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WHAT IS A PATENT WORTH? EVIDENCE FROM THE U.S. PATENT “LOTTERY”

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ABSTRACT

We provide evidence on the value of patents to startups by leveraging the random assignment of applications to examiners with different propensities to grant patents. Using unique data on all first-time applications filed at the U.S. Patent Office since 2001, we find that startups that win the patent “lottery” by drawing lenient examiners have, on average, 55% higher employment growth and 80% higher sales growth five years later. Patent winners also pursue more, and higher quality, follow-on innovation. Winning a first patent boosts a startup’s subsequent growth and innovation by facilitating access to funding from VCs, banks, and public investors.

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Patents award temporary monopoly rights over inventions to their inventors. Patent rights can benefit their holders through several mechanisms: by deterring copycats, as defensive shields in litigation suits, as bargaining chips in licensing negotiations, and as signaling devices to attract investors and customers. (Williams 2017 surveys the literature on these benefits.)

Patents can also be costly for inventors. First and foremost, patentees are required by law to disclose their valuable know-how to the public. Patents also involve monetary costs. The average U.S. patent costs an estimated $20,000 to obtain and thousands more to keep from expiring before its term, which is 20 years from the application date (Lemley 2001). Merely obtaining a patent and keeping it alive does not guarantee benefits. Unlike traditional property rights, such as title to a piece of land, patents are awarded for technological inventions, the legal boundaries of which tend to be uncertain and costly to enforce (Lemley and Shapiro 2005). The U.S. Patent Office is blamed for granting too many patents with overlapping rights, thereby aggravating the uncertainty and diminishing the private value of patents (Heller and Eisenberg 1998, Becker and Posner 2013). Critics also point to absurd inventions that have been granted patents to argue that U.S. patents are awarded without scrutiny and thus are often worthless (Jaffe and Lerner 2004).[1]

The ongoing debate about the benefits and costs of patents to inventors begs the questions: what is a patent actually worth to its holder, and how does a patent benefit its holder? In this study, we measure the economic effects of winning a first patent on a startup's growth in employment and sales and its ability to continue to innovate. We then provide evidence that winning a first patent boosts a startup's growth and follow-on innovation by helping it raise funding from venture capitalists, banks, and public investors.

The value of a patent to its holder is the incremental return generated by the patent, beyond

[1] For example, U.S. Patent #4,344,424 for an anti-eating mouth cage, U.S. Patent #5,934,226 for a bird diaper, and U.S. Patent #6,293,874 for a buttock-kicking apparatus.

what could be earned if the invention were not granted a patent. Although measuring the private returns of patents is a fundamental step in assessing the overall economic effects of patents on society, endogeneity and data-related reasons have made the task challenging. Endogeneity concerns are rooted in unobserved quality differences across firms. Higher quality firms are both more likely to produce patentable innovations and to grow into successful companies, leading to a potentially spurious correlation between patent grants and performance.

To overcome this identification challenge, we exploit plausibly exogenous variation in the patent approval process through an instrumental-variables approach pioneered by Sampat and Williams (2015).[2] The validity of the approach rests on two features of the patent examination process at the U.S. Patent and Trademark Office (USPTO). First, the USPTO assigns applications in each technology field (or "art unit") to examiners based on a first-in-first-out system. Thus, after conditioning on art-unit-by-application-year fixed effects, which examiner an application is assigned to is random with respect to applicant or application quality (Lemley and Sampat 2012, Sampat and Williams 2015). Second, examiners vary in their propensity to approve applications: some are more lenient while others are stricter, leading Cockburn, Kortum, and Stern (2003) to observe that "there may be as many patent offices as patent examiners." The assignment of applications to examiners who randomly differ in their leniency imparts a lottery-like element to the patent review process: some applicants win patent rights while others do not, simply because the former were lucky enough to draw more lenient examiners.[3]

Data-related reasons that make the private value of patents challenging to measure are

[2] Sampat and Williams (2015) use the approach to measure the effect of gene patents on follow-on innovation in the human genome field.

[3] Gaule (2017) uses a similar instrument to study the effect of patents on the likelihood of going public or being acquired using a sample of 2,191 VC-backed startups. Galasso and Schankerman (2015) exploit variation in the leniency of judges at the U.S. Court of Appeals of the Federal Circuit to study the effect of patent invalidation on subsequent innovation in related technologies.

twofold. First, until recently, researchers have lacked access to data on patent applications that were denied and so have instead compared firms with and without patents. Of course, firms could be without patents for many reasons: in addition to perhaps having had their patent applications denied, they may have chosen other ways to protect their intellectual property (such as trade secrets) or they may have no inventions to protect in the first place. Comparing firms with and without patents thus cannot identify the private value of a patent, as distinct from the economic effects of alternative forms of IP protection or of the invention itself. We overcome this challenge thanks to special access to the USPTO's internal databases, which cover the population of granted and rejected applications.[4]

Second, data on privately held firms, which most startups are, are scarce in the U.S. We overcome this issue by assembling data on five types of firm-level outcomes from a variety of sources: (i) growth in sales and employment (from Dun & Bradstreet's National Establishment Time Series or NETS database); (ii) follow-on patenting and patent citations (from the USPTO's patent database); (iii) the pledging of patent applications as collateral to raise debt (from the USPTO's patent assignment database); (iv) venture funding (from VentureXpert); and (v) fundraising by startups through initial public offerings (IPOs) (from VentureXpert and Thomson-Reuters' SDC database).

Our sample covers all 34,215 first-time patent applications filed by U.S. startups at the USPTO since 2001 that received a final decision by December 31, 2013. Our estimates suggest that winning the patent lottery, by randomly drawing an examiner more likely to approve applications, increases the average startup's employment growth over the next five years by 54.5 percentage points. The effect on sales growth—a 79.5 percentage-point increase over five

[4] Access to the USPTO's internal databases was granted to one of the authors through the agency's Thomas Alva Edison Scholars program.

years—is even larger. For the average startup in our sample, these estimates imply that receiving a patent leads to 16 additional employees after five years, and $10.6 million in additional sales cumulated over five years after winning the patent lottery. A first patent grant also increases both the number of subsequent patents the firm is granted (by 49%) and their quality (with the average number of citations per subsequent patent increasing by 26%). Patent approvals appear to have a particularly strong effect on sales growth and follow-on innovation for startups in the IT sector—a result that contrasts with prior survey evidence that *large* IT firms consider patents to be among the least effective mechanisms to ensure the profitability of their R&D investments (Levin et al. 1987, Cohen, Nelson, and Walsh 2000).

How do patents convey such large and persistent benefits to startups? We find that a patent grant increases a startup's chances of securing funding from VCs by 47%, and of securing a loan by pledging the patent as collateral by 76%, within three years of the patent decision. A patent grant also more than doubles the odds of the startup raising funding from public investors through an IPO. The effect of patents on raising VC funding is strongest for startups that (i) had raised little or no VC funding before the USPTO's decision, (ii) were founded by inexperienced entrepreneurs, (iii) are located in areas where attracting investors' attention is harder, and (iv) operate in the IT sector. Collectively, these findings suggest that patent grants facilitate startups' access to external finance in contexts where information frictions, and thus contractual hazards, are high. A patent grant sets a startup on a growth path through funding that helps transform its ideas into products and services that generate jobs, revenues, and follow-on inventions.

Our study makes the following contributions. We provide the first causal estimates of the private returns of a patent to a startup.[5] Measuring patent value as the incremental growth in

[5] Schankerman (1998) provides the first, and only other, systematic evidence we are aware of on the private value of patents. His estimates are derived from patent renewal data for French patents granted between 1969 and 1982.

employment and sales and the increase in follow-on innovation activity, we show that patent rights confer economically large benefits on startups, over and above the value of the underlying invention. This finding informs the current debate on the relative costs and benefits of patents, particularly for startups that have to choose among various mechanisms (such as patents, trade secrets, or lead-time) to profit from their inventions. To the extent that startups are drivers of innovation and economic growth (Aghion and Howitt 1992, Acemoglu and Akcigit 2012), our findings highlight the important role of patents in encouraging startups to invest in innovation and thereby add to the micro-foundations of modern growth theory.

Second, we provide evidence that patents facilitate startup growth by enabling access to external funding,[6] particularly in settings associated with high information frictions. These findings are consistent with the view that patents, through their property rights function, can help startups attract funding by guaranteeing investors some level of legal recourse against expropriation (Johnson et al. 2002) or by mitigating information asymmetry problems that hamper contracting between inventors and investors (Arrow 1962).

Third, our identification strategy, based on quasi-random assignment of applications to patent examiners of varying leniency, highlights the profound impact the luck of the draw can have in determining startups' fortunes. The median examiner in our sample grants 61.5% of applications. After accounting for art-unit and year effects, we find that an applicant who is "lucky" enough to have drawn an examiner in the 75th percentile of leniency enjoys an 11.8 percentage-point higher probability of winning the patent lottery, and thus achieving the sales and employment growth associated with winning a patent, than an applicant who has drawn an examiner in the 25th percentile of lenience. We are agnostic about whether a system that results in such large variation

[6] Our evidence on this point echoes prior arguments made in correlation studies (Conti, Thursby, and Thursby 2013, Hsu and Ziedonis 2013), survey studies (Graham and Sichelman 2008), and law reviews (Long 2002).

in firms' fortunes is "good" or "bad," except to note that variation is to be expected in systems that depend on subjective human judgment for evaluations. For example, the peer-review process involves more or less lenient referees, funding bodies employ more or less stringent evaluators, the accused can draw a more or a less sympathetic jury, and so on.

Finally, we contribute to the ongoing debate about the welfare consequences of the patent system. Our evidence shows that securing a patent has economically large and positive effects on a startup's job creation, sales, and follow-on innovation. Patents being privately valuable to their holders is clearly not a sufficient condition for the patent system to improve welfare (we cannot ignore deadweight monopoly losses or negative externalities imposed on other inventors), but it *is* a necessary condition: patent rights are supposed to promote innovation through the promise of private value to inventors, and we establish that they do. The large economic magnitude of the private returns we document suggests that the negative externalities imposed by patents on others would have to be quite large for the patent system overall to stifle their beneficial effects.

1. Institutional setting and data

1.1 The patent examination process

The USPTO sends incoming applications to the appropriate "art unit" for review. Each art unit consists of a group of patent examiners who specialize in a narrowly defined technology field.[7] During our sample period, the USPTO employed some 13,000 examiners in over 900 art units. The median art unit has 13 examiners; the largest, more than 100.

Applications in each art unit's holding queue are assigned to one of the unit's examiners, who is responsible for assessing whether the claims in the application meet the legal thresholds of novelty, usefulness, and non-obviousness. Our interviews of examiners reveal that assignment

[7] To illustrate, the examiners in art unit 1641 are in charge of examining patent applications related to "peptide or protein sequence," examiners in art unit 2831 are in charge of applications related to "electrical connectors," examiners in art unit 3676 are in charge of applications related to "wells and earth boring," and so on.

within an art unit is based on a "first-in-first-out" principle: the application with the earliest filing date is assigned to the first available examiner. Thus, the matching of an application to an examiner within a given art unit is orthogonal to the quality of the application or of the applicant. This conditional random assignment is central to our identification strategy.

After receiving an assignment, the examiner evaluates the application and makes a preliminary ruling on its validity. This ruling, called the "first-action decision," is communicated to the applicant via an official letter, and it is from this letter that the applicant first learns the examiner's identity. On average, sample applications take 0.7 years to be assigned to an examiner, who then takes an additional year to make a first-action decision. The final accept/reject decision is on average made 1.5 years later (i.e., 3.2 years after the application date).[8]

1.2 Timing considerations

Firm outcomes could, in principle, be measured from three alternative starting points: the filing date, the first-action date, and the final-decision date. Our choice of starting point is guided by two considerations: how uncertainty about the patentability of a startup's invention evolves over time, and from what point onwards the startup's behavior could affect the timing of the USPTO's decision. Resolution of uncertainty is necessary (but not sufficient) for a patent application to affect firm outcomes. Endogenous timing of the approval decision may contaminate our causal estimates.

Because the first-action letter is the first communication about the merits of its application that an applicant receives from the USPTO, there is no resolution of uncertainty before the first-action date. This rules out using the filing date as the starting point. The timing of the final

[8] Strictly speaking, patent applications are never irrevocably rejected by the USPTO; they are abandoned by applicants following what technically are appealable rejections issued by examiners (Lemley and Sampat 2008). For expositional clarity, we follow Sampat and Williams (2015) and refer to abandoned applications (i.e., the complement of those applications that are approved) as "rejected."

decision is likely endogenous: the delay between first action and final decision is determined, in large part, by applicants' actions. This rules out using the final-decision date as the starting point. The appropriate choice of starting point in our setting is hence the first-action date. As Carley, Hegde, and Marco (2015) note, first-action letters contain a detailed summary of the merits the examiner sees in the application, so the first-action decision resolves a substantial amount of uncertainty about the application's ultimate fate, as required.

1.3 Patent data and sample selection

Establishing the private value of a patent requires data on both approved and rejected patent applications. Until recently, publicly available datasets, such as those maintained by the NBER or Harvard Business School, only covered approved patents (Lerner and Seru 2015), and even now, public disclosure of rejected applications is incomplete.[9] Instead, we obtain patent data directly from the USPTO's internal databases, which contain a complete record of both approved and rejected patent applications going back to 1976.[10] For applications filed since 2001, when the American Inventors Protection Act came into force, we know the applicant's identity, regardless of the USPTO's final decision. For earlier applications, the applicant's name is not recorded for rejected applications, though all other relevant aspects of the application are available. Our sample hence starts in 2001 (though we use the earlier data in the coding of our instrument).

Our goal is to identify the real effects of early patent grants on the success of startups. The USPTO does not tag whether an applicant is a startup, so to code startups we proceed as follows. First, we restrict the sample to incorporated applicants based in the U.S. Second, we screen out not-for-profit entities such as charities, universities, or government research labs. Third, using

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[9] The USPTO's Patent Application Information Retrieval (PAIR) system, which is publicly accessible, provides no data on applications that are abandoned prior to public disclosure (around 15% of all unsuccessful applications) and no data on rejected applications filed before 2001.
[10] Carley, Hegde, and Marco (2015) provide a comprehensive description of these data.

data from a variety of sources, we manually screen out applicants that are or have been listed on a stock market or are or have been a subsidiary of another firm (whether listed or privately held, and whether domestic or foreign), as of the time of the application.[11] These three steps leave a set of patent applications filed by stand-alone for-profit U.S. firms. Not all of these are startups. To narrow in on applicants likely to be startups, we apply two further filters. First, we focus on filers that qualify for reduced fees at the USPTO by virtue of satisfying the criteria defining a "small business entity" under Section 3 of the Small Business Act. Second, we focus on first-time patent applicants. To ensure that we capture each filer's first application, we screen for firms that have filed at least one application on or after January 1, 2001 and no applications in the previous 25 years. This step requires standardizing applicant names and checking for name changes. Since many patents are subsequently reassigned, this step also requires identifying each patent's original applicant.

Our analysis focuses on how the outcome of a firm's first patent application affects its ability to grow, continue innovating, and raise funding. To ensure we have sufficient time to study the long-term effects of patent grants, we require firms to receive a first-action decision on their first application by the end of 2009 and a final decision by the end of 2013.[12]

Our final sample consists of 34,215 first-time patent applicants (called startups from here on). Of these, 31.6% operate in the electronics, computers, and communications industries (henceforth, IT); 17.8% are active in the pharmaceutical and biochemical sectors (henceforth, biochemistry); and the remaining 50.6% operate in "other" industries including transportation, construction, mechanical engineering, and manufacturing. Just under two-thirds (64.5%) of first-

[11] We also screen out a small number of applicants that are acquired between filing and first-action, on the ground that we cannot disentangle the effects of the patent decision from the effects of the acquisition.
[12] The firm's "first application" is the first application the USPTO rules on. (In 8% of cases, the first ruling a firm receives is not for its first-ever application but for a later application.)

time patent applications in our sample are successful over our sample period.

1.4 Data on firm outcomes

Being privately held, the startups in our sample are not covered in standard financial databases such as Compustat, so we assemble data on firm outcomes from five other sources.

- *Dun and Bradstreet's National Establishment Time Series (NETS) database.* NETS is similar to the U.S. Census Bureau's Longitudinal Business Database (LBD) in that it aims to cover the universe of business establishments in the U.S., but offers the advantage of not requiring special permission for access. Matching patent assignees to NETS (and to other databases) requires matching on firm names and locations. We use a "fuzzy" matching algorithm (with each potential match manually verified), supplemented with information on name changes and location moves obtained from Capital IQ and the USPTO's firm name and address register. We are able to match 80.01% of sample startups to firms in NETS – a higher match rate than that achieved by studies using the Census Bureau's data.[13]
- *The USPTO's patent database*. This database allows us to track each sample company's subsequent patent applications as well as citations to each sample company's patents.
- *The USPTO's patent assignment database.* This dataset records transactions between patent owners and entities to whom owners transfer patent rights. We use it to track instances of startups pledging their patents or patent applications as collateral for loans.
- *VentureXpert*. This database tracks VC funding events. We use it to identify which of the 34,215 sample firms go on to raise VC funding at some point after the first-action date.
- *The Thomson Reuter's Securities Data Company (SDC) database.* We use data from SDC

[13] Balasubramanian and Sivadasan (2001) are able to match 63.7% of patent assignees to firm names in the Census Bureau's Business Register, often considered the "gold standard" for its coverage of the entire population of U.S. business establishments with paid employees filing taxes with the Internal Revenue Service. Kerr and Fu (2008) report a match rate of about 70%.

(and VentureXpert) to identify firms that raise capital from public investors via an IPO.

Table 1 compares startups whose first patent application is approved or rejected. Panel A shows that at the time of application, the median startup is 2 years old, has 8 employees, and $800,000 in sales. Unsuccessful applicants have lower pre-filing growth in employment and sales than successful ones, consistent with our claim that endogeneity concerns are rife in patent application data. After the USPTO's decision, successful applicants grow employment and sales at substantially higher rates than unsuccessful applicants (Panel B), produce more and higher-quality follow-on inventions (Panel C), are more likely to raise funding from VCs or the IPO market (Panel D), and are more likely to raise debt by pledging their patent applications as collateral, even when not funded by VCs (Panel E). These simple correlations suggest that startups whose first patent application is approved have superior outcomes.

2. The real effects of patent grants

2.1 Empirical setup and identification challenge

In order to identify how the approval of a startup's first patent application affects subsequent outcomes at the firm, we estimate regressions of the following general form:

$$Firm\ outcome_{itja} = \beta First\ patent\ application\ approved_{itja} + \Phi X_{itja} + \varepsilon_{itja}\,, \tag{1}$$

where i indexes startups, t application years, j examiners, and a art units. In this section, we model three outcomes: (i) growth in the startup's employment, (ii) growth in its sales, and (iii) subsequent innovative activity (as measured by the quantity and quality of its later patents).

Broadly speaking, there are two concerns in estimating equation (1). The first concern is that OLS estimates of β are likely biased, as they capture both the average treatment effect of patent grants on firm outcomes and the bias induced by unobserved differences in firm quality. We expect an upward bias to the extent that firms of higher unobserved quality at the time of filing are both more likely to have produced a “novel, useful, and non-obvious” invention worthy of a patent and to perform better going forward, regardless of the patent. The ideal experiment to identify the causal contribution of a patent to a firm’s success would randomize patent approvals, thus ensuring that successful applicants do not differ systematically from unsuccessful ones ex ante. As argued earlier, the lottery-like features of the USPTO’s review process allow us to get close to this ideal experiment.

The second concern is the potential for unobserved demand or technology shocks to affect both patent applications and firm outcomes. For example, a breakthrough in a technology field may lead to an increase in both the number of patentable inventions and the growth rate of firms operating in that field. To deal with this confound, we include a full set of 2,779 art-unit-by-application-year fixed effects.[14] Since art units are quite narrowly defined (the art units in our sample span 495 different technology fields), including these fixed effects allows us to hold demand and technological conditions constant at a very fine level and so ensures that our findings are not confounded by unobserved industry-level shocks.

Following Lerner and Seru (2015), we also control for geographical differences in outcomes by including firm-headquarter-state fixed effects. Standard errors are clustered at the art unit level to allow for arbitrary correlation of the errors within each art unit.

2.2 Identification strategy: Patent examiners’ approval rates as IV

To identify the causal effect of patent grants on firm outcomes, we leverage the quasi-random assignment of applications to examiners within art units and exogenous variation in examiners’ propensity to approve patents. Specifically, we use the examiner’s past approval rate as an instrument for whether a firm’s first application is approved and estimate equation (1) using two-stage least squares (2SLS). We calculate the approval rate of examiner j belonging to

[14] Including art-unit-by-year fixed effects subsumes art-unit (i.e., industry or technology field) fixed effects.

art unit *a* assigned to review firm *i*'s first patent application submitted at time *t* as follows:

$$Examiner\ approval\ rate_{ijta} = \frac{n_{\text{granted}_{jta}}}{n_{\text{reviewed}_{jta}}}, \tag{2}$$

where $n_{\text{reviewed}_{jta}}$ and $n_{\text{granted}_{jta}}$ are the numbers of patents examiner *j* has reviewed and granted, respectively, prior to date *t*.[15] Prior work uses a somewhat noisier instrument, sometimes called the "leave-one-out" estimator and defined using an examiner's future decisions as well as her past ones. Our results are little different using this alternative way of coding up the instrument, reflecting the fact that an examiner's leniency is quite persistent over time.

2.2.1 Instrument relevance

Inclusion of art-unit-by-application-year fixed effects in our regressions ensures that we identify off quasi-random examiner assignments within an art unit.[16] For our IV to predict whether a patent application is approved, there needs to be sufficient variation in leniency among the various examiners active in an art unit in a given year. Previous research suggests that the patent review process leaves enough discretion in the hands of examiners for this to be the case (Lichtman 2004, Sampat and Lemley 2010, Lemley and Sampat 2012, Sampat and Williams 2015). Our data confirm the existence of meaningful variation in leniency, even within art unit and year. Figure 1 shows considerable variation in the distribution of examiner approval rates, defined as in equation (2) and after stripping out art-unit-by-year fixed effects. The interquartile range is 17.6 percentage points.[17]

Table 2 reports the first stage of our 2SLS models, that is, the results of regressing patent

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[15] Neither the numerator nor the denominator in (2) includes patent application *i*, as it has not been reviewed prior to date *t*. Also, to ensure that we measure approval rates accurately, we exclude firms whose first patent application is assigned to an examiner with fewer than 10 prior reviews. All results are robust to using alternative cutoffs.
[16] Applications belonging to art-unit-by-year singletons do not contribute to identification and are excluded.
[17] Our approval rates are based on a large number of reviewed applications: the average (median) examiner has reviewed 770 (409) applications by the time we measure her approval rate (the 10th percentile is 51). This suggests that the variation shown in Figure 1 reflects persistent inherent differences in examiners' propensity to approve applications and not small-sample random differences in the quality distribution of the applications they review.

approval on the instrument using the following linear-probability model:

$$\textit{First patent application approved}_{itja} = \theta \textit{Examiner approval rate}_{itja} + \Pi X_{itja} + u_{itja}. \tag{3}$$

As required for identification, the instrument is a strong predictor of whether an application is approved. The coefficient estimate in column 1 implies that each percentage-point increase in an examiner's approval rate leads to a 0.67 percentage-point increase in the probability that a patent she reviews is approved (p<0.001). Thus, moving from an examiner in the 25th percentile to one in the 75th percentile would increase the approval probability by 11.8 percentage points (=0.67 × 17.6), all else equal. Controlling for the startup's size using the log number of employees (column 2) or log sales (column 3) has next to no bearing on the point estimate.

The effect of an examiner's past approval rate on the probability of receiving a patent is not only large economically, it is also strong statistically, with F statistics exceeding the critical value of 10. This ensures that our results are not subject to weak-instrument bias.

2.2.2 Exclusion restriction

In order to satisfy the exclusion restriction, the IV must only affect a firm's subsequent outcomes through its effect on the likelihood that the firm's application is approved. As Angrist and Pischke (2009, p. 117) note, for the exclusion restriction to be satisfied, the instrument must be "as good as randomly assigned conditional on covariates." Since applications are assigned to an art unit's examiners *randomly* with respect to quality, the IV has a plausible claim to satisfying the exclusion restriction once we include art-unit-by-application-year fixed effects.

We examine the plausibility that the exclusion restriction is satisfied by regressing the instrument on observable characteristics of the firm (the prior level of and growth in the firm's employment and sales; the number of prior funding rounds received from VCs) and of the application (the number of and length of claims in the patent application), all measured as of the filing date. As Table 3 shows, none of these variables predicts the leniency of the examiner assigned to review the application. This finding is consistent with the quasi-random assignment of applications to examiners and confirms the institutional narrative outlined in Section 1.1.

2.3 Empirical results

2.3.1 Firm survival, employment growth, and sales growth

Table 4 shows the effect of a patent grant on a startup's probability of survival over the next few years. We code a firm as dead using data from NETS which we cross-check with information from Capital IQ.[18] Panel A uses the full sample of NETS-matched startups, covering 80% of the startups filing a first patent application with the USPTO over our sample period. The OLS estimates, which ignore the endogeneity of patent grants, suggest that successful applicants are 4.6%, 6.9%, and 8% more likely to survive one year, three years, and five years after the first-action decision than are startups denied a patent (see columns 1, 3, and 5).[19] The 2SLS estimates are around one percentage point smaller, consistent with the predicted upward bias in a naïve OLS regression: startups capable of producing great inventions are likely to survive regardless of whether they secure a patent right, which inflates the OLS estimates. Economically, the 2SLS estimates are quite large. Over a five-year horizon, for example, startups are 6.7 percentage points more likely to survive as a result of receiving a patent grant (the unconditional survival probability is 76.3%).

For 21.9% of the NETS-matched firms, NETS reports employment and/or sales of zero for the year of the first-action decision. Table 4, Panel B restricts the NETS-matched sample to those startups for which NETS reports non-zero sales and employment for the year of the first-action

[18] A firm is coded as dead if its NETS data end before 2011, our final year of NETS coverage. We cross-check this coding with Capital IQ data, which appear in text form (e.g., "On April 22, 2009, Technologies to Be, Inc. filed a voluntary petition for liquidation under Chapter 7 in the U.S. Bankruptcy Court for the Middle District of Florida.").
[19] We estimate linear-probability (least-squares) rather than duration models, because duration models cannot accommodate instrumental-variable techniques.

decision. The restriction removes "infant firms", i.e., those that have yet to employ anyone besides the founder(s) and have yet to earn revenue at the time of the USPTO's first-action decision. Infant firm mortality is clearly especially high: removing infant firms increases the five-year unconditional survival probability from 76.3% to 79.7%.

While the OLS estimates remain large and significantly positive in the restricted sample, the 2SLS estimates are very close to zero. Taken together, the estimates in Panels A and B suggest that a patent grant has a large causal effect on the survival of infant firms, but a more muted effect for the slightly more mature startups in the restricted sample.[20]

We next turn to employment and sales growth. Since we measure growth from first-action, we use the restricted sample that removes infant firms with zero employees and zero sales at first-action. Table 5, Panel A reports results for employment growth.[21] The employment effects of quasi-randomly being granted a patent take some time to get going. After one year, a patent grant raises a startup's employment growth rate by a marginally significant 6.1 percentage points (p=0.066), all else equal.[22] After two years, the employment growth rates of successful and unsuccessful patent applicants differ by 22.8 percentage points, rising to 33.3, 48.9, and 54.5 percentage points after three, four, and five years, respectively (all significant at p<0.001). Panel A of Figure 2 visualizes this steady increase over time in the differential employment growth rates of successful and unsuccessful patent applicants.

To gauge the economic significance, consider the median startup, which has eight employees at first-action. All else equal, patent approval results in the startup having 4.4 (= 8 × 0.545) more

[20] Consistent with this interpretation of the evidence in Table 4, we find a 12.5 percentage-point increase in the five-year survival rate following a patent grant when restricting the sample to infant firms only (not tabulated).
[21] To streamline the discussion, we report only 2SLS estimates from here on. The corresponding OLS estimates can be found in the Internet Appendix. We discuss differences between the 2SLS and OLS estimates in Section 2.4.
[22] In addition to including art-unit-by-year and headquarter-state fixed effects, we also control for the log number of employees that the firm has at first-action (not shown). As expected, larger firms tend to grow more slowly.

employees five years later than if the application had been rejected as a result of being assigned to a stricter examiner. Summed over five years, a patent grant supports an additional 13.2 man-years of employment at the median startup. The equivalent numbers for the average successful applicant are 16.1 more employees by year 5 and 49 additional man-years of employment.

Table 5, Panel B and Figure 2, Panel B show a similar pattern for sales growth. On average, successful applicants grow their sales by a cumulative 9.6, 27.6, 51.2, 79.6, and 79.5 percentage points more than do their unsuccessful counterparts over the one through five years following patent approval (p<0.01 or better). For the median startup, which in our sample has sales of $800,000 at first-action, patent approval leads to sales being $636,000 (=$800,000 × 0.795) higher in year 5 than if the application had been rejected. Summed over the five years, a patent grant allows the median startup to make an additional $2 million in sales, all else equal. The equivalent numbers for the average successful applicant are $3.4 million higher sales by year 5 and a cumulative $10.6 million more in sales over the five years.

A causal interpretation of the estimates in Table 5 requires, besides relevance and a plausible exclusion restriction, that our leniency instrument is uncorrelated with omitted variables that affect firm outcomes. A possible violation of this condition could arise if lenient examiners were also faster and review speed had an independent effect on outcomes. If so, our instrument would confound the benefits of patent approval with the benefits of speedy resolution of uncertainty about the application's fate. Table IA.3 in the Internet Appendix investigates this concern by purging the leniency instrument of the effects of review speed. This yields point estimates that are well within the 95% confidence intervals around the Table 5 2SLS coefficients.

2.3.2 Subsequent innovation

We next model how the outcome of a startup's first patent application affects its ability to continue innovating. We capture a startup's subsequent innovation using the log number of patent applications it files after the first-action decision on the first application; the log number of such subsequent applications that are approved; the approval rate of subsequent applications; the log number of citations received by all subsequent applications combined; and the log average number of citations per subsequent approved patent. (See Table 1 for descriptive statistics.) Since these models do not require NETS data, we use the full sample of startups. As before, we include art-unit-by-year and headquarter-state fixed effects.

Table 6 reports the 2SLS results. Columns 1 and 2 show that approval of its first patent application leads to a 56.5% ($=e^{0.448}-1$) increase in the number of patents the startup subsequently applies for and a 42.3% increase in the number of patents it subsequently obtains ($p<0.001$ in each case). This may not be surprising; after all, Table 5 shows that successful applicants enjoy faster growth, and that faster growth may, directly or indirectly, support investment in R&D. Column 3 shows that it is not just the volume of subsequent patent applications and grants that increases: success in the first application leads to a 24.4 percentage-point increase in the approval *rate* of a startup's subsequent applications ($p<0.001$), suggesting that later applications may be of higher quality. Consistent with this interpretation, we find that a first patent grant boosts the number of citations received by the patents the firm is subsequently granted, both overall (up by 60.3% in column 4) and per patent (up by 33% in column 5).

We emphasize that these IV estimates are not contaminated by unobserved quality differences between successful and unsuccessful first-time applicants: by virtue of the quasi-random nature of the decision on a startup's first patent application, the observed increases in both the quantity and quality of its subsequent inventions can be interpreted as being causal.

2.3.3 Variation across industries

Previous studies report large variation across industries in the effectiveness of patents and hence in the intensity of patenting (e.g., Schankerman 1998, Galasso and Schankerman 2015). Two influential surveys report that large U.S. companies in the IT sector consider patents the least effective mechanism to protect their R&D investments (Levin et al. 1987, Cohen, Nelson, and Walsh 2000). Instead, respondents rely on trade secrets, lead time, and design and manufacturing capabilities to profit from their innovations. IT products also tend to be complex and involve multiple patentable elements, making it difficult for any single patent to effectively protect a product (Cohen, Nelson and Walsh 2000).

We revisit these survey findings using our data on startups. Table 7 presents subsample analyses for three broad industry groupings: IT, biochemistry, and "other" industries. Two observations stand out. First, the estimated effects of patent approval on employment growth, sales growth, and subsequent innovation are quite large across all three industry groupings.[23] Second, the positive effects of patent approval on sales growth and follow-on innovation appear especially strong in the IT sector, contrary to the survey evidence from established IT firms. A plausible explanation for the difference in importance is that IT startups use patents as bargaining chips in licensing negotiations or as defensive shields that preserve their independence to operate in product markets (Hall and Ziedonis 2001).

2.4 External validity

We report the OLS counterparts to our 2SLS estimates of the effects of patent grants on employment and sales growth and on subsequent innovation in the Internet Appendix. A comparison of Tables 5 and 6 to Tables IA.1 and IA.2 reveals that the OLS estimates are smaller

[23] Some of the coefficients are estimated with considerable noise, especially in biochemistry. This lack of precision could be due to either the relatively smaller sample of biochemical startups, or, as noted by Schankerman (1998), the relatively larger variation in patent value in the biochemical sector.

than the 2SLS estimates. To understand why this is the case, even though we expect OLS to be upwardly biased, it is necessary to be clear about what our instrument identifies.

When treatment affects different firms differently, an instrument identifies a local average treatment effect (LATE) (Angrist and Pischke 2009). This means, in our context, that our 2SLS estimates identify the effect of patent grants on firm outcomes only for the subpopulation of startups whose first patent application is affected by their examiner's leniency. Applications that are obviously bad will be rejected even by lenient examiners; they are hence "never-takers." Applications that are obviously great will be approved even by harsh examiners; they are hence "always-takers." The compliant subpopulation that is responsive to our instrument is thus the group of applications of middling quality.[24] Accordingly, the leniency instrument identifies the value of patent rights on middling inventions. Given that our estimates are local average treatment effects, they should not be generalized to the average startup.

It is likely that our LATE estimates overstate the value of patents for the average startup. This is because we expect smaller treatment effects among never-takers and among always-takers than among the compliant subpopulation of startups with middling inventions. Startups with clearly bad inventions are unlikely to prosper even if they were somehow granted a patent; startups with clearly great inventions are likely to prosper regardless of whether they receive a patent. Average treatment effects (or ATE) are hence likely smaller than our LATE estimates.

This discussion helps explain why our 2SLS estimates in Tables 5 and 6 are larger than our OLS estimates. By definition, OLS estimates equal ATE plus the selection bias. As argued in Section 2.1, we expect a positive selection bias: applicants of higher unobserved quality are both more likely to have produced a "novel, useful, and non-obvious" invention worthy of a patent

[24] There is no reason to expect the presence of "defiers" in our setting: no startup should have become *less* likely to receive a patent as a result of being randomly assigned to a more lenient examiner. The monotonicity assumption that is necessary for our IV estimates to be LATE is hence likely satisfied in our setting.

and to perform better going forward, regardless of the patent. If ATE<LATE, 2SLS will be greater than OLS if the selection bias is indeed positive, as conjectured.

The 2SLS estimates in Table 4, Panel B suggest that the local average treatment effect of a patent grant on survival is effectively zero among compliers once we exclude infant firms, while the OLS estimates are large and positive. It is reasonable to expect that the treatment effect is zero among always-takers: startups with great inventions survive with or without a patent. If the selection bias is indeed positive, as our results suggest, it follows that the treatment effect among never-takers is also zero or at best mildly positive: startups with bad inventions either die anyway or may limp along for a short while if, against the odds, they receive a patent.

3. What drives the real effects of patents?

Our findings so far establish that winning the patent lottery helps startups grow and innovate. As Figure 2 shows, the gains in employment and sales growth are not instantaneous. The same is true for follow-on innovation: the average sample startup submits its next patent application 1.5 years after first-action on its first application. These time lags suggest that the mechanism linking patent approval to positive firm-level outcomes is one that requires time to take effect. A prime candidate mechanism is access to external capital. Transforming a startup's patented ideas into new products and processes that eventually support jobs and yield revenues typically requires investments in operations and marketing, and these investments in turn require upfront funding.

In this section, we investigate whether patents facilitate startups' access to three sources of capital: VCs, public investors in the IPO market, and banks and specialized lenders. A significant body of research discusses the importance of these sources for startups (Gorman and Sahlman 1989, Hellmann and Puri 2000, Gompers and Lerner 2001, Hochberg, Ljungqvist, and Lu 2007, Hochberg, Serrano, and Ziedonis 2014, Bernstein, Giroud, and Townsend 2015, and Mann

2016). However, establishing a causal link between a patent grant and access to funding is subject to the same identification challenges researchers face when measuring the effect of patents on startup growth and follow-on innovation. A key contribution of our study is to provide a way to overcome these challenges.

3.1 Empirical strategy

To identify how patents affect access to capital, we estimate linear-probability models of the following general form:

$$\textit{Capital access}_{itj\alpha} = \beta \textit{First patent application approved}_{itj\alpha} + \Phi X_{itj\alpha} + \varepsilon_{itj\alpha}\,, \qquad (4)$$

separately for each of our three capital sources, (i) VC funding, (ii) an initial public offering of equity, or (iii) a loan obtained by pledging a patent or patent application as collateral. We again use the examiner's prior approval rate to instrument for the likelihood that the application is approved and report OLS results in the Internet Appendix for completeness.

As before, we include art-unit-by-year and headquarter-state fixed effects in all regressions. In addition, we control for the log number of prior VC rounds the firm has raised in regressions that estimate the probability of receiving funding from a VC or through an IPO.[25] Pledging a patent application as collateral before the first-action date is virtually unheard of, and none of the sample startups had filed for an IPO before first-action.

3.2 Venture capital funding

Table 8 reports the results for VC funding. Approval of a firm's first patent application causes a startup's chances of obtaining VC funding in the following year to increase by 1.2 percentage points (p=0.048 in column 1). Extending the window increases the effect to 2.1, 2.3,

[25] Of the 34,215 startups in our sample, 92.5% have raised no VC funding before the first-action date. For these, equation (4) identifies the effect of patent approval on their ability to raise their first VC round. For firms with at least one prior VC round, equation (4) identifies the effect on their ability to raise a follow-on round. Specifically, 2.4% of our sample firms have raised one VC round before their first-action; 1.9% have raised two prior VC rounds; 1.4% have raised three prior rounds; and the remaining 1.8% have raised four or more prior rounds.

2.7, and 2.8 percentage points over two, three, four, and five years, respectively ($p<0.01$ in columns 2 to 5). These effects are economically large. To illustrate, the 2.3 percentage-point increase in column 3 represents a 53% increase relative to the 4.3% unconditional probability of a sample firm raising VC funding in the three years following the first-action decision.

These estimates point to a steep change in a startup's ability to raise VC funding around one to two years after the first-action date. The raw data support the inference that startups that win the patent lottery tend to raise VC funding quite quickly: the median successful applicant that raises VC funding during our five-year window does so a mere 10 months after the first-action date. Figure 3 illustrates the extent to which fundraising events are bunched shortly after first-action. This timing fits our conjectured mechanism well: startups use patent grants to first raise external capital; they then use the capital to fund investments in operations and marketing to turn their patented ideas into new products and processes which subsequently yield increases in sales.

3.3 Fundraising in the IPO market

While the IPO market is sometimes viewed narrowly as a venue in which venture capitalists can "exit" their investments in startups, its dominant function in the U.S. has in fact traditionally been to help firms raise relatively large amounts of new capital at a relatively low cost.[26] We thus investigate the extent to which a patent grant facilitates a firm's access to the IPO market. 228 (or 0.67%) of the 34,215 startups in the sample go public between their first-action date and the end of 2014, with the median startup taking 4.6 years to do so.[27]

Column 6 of Table 8 reports the results. The point estimate suggests that a successful patent

[26] Ljungqvist and Wilhelm (2003) report that 85.6% of VC-backed firms that went public between 1996 and 2000 saw the VCs sell no shares at all in the IPO. Including non-VC-backed firms, 92.5% of shares sold to IPO investors were "primary," representing fundraising from IPO investors, rather than "secondary" sales by existing investors.

[27] Firms that remain private by the end of 2014 may yet go public in the future. The traditional way to deal with right-censoring of this kind is to estimate a duration model. However, as mentioned earlier, duration models cannot accommodate instrumental-variable techniques, so we estimate a simple linear-probability model instead. The model includes art-unit-by-application-year fixed effects, which control for the fact that startups that applied for their first patent in the later years of our sample have had less time to go public than earlier applicants.

application boosts a startup's chances of raising capital through an IPO by one percentage point (p=0.014), a 149% increase over the unconditional sample probability of 0.67%.

3.4 Loans from banks and specialized lenders

As Hochberg, Serrano, and Ziedonis (2014) document, firms frequently pledge their patent rights as collateral for loans obtained from banks or specialized patent lenders. What is less well known is that firms can also pledge pending patent *applications* (after first-action but before final approval) and even *rejected* patent applications. Typically, firms pledge not single patent rights (or applications) but a bundle of their intangible assets, which can include either accepted or rejected applications alongside trademarks, copyrights, etc. A rejected patent application may not have passed the standards of patentability but is still considered prior art and may serve as a description of the holder's intellectual assets, particularly when offered as part of a bundle.

This observation is important, because it allows us to estimate whether startups have an easier time obtaining a collateralized patent loan if their patent application was approved rather than denied: even those with denied patent applications can, in principle, obtain such a loan.

Table 9, Panel A shows that patent grants increase the probability of securing a loan from a bank or specialized patent lender by 8.6 percentage points (p<0.001), a 119% increase over the unconditional sample probability of 7.2%. We find similar results in Panel B, which leaves out sample startups that receive VC funding. For this restricted sample of startups, a successful patent application increases the probability of securing a collateralized patent loan by 5.9 percentage points (p<0.001), a 109% increase over the unconditional probability of 5.4%.

4. How do patents facilitate access to capital?

Why do suppliers of external funding favor startups that have secured patents? Prior work suggests several factors may be at play. First, to the extent that patents are monopoly rights, the market power they confer may increase profits. Second, patents can facilitate transactions such as licensing agreements and alleviate investors' concerns regarding the firm's ability to monetize an invention (Arora, Fosfuri, and Gambardella 2001). Third, entrepreneurs with patents may be more willing to share the details of their invention with investors without fear of expropriation (Arrow 1962, Anton and Yao 1994, Biais and Perotti 2008). Fourth, the patent application itself can help to credibly communicate the technical details of the invention (Hegde and Luo 2016). Finally, since patents are certified to have cleared the USPTO's requirements of novelty, non-obviousness, and utility, they can serve as a quality signal to investors in a market characterized by information asymmetries that are often severe (Long 2002, Hsu and Ziedonis 2013).

In this section, we explore whether financiers respond to patents differently under different circumstances, which in turn may reveal the reasons behind their preference for startups that have been granted a patent. Our exploration of heterogeneous effects is guided by the idea that patent rights facilitate financial contracting by reducing information frictions between entrepreneurs and suppliers of external capital. If this is indeed the case, we expect the marginal benefit of a patent right to be greatest for startups facing the greatest frictions.

While it is difficult to measure the extent of information-related frictions, we conjecture that frictions are likely greatest among startups (i) trying to raise a first (or at least early) VC round, (ii) led by inexperienced founders, (iii) located in states with a large startup population, where attracting investors' attention is more challenging, and (iv) operating in industries in which the quality of ideas and of founders is difficult to evaluate and where patents are most effective at mitigating expropriation risk.

To keep the amount of hand-collection of the required data manageable, we focus on estimating heterogeneous effects in the context of a startup's ability to raise VC funding (rather than an IPO or a collateralized patent loan). To conserve space, we report results for a three-year window following first-action; our conclusions are robust to using alternative time windows.

4.1 Variation in funding round

Table 10 splits startups by the number of VC rounds raised before first-action. If early-stage startups face the greatest frictions, we expect patent approval to be most beneficial to them. The data support this prediction: startups without prior VC funding, or those raising a second round, experience a large boost from randomly being granted a patent; those raising higher-numbered rounds do not. Specifically, approval increases the likelihood of subsequently raising a first VC round by 1.3 percentage points (p=0.044 in column 1), more than doubling the unconditional probability of 1.2%. Among those that have already raised a first VC round, patent approval increases the chances of raising a second round by as much as 46.7 percentage points (p=0.003 in column 2), compared to the conditional probability of 39.6%. Beyond the second round, the effect of patent approval on access to VC funding all but disappears. The effect is insignificant in column 3, which focuses on startups with two prior VC rounds by the time of first-action (p=0.354), and in column 4, which pools all firms that have raised three or more VC rounds before their first application is decided (p=0.307).[28]

These patterns are what we would expect if patents alleviate information frictions by serving as easy-to-acquire signals of startup quality or by allowing early-stage entrepreneurs to credibly communicate their ideas to investors without fear of expropriation. Indeed, by the time a startup is trying to raise a third (or subsequent) funding round, VC investors—who typically sit on the firm's board and monitor it closely—already have a wealth of information about the firm. As a result, the incremental information content of a patent grant should be much smaller then than

[28] These insignificant effects do not appear to be the result of our instrument being weak in these relatively small subsamples: in both columns 3 and 4, the first-stage F statistic is over 10, and the standard errors of the patent approval effect are similar to the standard error of column 2's highly significant patent approval effect.

when VCs evaluate a firm for the first or second time.

4.2 Variation in prior entrepreneurial experience

An alternative proxy for the uncertainty surrounding a startup is the experience of its founders: all else equal, startups founded by experienced entrepreneurs are less risky and thus easier for investors to finance (Hsu and Ziedonis 2013). To code prior founder experience, we use hand-collected data from Capital IQ for startups that raise VC funding at some point in their lives. The sample is thus restricted to firms with at least one prior VC round before first-action. Of these firms, 57% have a founding team with at least one experienced founder, while the rest are run by teams made up exclusively of first-time entrepreneurs.

Column 5 of Table 10 allows the effect of a patent grant on the likelihood of raising VC funding to vary with prior founder experience. This confirms that patent approval facilitates access to capital the most among inexperienced founders. Patent approval increases a startup's likelihood of raising VC funding in the next three years by nearly 33 percentage points among inexperienced founders (p=0.047); for experienced founder teams, the effect is virtually zero (p=0.989).

4.3 Variation in startup agglomeration across U.S. states

Two facts combine to suggest that the value of a patent grant in obtaining VC funding varies geographically. First, VCs have a well-known preference for investing locally (Lerner 1995, Sorenson and Stuart 2001). Second, startup activity varies considerably across the country, with hotspots like California, Massachusetts, and New York being particularly popular places to start an innovative business. Combined, this implies that VCs operating in areas with larger startup populations have more potential investments to choose among than those operating in areas with fewer startups. To deal with the larger number of investments to screen, VCs may rely more on easily observable signals such as patent grants in areas with high startup activity.

Column 6 of Table 10 allows the effect of a patent grant on the likelihood of raising VC funding to differ between startups headquartered in a state with an above- or below-median startup agglomeration in the year of its first patent application.[29] This yields results consistent with the idea that patents play a key role in helping startups located in hubs of innovative activity to stand out from the crowd. Startups that randomly win the patent lottery are 2.7 percentage points more likely to raise VC funding in a startup hub like California, Massachusetts, or New York than those located in a state with low startup activity (p=0.012). This differential is sizeable compared to the unconditional probability of 6.4%.

4.4 Variation across industries

IT and biochemistry have, for a long time, been the main focus of VCs in the U.S. (Gompers and Lerner 2001, Graham et al. 2009). There are reasons to expect the information value of a patent to be different in these two industries (Cohen, Nelson, and Walsh 2000). IT startups tend to be founded by younger entrepreneurs (Ewens, Nanda, and Rhodes-Kropf 2015) and their inventions often face substantial demand uncertainty and imitation risk. Thus, a favorable decision on an IT startup's first patent application can provide a particularly valuable early signal about the quality of its technology and its founders, while also allowing the founders to more freely discuss their idea with VCs without the fear of expropriation. Evidence from interviews at semiconductor firms suggests that the primary function of a patent in that industry is "securing capital from private investors [for firms] in the startup phase" (Hall and Ziedonis 2001).[30]

Biochemistry startups, in contrast, tend to be founded by experienced scientists, the quality of

[29] We measure startup agglomeration using the number of first-time patent applicants in the state. We obtain similar results if we simply code California, Massachusetts, and New York (which have consistently been the three states with the most startup activity according to the 2016 NVCA Yearbook) as states with high startup agglomeration.
[30] Hochberg, Serrano, and Ziedonis (2014) and Mann (2016) document the existence of a well-developed secondary market for IT patents, which alleviates investors' downside risk if the firm ends up being unviable.

whose research can be evaluated using a variety of sources such as academic publications or National Institutes of Health grants (Li and Agha 2015). Biochemistry startups face relatively little demand uncertainty or risk of imitation, with the greatest uncertainty instead coming from the probability of technical success and the regulatory process (DiMasi, Hansen, and Grabowski 2003). As a result, early patent decisions reveal relatively little information about the quality of the founders or the potential commercial success of their inventions.

Column 7 of Table 10 shows that the approval of an IT firm's first patent increases its probability of raising VC funds in the next three years by 6.3 percentage points (p=0.002). In biochemistry, on the other hand, patent approval has a significantly smaller effect on VC funding (p=0.002).

5. Conclusions

We estimate the causal effects of a firm's first patent on its growth and follow-on innovation. We use plausibly exogenous variation in patent approvals generated by the random allocation of patent applications to examiners with varying propensity to approve applications at the USPTO. Our analysis shows that patent approvals have a substantial and long-lasting impact on startups: firms whose first patent application is approved create more jobs, enjoy faster sales growth, and are more innovative.

The positive effects of patent rights appear to be due to their role in facilitating startups' access to capital, which helps startups turn ideas into products and products into revenues. We further show that patents are particularly beneficial to early-stage firms, for startups founded by inexperienced entrepreneurs, for those located in states with many startups, and for firms in the IT sector. Collectively, these patterns suggest that patent rights help overcome information frictions between startups and financiers.

While our results by no means rule out the existence of negative effects of patents, they show that patents convey substantial economic benefits on startups by facilitating contracting between them and their investors. We emphasize that our findings do not imply that the patent system is optimal, or even net welfare-increasing. Instead, taken together with empirical analyses of the patent system's spillover effects on other firms (Griliches 1984, Jaffe 1986, Heller and Eisenberg 1998, Williams 2013, Galasso and Schankerman 2015, Sampat and Williams 2015), our findings on the beneficial effects of patent rights on their owners contribute to a more complete understanding of the patent system.

The modern patent system is complex. In theory, it delivers private benefits and costs to patentees but also generates positive and negative spillovers through many distinct channels, thus making it impossible for any single empirical study to measure the overall welfare consequences of the patent system. Despite the abundance of evidence highlighting the spillover effects of patent rights, empirical evidence of the direct private benefits of patents to their owners remains scarce. Our study helps fill this gap by providing causal evidence of the benefits of patent rights in a large sample of startups and by pinpointing an important channel for how these benefits arise. Reforms of the patent system that do not take this channel into account run the risk of stifling growth by negatively impacting the availability of capital for innovative startups.

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Appendix A. Variable definitions.

Firm survival during year *t* after the first-action decision on a firm's first patent application is set to 1 if the firm is matched with the NETS sample and employment (or sales) data are available either for the year *t* or for any year after *t*. The variable is set to zero if the firm is matched with the NETS sample and employment (or sales) data are not available for the year *t* or for any year after *t*.

Employment growth after the first-action decision on a firm's first patent application is $\text{employment}_{t+j} / \text{employment}_t - 1$, where *t* is the first-action year and *j* =1…5. If a firm dies and thus does not appear in NETS in year *t*+*j*, we set $\text{employment}_{t+j} = 0$.

Sales growth after the first-action decision on a firm's first patent application is $\text{sales}_{t+j} / \text{sales}_t - 1$, where *t* is the first-action year and *j* =1…5. If a firm dies and thus does not appear in NETS in year *t*+*j*, we set $\text{sales}_{t+j} = 0$.

Pre-patent-filing employment growth is $\text{employment}_t / \text{employment}_{t-1} - 1$, where *t* is the year that a firm's first patent application is filed.

Pre-patent-filing sales growth is $\text{sales}_t / \text{sales}_{t-1} - 1$, where *t* is the year that a firm's first patent application is filed.

No. subsequent patent applications is the number of applications with a filing date greater than the first-action date of a firm's first application.

No. subsequent approved patents is the number of approved applications with a filing date greater than the first-action date of a firm's first application.

Approval rate of subsequent patent applications is defined as (no. subsequent approved patents) / (no. subsequent patent applications). It is only defined for firms with at least one subsequent patent application.

Total citations to all subsequent patent applications is the number of citations received by all subsequent patent applications combined. (This number is zero for firms with no subsequent applications.) We measure citations over the five years following each patent application's public disclosure date, which is typically 18 months after the application's filing date.

Average citations-per-patent to subsequent approved patents is the average number of citations received by those subsequent patent applications that are approved. It is only defined for firms with at least one subsequent approved patent.

Experienced founder is an indicator set equal to one if at least one of the up to five key executives of the startup listed in Standard & Poor's Capital IQ database previously founded a different firm, according to the professional background provided by Capital IQ.

High startup agglomeration state is an indicator set equal to one if the startup is headquartered in a state with above median startup agglomeration in the year of the startup's first patent application. We measure startup agglomeration using the number of first-time patent applicants in the state.

Industry classification. IT startups are those whose first patent application is reviewed by an examiner belonging to an art unit in one of the following USPTO technology centers: 21 (computer architecture, software, and information security); 24 (computer networks, multiplex communication, video distribution, and security); 26 (communications); or 28 (semiconductors, electrical and optical systems and components). Biochemistry startups are those whose first patent application is reviewed by one of the following technology centers: 16 (biotechnology and organic chemistry); or 17 (chemical and materials engineering). Startups belonging to other industries are those whose first patent application is reviewed by one of the following technology centers: 36 (transportation, construction, electronic commerce, agriculture, national security and license & review); or 37 (mechanical engineering, manufacturing, products).

Figure 1. Distribution of Patent Examiners' Approval Rates.

The figure shows the sample distribution of patent examiner approval rates, defined as in equation (2), estimated within an art unit and year using a regression of approval rates on a full set of art-unit-by-application-year fixed effects.

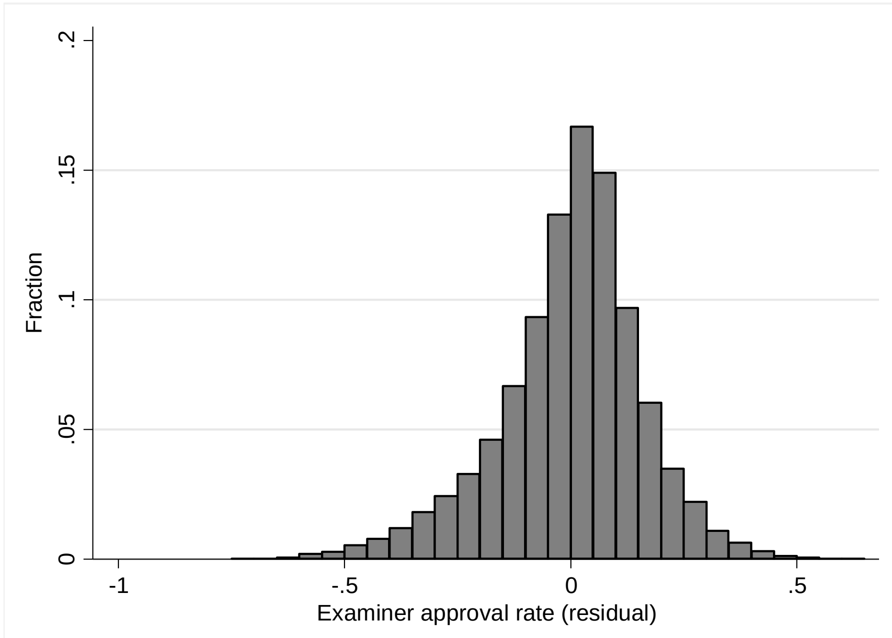
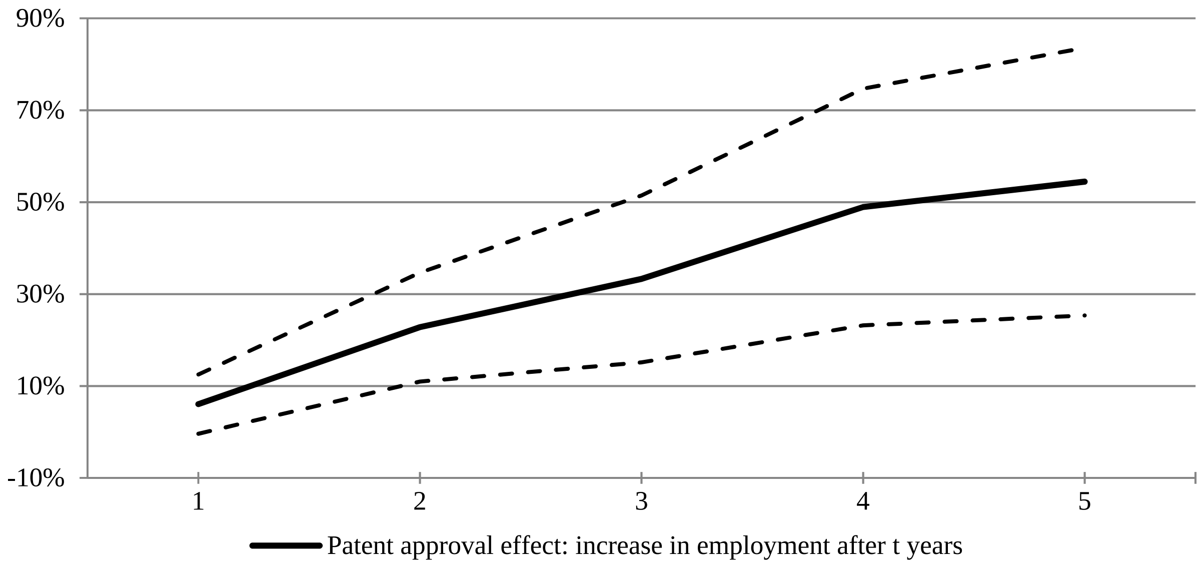


Figure 2. The Effect of Patent Grants on Startup Growth.
The figure plots the estimated patent approval effect on employment growth (Panel A) and sales growth (Panel B) over the five years following the first-action decision on a startup's first patent application. Specifically, the solid line shows the estimated patent approval effect obtained by estimating equation (1) by 2SLS separately over horizons from one to five years after the first-action date. We use the approval rate of the examiner reviewing each patent application as an instrument for the likelihood that the application is approved. The dashed lines show 95% confidence intervals.

Panel A. Employment growth.



Panel B. Sales growth.

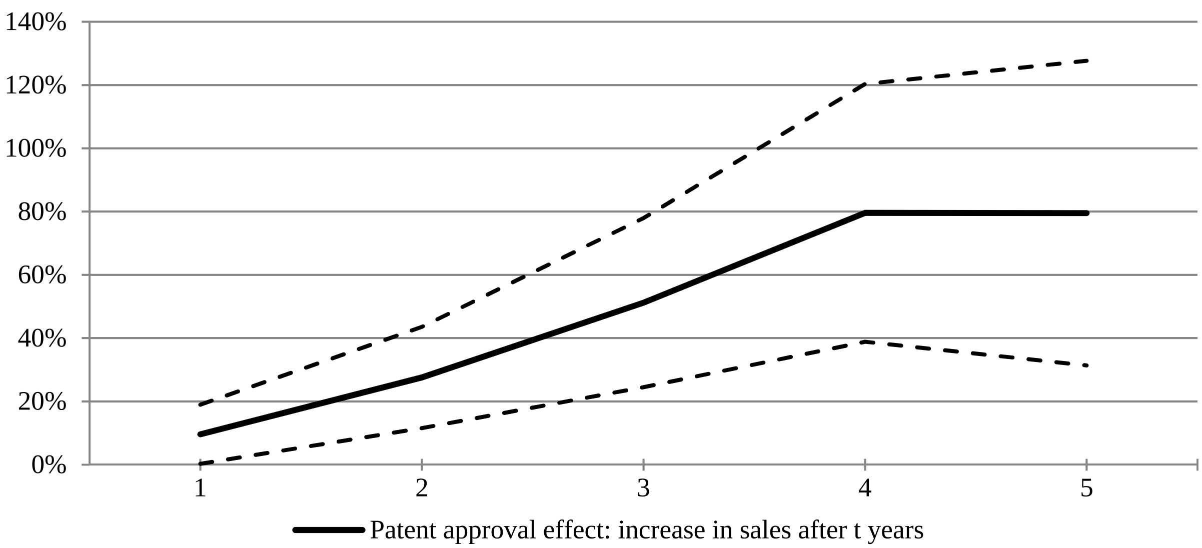


Figure 3. Time Lag between Patent Decision and VC Funding Round.
The figure shows the distribution of the time lag (in months) between the first-action date and the VC investment date for successful first-time patent applicants that go on to raise funding from a VC. VC funding events that take place more than five years after the first-action decision are not shown.

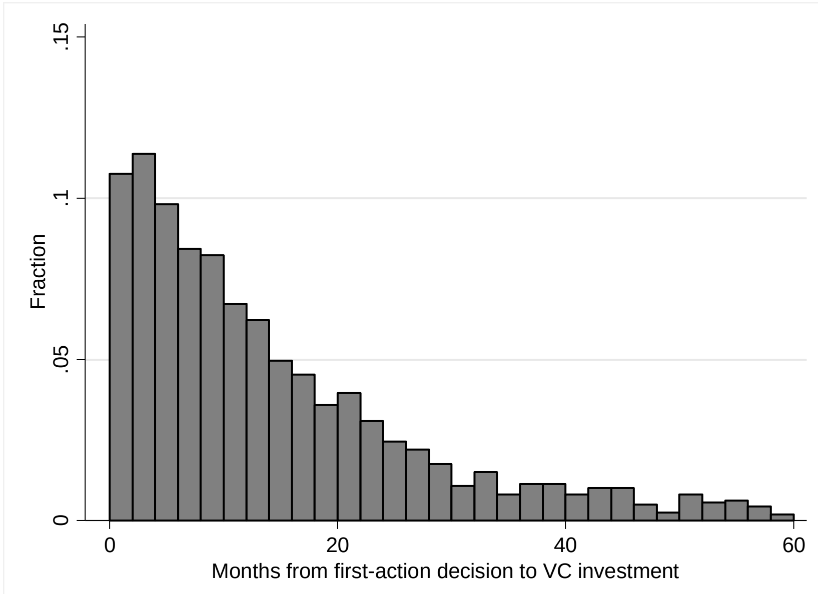


Figure 4. Time Lag between Patent Decision and Collateralized Patent Loan.
The figure shows the distribution of the time lag (in months) between the first-action date and the date when a startup pledges its patent application as collateral for a patent loan from a bank or specialized patent lender. Loans obtained more than five years after the first-action decision are not shown.

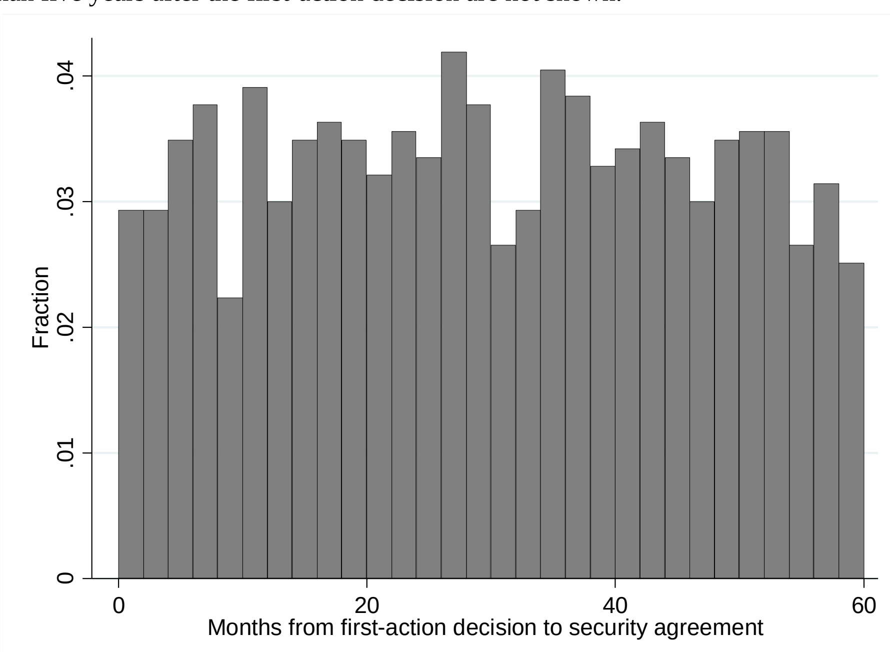


Table 1. Summary Statistics.

The table reports summary statistics for the firms in our sample of first-time patent applicants (or "startups"), broken down by whether their first application is approved or rejected. Data on age, employment, and sales are only available for those startups that can be matched to the National Establishment Times Series (NETS) database. For variable definitions and details of their construction see Appendix A.

		Firms whose first patent application is …	
		approved	rejected
No. firms		22,084	12,131
% of firms		0.6454	0.3546
Panel A. Pre-filing characteristics			
Age at first patent filing (years)	median	2.0	2.0
Employees at filing date	mean	29.6	29.0
	median	8.0	8.0
	st.dev.	*61.9*	*61.2*
Sales at filing date ($ million)	mean	4.3	4.2
	median	0.8	0.7
	st.dev.	*9.9*	*10.0*
Pre-patent-filing employment growth (%)	mean	16.2	16.0
	st.dev.	*68.7*	*68.1*
Pre-patent-filing sales growth (%)	mean	20.1	18.4
	st.dev.	*87.9*	*83.8*
Panel B. Subsequent growth in employment and sales			
Employment growth after first-action decision on the firm's first patent application, measured over the following …			
… 1 year	mean	6.6	-0.1
	st.dev.	*50.1*	*47.8*
… 3 years	mean	19.3	2.3
	st.dev.	*122.2*	*111.0*
… 5 years	mean	24.7	-2.1
	st.dev.	*159.3*	*124.7*
Sales growth after first-action decision on the firm's first patent application, measured over the following …			
… 1 year	mean	11.1	2.5
	st.dev.	*73.7*	*66.1*
… 3 years	mean	34.3	11.7
	st.dev.	*184.0*	*161.2*
… 5 years	mean	50.2	16.1
	st.dev.	*255.9*	*211.8*

Table 1. Continued.

		Firms whose first patent application is …	
		approved	rejected
Panel C. Subsequent patenting: patent applications filed after first-action decision on firm's first application			
No. subsequent patent applications	mean	3.1	1.2
	st.dev.	*11.7*	*5.7*
No. subsequent approved patents	mean	1.8	0.5
	st.dev.	*7.4*	*2.7*
Approval rate of subsequent patent applications (%)		70.5	47.9
Total citations to all subsequent patent applications	mean	8.3	2.2
	st.dev.	*77.8*	*26.6*
Average citations-per-patent to subsequent approved patents	mean	2.0	1.5
	st.dev.	*3.8*	*3.0*
Panel D. Subsequent VC funding and IPOs			
% of startups that raise VC funding after first-action		8.0	5.6
% of startups that go public after first-action		0.8	0.5
Panel E. Subsequent pledges of patents as collateral			
% of startups that pledged their first patent application as collateral after first-action decision, measured after the following …			
… 1 year	mean	1.3	0.9
… 3 years	mean	4.0	2.1
… 5 years	mean	6.6	2.6
% of startups without VC funding that pledged their first patent application as collateral after first-action decision, measured after the following …			
… 1 year	mean	0.9	0.7
… 3 years	mean	3.1	1.6
… 5 years	mean	5.1	2.0

Table 2. Examiner Leniency: First-stage Results.

The table reports the results of estimating the first-stage equation (3) of our 2SLS analysis of the real effects of patent grants. Specifically, we use the approval rate of the patent examiner in charge of reviewing a startup's first patent application to predict whether the application will be approved. In column 1, equation (3) is estimated in the full sample. In columns 2 and 3, we control for firm size using the log number of employees or log sales, which are only available for startups that can be matched to NETS. All specifications are estimated using least squares and include art-unit-by-year and headquarter-state fixed effects. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	First patent application approved?		
	(1)	(2)	(3)
IV: Patent examiner approval rate	0.670***	0.669***	0.671***
	0.018	*0.022*	*0.022*
Log (employees at first-action)		0.001	
		0.002	
Log (sales at first-action)			0.002
			0.002
Art unit × year fixed effects	Yes	Yes	Yes
HQ state fixed effects	Yes	Yes	Yes
Diagnostics			
R^2	25.7%	27.8%	27.9%
F test: IV (examiner approval rate) = 0	1,391.4***	951.4***	952.5***
No. of observations (firms)	34,215	21,564	21,530

Table 3. Examiner Leniency: Instrument Validity.

The table shows the results of regressing the approval rate of the examiner reviewing each firm's first patent application on several pre-filing firm and application characteristics. Columns 2 and 3 are estimated using the sample of startups that can be matched to NETS and for which NETS reports non-zero sales and employment for the year of their first patent application. Columns 4 and 5 are estimated using the sample of startups that can be matched to NETS and for which NETS reports non-zero sales and employment for the two years prior to their first patent application. Columns 6 and 7 are estimated using the sample of startups for which the number of claims and the number of words in their first patent application are available. All specifications are estimated by OLS and include art-unit-by-year and headquarter-state fixed effects. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	IV: Patent examiner approval rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log (1 + no. VC rounds raised at filing date)	0.005						
	0.004						
Log (employees at filing date)		0.001					
		0.001					
Log (1 + sales at filing date)			0.000				
			0.001				
Employment growth during year prior to patent filing				-0.001			
				0.002			
Sales growth during year prior to patent filing					-0.001		
					0.002		
Log (no. of claims in application)						0.002	
						0.002	
Log (no. of words in application)							0.001
							0.002
Art unit × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HQ state fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Diagnostics							
R^2	57.1%	59.2%	59.2%	59.9%	59.9%	57.2%	57.2%
No. of observations (firms)	34,215	20,424	20,424	17,864	17,846	29,087	29,087

Table 4. How Do Patent Grants Affect Firm Survival?

The table reports the results of linear probability models of firm survival. We code a sample startup as being alive in year *t* if it continues to be included in the NETS database that year. (Sample firms that applied for a patent but cannot be matched to NETS are thus excluded.) The variable of interest is approval of a startup's first patent application. We model survival over one-, three-, and five-year windows following the first-action date. The sample size falls as we consider longer windows because NETS data are available only through 2011. Columns 1, 3, and 5 report OLS estimates. Columns 2, 4, and 6 report 2SLS estimates using the approval rate of the examiner reviewing the patent application as an instrument for application approval. For variable definitions and details of their construction see Appendix A. All specifications include art-unit-by-year and headquarter-state fixed effects. Panel A uses the full sample of patent applicants that can be matched to NETS, covering 80% of the USPTO sample of startups with first patent applications over our sample period. Panel B restricts the NETS-matched sample to those for which NETS reports non-zero sales and employment for the year of the first-action decision. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Is the firm alive … years after the patent decision?					
	1 year		3 years		5 years	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full NETS-matched sample						
First patent application approved	0.046***	0.033*	0.069***	0.059***	0.080***	0.067*
	0.005	*0.018*	*0.006*	*0.023*	*0.009*	*0.035*
Diagnostics						
R^2	10.9%	n.a.	11.3%	n.a.	12.4%	n.a.
Unconditional mean of dep. variable	89.4%	89.4%	81.6%	81.6%	76.3%	76.3%
F-test: IV (examiner approval rate) = 0		1,129.7***		934.3***		473.8***
No. of observations (firms)	27,240	27,240	23,751	23,751	16,309	16,309
Panel B: Matches with NETS data in first-action year						
First patent application approved	0.029***	0.002	0.060***	0.039*	0.078***	0.032
	0.004	*0.014*	*0.006*	*0.023*	*0.009*	*0.039*
Log (employees at first-action)	0.007***	0.007***	0.019***	0.019***	0.021***	0.021***
	0.001	*0.001*	*0.002*	*0.002*	*0.003*	*0.003*
Diagnostics						
R^2	12.7%	n.a.	14.3%	n.a.	15.6%	n.a.
Unconditional mean of dep. variable	95.6%	95.6%	86.7%	86.7%	79.7%	79.7%
F-test: IV (examiner approval rate) = 0		928.9***		794.9***		469.3***
No. of observations (firms)	21,564	21,564	18,745	18,745	12,655	12,655

Table 5. How Do Patent Grants Affect Employment and Sales Growth?

The table reports the results of estimating equation (1) to examine how the approval of a startup's first patent application affects the startup's subsequent growth in employment (Panel A) and sales (Panel B) over the next one to five years. For firms that die, we set the growth rate to –100% in the year of exit. Retaining only firm-year observations for which data on firm growth rates are available (i.e., eliminating firm-years after firm exit rather than setting their growth rate to –100%) does not significantly alter the estimates. All columns report 2SLS results using the approval rate of the examiner reviewing the patent application as an instrument for the likelihood that the application is approved. Employment and sales data come from NETS; thus, startups that cannot be matched to NETS are excluded. NETS data are available through 2011, resulting in reduced sample sizes as we widen the window from one to five years. For variable definitions and details of their construction see Appendix A. All specifications include art-unit-by-year and headquarter-state fixed effects. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Employment or sales growth after USPTO first-action on the firm's first patent application, measured over the following …				
	1 year (1)	2 years (2)	3 years (3)	4 years (4)	5 years (5)
Panel A. Employment growth					
First patent application approved	0.061*	0.228***	0.333***	0.489***	0.545***
	0.033	*0.060*	*0.093*	*0.131*	*0.149*
Log (employees at first-action)	-0.020***	-0.053***	-0.071***	-0.089***	-0.104***
	0.002	*0.005*	*0.006*	*0.008*	*0.010*
Diagnostics					
F-test: IV (examiner approval rate) = 0	951.4***	951.4***	786.8***	555.1***	436.9***
Unconditional mean of dep. variable	4.3%	10.2%	13.8%	17.2%	17.4%
No. of observations (firms)	21,564	21,564	18,745	15,417	12,655
Panel B. Sales growth					
First patent application approved	0.096**	0.276***	0.512***	0.796***	0.795***
	0.048	*0.082*	*0.136*	*0.208*	*0.246*
Log (sales at first-action)	-0.022***	-0.056***	-0.084***	-0.122***	-0.144***
	0.003	*0.006*	*0.009*	*0.013*	*0.016*
Diagnostics					
F-test: IV (examiner approval rate) = 0	952.5***	952.1***	787.4***	555.5***	439.6***
Unconditional mean of dep. variable	8.2%	18.3%	27.0%	36.5%	40.9%
No. of observations (firms)	21,530	21,537	18,729	15,410	12,651

Table 6. How Do Patent Grants Affect Subsequent Innovation?

The table reports the results of estimating equation (1) to examine how the approval of a startup's first patent application affects the startup's subsequent innovation. Data on subsequent applications come from the USPTO internal databases and include all applications that receive a final decision through December 31, 2013. Column 3 includes only startups filing at least one patent application after the first-action decision on the startup's first patent application and for which we can measure the approval rate of subsequent applications. Column 5 includes only those startups with at least one subsequent patent approval and for which we can measure the average number of citations-per-patent to subsequently approved patents. We measure citations over the five years following each patent application's public disclosure date, which is typically 18 months after the application's filing date. In untabulated results, we find that the effects in columns 4 and 5 are even stronger when we measure citations over seven or ten years. For variable definitions and further details of their construction see Appendix A. All specifications are estimated by 2SLS and include art-unit-by-year and headquarter-state fixed effects. We use the approval rate of the examiner reviewing each patent application as an instrument for the likelihood that the application is approved. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Subsequent innovation				
	Log (1 + subsequent patent applications)	Log (1 + subsequent approved patents)	Approval rate of subsequent patent applications	Log (1 + total citations to subsequent patent applications)	Log (1 + avg. citations-per-patent to subsequent approved patents)
	(1)	(2)	(3)	(4)	(5)
First patent application approved	0.448***	0.353***	0.244***	0.472***	0.285***
	0.038	*0.030*	*0.043*	*0.049*	*0.094*
Diagnostics					
Uncond. mean of non-logged dep. var.	2.4	1.3	65.8%	6.1	1.9
F-test: IV (examiner approval rate) = 0	1,391.4***	1,391.4***	484.6***	1,391.4***	251.7***
No. of observations (firms)	34,215	34,215	12,595	34,215	9,793

Table 7. Cross-Industry Differences in the Effects of Patent Grants

The table reports the results of estimating equation (1) to examine how the approval of a startup's first patent application affects the startup's various outcomes in different industries. Each row represents one regression. Column 1 reports estimates obtained by running regressions in our full sample of startups, as reported in Tables 3, 4, and 5. Columns 2, 3, and 4 report estimates obtained by running regressions in subsamples of startups in the IT, biochemical, and other industries respectively. For variable definitions and further details of their construction see Appendix A. All specifications are estimated by 2SLS using the approval rate of the examiner reviewing each patent application as an instrument for the likelihood that the application is approved. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Effect of patent grants in …	All industries (1)	IT (2)	Bio-chemistry (3)	Other (4)
Employment growth				
1-year employment growth	0.061*	-0.022	0.074	0.111**
	0.033	*0.058*	*0.079*	*0.046*
2-year employment growth	0.228***	0.190*	0.273*	0.232***
	0.060	*0.109*	*0.140*	*0.086*
3-year employment growth	0.333***	0.271*	0.167	0.454***
	0.093	*0.149*	*0.255*	*0.128*
4-year employment growth	0.489***	0.283	0.508	0.665***
	0.131	*0.184*	*0.368*	*0.199*
5-year employment growth	0.545***	0.396*	0.554	0.677***
	0.149	*0.209*	*0.417*	*0.221*
Sales growth				
1-year sales growth	0.096**	0.006	0.072	0.178***
	0.048	*0.080*	*0.112*	*0.069*
2-year sales growth	0.276***	0.386***	0.091	0.268**
	0.082	*0.133*	*0.177*	*0.124*
3-year sales growth	0.512***	0.630***	0.094	0.619***
	0.136	*0.203*	*0.347*	*0.202*
4-year sales growth	0.796***	0.602**	0.577	1.080***
	0.208	*0.291*	*0.504*	*0.338*
5-year sales growth	0.795***	0.885***	0.526	0.839**
	0.246	*0.331*	*0.608*	*0.384*
Subsequent innovation				
No. subsequent patent applications	0.448***	0.569***	0.314***	0.419***
	0.038	*0.067*	*0.097*	*0.051*
No. subsequent approved patents	0.353***	0.445***	0.256***	0.330***
	0.030	*0.053*	*0.074*	*0.039*
Approval rate of subsequent patent applications	0.244***	0.262***	0.176**	0.271***
	0.043	*0.090*	*0.081*	*0.062*
Total citations to all subsequent patent applications	0.472***	0.725***	0.135	0.433***
	0.049	*0.093*	*0.104*	*0.062*
Average citations-per-patent to subsequent approved patents	0.285***	0.441**	0.010	0.330**
	0.094	*0.199*	*0.169*	*0.131*

Table 8. Do Patents Affect Access to VC Funding and the IPO Market?

The table reports the results of estimating equation (1) to examine how the approval of a startup's first patent application affects the startup's ability to raise funding from a VC or in the IPO market. The dependent variable in columns 1 through 5 is an indicator set equal to one if the startup raises VC funding at some point in the 1…5 years following the first-action decision, respectively. The dependent variable in column 6 is an indicator set equal to one if the startup goes public after the first-action decision on its first patent application, and zero otherwise. All specifications are estimated by 2SLS and include art-unit-by-year and headquarter-state fixed effects. We use the past approval rate of the examiner reviewing each patent application as an instrument for the likelihood that the application is approved. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Following the first-action decision on its first patent application, does the startup raise VC funding …					
	in the next 1 year? (1)	in the next 2 years? (2)	in the next 3 years? (3)	in the next 4 years? (4)	in the next 5 years? (5)	Does the startup raise capital in the IPO market? (6)
First patent application approved	0.017*	0.027***	0.030***	0.034***	0.036***	0.010**
	0.009	*0.010*	*0.010*	*0.011*	*0.011*	*0.004*
Log (1 + no. prior VC rounds)	0.272***	0.380***	0.416***	0.425***	0.429***	0.040***
	0.009	*0.009*	*0.009*	*0.009*	*0.009*	*0.004*
Diagnostics						
Mean of dep. variable	3.9%	5.7%	6.4%	6.8%	7.0%	0.67%
Median no. months from first-action to VC round or IPO for successful applicants	5.2	8.1	9.2	10.0	10.3	55.2
F-test from 1st stage: IV (examiner approval rate) = 0	1,385.6***	1,372.2***	1,372.0***	1,372.3***	1,374.2***	1,390.5***
No. of observations (firms)	34,167	34,111	34,060	34,013	33,981	34,215

Table 9. Do Patents Affect Access to Debt?

The table reports the results of estimating equation (1) to examine how the approval of a startup's first patent application affects the startup's ability to raise debt. The dependent variable in columns 1 through 5 is an indicator set equal to one if the startup pledges its patent application as collateral in a security agreement (recorded as a patent reassignment by the USPTO) at some point in the 1…5 years following the first-action decision, respectively; the dependent variable in column 6 is an indicator set equal to one if the startup pledges its patent application as collateral in a security agreement at any point after first-action. All specifications are estimated by 2SLS and include art-unit-by-year and headquarter-state fixed effects. We use the past approval rate of the examiner reviewing each patent application as an instrument for the likelihood that the application is approved. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Following the first-action decision on its first patent application, does the startup pledge the application as collateral …					
	in the next 1 year? (1)	in the next 2 years? (2)	in the next 3 years? (3)	in the next 4 years? (4)	in the next 5 years? (5)	at any point in the future? (6)
Panel A: All firms						
First patent application approved	0.004	0.018**	0.029***	0.039***	0.058***	0.086***
	0.006	*0.008*	*0.009*	*0.010*	*0.010*	*0.012*
Diagnostics						
Mean of dep. variable	1.1%	2.3%	3.3%	4.3%	5.2%	7.2%
Median no. months from first-action to application pledge	6.1	12.4	18.6	24.7	29.6	42.7
I-test from 1st stage: IV (examiner approval rate) = 0	1,409.1***	1,409.1***	1,409.1***	1,409.1***	1,409.1***	1,409.1***
No. of observations (firms)	33,520	33,520	33,520	33,520	33,520	33,520
Panel B. Firms without VC funding						
First patent application approved	0.002	0.011	0.019**	0.026***	0.044***	0.059***
	0.005	*0.007*	*0.008*	*0.009*	*0.010*	*0.011*
Diagnostics						
Mean of dep. variable	0.9%	1.7%	2.5%	3.2%	3.9%	5.4%
Median no. months from first-action to application pledge	6.1	12.6	19.3	24.5	29.8	43.6
F-test from 1st stage: IV (examiner approval rate) = 0	1,255.8***	1,255.8***	1,255.8***	1,255.8***	1,255.8***	1,255.8***
No. of observations (firms)	31,161	31,161	31,161	31,161	31,161	33,885

Table 10. How Do Patents Affect Access to VC Funding? Subsample Analyses.

The table examines how the effect of a patent grant on facilitating access to VC funding varies across different types of startups. The dependent variable equals one if the startup raises VC funding at some point in the three years following the first-action decision on its first patent application. Columns 1 through 4 split startups by the number of VC rounds raised before the first-action date. Column 5 captures variation in founders' prior entrepreneurial experience. Data on founder experience come from Capital IQ. Capital IQ's coverage of founders' backgrounds is most complete for firms that have raised VC funding, and so column 5 restricts the sample to firms that have raised at least one VC round before first-action. Column 6 splits startups according to whether they are headquartered in a state with above-median startup agglomeration in the year of their first patent application. (This indicator is time-varying and so is identified in the presence of headquarter-state fixed effects.) Column 7 splits startups by industry. For variable definitions and details of their construction see Appendix A. All specifications are estimated by 2SLS using the approval rate of the examiner reviewing each patent application as an instrument for the likelihood that the application is approved. Columns 5 through 7 include the interaction of the examiner approval rate and the splitting variable as instrument for the interacted patent approval indicator(s). In these cases, the *F*-test we report is a Cragg-Donald weak identification test. All specifications include art-unit-by-year fixed effects and headquarter-state fixed effects. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	In the three years following the first-action decision on its first patent application, does the startup raise …						
	its first VC round?	its second VC round?	its third VC round?	its fourth or higher VC round?	any VC funding?		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
First patent application approved	0.013^{*}	0.455^{**}	0.130	0.264	0.002	0.016	0.063^{***}
	0.007	*0.218*	*0.281*	*0.181*	*0.175*	*0.011*	*0.021*
… × inexperienced founder					0.326^{**}		
					0.164		
… × high startup agglomeration state						0.027^{**}	
						0.011	
… × life sciences							-0.107^{***}
							0.035
… × other industries							-0.028
							0.024
Inexperienced founder					-0.262^{**}		
					0.107		
High startup agglomeration state						-0.016^{*}	
						0.009	
Log (1 + # prior VC rounds)				0.425^{**}	0.121^{***}	0.416^{***}	0.415^{***}
				0.166	*0.047*	*0.009*	*0.009*
Diagnostics							
Mean of dep. variable	1.7%	46.8%	58.8%	61.8%	61.3%	6.4%	6.4%
F-test from 1^{st} stage: IV = 0	$1,162.2^{***}$	11.0^{***}	3.0^{*}	11.7^{***}	23.4^{***}	$1,543.6^{***}$	645.1^{***}
No. of observations (startups)	31,057	415	294	735	1,098	34,060	34,060

INTERNET APPENDIX

(NOT INTENDED FOR PUBLICATION)

Table IA.1. How Do Patent Grants Affect Employment and Sales Growth? OLS Results.

The table reports the results of estimating equation (1) to examine how the approval of a startup's first patent application affects the startup's subsequent growth in employment (Panel A) and sales (Panel B). The analysis here is analogous to Table 5, with the only difference being that we use OLS instead of 2SLS. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Employment or sales growth after USPTO first-action on the firm's first patent application, measured over the following …				
	1 year (1)	2 years (2)	3 years (3)	4 years (4)	5 years (5)
Panel A. Employment growth					
First patent application approved	0.065***	0.126***	0.152***	0.212***	0.247***
	0.008	*0.015*	*0.020*	*0.028*	*0.034*
Log (employees at first-action)	-0.020***	-0.053***	-0.071***	0.212***	-0.105***
	0.002	*0.005*	*0.007*	*0.028*	*0.011*
Diagnostics					
R^2	13.0%	13.6%	13.8%	14.9%	14.5%
Unconditional mean of dep. variable	4.3%	10.2%	13.8%	17.2%	17.4%
No. of observations (firms)	21,564	21,564	18,745	15,417	12,655
Panel B. Sales growth					
First patent application approved	0.083***	0.153***	0.214***	0.297***	0.333***
	0.012	*0.022*	*0.032*	*0.046*	*0.057*
Log (sales at first-action)	-0.022***	-0.056***	-0.083***	-0.122***	-0.145***
	0.003	*0.006*	*0.009*	*0.014*	*0.017*
Diagnostics					
R^2	12.3%	13.1%	14.0%	13.7%	13.8%
Unconditional mean of dep. variable	8.2%	18.3%	27.0%	36.5%	40.9%
No. of observations (firms)	21,530	21,537	18,729	15,410	12,651

Table IA.2. Patent Grants Affect Subsequent Innovation? OLS Results.

The table reports the results of estimating equation (1) to examine how the approval of a startup's first patent application affects the startup's subsequent innovation. The analysis here is analogous to Table 6, with the only difference being that we use OLS instead of 2SLS. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Subsequent innovation				
	Log (1 + subsequent patent applications) (1)	Log (1 + subsequent approved patents) (2)	Approval rate of subsequent patent applications (3)	Log (1 + total citations to all subsequent patent applications) (4)	Log (1 + average citations-per-patent to subsequent approved patents) (5)
First patent appl. approved	0.361***	0.294***	0.199***	0.344***	0.079***
	0.013	*0.010*	*0.012*	*0.017*	*0.022*
Diagnostics					
R^2	21.5%	20.6%	21.0%	21.0%	29.6%
Mean of non-logged dep. var.	2.4	1.3	65.8%	6.1	1.9
No. of observations (startups)	34,215	34,215	12,595	34,214	9,793

Table IA.3. Purged Effects of Patent Grants on Employment and Sales Growth.

The table reports the results of purging the leniency instrument of the effects of review speed. Doing so removes a possible confound that could arise if lenient examiners were also faster and review speed had an independent effect on outcomes. To purge the leniency instrument, we include review speed (the time between application filing and first-action decision). To account for the possibility that startup growth and review speed are endogenously determined, we instrument for review speed using a measure of administrative delays described in Hegde and Ljungqvist (2017). Specifically, we instrument review speed using the sum of the time a patent application takes from the filing date to the date it is assigned to an examiner's docket and the average time that examiner has taken in the past from docket to first-action. Panel A models the effect of patent approval of a startup's first patent application on the startup's subsequent growth in employment over the next 1 to 5 years. Panel B models the effect on subsequent sales growth. All columns report 2SLS results. Employment and sales data come from NETS; thus, startups that cannot be matched to NETS are excluded. NETS data are available through 2011, resulting in reduced sample sizes as we widen the window from 1 to 5 years. For variable definitions and details of their construction see Appendix A. All specifications include art-unit-by-year and headquarter-state fixed effects. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Employment or sales growth after USPTO first-action on the firm's first patent application, measured over the following …				
	1 year (1)	2 years (2)	3 years (3)	4 years (4)	5 years (5)
Panel A. Employment growth					
First patent application approved	0.032	0.178***	0.285***	0.418***	0.465***
	0.036	*0.066*	*0.101*	*0.148*	*0.160*
Log (employees at first-action)	-0.021***	-0.054***	-0.072***	-0.090***	-0.105***
	0.002	*0.005*	*0.006*	*0.008*	*0.010*
Diagnostics					
F-test: IV = 0	474.9***	474.9***	391.8***	272.6***	216.7***
Unconditional mean of dep. variable	4.3%	10.2%	13.8%	17.2%	17.4%
No. of observations (firms)	21,531	21,531	18,745	15,417	12,655
Panel B. Sales growth					
First patent application approved	0.060	0.225**	0.461***	0.664***	0.652**
	0.051	*0.089*	*0.148*	*0.229*	*0.263*
Log (sales at first-action)	-0.023***	-0.057***	-0.085***	-0.124***	-0.147***
	0.003	*0.006*	*0.009*	*0.013*	*0.016*
Diagnostics					
F-test: IV = 0	475.4***	475.4***	392.2***	272.9***	218.3***
Unconditional mean of dep. variable	8.2%	18.3%	27.0%	36.5%	40.8%
No. of observations (firms)	21,498	21,504	18,695	15,383	12,628

Table IA.4. Do Patents Affect Access to VC Funding and the IPO Market? OLS Results.

The table reports the results of estimating equation (4) to examine how the approval of a startup's first patent application affects the startup's ability to raise funding from a VC or in the IPO market. The analysis here is analogous to Table 8, with the only difference being that we use OLS instead of 2SLS. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Following the first-action decision on its first patent application, does the startup raise VC funding …					
	in the next 1 year? (1)	in the next 2 years? (2)	in the next 3 years? (3)	in the next 4 years? (4)	in the next 5 years? (5)	Does the startup raise capital in the IPO market? (6)
First patent application approved	0.012***	0.020***	0.023***	0.024***	0.036***	0.004***
	0.002	*0.003*	*0.003*	*0.003*	*0.011*	*0.001*
Log (1 + no. prior VC rounds)	0.272***	0.380***	0.416***	0.425***	0.429***	0.040***
	0.009	*0.009*	*0.009*	*0.010*	*0.009*	*0.004*
Diagnostics						
Mean of dep. variable	3.9%	5.7%	6.4%	6.8%	7.0%	0.7%
Median no. months from first-action to VC round or IPO for successful applicants	5.2	8.1	9.2	10.0	10.3	55.2
R^2	35.3%	44.0%	46.3%	46.7%	34.5%	14.8%
No. of observations (firms)	34,167	34,111	34,060	34,013	33,981	34,215

Table IA.5. Do Patents Affect Access to Debt? OLS Results.

The table reports the results of estimating equation (4) to examine how the approval of a startup's first patent application affects the startup's ability to raise debt. The analysis here is analogous to Table 9, with the only difference being that we use OLS instead of 2SLS. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	Following the first-action decision on its first patent application, does the startup pledge the application as collateral …					
	in the next 1 year? (1)	in the next 2 years? (2)	in the next 3 years? (3)	in the next 4 years? (4)	in the next 5 years? (5)	at any point in the future? (6)
Panel A: All firms						
First patent application approved	0.004***	0.011***	0.022***	0.033***	0.044***	0.068***
	0.001	*0.002*	*0.002*	*0.003*	*0.003*	*0.004*
Diagnostics						
Mean of dep. variable	1.1%	2.3%	3.3%	4.3%	5.2%	7.2%
Median no. of months from first-action to application pledge	6.1	12.4	18.6	24.7	29.6	42.7
R^2	12.0%	11.8%	11.6%	11.5%	11.4%	12.2%
No. of observations (firms)	33,758	33,758	33,758	33,758	33,758	33,758
Panel B. Firms without VC funding						
First patent application approved	0.003**	0.009***	0.017***	0.025***	0.034***	0.054***
	0.001	*0.002*	*0.002*	*0.002*	*0.003*	*0.003*
Diagnostics						
Mean of dep. variable	0.9%	1.7%	2.5%	3.2%	3.9%	1.4%
Median no. of months from first-action to application pledge	6.1	12.6	19.3	24.5	29.8	43.6
R^2	12.8%	12.0%	11.3%	11.0%	10.7%	11.2%
No. of observations (firms)	31,461	31,461	31,461	31,461	31,461	31,461

Table IA.6. How Do Patents Affect Access to VC Funding? OLS Subsample Analyses.

The table examines how the effect of patent grants on facilitating access to VC funding varies across different subsamples. The analysis here is analogous to Table 10, with the only difference being that we use OLS instead of 2SLS. Heteroskedasticity consistent standard errors clustered at the art unit level are shown in italics underneath the coefficient estimates. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

	In the three years following the first-action decision on its first patent application, does the startup raise …						
	its first VC round?	its second VC round?	its third VC round?	its fourth or higher VC round?	any VC funding?		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
First patent application approved	0.009***	0.199**	0.147	0.149**	0.167**	0.016***	0.044***
	0.002	*0.092*	*0.132*	*0.061*	*0.070*	*0.003*	*0.006*
… × inexperienced founder					-0.034		
					0.105		
… × high startup agglomeration state						0.013***	
						0.004	
… × life sciences							-0.031***
							0.009
… × other industries							-0.030***
							0.007
Inexperienced founder					-0.045		
					0.082		
High startup agglomeration state						-0.007	
						0.006	
Log (1 + # prior VC rounds)				0.401*	0.117**	0.416***	0.415***
				0.229	*0.058*	*0.009*	*0.009*
Diagnostics							
R^2	13.0%	59.9%	58.1%	50.4%	51.0%	46.3%	46.4%
Mean of dep. variable	1.7%	46.8%	58.8%	61.8%	61.3%	6.4%	6.4%
No. of observations (startups)	31,057	415	294	735	1098	34,060	34,060