' low innovation output, the coefficient on *ln(# Patents applied)* should be negative. In contrast, the coefficient equals 0.059 and is statistically significant at the 1% level, meaning that a 10% increase in the number of internal patent applications is associated with a 0.59% higher probability of buying external patents, controlling for other covariates. When compared to the unconditional probability of patent acquisition of 1.79% during this sample period, this corresponds to 33% of the baseline probability (0.59 / 1.79 = 0.33).

Simply counting the number patent applications may not distinguish between breakthrough innovation and incremental discoveries (see, e.g., Griliches, 1990). To address this point, column

[19] This process drops 167 companies that raise initial VC round and exit in the same year, leaving 27,703 unique companies.

2 uses the natural logarithm of one plus the number of forward citations, which is widely viewed as capturing the innovation quality of a patent. Following the literature, I count forward citations over the three years following each patent's grant date (see, e.g. Bernstein, 2015). If a firm applies for multiple patents in the same year, I use the average.

Looking at column 2, the coefficient on *ln(# Citations)* equals 0.039 and statistically significant at the 1% level, implying that a 10% increase in patent quality is associated with a 0.39% higher probability of patent acquisition. In sum, the results in columns 1 and 2 suggest that there is a strong positive correlation, rather than a negative one, between internal innovation output and the propensity to buy external patents.

Columns 3 and 4 repeat the analyses in columns 1 and 2, respectively, including firm fixed effects. Since these specifications focus on the within-firm variation of innovation output, they capture the extent to which firms experiencing declines in internal productivity or innovation are more likely to buy external patents. I also include stage and industry-by-year fixed effects to control for the stages of development and industry-specific time trends, respectively.

Again, the results are not consistent with the prediction that firms buy external patents when internal innovation declines. Column 3 indicates that a 10% increase in the number of patent applications within a firm is associated with a 0.3% higher probability of acquiring patents. Similarly, column 4 indicates that a 10% increase in the quality of patents within a firm is associated with a 0.19% higher probability of acquiring patents.

Finally, columns 5–8 repeat the analyses in columns 1–4, respectively, by replacing the dependent variable with the natural logarithm of one plus the number of patents acquired. The positive relations between internal innovation output and the propensity to buy patents remain robust and significant.

An alternative explanation for the results in Panel B of Table 2 is that patents are simply inputs for some firms, and that these firms apply for more patents and buy more patents by nature. In addition, the patents of these firms might have higher citations simply because there are more patents. Under this explanation, such unobserved heterogeneity leads to a positive correlation between internal patents and external patents. While the inclusion of industry fixed effects or firm fixed effects largely mitigates such concern, I further address this issue by controlling for complex vs. discrete technologies. As described in Cohen, Nelson, and Walsh (2000), among others, the key difference between a complex and a discrete technology is whether a product or process is comprised of numerous separately patentable elements (e.g. electronic products) vs. relatively few (e.g. new drugs or chemicals).[20]

In Appendix Table A2, I include a dummy variable *Complex industry* which equals one if a firm's SIC code is greater than or equal to 2900.[21] To the extent that *Complex industry* captures firms' product characteristics (i.e. reliance on patents), if the alternative explanation were true, the internal innovation measures should substantially lose the explanatory power once the specification controls for such product characteristics. Yet, the coefficients on internal innovation measures remain stable and statistically significant across columns, lending little support to the alternative explanation described above.

Overall, contrary to the productivity hypothesis, neither weak internal innovation capabilities nor low innovation output explains startup firms' decisions to buy patents. Rather, external patents seem to complement firms' internal innovation.

4. Do startup firms buy patents because of the threat of litigation?

Given the lack of support for the productivity hypothesis, this section investigates whether patent acquisition is a response to the threats stemming from firms' IP environment. Under the litigation hypothesis, firms facing a high threat of patent litigation should be more likely to acquire external patents.

4.1. Patent lawsuits

As a first step, I identify startup firms sued in patent lawsuits. While conceptually simple, identifying litigated firms has been a challenging task until recently because there was no publicly available, comprehensive database. Recently, the Office of the Chief Economist (OCE) at the United States Patent and Trademark Office (USPTO) released a patent litigation dataset for public

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[20] Cohen, Nelson, and Walsh (2000) conclude that firms appear to use their patents to (1) block the development of substitutes by rivals in discrete product industries and (2) force rivals into negotiations in complex product industries.

[21] The definition of complex industry follows Cohen, Nelson, and Walsh (2000). About 18% of firms in the sample do not have SIC codes. For such cases, I impute SIC codes by creating a mapping between VC industries and SIC codes. Conditional on having a non-missing SIC code, I create a frequency distribution of SIC codes per each VC industry. For each VC industry, an SIC code with the highest frequency is chosen as the representative SIC code. The results are robust to excluding firms whose SIC codes are imputed.

usage (Marco, Tesfayesus, and Toole, 2017). The dataset uses docket reports on the universe of patent litigation cases in Public Access to Court Electronics Records (PACER) and RECAP, and includes information on case identifier, parties involved, filing date, and district court location for the cases filed between 1963–2015.[22] The litigation dataset is merged with the sample of VC-backed companies using the name-matching procedure described in Appendix A.2. The matching procedure identifies 5,024 case-party pairs associated with 3,214 unique cases and 1,641 startup firms.[23] Patent lawsuits are tracked up to the earliest of (exit date, last financing round date + 365*4, or 12/31/2015).

Before formally testing the litigation hypothesis, I provide some description of the data. Panel A of Table 3 presents the cross-sectional distribution of party types across startup firms. The sample consists of 5,024 case-party pairs described above. The table shows that startup firms are classified as defendants in 58.9% of cases and as plaintiffs in 39.7% of cases.[24] Panel A of Figure 3 provides evidence on the time-series evolution of patent lawsuits involving startup firms. The figure shows that the number of patent lawsuits involving startup firms is increasing over time. While there were only 7.4 lawsuits per year in the 1980s, the number increased to 227.3 in the 2010s. It also shows that, consistent with the statistics shown in Panel A of Table 3, startup firms are more likely to be defendants. Panel B of Figure 3, which plots the fraction of firms involved in patent litigation each year, shows that the increase in patent lawsuits is not driven by a few outliers.

Panel B of Table 3 investigates the types of firms being targeted in patent lawsuits by splitting startup firms into two groups, depending on whether they get sued at least once prior to exit or leaving the sample. To cleanly identify firms targeted in patent litigations, other types of defendants such as counter defendant, cross defendant, consolidated defendant, etc. are classified

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[22] RECAP is an online archive and free extension for web browsers that improves the access for PACER. RECAP can be accessed at https://free.law/recap/.

[23] The number of unique patent lawsuit cases is based on *case_row_id,* which represents the case-level unique identifier defined in the USPTO patent litigation dataset.

[24] A firm can be classified as multiple parties within a case. For example, a counterclaim is a claim made to offset another claim, especially one made by the defendant in a legal action. Therefore, a counter claimant (the party that files a counterclaim) will be defined as a defendant in the previous case (or sometimes in the current case) but as a plaintiff in the case at hand. Panel A of Table 3 shows that the frequency of counter defendant (9.0%) is much smaller than that of counter claimant (21.3%). Therefore, Panel A of Table 3 is likely to overestimate the probability of a startup firm being a plaintiff.

as not litigated. The first set of rows indicates that firms sued for patent infringement are higher-quality firms to begin with: they raise funding from VCs that are more experienced and have better investment performance. The second set of rows suggests that these firms achieve later stages of development and raise significantly larger amount of capital from VCs. Finally, the third set of rows shows that litigated firm are more likely to apply for patents and apply for more patents. These findings are consistent with the idea that successful companies and companies achieving later stages of development are much more likely to be on the radar of patent owners (Chien, 2013). Moreover, in line with the litigation hypothesis, these firms are significantly more likely to buy external patents.

Table 4 formally tests the litigation hypothesis by examining the relation between patent lawsuits and startup firms' decisions to buy patents. As in Panel B of Table 2, the unit of observation is at the firm-year level. Since patent lawsuits are tracked up to 2015 due to data availability, firm-years are tracked up to 2016 (because the main variable of interest is lagged one year). In Panel A, the dependent variable equals one if a firm buys at least one patent in year *t*, and zero otherwise. The main independent variable of interest, *I(Litigated)*, equals one if a firm is a defendant (excluding other types of defendants such as counter defendant, cross defendant, etc.) in a patent lawsuit in year $t - 1$.

Columns 1–3 focus on the cross-sectional variation and examine whether litigated startup firms are more likely to buy external patents. Looking at column 1, the coefficient on *I(Litigated)* is 0.043 and statistically significant, meaning that litigated firms are 4.3% more likely to acquire external patents after controlling for firms' financing conditions, firm size, VC investors' experience/quality, and a variety of fixed effects (location, stage, industry, and year). In terms of magnitude, this equates to 2.5 times the unconditional probability of patent acquisition (1.75%). In columns 2–3, I control for firms' innovation output by including *ln(# Patents applied)* as an additional control variable. Also, in column 3, firm-years 2014–2016 are dropped as a robustness check for the truncation bias in patent data. The magnitude and the significance of the coefficient on *I(Litigated)* remain robust across both columns.

Columns 4–6 focus on the within-firm variation and examine whether firms are more likely to buy patents when they are litigated. I retain all control variables used in columns 1–3 and include stage, firm, and industry-by-year fixed effects. Column 4 shows that firms are 1.7% more likely to buy external patents when they are litigated. Similar to columns 2–3, I control for firms' innovation output in columns 5–6 and exclude firm-years 2014–2016 in column 6. The results suggest that firms' patent acquisition decisions are explained not only by cross-sectional variation in patent litigation risks but also by within-firm variation in litigation risks.

In Panel B, I repeat the analyses in Panel A by replacing the dependent variable with the natural logarithm of one plus the number of patents acquired in year *t*. The results are qualitatively similar and statistically significant.

If patent lawsuits trigger patent acquisition, the relation between patent litigation and the decision to buy patents should be stronger in the short term. Table A3 shows that this is indeed the case. In Table A3, I add a dummy variable *Litigated(t – 2)*, which equals one if a firm is sued in patent lawsuits in year *t* – 2, in the regression. Looking at Panel A, the coefficient on *Litigated(t – 2)* is smaller than *Litigated(t – 1)* across all specifications. Moreover, when firm fixed effects are included, *Litigated(t – 2)* becomes insignificant while *Litigated(t-1)* remains robust and statistically significant. The results are qualitatively similar when I replace the dependent variable with the natural logarithm of one plus the number of patents acquired (Panel B).

4.2. Intellectual property rights of incumbents

The findings in Section 4.1 show that (1) startup firms are more likely to be defendants in patent lawsuits and (2) these litigated firms are significantly more likely to buy external patents. However, realized threats may not fully explain firms' behavior. Entry models in the industrial organization literature highlight that firms have incentives to block potential entrants to remove future competition: for example, via limit pricing (Milgrom and Roberts, 1982) or pre-emptive acquisitions (Nilssen Sørgard, 1998). Therefore, if the litigation hypothesis were true, startup firms' patent acquisition behavior should be also explained by the potential threat of litigation.

To address this point, I examine whether firms facing a high threat of patent litigation are more likely to buy external patents. To do so, I must identify the source of threats. Miller (2018) documents that product companies (entities making/selling products or offering services), or also known as practicing entities (PEs), are the most common plaintiffs in patent litigations, comprising approximately 60% of all litigation cases.[25] Among the practicing entities, public firms are likely

[25] The findings in Milller (2018) are based on Stanford NPE litigation database, which tracks every lawsuit filed in U.S. district courts from 2000 and categorizes each patent plaintiff as either a practicing entity (PE) or as non-practicing

to be the main threats to startup firms. First, as incumbents, public firms are likely to possess older patents and larger patent portfolios, which are both effective in patents lawsuits. Secondly, public firms generally have better financial and legal resources to pursue costly and time-consuming patent lawsuits than other parties. Finally, public firms have strong incentives to block startup firms when these young firms pose potential competition threats.

Consistent with this reasoning, Panel C of Figure 3 shows that public firms are indeed one of the major plaintiffs suing startup firms. The figure shows the fraction of lawsuits in which a startup is a defendant and at least one plaintiff is a public firm. While there has been a drop in recent years, public firms consistently comprised approximately 40% of all lawsuits.[26] Similarly, Panel D of Figure 3 looks at the fraction of lawsuits in which a startup is a plaintiff and at least one defendant is a public firm. It shows that approximately 30% of lawsuits initiated by startup firms have at least one public firm as a defendant. Quantifying the relative importance of public firm-initiated patent lawsuits on startup firms is challenging without detailed information about individual cases. Nonetheless, the evidence shown in Panels C and D in Figure 3 is consistent with the conjecture that public firms are one of the main sources of threat of patent litigation to startup firms.

To construct a proxy measuring the threat of patent litigation posed by public firms, I focus on the patent scope of public firms. Broad patents provide more intellectual property protection to the owner, so they represent higher barriers to follow-on innovators.[27] This is because broad patents are difficult to invent around, which could result in higher litigation costs (Marco, Sarnoff, and deGarzia, 2016). A higher difficulty of inventing around increases the cost of developing patents in-house, which makes buying external patents an attractive alternative. These considerations suggest that firms surrounded by broad patents will be more likely to buy external patents.

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entity (NPE). It is one of the most comprehensive databases that track plaintiffs in patent lawsuits. Other categories include “acquired patents”, “university heritage or tie”, “failed startup”, “corporate heritage”, “individual-inventor-started company”, “university/government/non-profit”, “startup, pre-product”, “individual”, “industry consortium”, “IP subsidiary of product company”, “corporate-inventor-started company”, and “undetermined”.

[26] The sample mean is 37.1%. These patterns are consistent with the findings of Miller (2018), who also reports that the share of patent litigations attributable to PEs decreased significantly.

[27] Patents are valuable because of what they protect, and the ability of a patent to exclude others from utilizing the invention comes from patent claims (Kuhn and Thomson, 2017).

Following Marco, Sarnoff, and deGarzia (2016) and Kuhn and Thomson (2017), I use the claim length of a patent as a proxy for patent scope, with more words corresponding to less scope. The intuition is that a competitor's offering must meet every condition of a claim in order to infringe it, so a longer claim implies more conditions that must be met for a patent to be violated.[28] Kuhn and Thomson (henceforth KT) use the word count of the first independent claim. Under the U.S. patent law, the broadest claim, which is necessarily an independent claim, should be presented first. In comparison, Marco, Sarnoff, and deGarzia (henceforth MSD) use the word count of the shortest independent claim, which is often, but not always, the first claim. The advantage of the KT measure is that it is validated by practitioners, but a shortcoming is that the data are only available for patents granted during 2005–2012.[29] On the other hand, while the MSD measure has not been officially validated, the data are available for patents granted during the period 1976–2015. Reassuringly, the two measures are highly correlated and exhibit consistent patterns, as shown below.

For each startup firm, I identify all public firms operating in the same 2-digit SIC code.[30] I retain all patents granted to those public firms using the data provided by Kogan, Papanikolaou, Seru, and Stoffman (2017) (henceforth KPSS). Within each 2-digit SIC code-year, I calculate the average claim length of patents granted to public firms. This industry-average is used as a proxy for the patent scope of public firms.[31] Panel A of Figure 4 presents the distribution of the number of words in the first independent claim (KT measure) for the period 2005–2010. The mean (median) length of the first independent claim is 164 (156), with a large dispersion in patent claim length. Panel B of Figure 4 presents the distribution of words in the shortest independent claim (MSD measure) for the period 1980–2010. The mean and the median are 144 and 139, respectively. Finally, Panel C of Figure 4 plots the MSD measure against the KT measure for the period 2005–2010. They are highly correlated with the correlation coefficient of 0.85.

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[28] For example, a patent on an "engine" would be broader than a patent on a "car engine" and both would be broader than a patent on a "200 horsepower car engine" (Kuhn and Thomson, 2017).

[29] Specifically, Kuhn and Thomson (2017) show that their measure outperforms other previously introduced measures for patent scope (e.g., the number of patent classes, the number of forward citations, the number of claims) and explains nearly half of all the variation in patent scope judged by patent attorneys. They assigned 140 randomly selected US patents to 7 patent attorneys and had them complete a questionnaire to gauge the patent scope.

[30] As described in Section 3.2, SIC codes are imputed for a subset of firms (about 18%).

[31] Since the KPSS data is available for patents granted up to 2010, the analysis of patent scope is limited to patents granted to 2010.

Having established the measure for the threat of patent litigation for startup firms posed by public firms, I test whether this measure predicts startup firms' patent acquisition decisions. In columns 1–4 in Panel A of Table 5, the dependent variable equals one if a firm buys at least one patent in year *t*. Across columns, the main variable of interest, *ln(Narrowness of public firm patent scope)*, is the natural logarithm of one plus the number of words in the first independent claim of patents granted to public firms who share the same 2-digit SIC code with startup firms, measured as of year *t* – 1. I use the term "narrowness" because more words in a patent claim corresponds to narrower patent scope. The sample is limited to firm-years 2006–2011 (11,248 unique firms) because the intersection of KT the data (2005–2012) and the KPSS data (1926–2010) are available for 2005–2010. If broad patents owned by public firms motivate startup firms to rely on external patents, we should see a negative coefficient on *ln(Narrowness of public firm patent scope).*

Looking at column 1, the coefficient equals -0.033 and significant at the 1% level. This implies that, controlling for other covariates, a 10% increase in the patent claim length of public competitors is associated with a 0.33% lower probability of acquiring patents. When compared to the unconditional probability of patent acquisition of 2.26% during this sample period, this corresponds to 15% of the baseline probability (0.33 / 2.26 = 0.146).

One concern is that the threat of litigation posed by public firms may affect startup firms not only through the scope of patents they produce but also through the total number of patents they possess. This is because as the number of existing IP rights increases, it becomes harder for followers to invent around them. To address this point, I include the natural logarithm of one plus the total number of patents granted to public firms in year *t* – 1 as a control variable in column 2. Consistent with the prediction, the coefficient on *ln(# Public firm patents)* is positive and significant. Importantly, the coefficient on *ln(Narrowness of public firm patent scope)* remains stable, suggesting that the broadness of patents and the quantity of patents capture different sources of threats. In columns 3 and 4, I re-estimate the specifications in columns 1 and 2, respectively, by excluding biotech firms, as the KT measure does not include patents in biotechnology.[32] The results are largely unchanged.

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[32] Kuhn and Thomson (2017) mention that "…we exclude from our main sample patents examined by the biotechnology technology center because of the way language is used in their claims. Patents examined by art units within the USPTO's biotechnology center are the most likely to use Markush language, where lists are used to make a patent broader, e.g. "a compound consisting of drug A and a drug selected from the group consisting of: drug B, drug C, and drug D".

Columns 5–8 repeat the analyses in columns 1–4, respectively, by replacing the dependent variable with the natural logarithm of one plus the number of patents acquired in year *t*. Across columns, the results are similar both qualitatively and quantitatively: firms facing a high threat of patent litigation buy more external patents.

Panel B of Table 5 repeats the analysis using the MSD measure as a main variable of interest. The MSD measure allows me to test the litigation hypothesis with a longer sample period (1980–2011). The results robustly show that startup firms are more likely buy patents when their public competitors own broad patents. Importantly, the coefficient on *ln(Narrowness of public firm patent scope)* has a much larger magnitude in 2006–2011 (columns 3 and 6) than in 1980–2011 (columns 1, 2, 4, and 5), suggesting that the sensitivity of startup firms' patent acquisition decisions to public firms' patent scope has become higher in later years.

Finally, given that the life of a patent can be extended up to 20 years by paying maintenance fees to the USPTO, calculating the patent scope of public firms based on the patents granted in year $t-1$ only may not fully capture the threat of patent litigation posed by public firms.[33] While such measurement error will likely bias against finding a relation between patent scope and the patent acquisition decision, I address this issue by using a 4-, 8-, and 12-year running average as an independent variable.[34] The results remain strong and significant (untabulated).

In sum, the evidence in Section 4.2 suggests that the potential threat of litigation also contributes to startup firms' decisions to buy patents.

4.3. Do firms rely less on external patents when litigation risk is reduced?

The results so far provide strong support for the litigation hypothesis. Yet, firms facing a high threat of patent litigation are unlikely to be randomly distributed. Prior literature finds that firm characteristics such as stages of development, publicity (Chien, 2013), and cash level (Cohen, Gurun, and Kominers, 2014) are associated with a higher probability of being targeted in patent lawsuits. To the extent that these characteristics are correlated with the decision to buy patents, as

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[33] Utility patents applied before 6/8/1995 expire on max(grant date + 17 years, application date + 20 years). For utility patents filed on or after June 8, 1995, the term of the patent is 20 years since the filing date. Patent holders must pay maintenance fees to the USPTO 3.5, 7.5, and 11.5 years after the grant date.

[34] Due to shorter data coverage, this robustness check is not applicable to the KT measure.

shown in Table 2, the observed relation between the threat of patent litigation and the decision to buy patents is likely to be biased if the empirical specifications do not fully account for such selection effect.

To address such potential selection bias, I use the Supreme Court decision *Alice Corp. vs. CLS Bank* (henceforth Alice) which created a plausibly exogenous variation in patent litigation risk for a subset of firms. The Alice decision, which was decided on 6/19/2014, invalidated four *business method patents* on electronic methods and computer programs for financial-trading systems. Business method patents refer to patents whose main U.S. Patent Classification (USPC) class is 705, which is defined as "data processing: financial, business practice, management or cost/price determination" by the USPTO. One of the most famous examples of business method patents is Amazon's 1-Click shopping, which allows consumers to purchase items by clicking an order button on a website. The rational for the rule was that patents that claim the "building blocks" of human ingenuity cannot be patented, as opposed to ones that "integrate the building blocks into something more".[35] The case was widely considered as a decision that significantly reduced litigation risks for firms, especially for startups and small businesses. For example, Electronic Frontier Foundation (EFF), an international non-profit digital rights group based in San Francisco, collects stories of small businesses that used the Alice decision to defend themselves against attacks by entities asserting abstract software patents.

Srinivasan (2018) exploits this setting and finds that public firms with a greater proportion of business method patents in their portfolios prior to Alice increase R&D spending after the ruling, consistent with the previously overly broad IP rights deterring innovation. Utilizing this setting, I examine whether startup firms become less likely to buy external patents when patent litigation risk is reduced.

In this study's setting, firms whose litigation risks are reduced represent the ones whose products or technologies rely on business method patents. Unfortunately, directly measuring a firm's technological inputs is difficult. To overcome this issue, I follow Ziedonis (2004) and use patent citation networks to measure firms' dependence on technological inputs.[36] Specifically, a

[35] https://www.supremecourt.gov/opinions/13pdf/13-298_7lh8.pdf

[36] When a patent is granted, the front page of the published patent document lists citations or references to previous patents and other non-patented discoveries the invention has advanced upon, revealing technological linkages across generations of inventions (Jaffe and Trajtenberg, 2002; Ziedonis, 2004).

firm is classified as *treated* if it has at least one granted patent (which is granted within the last 10 years prior to the Alice decision date) that cites business method patents.[37] Using the USPC-IPC concordance map provided by Reed Tech, I identify all patents whose USPC main class is 705 (i.e. business method patents).[38]

Panel A of Table 6 shows the number of patents citing business method patents, decomposed by industry and time period. Consistent with the nature of business method patents focusing on data processing-related technology, the majority of firms relying on business method patents are concentrated in industries that heavily focus on data: computer software/services and internet industries.

Panel A of Figure 5 plots the number of patents acquired by startup firms, split into the control group and the treatment group. The sample is based on 3,330 patents acquired by 506 startup firms (103 treated firms and 403 control firms) during the three years before and after the Alice decision date. A transaction is assigned to the *post* period if the transaction date is after the Alice decision date. Consistent with the litigation hypothesis, the number of patents acquired by firms in the treatment group substantially drops by 82.4% (from 1,430 to 252). In comparison, the number of patents acquired by firms in the control group drops by a much smaller magnitude of 21.6% (from 924 to 724).

Panel B of Figure 5 compares the unconditional probability of patent acquisition by startup firms before and after the Alice decision. To limit the sample to firms that are actively staying private around Alice, I require firms to raise at least one financing round within the three years after the Alice decision date. The sample consists of 2,571 unique firms (207 treated firms and 2064 control firms). Firm-years are tracked three years before and after the Alice decision year, leaving 16,035 firm-years between 2011–2017. Firm-years are assigned in the *post* period if the year is greater than or equal to 2014. The figure shows that firms in the treatment group were much more likely to buy external patents than the firms in the control group before the ruling (5.28% vs. 1.26%). To the extent that business method patents are one of the most controversial classes of patents used in patent lawsuits, as documented by Matelan (2007) and Bessen and Meurer (2008a), among others, this pattern is consistent with the litigation hypothesis that firms facing a high threat

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[37] The results are robust to the alternative definitions of the treatment group. See Appendix Table A4.

[38] The USPC to IPC Concordance map is available at https://patents.reedtech.com/classdata.php.

of litigation are more likely to rely on external patents. After the ruling, the probability of acquiring patents drops substantially for the treatment group (from 5.28% to 2.53%) whereas the probability slightly increases for the control group (from 1.26% to 1.47%). The sharp drop in the propensity to buy external patents for the treatment group is again consistent with the litigation hypothesis: firms reduce patent acquisitions as the threat of litigation decreases. Overall, Panels A and B in Figure 5 provide preliminary evidence that firms significantly reduce patent acquisitions when the threat of litigation is reduced.

Finally, Panel B of Table 6 employs a standard difference-in-differences regression. The sample consists of the same 16,035 firm-years (2,571 unique firms) during 2011–2017 described in Panel B of Figure 5. In column 1, the dependent variable equals one if a firm buys at least one patent in year *t*, and zero otherwise. The main variable of interest is *Treated* x *Post*, which is a product of the two dummy variables *Treated* and *Post*. Control variables as well as location and stage fixed effects are included in the specification. The coefficient on *Treated* x *Post* equals -0.03 and significant at the 1% level, meaning that firms whose technologies were likely to rely on business method patents are 3% more likely to reduce patent acquisitions after the ruling compared to their counterparts. In terms of magnitude, this equates to 1.9 times the unconditional probability of patent acquisition.[39] Looking at column 2, the coefficient on *Treated* x *Post* remains robust (with the value of -0.031) to the inclusion of industry and year fixed effects. Importantly, the inclusion of industry fixed effects provides within-industry impacts of the treatment, reassuring the concern that the effect is simply driven by industry-related factors.[40]

Column 3 adds firm fixed effects, which absorbs any time-invariant firm heterogeneity that can affect firms' patent acquisition decisions. Since the specification includes firm fixed effects, the main effect of *Treated* is not identified. The specification additionally controls for a variety of firm characteristics as well as stage and year fixed effects. The coefficient on *Treated* x *Post* equals -0.029 and statistically significant. In column 4, the specification includes industry-by-year fixed effects, which absorbs industry-specific time trends. Again, the coefficient on *Treated* x *Post* equals -0.031 and remains statistically significant. Finally, columns 5–8 repeat the analyses in

[39] 0.03 / 0.016 = 1.875.

[40] Since the specification includes year fixed effects, the main effect of *Post* is not identified.

columns 1–4, respectively, by replacing the dependent variable with the natural logarithm of one plus the number of patents acquired. The results remain qualitatively similar.[41]

Insofar as the Alice decision is not correlated with the quality of firms, the results in Section 4.3 suggest that the relation between patent litigation risk and firms' decisions to rely on external patents is likely to be causal, providing strong support for the litigation hypothesis.

5. Firm performance

The findings so far indicate that startup firms' decisions to buy patents are motivated by litigation risk rather than low productivity. To the extent that patent litigation risk prevents firms from reaching their full potential (Tucker, 2014; Appel, Farre-Mensa, and Simintzi, 2019), the prospects of firms buying patents are characterized by a *negative* selection effect. At the same time, patent acquisition enables firms to build strong patent portfolios, which should have a *positive* treatment effect on the firm prospects. An important follow-on question is the extent to which patent acquisition can help firms to counterbalance the litigation risk. This section attempts to answer the question by looking at both the short-run and the long-run outcomes of startup firms.

5.1. Financing round characteristics

VCs learn interim signals about their portfolio companies via staged financing (Bergemann and Hege, 1998; Fluck, Garrison, and Myers, 2005). Depending on the interim signal, VCs may continue or terminate a project. Moreover, the interim signal can affect the characteristics of the follow-on rounds, for example the syndicate structure or the contract terms (Ewens, Rhodes-Kropf, and Strebulaev, 2016). Therefore, by examining financing round characteristics, we can infer how VCs, as informed investors, perceive startup firms' patent acquisitions. Depending on the relative magnitudes of the selection effect and the treatment effect, VCs may respond negatively, neutrally, or even positively to patent acquisitions.

Table 7 investigates this matter by regressing various financing round characteristics on the dummy variable *I(Patent acquisition)*, which indicates whether a firm acquired patents between the previous round and the current round. I also include *I(Patent application)*, which is defined in

[41] Panel A of Appendix Table A4 estimates the regression without control variables. The results remain robust.

the same manner, to control for firms' internal innovation activities and to provide a benchmark. To be included in the sample, firms are required to raise at least three financing rounds. This is because (1) the calculation of *I(Patent acquisition)* needs at least two rounds and (2) the inclusion of firm fixed effects, which is necessary for within-firm variation of financing round characteristics, requires one additional round per firm. Applying these filters leaves 13,505 firms with 60,374 financing rounds. In addition to firm fixed effects, the specification includes stage and industry-by-financing round year fixed effects.

In columns 1–3, the dependent variables equal round size, post-money valuation, and pseudo market-to-book ratio (the relative valuation of a company scaled by the amount of capital it raised), respectively. These measures capture valuations of startup firms. In columns 4–5, the dependent variables equal the average number of IPO exits of companies funded by the VCs and the number of top VCs, respectively. These measures capture the quality of investors. Finally, in columns 6–7, the dependent variables equal *Inside round* and *% Inside*, respectively. Prior literature documents that an inside round, a financing round where only previous investors participate, is generally used as a "backstop financing" for startup firms that cannot attract new money (Broughman, Fried, 2012) and tends to occur after negative shocks to the entrepreneurial firm (Ewens, Rhodes-Kropf, and Strebulaev, 2016). In this perspective, a lower probability of an inside round or a lower fraction of insiders can be interpreted as a positive signal.

Two findings emerge from the financing-round level regressions. First, VCs do not appear to respond negatively to patent acquisitions. After patent acquisitions, firms raise larger financing rounds (column 1), have lower probability of having an inside round (column 6), and are more likely to retain new VCs (column 7). In addition, there is no evidence that their post-money valuations (column 2) or relative valuations (column 3) drop after patent acquisitions. Finally, they are no less likely to retain reputable VCs (columns 4–5).

Second, patent applications appear to be viewed more favorably than patent acquisitions by VCs. Looking at column 1, even though both patent application and patent acquisition are associated with a larger round size, the magnitudes are different (24.4% for patent application vs. 9.6% for patent acquisition). In addition, while post-money valuation (column 2) and the pseudo market-to-book ratio (column 3) do not increase after patent acquisition, they increase by 12.9% and 3.9%, respectively, after patent application. Similarly, while the quality of VCs does not change after patent acquisition, it increases after patent application (columns 4–5). Finally, even though both patent application and patent acquisition are associated with a lower probability of inside financing, the magnitudes are larger for patent application (columns 6–7).

Overall, to the extent that there is no significant negative relation between patent acquisition and round characteristics, the results in Table 7 provide suggestive evidence that patent acquisition counterbalances patent litigation risk. However, the results also highlight that patent acquisitions are perceived by informed investors as a less positive signal than patent applications.

5.2. Exit performance

This section examines the long-run outcomes of startup firms by comparing the exit performance of firms that buy external patents with firms that do not. If the selection effect dominates, firms buying patents will exhibit worse exit performance (litigation risk preventing firms from reaching their full potential). If the treatment effect is sufficiently strong, these firms will exhibit similar, or even better exit performance than their counterparts.

Table 8 reports the results of firm-level regressions, where each observation represents a unique startup firm. VCs generate returns by exiting their portfolio companies, and the most common form of exits of VC-backed companies are IPOs and M&As. Following the literature, a firm is classified as "exited" if it goes public (IPO) or is acquired (M&A). The main variable of interest is *I(Patent acquisition)*, which equals one if a firm buys at least one external patent before exit or leaving the sample.[42] Across Panels, I control for VC characteristics (VC firm age, # Companies funded by VC, # IPO exits by VC, and # M&A exits by VC) as well as financing characteristics (# VCs invested and Capital raised).[43] Location, stage, industry, and initial financing year fixed effects are also included. In even-numbered columns (2, 4, 6, and 8), I include lead VC fixed effects to control for the lead investor's quality. The lead VC typically originates the deal and is often the most active investor (Nahata, 2008). Following the literature, I define the lead VC as the VC that participated in the first round and, conditional on such participation, made

[42] As described in Table 1, firms are tracked up to min(exit date, last financing round + 365*4, 12/31/2017).

[43] VC characteristics (VC firm age, # Companies funded by VC, # IPO exits by VC, and # M&A exits by VC) are measured at the initial financing round. Funding characteristics (# VCs invested and Capital raised) are measured as of the last financing round.

the largest total investment in the company across all financing rounds. Finally, I include the number of patent applications to control for firms' internal innovation activities.

In columns 1–4 in Panel A, the dependent variable equals one if a firm exits via either IPO or M&A, and zero otherwise. Looking at column 1, the coefficient on *I(Patent acquisition)* is insignificant, meaning that firms buying patents have similar exit rates as firms that do not. The result is robust to (1) the inclusion of lead VC fixed effects (column 2) and (2) using the number of patents acquired as an independent variable (columns 3–4).

Since some firms (9.8%) stay active at the end of the sample, as shown in Table 1, firms classified as "not exiting" contain both failed firms and active firms. Hence, in columns 5–8, I examine whether firms buying patents are more likely to fail.[44] The results show that the probability of failure is not statistically different between firms that are buying external patents versus firms that are not. At first glance, the results in Panel A suggest that the treatment effect (external patents strengthening firms' patent portfolios so that they can overcome the litigation risk) is sufficient to offset the selection effect (litigation risk preventing firms from reaching their full potential).

However, looking at the form of exit tells a different story. Column 1 of Panel B shows that the probability of an IPO is 3.1% lower for firms buying patents. Compared to the unconditional probability of an IPO of 7.6%, the economic magnitude is nontrivial (a 40% decrease relative to the baseline probability). The result is robust to (1) the inclusion of lead VC fixed effects (column 2) and (2) using the number of patents acquired as an independent variable (columns 3–4). In sharp contrast, there is a strong positive relation between patent application and the probability of an IPO. For example, column 4 suggest that a 10% increase in patent application is associated with a 0.35% higher probability of an IPO (4.6% of the baseline probability).

Columns 5–8 show that firms buying patents are instead more likely to exit by M&A (i.e. acquired). For example, column 5 indicates that the probability of an M&A exit is 5% higher for firms buying patents. Compared to the unconditional probability of an M&A of 25%, this corresponds to 20% of the baseline probability. In contrast, there is a negative relation between the patent application and the probability of an M&A exit. For example, column 8 suggest that a

[44] As described in Section 2.1, a firm is classified as failed (defunct) if it neither exits nor raises a financing round in the last four years prior to the end of the sample period (12/31/2017).

10% increase in patent application is associated with a 0.23% lower probability of an M&A (0.92% of the baseline probability).

In sum, the findings in Table 8 highlight that firms buying patents are more likely to be acquired rather than to go public.[45] To the extent that IPO is an exit option mainly available for higher-quality companies (see, e.g., Chemmanur et al., 2018), the results indicate that firms buying patents exhibit less successful exit performance in general. I interpret this as the treatment effect of acquiring external patents (strengthening firms' patent portfolios so that they can overcome the litigation risk) not fully offsetting the negative selection effect in the long run (litigation risk preventing firms from reaching their full potential).

While the preceding interpretation assumes that the treatment effect of acquiring external patents is positive, an alternative explanation is that patent acquisition itself has a negative treatment effect on firm value. This could be true if firms (1) buy low-quality patents or (2) overpay for patents. Appendix Table A5 shows that the difference in the quality of patents (as proxied by the number of forward citations) is not statistically significant across patents that are produced in-house and the ones that are acquired. Therefore, it is unlikely that the negative relation between patent acquisition and long-run performance is driven by the quality of patents. While I cannot explicitly rule out the second possibility, to the extent that VCs have strong control rights and extensively monitor their portfolio companies, it is unlikely that VCs would allow such behavior.

6. Other motives for patent acquisitions

In this section, I explore alternative mechanisms that might incentivize startup firms to buy patents. Specifically, I examine product market competition and investors' contractual horizon.

6.1. Product market competition

Growing fast is important for startup firms. Paul Graham, an influential venture capitalist, defines a startup as: "A startup is a company designed to grow fast…The only essential thing is

[45] I repeat the analysis using # Patents acquired / (# Patents applied + # Patents acquired) as a main variable of interest by limiting the sample to companies with at least one patent application or one patent acquisition (Table A6). The results are similar both qualitatively and quantitatively.

growth…Everything else we associate with startups follows from growth."[46] McKinsey & Co., one of the most reputable management consulting firms, also published a report documenting that growth predicts long-term success and matters more than margins or cost structure.[47] Finally, Gao, Ritter, and Zhu (2013) argue that the importance of getting big fast has increased over time due to an increase in the speed of technological innovation in many industries.

To the extent that one of the key advantages of inorganic growth is speed and efficiency, it is possible that patent acquisition is a strategy for startup firms to grow fast and achieve competitive advantages. Inderst and Mueller (2009) show that as product market competition becomes more intense, it becomes more likely that one firm has an (endogenous) first-mover advantage by strategically overinvesting early on, thus forestalling the other firms' future investment, growth, and market share.

Based on this intuition, I examine whether startup firms operating in competitive industries are more likely to acquire patents. I construct two variables to capture product market competition. The first measure is Herfindahl-Hirschman Index (HHI), which measures market competitiveness. Since the market share of each private firm is not available, I use the amount of venture capital investments flowing into each startup firm in the last three years, *Supply of VC investments*, as a proxy for market share.[48] The intuition is that the amount of capital supplied by VCs captures the relative importance of the startup firm or the size of the startup firm. *HHI(Supply of VC investments)* is then calculated by summing the squared market share (in percentage) of each firm in each industry. By construction, it ranges from 0 (perfect competition) to 10,000 (monopoly).

The second measure is four-firm concentration ratio, which measures the degree of industry concentration. Four-firm concentration ratio is similarly defined by (amount of capital raised by the top four startup firms in the industry in the last three years) / (amount of capital raised by all startup firms in the industry in the last three years) and ranges from 0 (perfect competition) to 100 (monopoly).

Table 9 reports regression results at the firm-year level. In columns 1–2, the dependent variable equals one if a firm buys at least one patent in year t, and zero otherwise. If the decision

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[46] http://www.paulgraham.com/growth.html

[47] https://www.mckinsey.com/industries/high-tech/our-insights/grow-fast-or-die-slow

[48] Industry classifications come from Thomson Reuters Private Equity.

to buy external patents is motivated by the strategic consideration to grow fast and achieve competitive advantages over rivals, the coefficients on *HHI (Supply of VC investments)* and *Four-firm concentration ratio* are expected to be negative. However, none of the coefficients are statistically different from zero. The results remain insignificant when I use the natural logarithm of one plus the number of patents acquired as a dependent variable in columns 3–4.

In sum, the results in Table 9 do not support the explanation that startup firms strategically overinvest in external patents to escape from product market competition.

6.2. VC investment horizon

I also consider the possibility that patent acquisition is motivated by venture capitalists' incentives to exit their portfolio companies faster. A typical VC fund has a lifespan of 10–12 years. Within this time frame, VCs make investments, sell their stakes in the portfolio companies, and return the money to their limited partners (Metrick and Yasuda, 2010).

Intuitively, as VC fund approaches its maturity, the pressure to liquidate its investments increases. In line with this intuition, prior literature documents that the liquidation pressure affects VCs' behavior. Masulis and Nahata (2011) find that targets backed by VC funds closer to liquidation receive significantly lower takeover premia. They interpret this as VC funds exerting pressure on target management to accept lower sale prices so as to ensure a profitable exit in a timely manner. Similarly, Bhattacharya and Ince (2015) find that companies backed by older VC funds exit more quickly and are more likely to exit via M&A rather than IPO, consistent with a growing preference for quick M&A exits as VCs face increasing liquidity pressure. In recent work, Barrot (2016) finds that VC funds invest in more mature companies as the funds get closer to the end of their investment life.

In this respect, older VC funds may encourage their portfolio companies to rely on external patents so that they can build their patent portfolios quickly. To the extent that the final accept/rejection decision generally takes about 3.2 years from the patent application date (Farre-Mensa, Hegde, and Ljungqvist, 2017), buying patents could help accelerating the exit process.

To investigate this possibility, I link each startup with its lead VC. For each firm-lead VC pair, I find the representative VC fund and use this fund's age as a proxy for liquidity pressure, where fund age is measured as the difference between the date a firm raises its initial VC financing from the fund and the fund creation date (vintage date).[49] Following Barrot (2016), the fund creation date is based on the "initial closing date" provided by Thomson Reuters Private Equity. When the initial closing date is not available, I set the fund creation date as January first of the "fund year", which is also provided by Thomson Reuters. If the fund makes investments prior to the fund creation date, the fund creation date is reset at the time of the fund's first investment date.[50] In most cases (89.8%), the lead VC invests via one fund. If a lead VC invests in a company via more than one fund, I choose the one with the older vintage.[51] This process leaves 17,296 unique firm-lead VC fund pairs.

Panel A of Table 10 shows the distribution of fund age as well as the fraction of firms that buy patents. Each observation represents a unique firm-lead VC pair. Consistent with industry practice, most VC funds make investments in the early years: about 67% (86%) of investments are concentrated in the first three (five) years of the fund investment horizon.[52] Looking at column 3 of Panel A, the propensity to acquire external patents is almost flat across fund age groups. The univariate results suggest that there is no noticeable pattern between fund age and patent acquisition decisions.

The results in Panel A do not control for time period, industry, stage of development, or firm characteristics. Therefore, I formally test the liquidation pressure explanation using a regression framework. In Panel B, each observation represents a unique startup firm. In columns 1–2, the dependent variable equals one if a firm buys at least one external patent before exit or leaving the sample. I control for VC characteristics (VC firm age, # Companies funded by VC, # IPO exits by VC, and # M&A exits by VC) as well as financing characteristics (# VCs invested and Capital raised).[53] Location, stage, industry, and initial financing year fixed effects are also included.

In column 1, the main variable of interest is *Fund age*, measured in years since the fund creation date. If the decision to buy patents is motivated by the liquidation pressure (older VC

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[49] In other words, fund age = (first round date – fund creation date) / 365.

[50] If the difference between the fund creation date and the fund's initial investment date is greater than one year, I excluded such funds from the analysis. See Barrot (2016) for details.

[51] If there are more than one fund with the same vintage (creation date), I choose the one with a larger fund size.

[52] Barrot (2016) also finds that 66% (86%) of investments occur within three (five) years since the fund creation date.

[53] All variables are measured at the initial financing round.

funds forcing their portfolio companies to rely on external patents), the coefficient on *Fund age* is expected to be positive and significant. However, consistent with the pattern shown in Panel A, there is no statistically significant relation between the age of the lead VC fund and the startup firm's decision to buy patents. The results remain insignificant when I use the natural logarithm of one plus the fund age (column 2) as an independent variable or use the natural logarithm of one plus the number of patents acquired as a dependent variable in columns 3–4.

In sum, the results in Table 10 lend little support to the explanation that the decision to buy patents is motivated by the liquidation pressure of VC investors.

7. Conclusion

In this study, I document that a nontrivial fraction of young entrepreneurial firms buy external intellectual property rights in the secondary patent market. My findings suggest that the decision to buy external patents is not motivated by low productivity, product market competition, or investors' contractual horizon. Rather, firms' decisions to access external patents in their early stages appear to be closely related to the intellectual property environment: startup firms are significantly more likely to buy external patents when they are sued for patent infringement or exposed to a high threat of litigation. The relation between patent litigation risk and firms' decisions to rely on external patents appears to be causal, as evidenced by the finding that firms whose litigation risks are reduced the most due to the Alice decision become significantly less likely to buy patents.

It is worth noting that firms buying patents are significantly more likely to be acquired rather than to go public. To the extent that firms buying patents are higher-quality firms to begin with, the patent litigation risk these firms face appears to be significant. As discussed by Gilbert and Newbery (1982), incumbent firms with market power have incentives to maintain their market power through patent rights. The increasing industry concentration in recent years (Doidge, Karolyi, and Stulz, 2017; Grullon, Larkin, and Michaely, 2018) suggests that such opportunities are also increasing. This could potentially put substantial burdens on young entrepreneurial firms' growth paths and reinforce market concentration.

A.1. Variable descriptions

Variable	Definition
Patent-related variables	
# Patents	Scaled number of patent applications. Truncation bias is corrected using the fixed-effects approach suggested in Hall, Jaffe, and Trajtenberg (2001). Source: USPTO.
# Citations	Scaled number of forward citations a patent receives within the three years since the grant date. Truncation bias is corrected using the fixed-effects approach suggested in Hall, Jaffe, and Trajtenberg (2001). Source: USPTO.
# Patents acquired	Number of patents acquired. Patents acquired through mergers are not included except for Panel B of Figure 2. Source: USPTO.
VC characteristics	
VC firm age	VC firm's age in years since its date founded. Source: Thomson Reuters Private Equity.
# Companies invested by VCs	Number of portfolio companies in which the VC invested in the last five years. Source: Thomson Reuters Private Equity.
# IPO exits by VC	Number of portfolio companies that received financing from the VC and exited via IPO in the last five years. Source: Thomson Reuters Private Equity, SDC New Issues database.
# M&A exits by VC	Number of portfolio companies that received financing from the VC and exited via M&A in the last five years. Source: Thomson Reuters Private Equity, SDC VC-backed M&A database.
Lead VC	The VC that participated in the first round and, conditional on such participation, made the largest total investment in the company across all financing rounds. Source: Thomson Reuters Private Equity.
Financing characteristics	
# Rounds received	The number of financing rounds a company raised. Source: Thomson Reuters Private Equity.
# VCs invested	The number of VCs invested in a company. Source: Thomson Reuters Private Equity
Capital raised ($ mil)	The amount of capital raised in financing rounds. Source: Thomson Reuters Private Equity.
Fixed effects	
Year	Calendar year.
Financing round year	The year when a firm raises its VC round.
Initial financing round year	The year when a firm raised its initial VC round.
Stage	Stage level has 4 categories: seed, early, expansion, and later.
Location	Location has 4 categories: CA, MA, NY, and Others.
Industry	Industry has 10 categories: Biotechnology, Communication, Computer HW, Computer SW, Consumer, Industrial, Internet, Medical, Semiconductor, and Others.

A.2. Name-matching procedure

First, I standardize names by removing words that describe legal structure, such as co, corp, limited, inc, etc. I also apply the name standardization algorithm provided by the NBER Patent Data Project when matching patent data.[54] Second, I create all possible pairs (Cartesian product) between the names in two datasets. The pair is constructed conditional on sharing the same initial character. For example, "Apple" will be paired with "American Airlines" but not with "Microsoft". Third, I calculate the generalized edit distance between the pairs and keep the top 3 matches for each name. When there is a perfect match, I mark them as "matched". Fourth, for the "unmatched" pairs, I apply the internet-based matching algorithm proposed by Autor, Dorn, Hanson, Pisano, and Shu (2016) that eliminates the need for the extensive manual work to deal with different spellings, abbreviations, and typos in firm names. Specifically, they exploit the fact that internet search engines show results that best match the input query.[55] Following Autor et al. (2016), I write a Python script that automatically saves the top five search results for each query. If there is at least one overlapping link, I mark it/them as "potential match". If there is no overlapping address, it is dropped from the sample. Finally, within this "potential match" pairs, I sort pairs based on the generalized edit distance and manually inspect the matches.

[54] https://sites.google.com/site/patentdataproject/Home/posts/namestandardizationroutinesuploaded

[55] For example, a standard string-matching algorithm would not be able to match 'Hewlett-Packard' and 'HP' easily. However, when we search either 'Hewlett-Packard' or 'HP' on search engines such as Google, the search results are pretty much the same.

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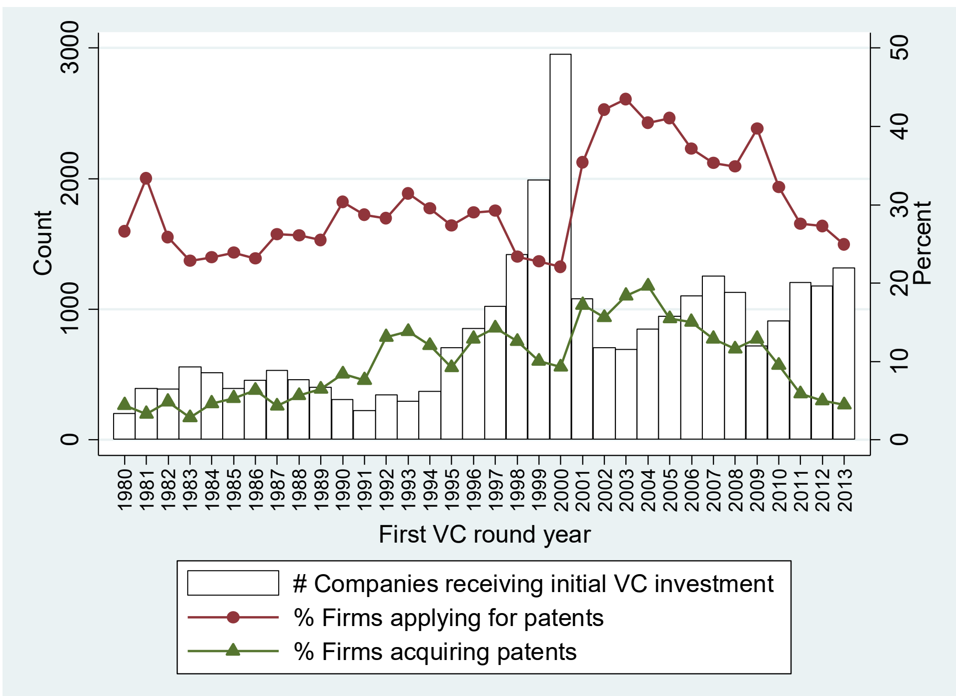
Figure 1

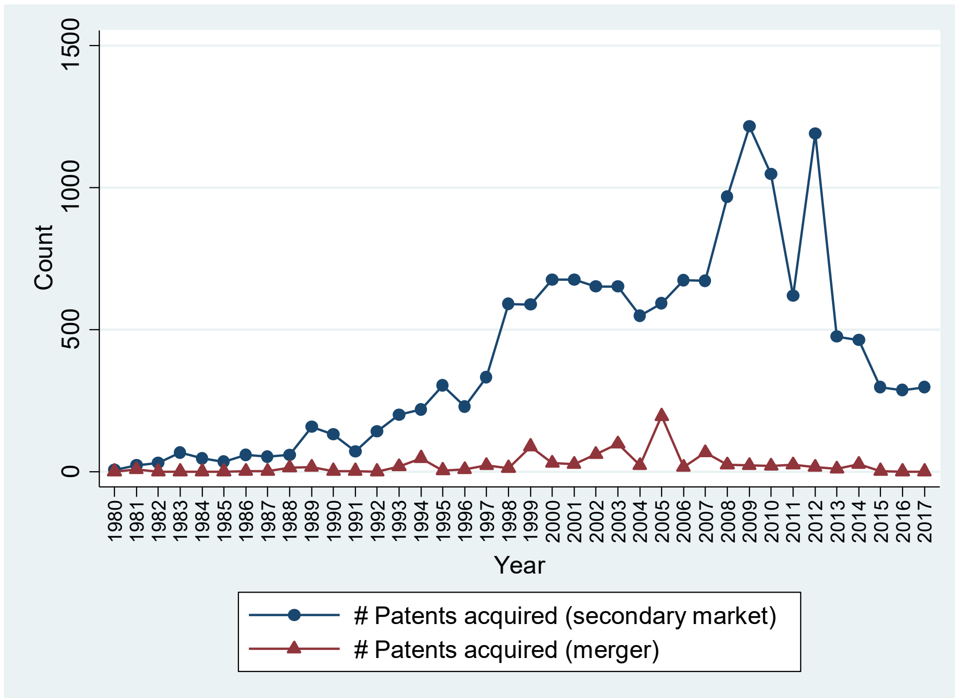
Patent applications and patent acquisitions by startup firms

Panel A shows the number of VC-backed private firms, the fraction of firms applying for patents, and the fraction of firms buying patents. The sample consists of 27,870 companies with initial venture capital financing rounds between 1980–2013. Panel B shows the number of patents acquired by VC-backed firms, plotted against the transaction year. Panel C shows the fraction of acquired patents in VC-backed firms' patent portfolios. The sample consists of 9,178 companies with at least 1 patent application or 1 patent acquisition. The composition is defined by (# patents acquired) / (# patents applied + # patents acquired). If a company exits by 12/31/2017, patent applications and acquisitions are tracked up to the exit date. If a company does not exit by 12/31/2017, patent applications and acquisitions are tracked up to min (last financing date + 365*4, 12/31/2017). Patent data are obtained from the USPTO.

Panel A: Fraction of startup firms applying for/buying patents



Panel B: Number of patents acquired by startup firms



Panel C: Composition of patent portfolios of startup firms

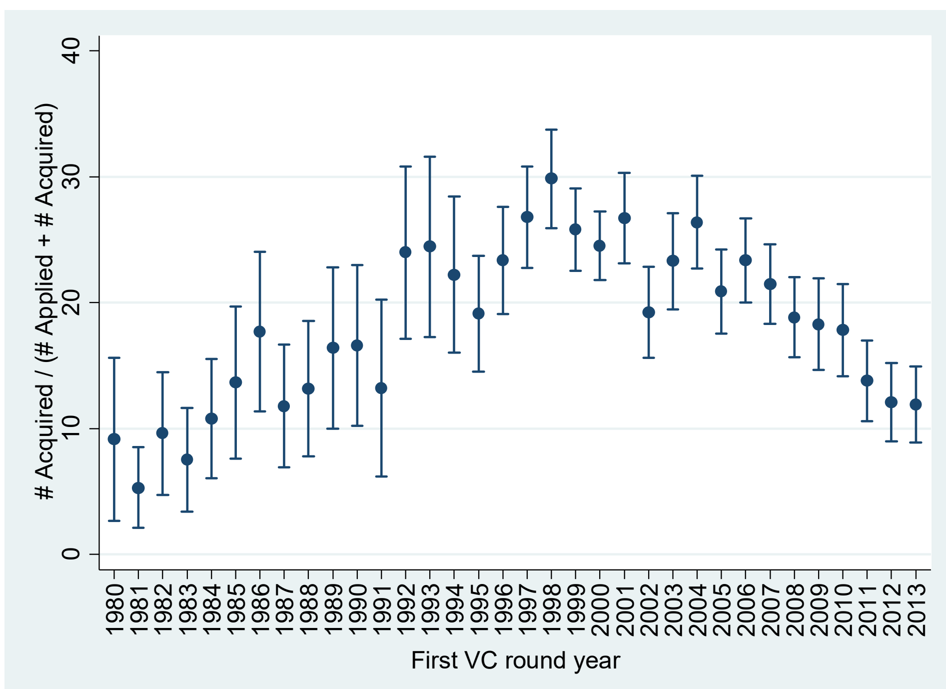
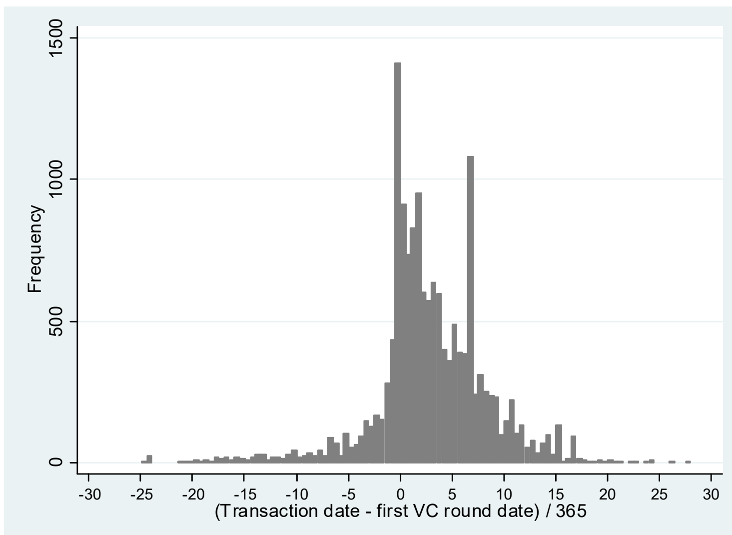


Figure 2

Timings of patent acquisitions

Panel A shows the distribution of timings of patent acquisitions, plotted against the number of years from the initial VC round. The sample consists of 15,339 patents purchased between 1980–2017 by 2,918 firms that raised initial venture capital financing rounds between 1980–2013. Panel B shows the distribution of timings of patent acquisitions, plotted against the number of years from the exit date. Exit event includes both IPOs and M&As. The sample consists of 8,056 patents purchased by 1,261 firms that raised initial venture capital financing rounds between 1980–2013 and exited by 12/31/2017. Exit information and dates are retrieved from the SDC New Issues database and VC-backed M&A database. Across Panels, each observation represents 1 patent acquisition. As in Figure 1, patent acquisitions are tracked up to the exit date if a company exits by 12/31/2017, and min (last financing round date + 365*4, 12/31/2017) otherwise.

Panel A: Number of years from the initial VC round



Panel B: Number of years from the exit date

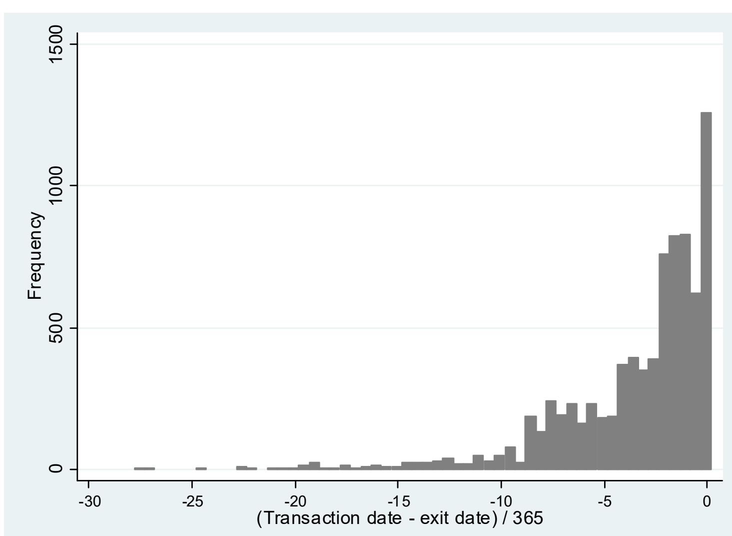
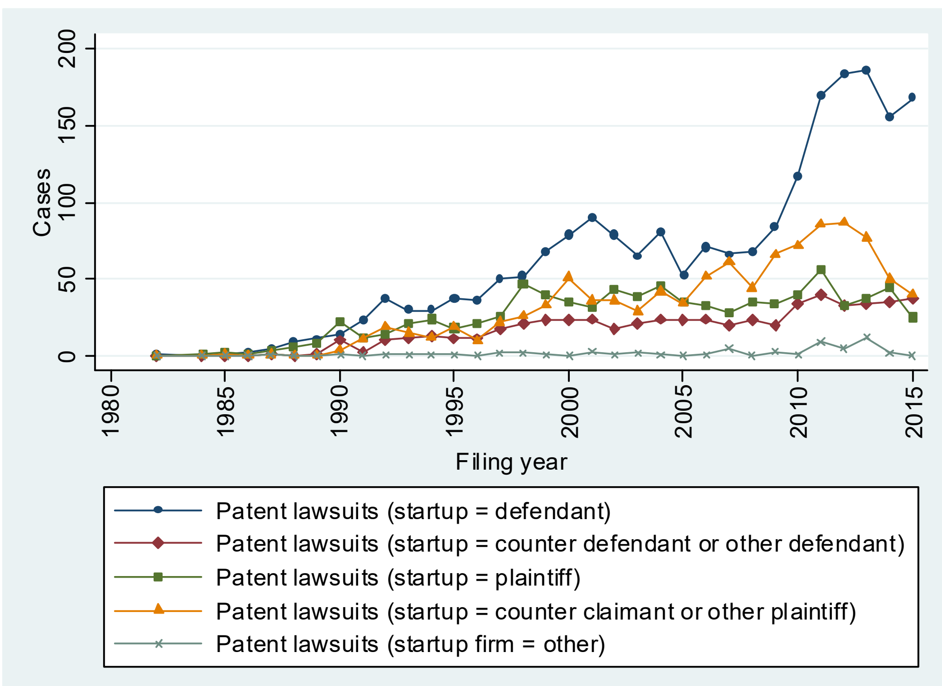


Figure 3

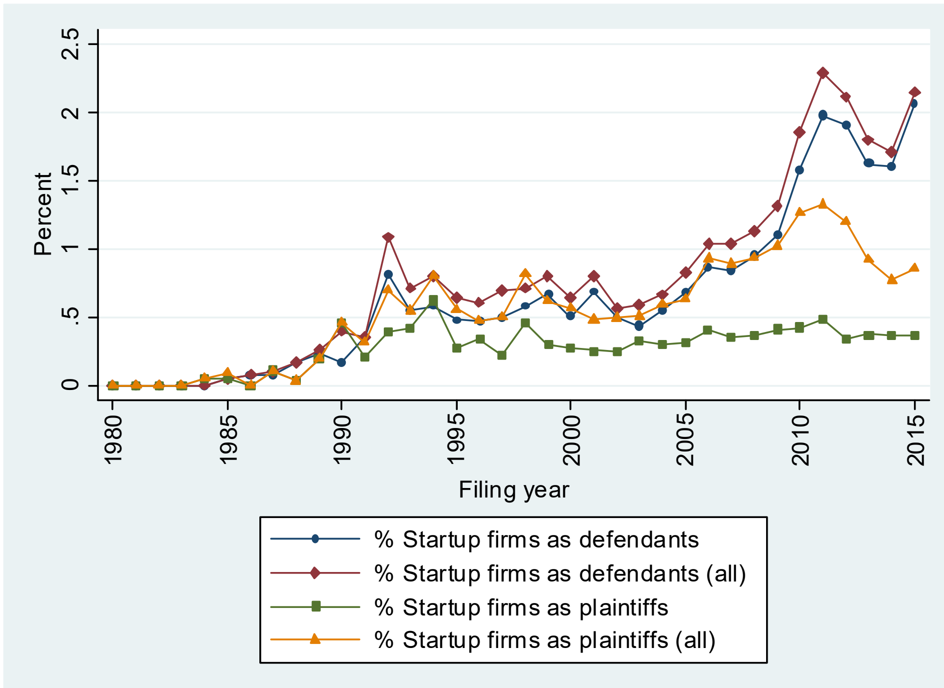
Patent lawsuits involving startup firms

Panel A shows the number of patent lawsuits in which a startup firm is a defendant, other types of defendant (counter defendant, cross defendant, consolidated defendant, etc.), a plaintiff, and other types of plaintiff (counter claimant, consolidated counter claimant, third party plaintiff, etc.). It also shows the number of remaining cases (labeled as other) where the startup firm's affiliation to the case is not directly related to defendant/plaintiff (movant, miscellaneous, interested party, etc.). The sample consists of 3,214 cases associated with 1,641 startup firms that raised initial venture capital financing rounds between 1980–2013. Patent lawsuits filed after startup firms' exit events (either IPO or M&A) are excluded. If a firm does not exit, patent lawsuits are tracked up to min (last financing round + 365*4, 12/31/2015). Panel B shows the fraction of startup firms involved in patents lawsuits as defendants or plaintiffs. Firms are tracked from the initial financing year to the earliest of (exit year – 1, last financing year + 4, or 2015). Panel C shows the fraction of patent lawsuits in which at least one plaintiff is a public firm. The sample consists of 2,123 cases (1,293 unique startup firms) in which a startup firm is a defendant (excluding other types of defendants such as counter defendant, cross defendant, consolidated defendant, etc.). Panel D shows the fraction of patent lawsuits in which at least one defendant is a public firm. The sample consists of 863 cases (492 unique startup firms) in which a startup firm is a plaintiff (excluding other types of plaintiffs such as counter claimant, consolidated counter claimant, third party plaintiff, etc.). Public status is identified by matching plaintiff-filing date pairs with firm-years in CRSP/Compustat. Patent litigation data are obtained from the USPTO.

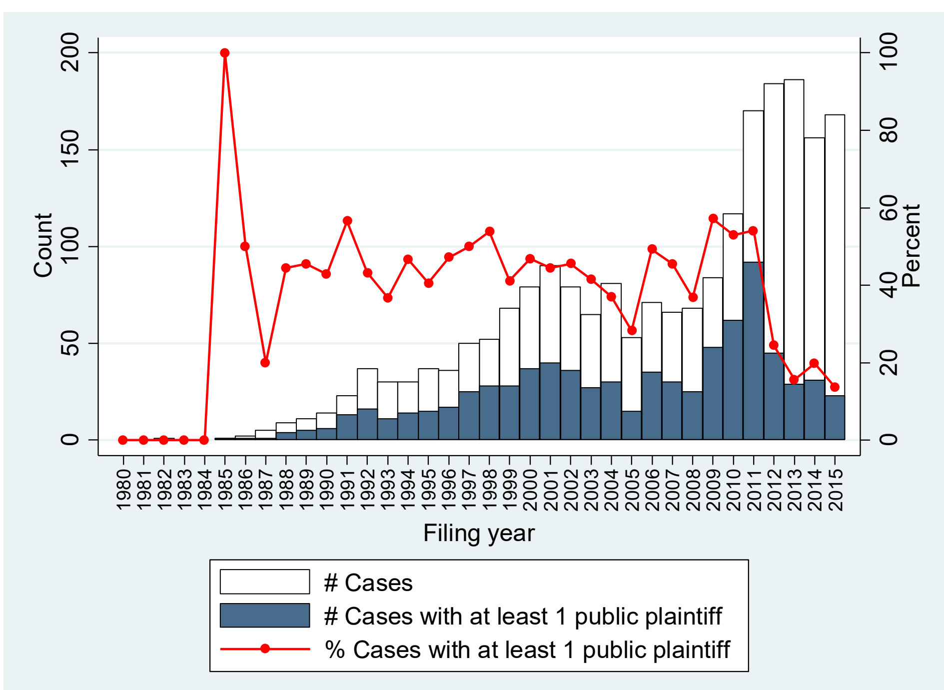
Panel A: Number of patent lawsuits



Panel B: Probability of patent litigation



Panel C: Fraction of lawsuits with public firm plaintiff



Panel D: Fraction of lawsuits with public firm defendant

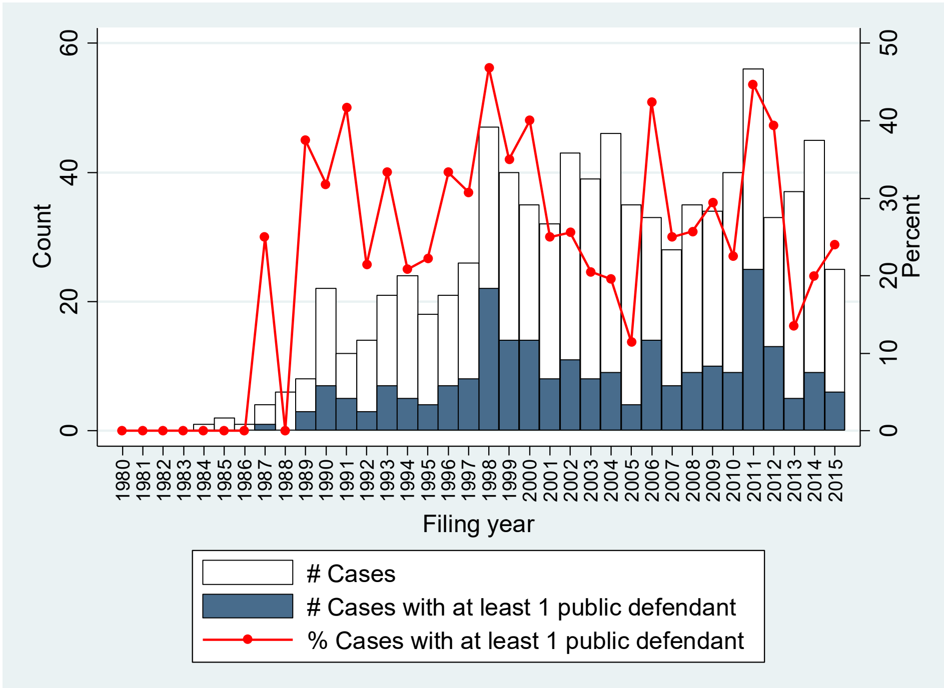
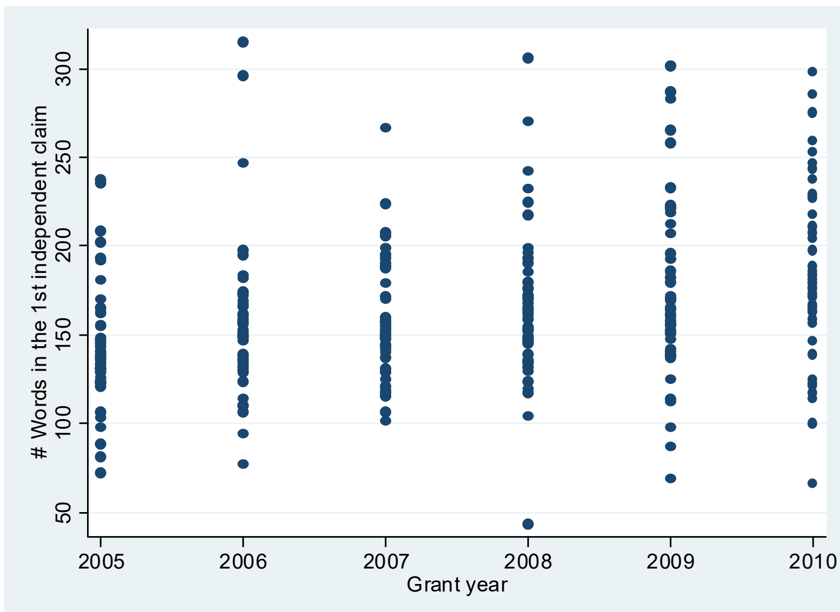


Figure 4

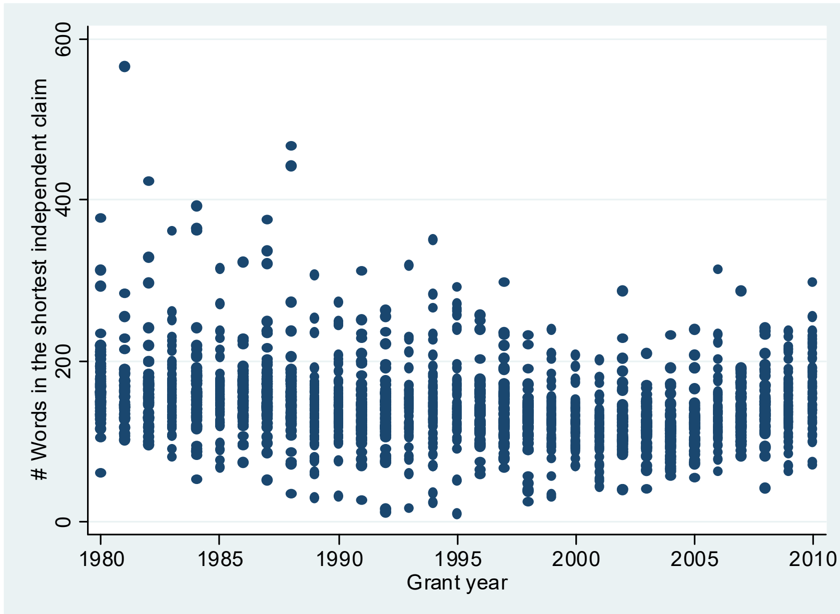
Patent scope of startup firms' public competitors

Panel A shows the distribution of the number of words in the first independent claim of a patent (KT measure). Panel B shows the distribution of the number of words in the shortest independent claim of a patent (MSD measure). The sample is based on all patents granted to public firms that share the same 2-digit SIC code with the VC-backed private firms in this study. Each observation represents the mean value within 2-digit SIC code. The number of words in the first independent claim in each patent is obtained from the dataset provided by Kuhn and Thomson (2017). The number of words in the shortest independent claim is obtained from the USPTO. Patents granted to public firms are identified using the dataset provided by Kogan, Papanikolaou, Seru, and Stoffman (2017). Panel C shows the correlation between the KT measure and the MSD measure for the years 2005–2010 at the 2-digit SIC code level.

Panel A: Number of words in the first independent claim



Panel B: Number of words in the shortest independent claim



Panel C: Correlation between the number of words in the first independent claim (KT measure) and the number of words in the shortest independent claim (MSD measure)

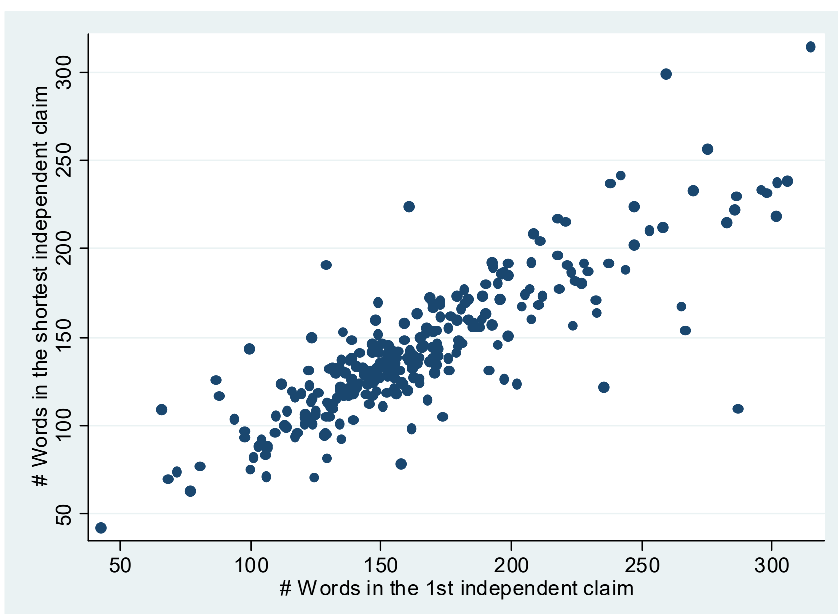
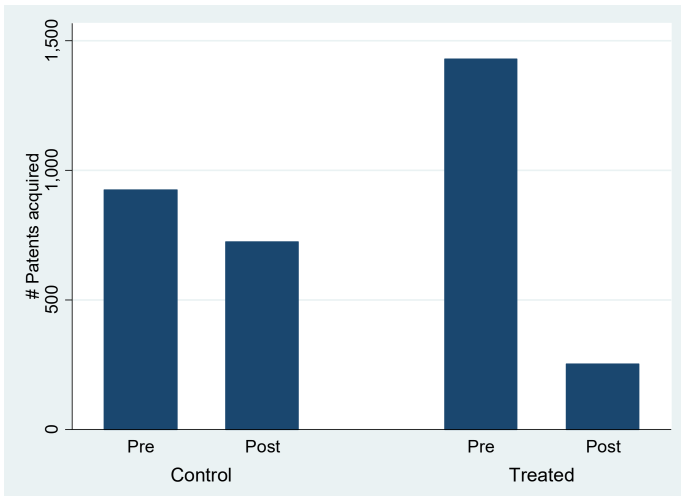


Figure 5

Patent acquisitions before and after the decision *Alice Corp. vs. CLS Bank*

Panel A plots the number of patents acquired by startup firms before and after the Alice ruling. Patent transactions are split into two groups, depending on whether the patent buyer (startup firm) cites at least one business method patent within the last 10 years prior to the Alice decision date (6/19/2014). A patent is defined as a business method patent if the main class of the primary classification (USPC) is 705. The sample is based on 3,330 patents acquired by 506 VC-backed firms during the three years before and after the Alice decision date (6/19/2014). Panel B compares the unconditional probability of patent acquisition before and after the Alice decision. To be included in the sample, firms should raise at least one financing round within the three years after the Alice decision date. *Treated* equals one if a firm has at least one granted patent (which is granted within the last 10 years prior to the Alice decision date) that cites business method patents. The sample consists of 16,035 firm-years (2,571 unique firms) between 2011–2017. A transaction is assigned to the post period if the transaction date is after the Alice decision date. P(Acquiring patents) equals one if a firm acquires at least one patent in a given year.

Panel A: Number of patents acquired



Panel B: Probability of acquiring patents

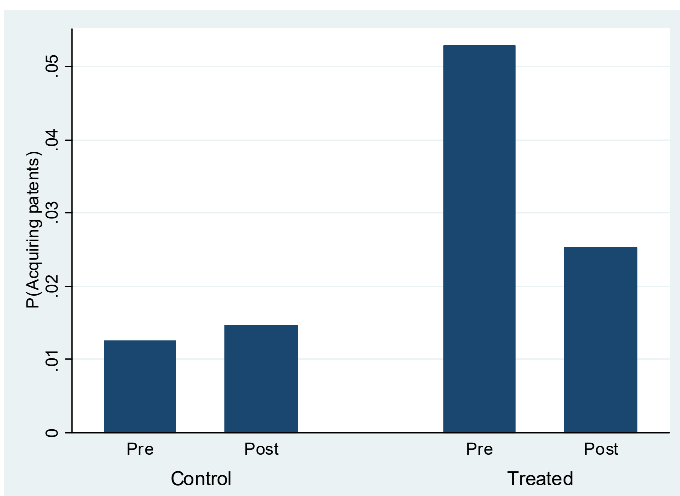


Table 1
Summary statistics
This table shows the characteristics of VC-backed companies used in this study. The sample consists of 27,870 companies with initial venture capital financing rounds between 1980–2013. Firms should be in seed, early, or expansion stage at the initial VC round. Stage, industry, and geographic location are measured as of the initial financing round. Financing characteristics are measured as of min(last financing round, 12/31/2017). Firm characteristics as well as VC financing characteristics are obtained from Thomson Reuters Private Equity (formerly known as VentureXpert). Exit information is obtained from the SDC IPO New Issues database and the SDC VC-backed M&A database. Variable definitions are in Appendix A.1.

VARIABLES	(1) Mean	(2) SD
Stage		
Seed	0.290	0.454
Early stage	0.477	0.499
Expansion stage	0.233	0.423
Industry		
Biotechnology	0.0649	0.246
Communications and media	0.0818	0.274
Computer HW	0.0511	0.220
Computer SW	0.239	0.427
Consumer related	0.0526	0.223
Industrial/Energy	0.0545	0.227
Internet	0.216	0.411
Medical/Health	0.103	0.304
Semiconductors/Other Electronics	0.0607	0.239
Other products	0.0765	0.266
Geographic location		
CA	0.360	0.480
MA	0.0961	0.295
NY	0.0696	0.254
Financing characteristics		
# Rounds raised	3.349	2.854
# VCs invested	3.472	3.319
Capital raised ($mil)	23.54	81.74
Status		
IPO	0.0760	0.265
Acquired	0.250	0.433
Active	0.0977	0.297
Defunct	0.576	0.494

Table 2

Do startup firms buy patents because they fail to innovate?

This table examines the relation between startup firms' internal innovation capabilities/innovation output and the decision to buy external patents. Panel A splits the VC-backed companies used in this study into two groups, depending on whether they buy at least one external patent prior to exit or leaving the sample. VC characteristics are measured at the initial financing round, and calculated based on the average value of each variable across all VCs that provided funding in the first round. Financing characteristics are measured as of min (last financing round, 12/31/2017), except for *Capital raised at R1 ($mil)*, which is measured as of the initial VC round. Patent applications and acquisitions are measured as of the earliest of (exit date, last financing round date + 365*4, or 12/31/2017). Means are shown for all variables. Panel B examines the relation between startup firms' internal innovation output and the decision to buy external patents using a firm-year panel. Analogous to the firm-level data, firms are tracked from the initial financing year to the earliest of (exit year – 1, last financing year + 4, or 2017). The sample consists of 27,703 unique firms after excluding 167 firms that raise initial VC round and exit in the same year. Firm-years 2014–2017 are dropped to minimize the potential patent application/citation truncation bias. In columns 1–4, the dependent variable equals one if a firm buys at least one patent in year *t*, and zero otherwise. In columns 5–8, the dependent variable equals the natural logarithm of one plus the number of patents acquired in year *t*. All independent variables are measured as of year *t* – 1. Both the number of patent applications and the number of forward citations are corrected for truncation bias using the fixed-effects approach as described in more detail in the body of the paper. All variables in log form represent the natural log of one plus the variable (i.e. ln(variable) represents ln(variable + 1)). Variable definitions are in Appendix A.1. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Univariate comparison

	Firms buying patents prior to exit/censoring Obs. = 2,918	Firms not buying patents prior to exit/censoring Obs. = 24,952	Difference
VC characteristics			
VC firm age	14.42	12.85	1.566***
# Companies invested by VCs	26.48	24.47	2.004***
# IPO exits by VCs	3.70	2.95	0.752***
# M&A exits by VCs	5.50	4.42	1.080***
Financing characteristics			
# Rounds raised	4.69	3.19	1.503***
# VCs invested	4.85	3.31	1.542***
Capital raised ($mil)	46.62	20.84	25.78***
Capital raised at R1 ($mil)	5.78	4.29	1.485***
Patents			
I(At least 1 patent application)	0.68	0.25	0.430***
I(At least 1 patent acquisition)	1.00	-	
# Patents applied	4.66	0.79	3.865***
# Patents acquired	5.26	-	
# Citations	1.03	0.28	0.752***

Panel B: Regression analysis

VARIABLES	(1) Patent acquisition = 1	(2) Patent acquisition = 1	(3) Patent acquisition = 1	(4) Patent acquisition = 1	(5) ln(# patents acquired)	(6) ln(# patents acquired)	(7) ln(# patents acquired)	(8) ln(# patents acquired)
ln(# Patents applied)	0.059***		0.030***		0.077***		0.038***	
	(15.853)		(8.165)		(12.615)		(7.032)	
ln(# Citations)		0.039***		0.019***		0.049***		0.021***
		(15.584)		(6.749)		(12.517)		(5.100)
ln(Capital raised)	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.001**	-0.001**
	(-0.080)	(0.151)	(-0.864)	(-0.811)	(-1.365)	(-1.153)	(-2.233)	(-2.168)
Raised VC round last year	0.004***	0.004***	0.002**	0.002**	0.004***	0.004***	0.003**	0.003**
	(4.480)	(4.667)	(2.048)	(2.006)	(3.394)	(3.620)	(2.034)	(1.998)
ln(# VCs invested)	0.004***	0.005***	0.005**	0.006***	0.006***	0.008***	0.007**	0.008***
	(3.616)	(4.618)	(2.466)	(2.854)	(3.720)	(4.621)	(2.482)	(2.870)
ln(VC firm age)	-0.002***	-0.003***	-0.002*	-0.002**	-0.003***	-0.003***	-0.004**	-0.004***
	(-3.871)	(-4.569)	(-1.890)	(-2.087)	(-3.381)	(-4.140)	(-2.391)	(-2.582)
ln(# Companies funded by VC)	-0.004***	-0.004***	-0.002**	-0.002**	-0.005***	-0.005***	-0.001	-0.001
	(-7.054)	(-7.348)	(-2.304)	(-2.358)	(-6.996)	(-7.309)	(-0.918)	(-0.977)
ln(# IPO exits by VC)	0.003***	0.003***	0.003**	0.003**	0.004***	0.004***	0.003**	0.003**
	(4.596)	(4.858)	(2.494)	(2.536)	(4.333)	(4.640)	(2.013)	(2.072)
ln(# M&A exits by VC)	0.004***	0.005***	0.002	0.002*	0.005***	0.006***	0.002	0.002
	(6.823)	(7.501)	(1.616)	(1.748)	(6.502)	(7.160)	(1.431)	(1.569)
Observations	156,915	156,915	154,845	154,845	156,915	156,915	154,845	154,845
R-squared	0.024	0.019	0.236	0.236	0.021	0.016	0.251	0.250
Location FE	Yes	Yes	No	No	Yes	Yes	No	No
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Year FE	Yes	Yes	No	No	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Ind. x Year FE	No	No	Yes	Yes	No	No	Yes	Yes

Table 3

Startup firms involved in patent lawsuits

Panel A shows the party type (affiliation to the case) distribution of startup firms in patent lawsuits. Party types are defined as of the current case. For example, a counterclaim is a claim made to offset another claim, especially one made by the defendant in a legal action. Therefore, a counter claimant (the party that files a counterclaim) will be defined as a defendant in the previous case (or sometimes in the current case) but as a plaintiff in the case at hand. The sample consists of 5,024 case-party pairs associated with 3,214 unique patent lawsuits and 1,641 unique startup firms. The sample is created by matching party names in patent litigation cases between 1980–2015 with firm names in the private firm sample described in Table 1. Patent lawsuits are tracked up to the earliest of (exit date, last financing round date + 365*4, or 12/31/2015). The number of unique cases is based on *case_row_id* which represents the case-level identifier used in the USPTO patent litigation dataset. Panel B splits the VC-backed companies used in this study into two groups, depending on whether they get sued at least once prior to exit or leaving the sample. Other types of defendants such as counter defendant, cross defendant, consolidated defendant, etc. are classified as not litigated. VC characteristics are measured at the initial financing round, and calculated based on the average value of each variable across all VCs that provided funding in the first round. Financing characteristics are measured as of min (last financing round, 12/31/2017), except for *Capital raised at R1 ($mil)*, which is measured as of the initial VC round. Patent applications and acquisitions are measured as of the earliest of (exit date, last financing round date + 365*4, or 12/31/2017). Means are shown for all variables. Variable definitions are in Appendix A.1. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Distribution of party type

Party type	Percent
Defendant (58.9%)	
Defendant	46.3%
Counter defendant	9.0%
Other defendant	3.6%
Plaintiff (39.7%)	
Plaintiff	17.2%
Counter claimant	21.3%
Other plaintiff	1.2%
Other (1.5%)	
Movant	0.4%
Miscellaneous	0.3%
Interested party	0.2%
Cross claimant	0.2%
Intervenor	0.1%
Other	0.3%

Panel B: Characteristics of firms sued for patent infringement

	Firms sued prior to exit/censoring Obs. = 1,293	Firms not sued prior to exit/censoring Obs. = 26,577	Difference
VC characteristics			
VC firm age	14.65	12.93	1.718***
# Companies invested by VCs	26.78	24.58	2.204***
# IPO exits by VCs	3.33	3.01	0.316*
# M&A exits by VCs	6.57	4.44	2.137***
Financing characteristics			
# Rounds raised	5.08	3.26	1.811***
# VCs invested	5.03	3.40	1.630***
Capital raised at R1 ($mil)	6.48	4.35	2.133***
Capital raised ($mil)	70.07	21.27	48.79***
Patents			
I(At least 1 patent application)	0.63	0.28	0.348***
I(At least 1 patent acquisition)	0.28	0.10	0.183***
# Patents applied	5.54	0.98	4.559***
# Patents acquired	3.09	0.43	2.658***
# Citations	0.90	0.34	0.561***

Table 4

Patent lawsuits and the decision to buy patents

This table examines the relation between patent lawsuits and firms' decisions to buy external patents. As in Panel B of Table 2, the unit of observation is at the firm-year level. Since patent lawsuits are tracked up to 2015 due to data availability, firm-years are tracked up to 2016 (because the main variable of interest is lagged one year). In Panel A, the dependent variable equals one if a firm buys at least one patent in year *t*, and zero otherwise. In Panel B, the dependent variable equals the natural logarithm of one plus the number of patents acquired in year *t*. The main independent variable of interest, *I(Litigated)*, equals one if a firm is classified as a defendant (excluding other types of defendants such as counter defendant, cross defendant, etc.) in a patent lawsuit in year *t* – 1. Across Panels, firm-years 2014–2016 are dropped to minimize the potential patent application/citation truncation bias in columns 3 and 6. All independent variables are measured as of year *t* – 1. All variables in log form represent the natural log of one plus the variable (i.e. ln(variable) represents ln(variable + 1)). Variable definitions are in Appendix A.1. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Are litigated firms more likely to buy patents?

VARIABLES	(1) Patent acquisition = 1	(2) Patent acquisition = 1	(3) Patent acquisition = 1	(4) Patent acquisition = 1	(5) Patent acquisition = 1	(6) Patent acquisition = 1
I(Litigated)	0.043***	0.033***	0.038***	0.017**	0.015**	0.016*
	(5.471)	(4.207)	(4.028)	(2.392)	(2.121)	(1.865)
ln(# Patents applied)		0.056***	0.058***		0.030***	0.030***
		(15.988)	(15.669)		(9.020)	(8.134)
ln(Capital raised)	0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(1.006)	(-0.301)	(-0.154)	(-0.422)	(-0.712)	(-0.870)
Raised VC round last year	0.005***	0.003***	0.004***	0.002***	0.002***	0.002**
	(6.258)	(4.616)	(4.574)	(2.736)	(2.709)	(2.051)
ln(# VCs invested)	0.007***	0.004***	0.004***	0.006***	0.004**	0.005**
	(6.156)	(3.976)	(3.570)	(3.134)	(2.385)	(2.427)
ln(VC firm age)	-0.004***	-0.002***	-0.002***	-0.003**	-0.002**	-0.002*
	(-6.120)	(-4.182)	(-3.913)	(-2.573)	(-2.161)	(-1.856)
ln(# Companies funded by VC)	-0.004***	-0.003***	-0.004***	-0.002**	-0.002**	-0.002**
	(-8.156)	(-7.063)	(-6.945)	(-2.389)	(-2.275)	(-2.299)
ln(# IPO exits by VC)	0.004***	0.003***	0.003***	0.003***	0.002***	0.003**
	(5.754)	(4.772)	(4.661)	(2.863)	(2.647)	(2.482)
ln(# M&A exits by VC)	0.005***	0.004***	0.004***	0.001	0.001	0.002
	(8.334)	(6.512)	(6.617)	(1.323)	(1.083)	(1.605)
Observations	174,016	174,016	156,915	173,218	173,218	154,845
Sample ends in	2016	2016	2013	2016	2016	2013
R-squared	0.013	0.024	0.024	0.223	0.225	0.236
Location FE	Yes	Yes	Yes	No	No	No
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes
Ind. x Year FE	No	No	No	Yes	Yes	Yes

Panel B: Do litigated firms buy more patents?

VARIABLES	(1) ln(# Patents acquired)	(2) ln(# Patents acquired)	(3) ln(# Patents acquired)	(4) ln(# Patents acquired)	(5) ln(# Patents acquired)	(6) ln(# Patents acquired)
I(Litigated)	0.074***	0.059***	0.062***	0.032**	0.029**	0.027*
	(5.079)	(4.274)	(4.177)	(2.429)	(2.251)	(1.803)
ln(# Patents applied)		0.077***	0.076***		0.042***	0.038***
		(12.371)	(12.504)		(7.290)	(7.007)
ln(Capital raised)	-0.000	-0.000	-0.000	-0.001*	-0.001**	-0.001**
	(-0.482)	(-1.578)	(-1.437)	(-1.677)	(-1.971)	(-2.241)
Raised VC round last year	0.005***	0.004***	0.004***	0.003***	0.003***	0.003**
	(5.191)	(3.558)	(3.505)	(2.682)	(2.647)	(2.038)
ln(# VCs invested)	0.009***	0.006***	0.006***	0.008***	0.006**	0.006**
	(5.743)	(3.814)	(3.679)	(3.238)	(2.485)	(2.439)
ln(VC firm age)	-0.005***	-0.003***	-0.003***	-0.005***	-0.004***	-0.004**
	(-5.909)	(-3.869)	(-3.425)	(-3.221)	(-2.820)	(-2.349)
ln(# Companies funded by VC)	-0.005***	-0.004***	-0.005***	-0.001	-0.001	-0.001
	(-8.154)	(-7.086)	(-6.892)	(-1.193)	(-1.070)	(-0.911)
ln(# IPO exits by VC)	0.005***	0.004***	0.004***	0.003***	0.003**	0.003**
	(5.740)	(4.718)	(4.419)	(2.612)	(2.397)	(1.995)
ln(# M&A exits by VC)	0.006***	0.005***	0.005***	0.002	0.001	0.002
	(8.091)	(6.342)	(6.306)	(1.324)	(1.070)	(1.418)
Observations	174,016	174,016	156,915	173,218	173,218	154,845
Sample ends in	2016	2016	2013	2016	2016	2013
R-squared	0.011	0.023	0.022	0.237	0.238	0.251
Location FE	Yes	Yes	Yes	No	No	No
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes
Ind. x Year FE	No	No	No	Yes	Yes	Yes

Table 5

Incumbent patent scope and the decision to buy patents

This table examines the relation between incumbent firms' patent scope and startup firms' decisions to buy external patents. As in Panel B of Table 2, the unit of observation is at the firm-year level. In columns 1–4 in Panel A, the dependent variable equals one if a firm buys at least one patent in year *t*, and zero otherwise. In columns 5–8 in Panel A, the dependent variable equals the natural logarithm of one plus the number of patents acquired in year *t*. The main variable of interest is the natural logarithm of one plus the average number of words in the first independent claim of patents granted to public firms who share the same 2-digit SIC code with startup firms, measured as of year $t-1$. The sample is limited to firm-years 2006–2011 (11,248 unique firms). In columns 3, 4, 7, and 8, firms in biotech industry are excluded. In columns 1–3 in Panel B, the dependent variable equals one if a firm buys at least one patent in year *t*, and zero otherwise. In columns 4–6 in Panel B, the dependent variable equals the natural logarithm of one plus the number of patents acquired in year *t*. The main variable of interest is the natural logarithm of one plus the average number of words shortest independent claim of patents granted to public firms who share the same 2-digit SIC code with startup firms, measured as of year $t-1$. The sample is limited to firm-years 1980–2011 (25,000 unique firms). In columns 3 and 6, the sample is limited to firm-years 2006–2011. All independent variables are measured as of year $t-1$. All variables in log form represent the natural log of one plus the variable (i.e. ln(variable) represents ln(variable + 1)). Variable definitions are in Appendix A.1. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A: The number of words in the first independent claim as a proxy for patent scope

VARIABLES	(1) Patent acquisition = 1	(2) Patent acquisition = 1	(3) Patent acquisition = 1	(4) Patent acquisition = 1	(5) ln(# Patents acquired)	(6) ln(# Patents acquired)	(7) ln(# Patents acquired)	(8) ln(# Patents acquired)
ln(Narrowness of public firm patent scope)	-0.033***	-0.035***	-0.029***	-0.031***	-0.039***	-0.040***	-0.035***	-0.036***
	(-6.353)	(-6.529)	(-5.445)	(-5.597)	(-4.835)	(-4.905)	(-4.156)	(-4.212)
ln(# Public firm patents)		0.002***		0.002***		0.002***		0.002**
		(4.591)		(4.347)		(2.670)		(2.310)
ln(# Patents applied)	0.055***	0.054***	0.060***	0.058***	0.079***	0.078***	0.084***	0.083***
	(9.669)	(9.407)	(9.552)	(9.275)	(6.947)	(6.755)	(6.643)	(6.444)
ln(Capital raised)	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	-0.002	-0.002
	(-0.081)	(-0.100)	(-1.070)	(-1.083)	(-1.136)	(-1.145)	(-1.584)	(-1.590)
Raised VC round last year	0.002	0.002	0.002	0.002	0.002	0.002	0.003	0.003
	(1.056)	(1.026)	(1.162)	(1.117)	(0.969)	(0.947)	(1.069)	(1.039)
ln(# VCs invested)	0.007***	0.007***	0.009***	0.008***	0.014***	0.014***	0.016***	0.016***
	(2.898)	(2.669)	(3.266)	(3.024)	(3.221)	(3.068)	(3.415)	(3.252)
ln(VC firm age)	-0.005***	-0.004***	-0.004***	-0.003**	-0.005**	-0.005**	-0.004	-0.003
	(-3.468)	(-3.156)	(-2.756)	(-2.440)	(-2.278)	(-2.133)	(-1.474)	(-1.330)
ln(# Companies funded by VC)	-0.003***	-0.003***	-0.003***	-0.004***	-0.005***	-0.005***	-0.005***	-0.005***
	(-2.912)	(-3.030)	(-3.032)	(-3.138)	(-3.027)	(-3.110)	(-3.220)	(-3.294)
ln(# IPO exits by VC)	0.007***	0.007***	0.007***	0.007***	0.009***	0.009***	0.008***	0.008***
	(3.154)	(3.276)	(2.802)	(2.904)	(2.978)	(3.081)	(2.607)	(2.694)
ln(# M&A exits by VC)	0.003**	0.003**	0.004**	0.004**	0.005**	0.005**	0.005**	0.005**
	(2.251)	(2.094)	(2.413)	(2.255)	(2.119)	(2.014)	(2.130)	(2.027)
Observations	40,392	40,392	36,599	36,599	40,392	40,392	36,599	36,599
Excludes biotech firms	No	No	Yes	Yes	No	No	Yes	Yes
R-squared	0.018	0.019	0.021	0.021	0.018	0.018	0.019	0.020
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	No
Ind. x Year FE	No	No	No	No	No	No	No	No

Panel B: The number of words in the shortest independent claim as a proxy for patent scope

VARIABLES	(1) Patent acquisition = 1	(2) Patent acquisition = 1	(3) Patent acquisition = 1	(4) ln(# Patents acquired)	(5) ln(# Patents acquired)	(6) ln(# Patents acquired)
ln(Narrowness of public firm patent scope)	-0.012***	-0.014***	-0.036***	-0.015***	-0.018***	-0.043***
	(-4.831)	(-5.856)	(-7.064)	(-4.543)	(-5.419)	(-5.563)
ln(# Public firm patents)		0.002***	0.002***		0.003***	0.002***
		(10.773)	(4.951)		(8.477)	(2.922)
ln(# Patents applied)	0.066***	0.064***	0.054***	0.084***	0.081***	0.078***
	(17.022)	(16.344)	(9.480)	(13.802)	(13.229)	(6.811)
ln(Capital raised)	-0.000	-0.000	-0.000	-0.001*	-0.001	-0.001
	(-0.683)	(-0.381)	(-0.119)	(-1.696)	(-1.488)	(-1.157)
Raised VC round last year	0.004***	0.004***	0.002	0.003***	0.003***	0.002
	(4.340)	(4.194)	(1.025)	(3.115)	(2.984)	(0.946)
ln(# VCs invested)	0.005***	0.004***	0.007***	0.007***	0.006***	0.014***
	(4.461)	(3.788)	(2.664)	(4.362)	(3.823)	(3.059)
ln(VC firm age)	-0.002***	-0.002***	-0.004***	-0.003***	-0.002**	-0.005**
	(-3.420)	(-3.001)	(-3.140)	(-2.884)	(-2.561)	(-2.137)
ln(# Companies funded by VC)	-0.004***	-0.004***	-0.003***	-0.005***	-0.005***	-0.005***
	(-6.724)	(-6.994)	(-3.090)	(-6.706)	(-6.940)	(-3.174)
ln(# IPO exits by VC)	0.004***	0.004***	0.007***	0.005***	0.005***	0.009***
	(5.501)	(5.913)	(3.272)	(5.171)	(5.536)	(3.067)
ln(# M&A exits by VC)	0.003***	0.003***	0.003**	0.004***	0.004***	0.005**
	(4.800)	(4.569)	(2.136)	(4.743)	(4.554)	(2.071)
Observations	139,049	139,049	40,682	139,049	139,049	40,682
Sample period	1980–2011	1980–2011	2006-2011	1980–2011	1980–2011	2006-2011
R-squared	0.021	0.022	0.019	0.018	0.019	0.018
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Ind. x Year FE	No	No	No	No	No	No

Table 6

Do firms rely less on external patents when patent litigation risk is reduced?

Panel A shows the number of patents granted to startup firms that cite at least one business method patent. A patent is defined as a business method patent if the main class of the primary classification (USPC) is 705. Panel B shows the differences-in-differences estimation results by comparing startup firms' patent acquisition behavior before and after the U.S. Supreme Court decision *Alice Corp. vs. CLS bank* (6/19/2014). To be included in the sample, firms should raise at least one financing round within the three years after the Alice decision date. *Treated* equals one if a firm has at least one granted patent (which is granted within the last 10 years prior to the Alice decision date) that cites business method patents. The sample consists of 16,035 firm-years (2,571 unique firms) between 2011–2017. Firm-years are assigned in the post period if the year is greater than or equal to 2014. Control variables include *ln(Capital raised), Raised VC round last year, ln(# VCs invested), ln(VC firm age), ln(# Companies funded by VC), ln(# IPO exits by VC), and ln(# M&A exits by VC)*. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Number of patents citing business method patents

Industry	1980-1984	1985-1989	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2018
Biotechnology	0	0	1	7	39	18	65	102
Communications and Media	0	4	10	46	199	353	457	210
Computer Hardware	2	8	38	32	100	190	515	388
Computer Software and Services	0	5	13	145	408	884	1,895	2,783
Consumer Related	0	1	1	0	3	7	31	18
Industrial/Energy	2	0	2	0	9	14	95	97
Internet Specific	0	0	1	20	244	390	1,153	1,417
Medical/Health	0	1	13	7	43	39	237	252
Semiconductors/Other Elect.	0	8	46	73	208	701	806	275
Other Products	0	2	1	2	12	21	104	30

Panel B: Patent acquisitions pre- vs. post-Alice

VARIABLES	(1) I(Patent acquisition)	(2) I(Patent acquisition)	(3) I(Patent acquisition)	(4) I(Patent acquisition)	(5) ln(# patents acquired)	(6) ln(# patents acquired)	(7) ln(# patents acquired)	(8) ln(# patents acquired)
Treated x Post	-0.030***	-0.031***	-0.029***	-0.031***	-0.039*	-0.039*	-0.038*	-0.041**
	(-2.985)	(-3.050)	(-2.834)	(-2.963)	(-1.900)	(-1.931)	(-1.891)	(-2.048)
Treated	0.036***	0.038***			0.050***	0.052***		
	(3.648)	(3.978)			(2.642)	(2.808)		
Post	-0.004				-0.004			
	(-1.558)				(-1.206)			
Observations	16,035	16,035	16,035	16,035	16,035	16,035	16,035	16,035
R-squared	0.008	0.013	0.210	0.214	0.007	0.011	0.240	0.244
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	No	No	Yes	Yes	No	No
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	Yes	No	No
Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Ind. x Year FE	No	No	No	Yes	No	No	No	Yes

Table 7

How do VCs respond to portfolio companies' patent acquisitions?

This table examines the relation between startup firms' patent acquisition activities and the follow-on financing round characteristics. The sample consists of 13,505 firms that received initial VC financing between 1980–2013. To be included in the sample, firms are required to raise at least three financing rounds. This is because (1) patent acquisition is measured in the interval [last financing round, current financing round) and (2) the specification requires firm fixed effects. Each observation represents firm-financing round. In column 1, the dependent variable is the natural logarithm of one plus the round size. In column 2, the dependent variable is the natural logarithm of one plus the post-money round valuation. In column 3, the dependent variable is the natural logarithm of one plus the pseudo market-to-book ratio (M/B), where pseudo M/B is defined by (post-money round valuation) / (cumulative capital invested in the company). In column 4, the dependent variable is the natural logarithm of one plus the average number of IPO exits of companies funded by the VCs (who participate in the current financing round) in the last five years. In column 5, the dependent variable is the natural logarithm of one plus the number of top VCs in the current round. A VC firm is defined as a top VC if it is included in the top 30 VC firm list in Nahata (2008). In column 6, the dependent variable is a dummy variable representing an inside round. An inside round is a financing round where only previous investors participate. In column 7, the dependent variable is the fraction of insiders in a round. *I(Patent application)* equals one if a firm applies for at least one patent in the interval [last financing round, current financing round). *I(Patent acquisition)* equals one if a firm buys at least one patent in the interval [last financing round, current financing round). The number of observations varies depending on the availability of data. Variable definitions are in Appendix A.1. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

VARIABLES	(1) ln(Round size)	(2) ln(Post-money valuation)	(3) ln(M/B)	(4) ln(# IPO exits by VC)	(5) ln(# Top VCs)	(6) Inside round	(7) % inside
I(Patent application)	0.244***	0.129***	0.039***	0.020**	0.017***	-0.065***	-0.031***
	(16.221)	(4.957)	(3.006)	(2.470)	(4.932)	(-9.060)	(-6.645)
I(Patent acquisition)	0.096***	-0.047	-0.013	0.002	-0.000	-0.030**	-0.023**
	(2.935)	(-1.000)	(-0.675)	(0.094)	(-0.049)	(-2.028)	(-2.376)
Observations	60,374	7,236	7,235	60,374	60,374	60,374	60,374
R-squared	0.549	0.844	0.774	0.760	0.737	0.364	0.353
Location FE	No	No	No	No	No	No	No
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	No	No
Financing round year FE	No	No	No	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. x Financing round year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8

Patent acquisition and long-run performance

This table examines the relation between startup firms' patent acquisition activities and the exit outcomes. Both Panels A and B consist of the 27,870 VC-backed companies described in Table 1. In columns 1–4 in Panel A, the dependent variable equals one if a firm exits via IPO or M&A, and zero otherwise. In columns 5–8 in Panel A, the dependent variable equals one if a firm neither exits nor raises a financing round in the last four years prior to the end of the sample period. In columns 1–4 in Panel B, the dependent variable equals one if a firm exits via IPO, and zero otherwise. In columns 5–8 in Panel B, the dependent variable equals one if a firm exits via M&A, and zero otherwise. Across Panels, even-numbered columns (2, 4, 6, and 8) include lead VC fixed effects, which reduces the sample size to 26,279 firms. Each observation represents unique firm. Patent applications and acquisitions are measured as of the earliest of (exit date, last financing round date + 365*4, or 12/31/2017). VC characteristics (VC firm age, # Companies invested by VC, # IPO exits by VC, and # M&A exits by VC) are measured at the initial financing round. Funding characteristics (the total number of VCs invested and the cumulative amount of capital raised) are measured as of the last financing round. All variables in log form represent the natural log of one plus the variable (i.e. ln(variable) represents ln(variable + 1)). Variable definitions are in Appendix A.1. Standard errors are clustered at the industry level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A: The probability of exit

VARIABLES	(1) I(Exit)	(2) I(Exit)	(3) I(Exit)	(4) I(Exit)	(5) Defunct	(6) Defunct	(7) Defunct	(8) Defunct
I(Patent acquisition)	0.018	0.014			-0.002	-0.003		
	(1.243)	(0.922)			(-0.173)	(-0.259)		
ln(# Patents acquired)			0.013	0.010			-0.001	-0.002
			(1.470)	(1.171)			(-0.152)	(-0.237)
ln(# Patents applied)	0.008	0.013	0.008	0.013	-0.030***	-0.034***	-0.030***	-0.034***
	(0.747)	(1.104)	(0.734)	(1.126)	(-3.365)	(-3.258)	(-3.511)	(-3.399)
ln(# VCs invested)	0.083***	0.088***	0.083***	0.088***	-0.099***	-0.094***	-0.099***	-0.094***
	(10.714)	(13.417)	(10.611)	(13.268)	(-9.302)	(-8.314)	(-9.268)	(-8.287)
ln(Capital raised)	0.046***	0.036***	0.046***	0.036***	-0.104***	-0.100***	-0.104***	-0.100***
	(5.547)	(3.962)	(5.587)	(3.986)	(-14.910)	(-12.865)	(-14.877)	(-12.851)
ln(VC firm age)	-0.015**	-0.009	-0.015**	-0.009	0.013**	0.002	0.013**	0.002
	(-3.118)	(-0.804)	(-3.113)	(-0.801)	(2.321)	(0.198)	(2.316)	(0.197)
ln(# Companies funded by VC)	-0.006	-0.005	-0.005	-0.005	0.010**	0.013**	0.010**	0.013**
	(-1.019)	(-0.903)	(-1.017)	(-0.913)	(3.095)	(2.635)	(3.094)	(2.635)
ln(# IPO exits by VC)	0.019***	0.002	0.019***	0.002	0.003	0.006	0.003	0.006
	(4.939)	(0.417)	(4.941)	(0.421)	(0.438)	(1.148)	(0.439)	(1.147)
ln(# M&A exits by VC)	0.021***	0.005	0.021***	0.005	-0.026***	-0.008	-0.026***	-0.008
	(4.380)	(0.714)	(4.328)	(0.711)	(-7.089)	(-1.289)	(-7.029)	(-1.288)
Observations	27,870	26,279	27,870	26,279	27,870	26,279	27,870	26,279
R-squared	0.124	0.218	0.124	0.218	0.221	0.308	0.221	0.308
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial financing round year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead VC FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: The form of exit

VARIABLES	(1) I(IPO)	(2) I(IPO)	(3) I(IPO)	(4) I(IPO)	(5) I(Acquired)	(6) I(Acquired)	(7) I(Acquired)	(8) I(Acquired)
I(Patent acquisition)	-0.031***	-0.032***			0.050**	0.046**		
	(-5.365)	(-4.367)			(3.193)	(2.596)		
ln(# Patents acquired)			-0.012*	-0.013*			0.026**	0.023**
			(-2.257)	(-1.968)			(3.067)	(2.505)
ln(# Patents applied)	0.035***	0.037***	0.033***	0.035***	-0.027**	-0.024**	-0.026**	-0.023**
	(6.318)	(7.440)	(5.717)	(6.651)	(-2.902)	(-2.319)	(-3.037)	(-2.379)
ln(# VCs invested)	0.031**	0.036***	0.031**	0.036***	0.052***	0.052***	0.052***	0.052***
	(3.051)	(3.360)	(3.032)	(3.338)	(4.000)	(4.487)	(3.997)	(4.463)
ln(Capital raised)	0.022***	0.020***	0.022***	0.020***	0.024***	0.016**	0.025***	0.016**
	(5.223)	(5.300)	(5.186)	(5.263)	(4.525)	(2.524)	(4.611)	(2.562)
ln(VC firm age)	-0.004**	0.010*	-0.004**	0.010*	-0.011**	-0.018*	-0.011**	-0.018*
	(-2.480)	(1.939)	(-2.502)	(1.898)	(-2.789)	(-2.092)	(-2.777)	(-2.079)
ln(# Companies funded by VC)	-0.002	-0.005*	-0.002	-0.005*	-0.003	0.000	-0.003	0.000
	(-1.105)	(-1.992)	(-1.107)	(-1.979)	(-0.873)	(0.081)	(-0.870)	(0.069)
ln(# IPO exits by VC)	0.017***	-0.012**	0.017***	-0.012**	0.002	0.014*	0.002	0.014*
	(10.281)	(-3.134)	(10.369)	(-3.153)	(0.459)	(2.241)	(0.445)	(2.259)
ln(# M&A exits by VC)	-0.007***	0.011**	-0.007***	0.011**	0.029***	-0.006	0.029***	-0.006
	(-3.409)	(2.839)	(-3.422)	(2.874)	(6.040)	(-0.811)	(5.959)	(-0.807)
Observations	27,870	26,279	27,870	26,279	27,870	26,279	27,870	26,279
R-squared	0.139	0.220	0.138	0.219	0.094	0.184	0.094	0.184
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial financing round year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead VC FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 9

Product market competition

This table examines the relation between startup firms' product market characteristics and the decision to buy external patents. As in Panel B of Table 2, the unit of observation is at the firm-year level. The sample consists of 27,703 unique firms after excluding 167 firms that raise initial VC round and exit in the same year. In columns 1 and 2, the dependent variable equals one if a firm buy at least one patent in year *t*, and zero otherwise. In columns 3 and 4, the dependent variable equals the natural logarithm of one plus the number of patents acquired in year *t*. HHI (supply of VC investments) is Herfindahl-Hirschman Index, measured using the amount of capital raised by each startup firm within the past three years as a proxy for market share. Four-firm concentration ratio is calculated by (amount of capital raised by the top four startup firms in the industry within the past three years) / (amount of capital raised by all startup firms in the industry within the past three years). All independent variables are measured as of year $t-1$. All variables in log form represent the natural log of one plus the variable (i.e. ln(variable) represents ln(variable + 1)). Variable definitions are in Appendix A.1. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

VARIABLES	(1) I(Patent acquisition)	(2) I(Patent acquisition)	(3) ln(# Patents acquired)	(4) ln(# Patents acquired)
HHI (Supply of VC investments)	0.000		0.000	
	(1.305)		(1.507)	
Four-firm concentration ratio		0.000		0.000
		(0.208)		(0.787)
ln(# Patents applied)	0.061***	0.061***	0.083***	0.083***
	(18.123)	(18.132)	(13.601)	(13.606)
I(Litigated)	0.031***	0.031***	0.057***	0.057***
	(3.936)	(3.939)	(4.092)	(4.093)
ln(Capital raised)	-0.000	-0.000	-0.000*	-0.000*
	(-0.570)	(-0.614)	(-1.706)	(-1.723)
Raised VC round last year	0.004***	0.003***	0.004***	0.004***
	(4.832)	(4.791)	(3.733)	(3.711)
ln(# VCs invested)	0.005***	0.005***	0.007***	0.007***
	(5.074)	(4.997)	(4.623)	(4.577)
ln(VC firm age)	-0.002***	-0.002***	-0.002***	-0.002***
	(-3.226)	(-3.062)	(-3.045)	(-2.970)
ln(# Companies funded by VC)	-0.004***	-0.004***	-0.005***	-0.005***
	(-7.813)	(-7.849)	(-7.720)	(-7.746)
ln(# IPO exits by VC)	0.004***	0.004***	0.005***	0.005***
	(6.160)	(6.120)	(5.817)	(5.803)
ln(# M&A exits by VC)	0.003***	0.003***	0.004***	0.004***
	(4.577)	(4.562)	(4.920)	(4.910)
Observations	177,786	177,786	177,786	177,786
R-squared	0.021	0.021	0.021	0.021
Location FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Ind. x Year FE	No	No	No	No

Table 10

VC investment horizon

Panel A shows the age of a lead VC fund at the time of the initial investment in a company, the number of companies raising initial VC financing from those lead VCs, and the fraction of companies buying at least one patent prior to exit or leaving the sample within each fund age bracket. For each VC-backed company described in Table 1, a lead VC is defined as the VC that participates in the first VC round and, conditional on such participation, makes the largest total investment in the company across all funding rounds. If a lead VC invests in a company via multiple funds, the fund with the older vintage and larger fund size is defined as the lead VC's fund for the company. Fund age is defined by (first round date – fund vintage date) / 365. Cases where fund's vintage year is missing or fund age is greater than 12 are excluded. This process leaves 17,296 unique startup firm–lead VC fund pairs. Panel B examines the relation between lead VC fund age and the decision to acquire external patents. The sample consists of the 17,296 VC-backed companies described in Panel A. In columns 1–2, the dependent variable equals one if a firm buys at least one patent prior to exit or leaving the sample, and zero otherwise. In columns 3–4, the dependent variable equals the natural logarithm of one plus the number of patents acquired prior to exit or leaving the sample. Patent acquisitions are measured as of the earliest of (exit date, last financing round date + 365*4, or 12/31/2017). All variables are measured as of the initial financing round. All variables in log form represent the natural log of one plus the variable (i.e. ln(variable) represents ln(variable + 1)). Variable definitions are in Appendix A.1. Standard errors are clustered at the industry level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Lead VC fund age and patent acquisition

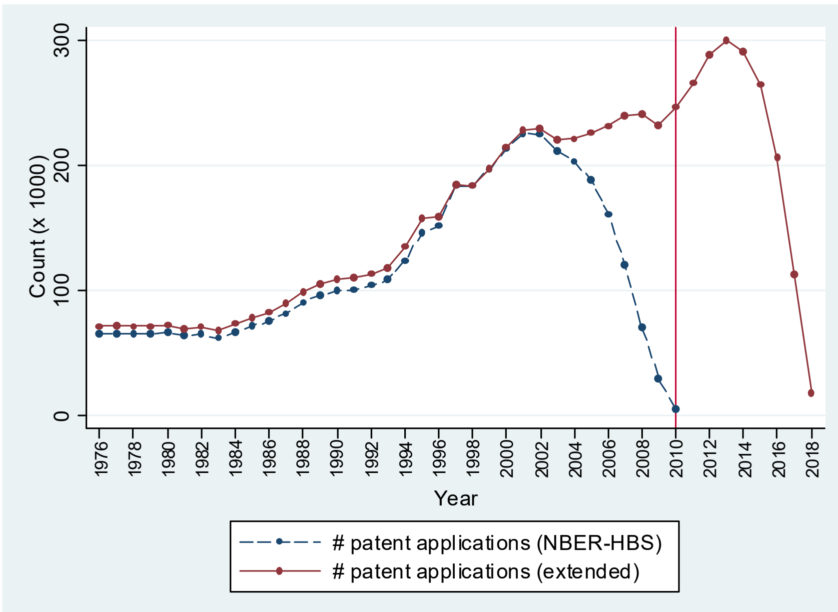
Fund age	# Firms	% Buying at least 1 patent
0–3	11,539	10.69%
3–5	3,284	11.30%
5–7	1,304	11.04%
7–10	804	9.08%
10+	365	10.41%
Total	17,296	10.75%

Panel B: Are startups funded by older VC funds more likely to buy patents?

VARIABLES	(1) I(Patent acquisition = 1)	(2) I(Patent acquisition = 1)	(3) ln(# Patents acquired)	(4) ln(# Patents acquired)
Fund age	-0.000		-0.001	
	(-0.175)		(-0.655)	
ln(Fund age)		-0.000		-0.003
		(-0.062)		(-0.372)
ln(# VCs invested)	0.019	0.019	0.026	0.026
	(1.771)	(1.772)	(1.626)	(1.621)
ln(Capital raised)	0.014**	0.014**	0.020**	0.020**
	(2.294)	(2.307)	(2.886)	(2.876)
ln(VC firm age)	0.005	0.005	0.009	0.008
	(0.842)	(0.802)	(1.032)	(0.970)
ln(# Companies funded by VC)	-0.001	-0.001	-0.003	-0.003
	(-0.183)	(-0.181)	(-0.530)	(-0.506)
ln(# IPO exits by VC)	0.004	0.004	0.006	0.006
	(1.118)	(1.140)	(1.433)	(1.430)
ln(# M&A exits by VC)	0.010*	0.010*	0.017*	0.017*
	(2.139)	(2.134)	(2.203)	(2.179)
Observations	17,296	17,296	17,296	17,296
R-squared	0.068	0.068	0.060	0.060
Location FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Initial financing round year FE	Yes	Yes	Yes	Yes
Lead VC FE	No	No	No	No

Figure A1
Extended patent data
This table shows the total number of utility patents granted by the USPTO. In Panel A, these statistics are plotted against the application year. In Panel B, these statistics are plotted against the grant year. Across Panels, the number of patents recorded in the NBER-HBS patent database is plotted as a benchmark (up to 2010).

Panel A: Number of patent applications



Panel B: Number of patent grants

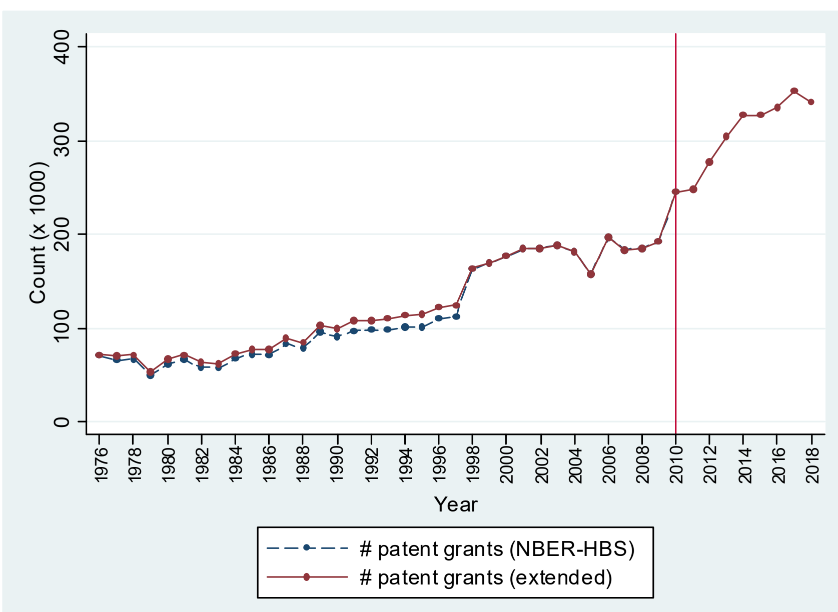


Figure A2

Composition of patent portfolios

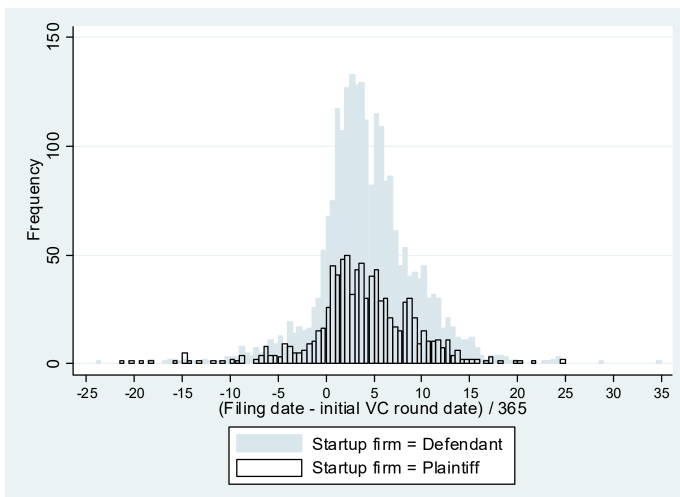
This figure shows the fraction of acquired patents in VC-backed companies' patent portfolios. The sample consists of 8,040 companies with at least 1 patent grant or 1 patent acquisition. The composition is defined by (# patents acquired) / (# patents granted + # patents acquired). If a company exits by 12/31/2017, patent applications and acquisitions are tracked up to the exit date. If a company does not exit by 12/31/2017, patent applications and acquisitions are tracked up to min (last financing date + 365*4, 12/31/2017). Patent data are obtained from the USPTO.

Figure A3

Timings of patent lawsuits

Panel A shows the distribution of (patent lawsuit filing date – initial VC round date) / 365. The sample consists of 2,123 cases associated with 1,293 defendants (excluding other types of defendants such as counter defendant, cross defendant, consolidated defendant, etc.) and 863 cases associated with 493 plaintiffs (excluding other types of plaintiffs such as counter claimant, consolidated counter claimant, third party plaintiff, etc.). Panel B shows the distribution of (patent lawsuit filing date – exit date) / 365 for a subset of cases in which startup firms exit the private status by the end of 2017. The sample consists of 946 cases associated with 590 defendants (excluding other types of defendants such as counter defendant, cross defendant, consolidated defendant, etc.) and 384 cases associated with 231 plaintiffs (excluding other types of plaintiffs such as counter claimant, consolidated counter claimant, third party plaintiff, etc.). Patent lawsuits filed after startup firms' exit events (either IPO or M&A) are excluded. If a firm does not exit, patent lawsuits are tracked up to min (last financing round + 365*4, 12/31/2015). Patent litigation data is obtained from the USPTO.

Panel A: Number of years between initial VC round date and filing date



Panel B: Number of years between exit date and filing date

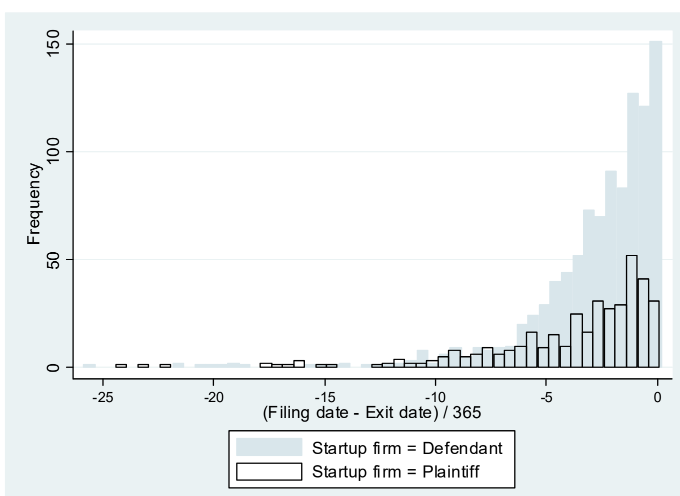
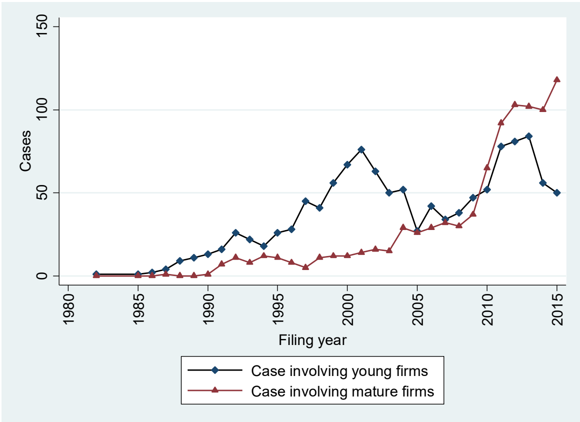


Figure A4

Patent lawsuits involving startup firms

Panel A shows the number of patent lawsuits involving startups in which a startup firm is a defendant (other types of defendants such as counter defendant, cross defendant, consolidated defendants, etc. are excluded). The sample consists of 2,123 cases associated with 1,293 startup firms that raised initial venture capital financing between 1980–2013. The cases are split into two groups. If at least one of the defendants (startups) in a given case raised its initial VC round more than five years prior to the case filing date, the case is defined as *Case involving mature firms*. Otherwise, the case is defined as *Case involving young firms*. Panel B shows the number of patent lawsuits involving startups in which a startup firm is a plaintiff (other types of plaintiffs such as counter claimant, consolidated counter claimant, third party plaintiff, etc. are excluded). The sample consists of 863 cases associated with 493 startup firms that raised initial venture capital financing between 1980–2013. The cases are split into two groups If at least one of the plaintiffs (startups) in a given case raised its initial VC round more than five years prior to the case filing date, the case is defined as *Case involving mature firms*. Otherwise, the case is defined as *Case involving young firms*. Patent lawsuits filed after startup firms' exit events (either IPO or M&A) are excluded. If a firm does not exit, patent lawsuits are tracked up to min (last financing round + 365*4, 12/31/2015). Patent litigation data is obtained from the USPTO.

Panel A: Startup firm age at patent lawsuits (startup firm = defendant)



Panel B: Startup firm age at patent lawsuits (startup firm = plaintiff)

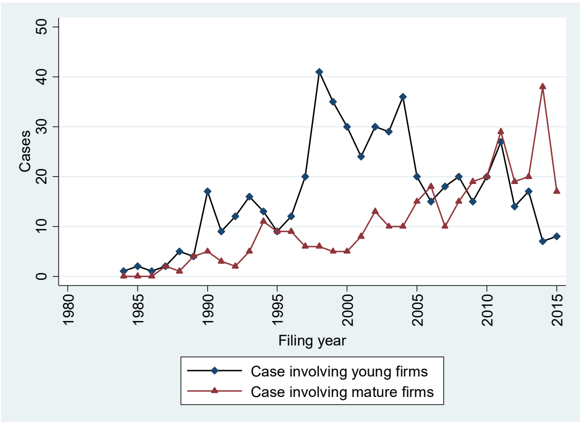
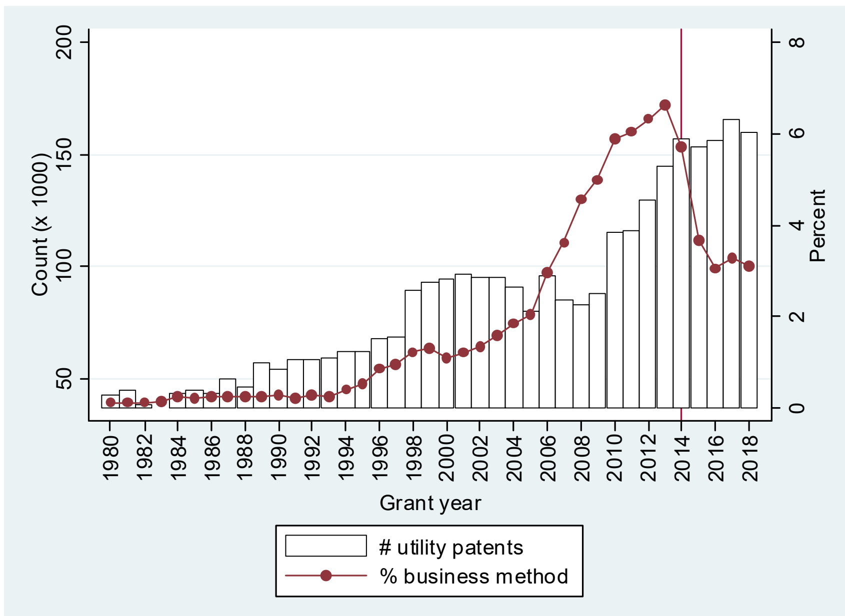


Figure A5

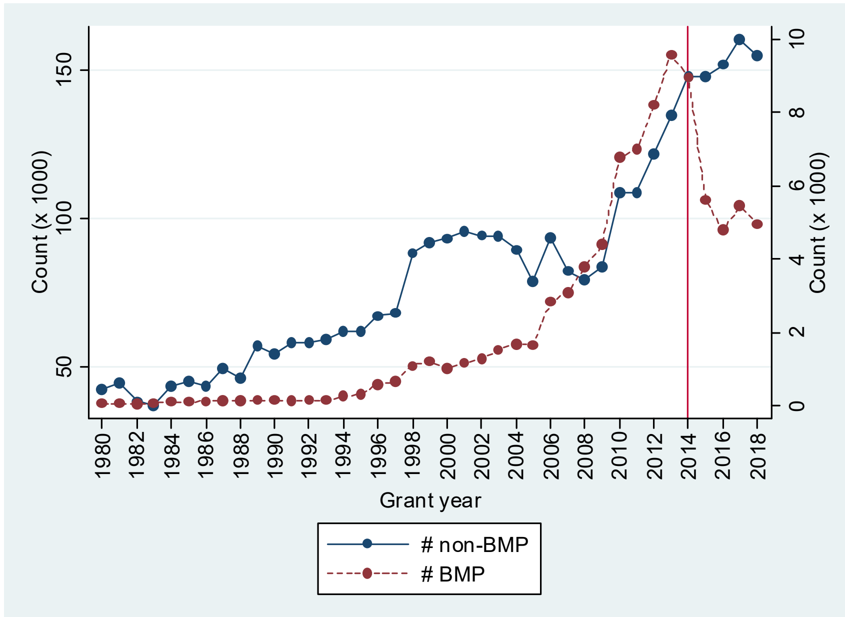
Business method patents

Panel A shows the total number of utility patents granted by the USPTO and the fraction of business method patents. A patent is defined as a business method patent if the main class of the primary classification (USPC) is 705. The vertical line represents the Alice decision year (2014). Panel B shows the number of non-business method patents, shown in the primary axis (left), and the number of business method patents, shown in the secondary axis (right). The vertical line represents the Alice decision year (2014). Panel C shows the number of non-business method patents, shown in the primary axis (left), and the number of business method patents, shown in the secondary axis (right), at a quarterly frequency. The vertical line represents the Alice decision quarter (6/19/2014).

Panel A: Business method patents / all patents



Panel B: Business method patents vs. non-business method patents



Panel C: Business method patents vs. non-business method patents (quarterly)

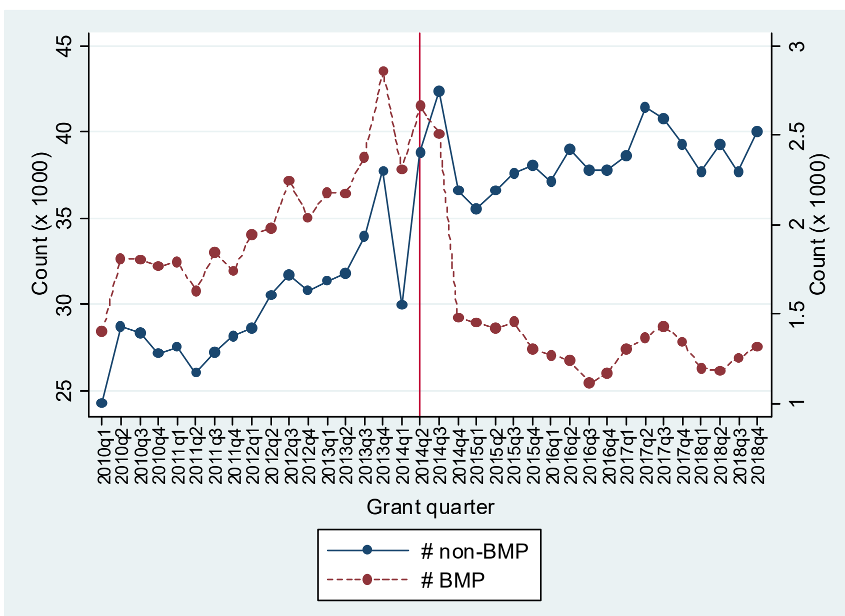


Table A1

Funding conditions and patent acquisitions

This table shows the relation between funding conditions and the probability of patent acquisition. In Panel A, the sample consists of 27,870 companies with initial venture capital financing rounds between 1980–2013. Firms are assigned into quintiles based on the total amount of capital raised from VCs prior to exit or leaving the sample. Panel B is based on the same sample used in Panel A, but firms are assigned into quintiles based on the amount of capital raised in the first VC round. In Panel C, the sample is restricted to 17,855 companies whose lead VC's fund size is non-missing. Firms are assigned into quintiles based on the lead VC's fund size. Across Panels, quintiles are calculated within initial VC round year-industry-stage triplet.

Panel A: Capital raised in VC rounds

Quintile	Amt. raised ($ mil)	# firms	% firms buying patents
1	0.88	6,244	5.9%
2	4.29	5,448	7.4%
3	10.97	5,479	10.2%
4	24.48	5,535	13.0%
5	83.57	5,164	16.8%

Panel B: Capital raised in the initial VC round

Quintile	Amt. raised ($ mil)	# firms	% firms buying patents
1	0.29	6,507	8.2%
2	1.26	5,341	9.0%
3	2.63	5,476	10.2%
4	5.04	5,494	12.4%
5	14.48	5,052	13.0%

Panel C: Lead VC fund size

Quintile	Fund size ($ mil)	# firms	% firms buying patents
1	16.53	4,100	8.3%
2	49.51	3,637	10.4%
3	109.57	3,486	10.5%
4	221.62	3,585	11.9%
5	669.63	3,047	12.4%

Table A2
Do startup firms buy patents because they fail to innovate?
This table examines the relation between startup firms' internal innovation output and the decision to buy external patents. As in Panel B of Table 2, the unit of observation is at the firm-year level. The sample consists of 27,703 unique firms after excluding 167 firms that raise initial VC round and exit in the same year. Firm-years 2014–2017 are dropped to minimize the potential patent application/citation truncation bias. In columns 1–2, the dependent variable equals one if a firm buys at least one patent in year *t*, and zero otherwise. In columns 3–4, the dependent variable equals the natural logarithm of one plus the number of patents acquired in year *t*. *Complex industry* which equals one if a startup firm's SIC code is greater than or equal to 2900. If a firm does not have an SIC code assigned by Thomson Reuters (about 18%), I impute SIC codes by creating a mapping between VC industries and SIC codes. Conditional on having a non-missing SIC code, I create a frequency distribution of SIC codes per each VC industry. For each VC industry, an SIC code with the highest frequency is chosen as the representative SIC code. All independent variables are measured as of year *t* – 1. Both the number of patent applications and the forward citations are corrected for truncation bias using the fixed-effects approach as described in more detail in the body of the paper. All variables in log form represent the natural log of one plus the variable (i.e. ln(variable) represents ln(variable + 1)). Variable definitions are in Appendix A.1. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

VARIABLES	(1) Patent acquisition = 1	(2) Patent acquisition = 1	(3) ln(# patents acquired)	(4) ln(# patents acquired)
ln(# Patents applied)	0.065***		0.084***	
	(17.997)		(14.253)	
ln(# Citations)		0.044***		0.055***
		(17.792)		(14.302)
Complex industry	-0.007***	-0.008***	-0.006***	-0.008***
	(-4.739)	(-5.522)	(-3.589)	(-4.549)
ln(Capital raised)	-0.000	-0.000	-0.001	-0.000
	(-0.443)	(-0.300)	(-1.605)	(-1.465)
Raised VC round last year	0.004***	0.004***	0.004***	0.004***
	(4.634)	(4.811)	(3.473)	(3.695)
ln(# VCs invested)	0.005***	0.007***	0.007***	0.009***
	(4.756)	(6.001)	(4.597)	(5.739)
ln(VC firm age)	-0.002***	-0.002***	-0.002***	-0.003***
	(-3.286)	(-3.945)	(-2.666)	(-3.353)
ln(# Companies funded by VC)	-0.004***	-0.004***	-0.005***	-0.006***
	(-7.433)	(-7.779)	(-7.358)	(-7.722)
ln(# IPO exits by VC)	0.004***	0.004***	0.004***	0.005***
	(5.541)	(5.761)	(5.147)	(5.438)
ln(# M&A exits by VC)	0.003***	0.004***	0.005***	0.005***
	(5.560)	(6.248)	(5.443)	(6.087)
Observations	156,915	156,915	156,915	156,915
R-squared	0.021	0.016	0.019	0.013
Location FE	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Ind. x Year FE	No	No	No	No

Table A3

Patent lawsuits and decision to buy patents

This table examines the relation between patent lawsuits and firms' decisions to buy external patents. As in Panel B of Table 2, the unit of observation is at the firm-year level. Since patent lawsuits are tracked up to 2015 due to data availability, firm-years are tracked up to 2016 (because the main variable of interest is lagged one year). In Panel A, the dependent variable equals one if a firm buys at least one patent in year *t*, and zero otherwise. In Panel B, the dependent variable equals the natural logarithm of one plus the number of patents acquired in year *t*. The main independent variables of interest are Litigated(t-1) and Litigated(t-2), which equal one if a firm is classified as a defendant (excluding other types of defendants such as counter defendant, cross defendant, etc.) in a patent lawsuit in year *t* – 1 and year t –2, respectively. Across Panels, firm-years 2014–2016 are dropped to minimize the potential patent application/citation truncation bias in columns 3 and 6. All independent variables are measured as of year *t* – 1. All variables in log form represent the natural log of one plus the variable (i.e. ln(variable) represents ln(variable + 1)). Variable definitions are in Appendix A.1. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Are litigated firms more likely to buy patents?

VARIABLES	(1) Patent acquisition = 1	(2) Patent acquisition = 1	(3) Patent acquisition = 1	(4) Patent acquisition = 1	(5) Patent acquisition = 1	(6) Patent acquisition = 1
Litigated(t-1)	0.039***	0.030***	0.034***	0.017**	0.015**	0.016*
	(5.323)	(4.141)	(3.997)	(2.393)	(2.121)	(1.864)
Litigated(t-2)	0.027***	0.018**	0.024**	0.003	0.001	0.003
	(3.082)	(2.075)	(2.188)	(0.456)	(0.170)	(0.306)
ln(# Patents applied)		0.055***	0.058***		0.030***	0.030***
		(15.894)	(15.574)		(9.023)	(8.137)
ln(Capital raised)	0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.947)	(-0.335)	(-0.179)	(-0.421)	(-0.712)	(-0.869)
Raised VC round last year	0.005***	0.003***	0.004***	0.002***	0.002***	0.002**
	(6.318)	(4.663)	(4.627)	(2.735)	(2.709)	(2.050)
ln(# VCs invested)	0.007***	0.004***	0.004***	0.006***	0.004**	0.005**
	(6.124)	(3.959)	(3.550)	(3.129)	(2.384)	(2.424)
ln(VC firm age)	-0.004***	-0.002***	-0.002***	-0.003**	-0.002**	-0.002*
	(-6.157)	(-4.216)	(-3.959)	(-2.571)	(-2.161)	(-1.854)
ln(# Companies funded by VC)	-0.004***	-0.003***	-0.004***	-0.002**	-0.002**	-0.002**
	(-8.043)	(-6.988)	(-6.879)	(-2.385)	(-2.273)	(-2.297)
ln(# IPO exits by VC)	0.004***	0.003***	0.003***	0.003***	0.002***	0.003**
	(5.760)	(4.781)	(4.689)	(2.857)	(2.645)	(2.480)
ln(# M&A exits by VC)	0.005***	0.004***	0.004***	0.001	0.001	0.002
	(8.220)	(6.436)	(6.527)	(1.322)	(1.083)	(1.604)
Observations	174,016	174,016	156,915	173,218	173,218	154,845
R-squared	0.013	0.024	0.024	0.223	0.225	0.236
Location FE	Yes	Yes	Yes	No	No	No
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes
Ind. x Year FE	No	No	No	Yes	Yes	Yes

Panel B: Do litigated firms buy more patents?

VARIABLES	(1) ln(# Patents acquired)	(2) ln(# Patents acquired)	(3) ln(# Patents acquired)	(4) ln(# Patents acquired)	(5) ln(# Patents acquired)	(6) ln(# Patents acquired)
Litigated(t-1)	0.068***	0.055***	0.058***	0.032**	0.029**	0.026*
	(4.967)	(4.228)	(4.124)	(2.427)	(2.248)	(1.791)
Litigated(t-2)	0.036***	0.024*	0.023*	-0.000	-0.003	-0.008
	(2.797)	(1.874)	(1.665)	(-0.001)	(-0.275)	(-0.686)
ln(# Patents applied)		0.077***	0.076***		0.043***	0.038***
		(12.353)	(12.440)		(7.321)	(7.018)
ln(Capital raised)	-0.000	-0.000	-0.000	-0.001*	-0.001**	-0.001**
	(-0.530)	(-1.604)	(-1.453)	(-1.677)	(-1.972)	(-2.244)
Raised VC round last year	0.005***	0.004***	0.004***	0.003***	0.003***	0.003**
	(5.252)	(3.607)	(3.547)	(2.681)	(2.648)	(2.041)
ln(# VCs invested)	0.009***	0.006***	0.006***	0.008***	0.006**	0.006**
	(5.725)	(3.804)	(3.666)	(3.248)	(2.496)	(2.451)
ln(VC firm age)	-0.005***	-0.003***	-0.003***	-0.005***	-0.004***	-0.004**
	(-5.938)	(-3.895)	(-3.454)	(-3.226)	(-2.826)	(-2.356)
ln(# Companies funded by VC)	-0.005***	-0.004***	-0.005***	-0.001	-0.001	-0.001
	(-8.083)	(-7.040)	(-6.842)	(-1.193)	(-1.072)	(-0.914)
ln(# IPO exits by VC)	0.005***	0.004***	0.004***	0.003***	0.003**	0.003**
	(5.746)	(4.727)	(4.442)	(2.615)	(2.403)	(2.000)
ln(# M&A exits by VC)	0.006***	0.005***	0.005***	0.002	0.001	0.002
	(8.015)	(6.288)	(6.245)	(1.324)	(1.071)	(1.419)
Observations	174,016	174,016	156,915	173,218	173,218	154,845
R-squared	0.011	0.023	0.022	0.237	0.238	0.251
Location FE	Yes	Yes	Yes	No	No	No
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes
Ind. x Year FE	No	No	No	Yes	Yes	Yes

Table A4

Do firms rely less on external patents when patent litigation risk is reduced?

This table shows the differences-in-differences estimation results by comparing startup firms' patent acquisition behavior before and after the U.S. Supreme Court decision *Alice Corp. vs. CLS bank* (6/19/2014). To be included in the sample, firms should raise at least one financing round within the three years after the Alice decision date. In Panel A, *Treated* equals one if a firm has at least one granted patent (which is granted within the last 10 years prior to the Alice decision date) that cites business method patents. In Panel B, *Treated* equals one if a firm cites at least two business method patents (through patents granted within the last 10 years prior to the Alice decision date). In Panel C, *Treated* equals one if a firm cites at least one business method patent (through patents granted within the last 5 years prior to the Alice decision date). Across Panels, the sample consists of 16,035 firm-years (2,571 unique firms) between 2011–2017. Firm-years are assigned in the post period if the year is greater than or equal to 2014. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A: No control variables

VARIABLES	(1) I(Patent acquisition)	(2) I(Patent acquisition)	(3) I(Patent acquisition)	(4) I(Patent acquisition)	(5) ln(# patents acquired)	(6) ln(# patents acquired)	(7) ln(# patents acquired)	(8) ln(# patents acquired)
Treated x Post	-0.030***	-0.031***	-0.029***	-0.029***	-0.039*	-0.039*	-0.038*	-0.040**
	(-2.962)	(-3.017)	(-2.776)	(-2.836)	(-1.910)	(-1.936)	(-1.880)	(-2.011)
Treated	0.037***	0.040***			0.053***	0.056***		
	(3.810)	(4.198)			(2.776)	(2.976)		
Post	0.000				0.002			
	(0.134)				(0.470)			
Observations	16,035	16,035	16,035	16,035	16,035	16,035	16,035	16,035
R-squared	0.005	0.011	0.210	0.214	0.005	0.009	0.240	0.243
Controls	No	No	No	No	No	No	No	No
Location FE	Yes	Yes	No	No	Yes	Yes	No	No
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	Yes	No	No
Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Ind. x Year FE	No	No	No	Yes	No	No	No	Yes

Panel B: Treated = 1 if a firm cites at least two business method patents within the last 10 years pre-Alice

VARIABLES	(1) I(Patent acquisition)	(2) I(Patent acquisition)	(3) I(Patent acquisition)	(4) I(Patent acquisition)	(5) ln(# patents acquired)	(6) ln(# patents acquired)	(7) ln(# patents acquired)	(8) ln(# patents acquired)
Treated x Post	-0.032***	-0.033***	-0.031***	-0.032***	-0.045*	-0.046*	-0.045*	-0.047*
	(-2.731)	(-2.793)	(-2.638)	(-2.735)	(-1.805)	(-1.834)	(-1.800)	(-1.908)
Treated	0.035***	0.038***			0.056**	0.058**		
	(3.115)	(3.404)			(2.404)	(2.535)		
Post	-0.004*				-0.005			
	(-1.849)				(-1.308)			
Observations	16,035	16,035	16,035	16,035	16,035	16,035	16,035	16,035
R-squared	0.007	0.012	0.210	0.214	0.008	0.011	0.240	0.244
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	No	No	Yes	Yes	No	No
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	Yes	No	No
Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Ind. x Year FE	No	No	No	Yes	No	No	No	Yes

Panel C: Treated = 1 if a firm cites at least one business method patent within the last 5 years pre-Alice

VARIABLES	(1) I(Patent acquisition)	(2) I(Patent acquisition)	(3) I(Patent acquisition)	(4) I(Patent acquisition)	(5) ln(# patents acquired)	(6) ln(# patents acquired)	(7) ln(# patents acquired)	(8) ln(# patents acquired)
Treated x Post	-0.033***	-0.033***	-0.033***	-0.034***	-0.041*	-0.042**	-0.041*	-0.044**
	(-3.115)	(-3.186)	(-3.060)	(-3.190)	(-1.939)	(-1.974)	(-1.952)	(-2.086)
Treated	0.037***	0.040***			0.052***	0.055***		
	(3.623)	(3.989)			(2.653)	(2.842)		
Post	-0.004				-0.004			
	(-1.579)				(-1.216)			
Observations	16,035	16,035	16,035	16,035	16,035	16,035	16,035	16,035
R-squared	0.008	0.013	0.210	0.215	0.008	0.012	0.240	0.244
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	No	No	Yes	Yes	No	No
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	Yes	No	No
Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Ind. x Year FE	No	No	No	Yes	No	No	No	Yes

Table A5

Comparison of patent quality: applied vs. acquired

This table compares the number of forward citations of patents. Forward citations are counted over the three years following each patent's grant date. The sample consists of 92,945 patents, among which 79,923 are produced in-house (i.e. applied by the firm) and 15,339 are acquired. The truncation bias in patent data is corrected using the fixed-effects approach suggested in Hall, Jaffe, and Trajtenberg (2001). Patent applications and acquisitions are tracked up to the earliest of (exit date, last financing round date + 365*4, or 12/31/2017). All variables in log form represent the natural log of one plus the variable (i.e. ln(variable) represents ln(variable + 1)). Standard errors are clustered at the technology class level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

VARIABLES	(1) # Citations	(2) # Citations	(3) # Citations	(4) ln(# Citations)	(5) ln(# Citations)	(6) ln(# Citations)
Acquired	0.029	0.116	0.154	0.016	0.005	0.014
	(0.240)	(1.276)	(1.570)	(1.039)	(0.423)	(1.042)
Observations	92,945	92,945	92,945	92,945	92,945	92,945
R-squared	0.000	0.011	0.011	0.000	0.017	0.015
Application year FE	No	Yes	No	No	Yes	No
Grant year FE	No	No	Yes	No	No	Yes
Tech class FE	No	Yes	Yes	No	Yes	Yes

Table A6

Patent acquisition and long-run performance

This table examines the relation between startup firms' patent acquisition activities and the exit outcomes. The sample consists of 9,178 VC-backed companies with at least one patent application or one patent acquisition. Each observation represents unique firm. In columns 1–2, the dependent variable equals one if a firm exits via IPO or M&A, and zero otherwise. In column 3–4, the dependent variable equals one if a firm neither exits nor raises a financing round in the last four years prior to the end of the sample period (12/31/2017). In column 5–6, the dependent variable equals one if a firm exits via IPO, and zero otherwise. In column 7–8, the dependent variable equals one if a firm exits via M&A (acquired), and zero otherwise. Even-numbered columns (2, 4, 6, and 8) include lead VC fixed effects, which reduces the sample to 8,107 VC-backed companies. Patent applications and acquisitions are tracked up to the earliest of (exit date, last financing round date + 365*4, or 12/31/2017). VC characteristics (VC firm age, # Companies invested by VC, # IPO exits by VC, and # M&A exits by VC) are measured at the initial financing round. Funding characteristics (the total number of VCs invested and the cumulative amount of capital raised) are measured as of the last financing round. All variables in log form represent the natural log of one plus the variable (i.e. ln(variable) represents ln(variable + 1)). Variable definitions are in Appendix A.1. Standard errors are clustered at the industry level. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

VARIABLES	(1) I(Exit)	(2) I(Exit)	(3) Defunct	(4) Defunct	(5) I(IPO)	(6) I(IPO)	(7) I(Acquired)	(8) I(Acquired)
# Acquired / (# Applied + # Acquired)	0.015	-0.003	0.012	0.020	-0.041***	-0.044***	0.056**	0.041**
	(0.695)	(-0.218)	(0.604)	(1.235)	(-5.059)	(-3.685)	(2.700)	(2.758)
ln(# VCs invested)	0.060***	0.073***	-0.069***	-0.068***	0.027*	0.037**	0.033*	0.036**
	(7.251)	(5.764)	(-7.737)	(-3.699)	(1.861)	(2.908)	(1.986)	(2.295)
ln(Capital raised)	0.043***	0.030*	-0.113***	-0.110***	0.034***	0.031***	0.008	-0.001
	(3.793)	(1.901)	(-19.310)	(-9.495)	(4.784)	(4.277)	(1.105)	(-0.100)
ln(VC firm age)	-0.018**	-0.012	0.023**	0.022**	-0.003	0.014	-0.015**	-0.026*
	(-2.299)	(-1.064)	(3.158)	(2.751)	(-0.544)	(1.203)	(-2.818)	(-2.127)
ln(# Companies funded by VC)	-0.008	-0.009	0.006	0.008	-0.005	-0.008	-0.004	-0.001
	(-1.029)	(-0.819)	(1.030)	(0.846)	(-1.073)	(-1.100)	(-0.446)	(-0.096)
ln(# IPO exits by VC)	0.029**	0.012	-0.012	-0.007	0.017***	-0.021***	0.012	0.032**
	(2.592)	(1.073)	(-1.309)	(-0.841)	(3.933)	(-3.567)	(1.150)	(2.915)
ln(# M&A exits by VC)	0.024	0.014	-0.013	-0.007	-0.004	0.018*	0.028**	-0.004
	(1.675)	(0.879)	(-1.258)	(-0.529)	(-0.446)	(1.909)	(2.814)	(-0.322)
Observations	9,178	8,107	9,178	8,107	9,178	8,107	9,178	8,107
R-squared	0.125	0.255	0.204	0.330	0.150	0.260	0.093	0.221
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial financing round year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead VC FE	No	Yes	No	Yes	No	Yes	No	Yes