Patents and the Success of Venture-Capital Backed Startups: Using Examiner Assignment to Estimate Causal Effects

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May 27, 2016

Abstract

I study whether patent protection has a causal effect on entrepreneurial firm outcomes using a measure of patent examiner leniency as an instrument for getting patents. The analysis is based on sample of 2,191 U.S. startups applying for patent protection in the two years following their first round of venture capital funding. I find a positive and large effect of patents on firm success but only for life science firms and more important inventions. I interpret these results as reflecting the importance of patents in appropriating returns to invention in the life science industry.

Keywords: Patents, Entrepreneurship, Venture Capital, Patent Examiners, Acquisition, Initial Public Offering

JEL Classification: O34, G24, L26

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1 Introduction

Intellectual property and patents in particular are often thought to be central to the strategy and success of young high technology firms. The legal protection conferred by patents may enable such firms to slow or prevent the entry of competitors in product markets, thus providing a key source of competitive advantage. Patents may also provide a hosts of other benefits from enhancing the reputation of firms towards investors to being a bargaining chip in cross-licensing negotiations.[1]

However, it has proved difficult to establish empirically a direct causal link between patents and entrepreneurial firm success. If patents are milestones for entrepreneurial firms, one would clearly expect a correlation between patents and firm success. However, it is unclear that this correlation merely reflects the fact that more innovative firms tend to be more successful or whether it indicates that getting patents actually improves firms' outcomes.

In this paper, I use differences in leniency across patent examiners as a plausibly exogeneous source of variation in getting patents, and use this variation to investigate the causal effect of patents on the success of venture-backed firms in a standard instrumental variables framework. The main task of patent examiners - evaluating the novelty and non-obviousness of an application - necessarily involves judgement, and thus discretion. As initially suggested by Cockburn, Kortum & Stern (2003), this can lead to considerable heterogeneity across patent examiners: there may be as many different patent offices as there are patent examiners. One type of patent examiner heterogeneity has been documented in recent work by Lemley & Sampat (2012) and Frakes & Wasserman (2014):

[1]Patents involve costs as well, both in terms of preparing, filing and prosecuting patent applications, as well disclosing information to competitors.

more senior examiners cite less prior art and are more likely to grant patents.[2]

The empirical strategy employed in this paper is similar in spirit to the literature using exogeneous allocation of cases to judges or examiners to estimate the effect of court decisions or program receipt on a variety of outcomes (Kling 2006, Doyle 2007, Doyle 2008, Chang & Schoar 2008, Maestas et al. 2015, Dobbie & Song 2015, Galasso & Schankerman 2015, and others). Closest to this paper, Sampat & Williams (2015) use patent examiner heterogeneity in their study of patents and cumulative innovation.[3]

My analysis is based on a sample of 2,191 U.S. entrepreneurial firms that file one or more patent applications between 2001 and 2006 and within two years of raising their first round of venture capital (VC) financing. I code firm success as going through an initial public offering or being acquired for more than twice the amount of VC financing raised. I measure examiner leniency through the grant rate for applications filed in the same year assigned to the same examiner (excluding the focal application and normalizing by the average grant rate for the technology type). The regression analysis compares firms that filed the same number of patents but were more or less successful in converting applications into granted patents due to examiner assignment.

I find a positive and economically large effect of patents on firm success for life science firms but not for IT firms, where the point estimates are small and not significant. I further show that in the life science sector the effect of patents is entirely driven by more important inventions, as proxied by whether the firm chose to incur the costs of filing

[2]Besides variation within examiners, we might also expect variation across examiners in terms of how intensively they search for prior art or their receptiveness to arguments raised by applicants in the patent prosecution process.

[3]After the original version of this paper (Gaule 2015) was completed and circulated, the working paper of Farre-Mensa, Hedge & Ljungqvist (2016) came to my attention. They also use an examiner leniency instrument but for a different sample of startups. They find an effect of patents on job creation and job growth and suggest that these effects are driven by access to capital.

not just in the U.S. but also in Europe and Japan. Back of the envelope calculations for the life science firms and more important inventions suggests that the value of patent protection in the U.S. for these firms and inventions may be between 20 and 35 million USD. Finally, I find no effect of patents on re-financing raised from venture capitalists.

To interpret these results, I rely on the prior literature -surveyed in the related literature section below- and in particular the literature based on interviews and surveys of R&D managers and entrepreneurs. This literature has identified three main motivations for firms seeking patents, which I will refer to as *appropriation*, *bargaining chip* and *access to capital*, respectively. First, firm file patents to protect their inventions against copying by other firms. A robust finding is that patent protection is perceived to be very effective only in certain industries -typically biotechnology, chemicals and pharmaceuticals. Second, firms file patents to enhance their own freedom to operate and strengthen their bargaining positions with respect to other firms that held complementary intellectual property. Such considerations are deemed important in industries where products embody multiple technologies, such as in telecommunications or semiconductors. Third, young firms file patents to enhance their access to capital. Entrepreneurial finance markets are often characterized as featuring considerable asymmetric information between investors and entrepreneurs. Patents then act either as a signal or certification device to reduce asymmetric information and hence facilitate access to capital.

Given that I find no effect of patents on refinancing, access to capital appears unlikely to explain the effect of patents on firm success identified in this paper. Distinguishing among the two other mechanisms - appropriation and bargaining chip - is inherently more difficult. However, industry differences in the results may shed some light. I find patents to have a large effect in life science, where the effectiveness of patents for appropriation is reported to be important, but not in IT, where appropriation is reported to be less important. Conversely, the bargaining chip motivation is expected to be important in IT, where I do not find an effect of patent on firm success, but less important in life science, where I do. I thus suggest that the effect of patents on firm successes found in the empirical analysis may reflect the effectiveness of patents in appropriating returns to invention in the life science sector.

This paper contributes to the literature on the determinants of success for venture capital-backed firms and entrepreneurial firms more generally. A large branch of this literature investigate whether venture capitalists have a causal effect on firms exits (see, among others, Hellman & Puri 2000, Puri & Zarutskie 2012, Bernstein et al. 2015). Other studies consider the role of social networks (Hochberg et al. 2007), the characteristics of founding teams (Beckman et al. 2007), the regional supply of young workers (Ouimet & Zarutskie 2014), or investment cycles (Nanda & Rhodes-Kopf 2013). Closer to this paper, Mann and Sager (2007) and Cockburn & MacGarvie (2009) find that software venture-capital backed firms that have patents are more likely to have an initial public offering but their results are descriptive, rather than causal. Hsu and Ziedonis (2013) find that that increases in patent stocks lead to increases in venture capitalists' estimates of company value for a sample of semiconductor startups. The present paper provides causal evidence on the role of legal protection to invention in the form of patents as a key determinant of entrepreneurial success in some industries.

The rest of this paper proceeds as follows. Section 2 briefly reviews the previous literature on why firms patent, and further positions the paper. Section 3 provides background information on patent prosecution and the assignment of patents to examiners at the United States Patent and Trademark Office (USPTO). Section 4 describes the data source and construction. Section 5 presents the empirical strategy and evidence on the relevance and validity of the instrument. The results are in section 6 and section 7 concludes.

2 Why do firms patent? Related literature

The patent system is predicated on the notion that in the absence of legal protection inventions can be imitated at relatively cost and this may disincentive innovative effort. Exclusive rights to the invention for a temporary period, in the form of patents, are thus meant to reward innovative activity by preventing imitation. A series of studies (Mansfield at al. 1981, Mansfield 1986, Levin et al. 1987, Cohen et al. 2000) have asked R&D managers whether they found patents to be effective in preventing copying and thus appropriating the returns to innovation. Patents were reported to effective in the pharmaceutical, medical equipment and to a lesser extent chemical industry, but not in other industries. Technology entrepreneurs surveyed by Graham et al. (2008) also report patents to be very important in securing competitive advantage in biotechnology and medical devices but only moderately important in information technology.

A puzzle arising from these surveys is why firms patent in industries where patents are reported to be of limited effectiveness. This puzzle has spurred a research agenda on other reasons firms might have to seek patents. Cohen et al. (2000) ask R&D managers why their firms patent. After preventing copying, other reasons mentioned were preventing suits, blocking other firms from patenting and using patents for negotiation. These reasons were most often mentioned in "complex products" industries such as telecommunications and semiconductors, where products combine many distinct components.

Similar strategic patenting motives are highlighted in Hall & Ziedonis (2001) qualitative and quantitative study of patenting in the semiconductors. Graham et al (2008) also report preventing suits and improving negotiating positions as important reasons for seeking patents.

A related stream of literature argues that patents help young firms raise financing. Young high technology firms need capital to grow, especially when product development takes time or significant capital expenditures. However, a high technology firm's access to capital markets may be hampered by lack of collaterals, asymmetric information between inventors and investors or more general uncertainty about the quality of the firm's technology or management (Hall & Lerner 2010). Graham et al. (2008) report that high-technology entrepreneurs perceive patents to be important to improving their chances of securing funding. In terms of specific mechanisms, Conti, Thursby & Thursby (2013), Conti, Thursby & Rothaermel (2013) and Hsu & Ziedonis (2013) emphasize the role of patents as signal of quality while Haussler, Harhoff & Mueller (2013) point out that information generated by the patent office can play an important function in terms of certifying the quality of the firm's innovation.

Given the richness of insights provided by the qualitative literature on patents as means of capturing returns to innovative activity, one might wonder whether there is a point to empirical analyses of the type undertaken in this paper. As pointed out by Diamond (2003), while reviewing Edwin Mansfield's work, an important precept in economics is that economists should study what agents do, rather than what they say. Another interpretation of the fact file patents in the IT industry is that they are actually useful for appropriation despite what respondents may say. Conversely, Cohen (2010) notes that responding that patents are filed to prevent copying may reflect a social desirability bias, as respondents may believe this is is what patents are supposed to do. Empirical studies that rely on observed outcomes only may thus be useful to confirm or disprove the earlier qualitative insights and quantify the relationship between patents and firm outcomes.

3 Examiners and patent prosecution at the USPTO

Upon arriving at the U.S. Patent and Trademark Office, patent applications are sorted by a dedicated classification office and allocated to "art units" specialized in given technology areas (Cockburn, Kortum & Stern 2003).[4] Within an art unit, a Supervisory Patent Examiner assigns patents to individual examiners (ibid.). Details on how applications are allocated within the art unit are not made public by the U.S. patent office but previous studies (Cockburn, Kortum & Stern 2003, Lemley & Sampat 2012) report the results of interviews regarding allocation of patents to examiners. A common practice is for supervisory examiners to assign patents based upon the last digit of the application serial number, which itself is assigned sequentially by a central office (Lemley & Sampat 2012). A minority of supervisory examiners gave the oldest unassigned application to an examiner when that examiner finished examining a prior application (ibid.).[5]

Whether assignment to examiners within art units is as good as random is an open question but it seems plausible. Lemley & Sampat (2012) conclude from interviews that there is no purposeful allocation of applications to examiners. As noted by Sampat & Williams (2015), there is limited scope for purposeful allocation within the art unit given that the supervisory examiner has limited information on the likely patentability of an

[4]This section draws heavily upon Cockburn, Kortum & Stern (2003), Lemley & Sampat (2008, 2010 and 2012)

[5]Cockburn, Kortum & Stern (2003) report that in some mechanical art units an examiner would specialize in a narrow technological area and deal with all incoming patents in that area. However, this does not appear to be a general pattern.

application (short of doing a substantive evaluation himself/herself). Previous studies report no difference in observables across patents assigned to lenient examiners (Sampat & Williams 2015) and more senior examiners (Lemley & Sampat 2012) respectively.

Once a patent application is assigned to an examiner, (s)he will typically have continuing responsibility for the case. The examiner is tasked with searching the prior art to determine whether the application and its claims meet the requirement of novelty and non-obviousness.[6] Based upon his/her assessment the examiner issues a "first office action" in which the application is either accepted or rejected. Less than 15% of first office actions are acceptances (Lemley & Sampat 2010). However, if the application is rejected, the applicant can argue against the examiner's objections (laid down in the rejection letter) or choose to narrow the claims. A back and forth process between the applicant and the examiner ensues. Eventually, around 56% of applications are granted (Carley, Hegde & Marco 2015).[7] While the patent prosecution process is heavily codified, examiners nonetheless have considerable discretion. However, examiner discretion is counterbalanced by the applicants' ability to appeal UPSTO decisions as well as the possibility for granted patents to be invalidated by courts.

4 Data

This section provides an overview of the data used in the paper, with further details available in the data appendix. The starting point for the data construction was Thomson Reuters' VentureXpert. VentureXpert is one of the main sources of information on venture-backed companies and has been widely used in entrepreneurship and innovation

[6]The examiner also checks a number of legal requirements including whether the application covers a patentable subject matter.

[7]This figure excludes continuation procedures to create related applications.

research. I focused on firms listed in VentureXpert that had their first venture capital round between 1999 and 2006. This choice of time frame was driven by two considerations. First, data on unsuccessful patent applications is only reliable after the implementation of the American Inventors Protection Act.[8] Second, I wanted to have sufficient time to observe firm outcomes. I also chose to exclude firms classified as "Non-High Technology" since I expected patent protection to be less relevant for the group.

I then matched firm names to patent application data from the USPTO. The matching procedure is detailed in the data appendix. Importantly, I chose to focus on patents applications filed in the first two years since the first venture capital round, since I expected these patents to be more relevant for firm outcomes. For the 11,756 high technology companies who had their first venture capital round between 1999 and 2006, the matching procedure identified 7,978 patent applications corresponding to 2,274 distinct firms. For each of these patent applications, I used patent application bibliometric data from USPTO PAIR to find the set of applications that were filed in the same year and allocated to the same examiner, as well as the set of applications that were filed in the same year and allocated to the same art unit. On average, the set of applications filed in the same year and allocated to the same examiner had 41 elements. To avoid error in measuring examiner leniency when the set of applications is small, I dropped 500 applications for which the set of applications filed in the same year and allocated to the same examiner had 5 elements or less. The final analysis sample for VC-backed companies has 2,191 firms.

[8] Prior to November 2000, the USPTO did not publish patent applications, though patent offices in most other countries published applications 18 months after the filing date. The American Inventors Protection Act (AIPA) required inventors applying for patents at USPTO on or after November 29, 2000 to publish their applications 18 months after the filing date. There is an opt-out provision for applications that will not be filed outside the U.S. but this provision has been used in less than 10% of applications (Graham & Hegde 2015).)

I coded a patent as granted if the USPTO pair database includes the following status associated with the application: "Patented Case" or "Patent Expired Due to NonPayment of Maintenance Fee". Collectively, they account for 64% cases. Around 30% of applications were abandoned with pending cases accounting for the remaining 6%.

In order to attempt to distinguish between more or less important patent applications, I tagged patent applications that were also filed in Europe and in Japan using the OECD triadic patents database (OECD). Triadic patent families are sets of patent applications that cover the same invention and for which protection was sought in all three major patent offices (US, Europe and Japan). Pioneered by the OECD (Denis & Khan 2004), the use of triadic patent families is predicated on the notion that filing patents in multiple jurisdiction involves more significant costs thus reveals which patents are considered more valuable by applicants. Importantly, the decision to apply in Europe and Japan is unlikely to be impacted by the USPTO examiner and office actions. This is because the decision to apply in Europe and Japan must be made within a year of the USPTO filing (otherwise the applicant loses the original priority date) and this implies that the applicant must decide whether to apply before hearing back from the USPTO.

[Insert table 2 about here]

I present descriptive statistics on selected variables for the analysis sample for VC-backed companies in table 2. The majority firms in my sample are in IT (76%) with the rest (24%) in Medical/Health/Life science (hereafter: "Life Science"). This industry classification corresponds to "company industry class" in VentureXpert. About 8% of firms in my sample went public while 40% of firms were still active as of 2014 and 10% were coded as 'defunct' in VentureXpert. The remainder - 42%- are firms that were acquired by, or merged with, another company. Acquisitions by other companies clearly cover very heterogeneous scenarios, ranging from exits that are very lucrative for the entrepreneur and his/her VC backers to essentially firesales. Following Ewens & Marx (2014), I classified an acquisition as 'High acquisition' if the acquisition price was more than 200% the total amount of venture capital raised by the firm, 'Unknown acquisitions' if the terms of the acquisition were not disclosed or the price was between 100% and 200% of the total amount of venture capital raised by the firm and 'Low acquisition if the acquisition price was less than 100% of total amount of venture capital raised by the firm. The main outcome variable for the empirical regress is firm success which I defined as either going public or being the subject of 'high acquisitions'. Around 19% of firms were deemed successful according to that coding.

An average firm files 3.3 applications in the two years following their first VC round, of which 2.1 are granted., [9] The average number of applications filed in Europe and Japan in addition to the U.S ('triadic patent applications') is 0.9, of which 0.6 are granted in the U.S. ('triadic patents').

As a comparison point for the venture capital backed sample, I also constructed two samples of startups that do not yet have venture capital backing when filing for protection. The first sample is based on firms are recipients of Small Business Innovation Research grants from the NIH between 1999 and 2006. These firms are thus small innovative firms active in the life science area, and they have been used as a comparison group to VC-backed firms in prior research (see e.g. Hsu 2006). The second sample is based on firms that have filed a form D report to the SEC between 1999 and 2006. The 'form D' is a SEC

[9] Applications are observed with some error. For instance for firms that had their first round in 2006, I do not observe applications in 2008 even though that would be within 24 months of the first VC round. Conversely, I do not see applications filed in 2000 for firms that had their first round in 1999 or 2000.

form enabling firms to sell securities without registering with the SEC. Private firms that raise some form of capital (such as angel investment) are thus expected to file such forms. In both samples, I excluded firms that already have raised a venture capital round at the time when they received a SBIR grant or filed the first form D that I observed. I then matched these firms to patent applications in a similar manner as for the VC sample. To maintain consistency with the construction of the VC sample, I focused on applications filed within two years of the SBIR grant receipt or first form D filing. In either sample, I observe whether firms went public, have been acquired, have been acquired for more than 25 millions, or subsequently received venture capital.

5 Empirical strategy

A natural starting point to understand the effect of patent on entrepreneurial firms is to compare firms that have patents to those that do not. A problem with that approach is that firms without patents include both firms that did not generate patentable inventions, firms that had patentable inventions but chose not to apply for protection and firms that applied for patent but did not get patent protection. To derive meaningful inference about the effect of patents, it is clearly important to distinguish among these three groups of control firms. The firms that do not generate inventions are not an appealing control group as the difference with patenting firms mechanically conflates the effect of the patent with the effect of the invention itself. Firms that had patentable inventions but chose not to apply for patent protection are a more interesting control group but it is empirically difficult to distinguish them from firms that do not generate inventions. Moreover, the decision to patent is clearly a choice of the firm that is made considering the returns to different appropriations strategies (patenting versus secrecy).

Another possible control group is firms that apply for patent protection but do not get it. The key empirical challenge here is that the USPTO does not randomly grant patents. Instead, the USPTO conducts a detailed investigation to determine the patentability of inventions. This makes it intrinsically difficult to separate the causal effect of patents from differences in the firms that submit these inventions as patent applications. While the patent office is not evaluating the quality of a technology as such, it is searching for prior art and evaluating novelty and non-obviousness. A patent applicant that has a radical and cutting edge invention will presumably find it easier to convince the patent office that the claimed invention meets the non-obviousness requirement. Alternatively, a better firm may hire more skilled patent attorneys that navigate the patent prosecution more effectively.

The empirical strategy in this paper is based on comparing firms that file the same number of patent applications (in a 24 month time window from receiving venture capital) but were more or less successful in converting their applications into granted patents. I aim to identify the causal effects of patents on firm success by using differences across firms in examiner leniency. Intuitively, some firms 'get lucky' by drawing more lenient patent examiners and I use variation in patents granted that are induced by the assignment to such examiners. I use a time-varying measure of examiner leniency, as it has been found that examiners tend to get more lenient as they are promoted and their case loads increase (Frakes & Wasserman 2014).[10] However, the variation in examiner leniency comes not only from the variation within examiners but also from variation across examiners, as different examiners may be different in the effectiveness of their search for prior art, or in their standard for for assessing non-obviousness.

[10] A more practical reason for using time-varying leniency is that I do not observe leniency for patents applied before 2001.

Let us consider a patent application j, filed in year t, allocated to art unit u and assigned to patent examiner k. I define the following quantities:

$$E_{jt} = \frac{grants_{kt} - \mathbf{1}(grant_j = 1)}{applications_{kt} - 1} \tag{1}$$

$$U_{jt} = \frac{grants_{ut} - \mathbf{1}(grant_j = 1)}{applications_{ut} - 1} \tag{2}$$

where $grants_{kt}$ is the number of patents filed in year t and granted by examiner k, $grants_{ut}$ is the number of patents filed in year t and granted by art unit u, $application_{kt}$ is the number of applications filed in year t and assigned to examiner k, $application_{ut}$ is the number of applications filed in year t and allocated to art unit u. E_{jt} is thus simply the share of applications that have the same application year as j that were granted by the examiner dealing with that application, excluding the focal patent. Similarly, U_{jt} is the share of applications that have the same application year as j that were granted by art unit u, excluding the focal patent. The difference $E_{jt} - U_{jt}$ is thus the difference between the leniency of an examiner and the average leniency facing an applicant filing in year t in the technological area corresponding to art unit u.

For firms that file a single patent application, the difference $E_{jt} - U_{jt}$ between the leniency of an examiner and the average leniency of the art unit can be used as an instrument for whether that application is granted. The resulting empirical setup would track closely prior studies on judges and examiners that uses a leave-one-out measure of leniency (see in particular Dobbie & Song 2014).[11] However, firms may apply for multiple patents and thus get 'treated' by more or less stringent examiners multiple times. I deal with this by averaging the difference $E_{jt} - U_{jt}$ across the patents applied for by firm i,

[11]The alternative to using a leave-one-out measure of leniency is to estimate sets of judge/examiner fixed effects (see e.g. Angrist, Imbens & Krueger 1999).

leading to the instrument:

$$Z_i = \frac{1}{n} \sum_j (E_{jt} - U_{jt}) \tag{3}$$

One concern with averaging examiner leniency across applications is that firms may react to getting a stringent examiner on the first application by filing more applications. In my sample by construction all applications are made in a two year window (after the first VC round), which limits the scope for such behavior since the outcome of the examination process and/or the identity of the examiner would not be known within the first year of filing. Empirically, I do not observe a correlation between examiner leniency in the first application and the number of subsequent applications filed (cf table 4 column 1).

I use the instrument Z_i for the number of patents the firm gets in a standard two stages least squares framework.

$$Patents_i = \beta_0 + \beta_1 Z_i + \beta_2 X_i + \epsilon_i \tag{4}$$

$$Y_i = \delta_0 + \delta_1 \widehat{Patents}_i + \delta_2 X_i + u_i \tag{5}$$

Where Y_i is a firm outcome, such as entrepreneurial success and X_i is a set of controls. Following prior literature (Kling 2006, Chang & Schoar 2008, Doyle 2007, Doyle 2008, Ayzer & Doyle 2013, Maestas et al. 2013, Sampat & Williams 2015, Dobbie & Song 2015), I do not adjusted the standard errors to account for the fact that examiner leniency is estimated.

The set of controls X_i includes two types of fixed effects. The first are fixed effects for the number of applications filed by the firm, as I want to compare firms that filed the same number of applications. The second are technology sector by first round year fixed effects.[12] I control for these for efficiency reasons as technology sector and the year of the first round are powerful determinants of firm outcomes. I obtain very similar point estimates, but somewhat larger standard errors when I omit these controls.

5.1 Instrument relevance

The two-stage least squares estimates will measure the local average treatment effect of patents for firms whose patent outcomes were changed by examiner assignment under two conditions: (1) examiner assignment is associated with patent protection and (2) examiner assignment is related to firm outcomes only through the granting of patents.

The first assumption is empirically testable. In table 3, I show a regression of granted patents on examiner leniency, i.e. the first stage of the two-stage least squares estimation. A one standard deviation in the leniency of the examiners a firm was assigned increases the number of patents granted by 0.219. Differences across examiners appear to be a driver of differences in the likelihood that a patent will be issued, even for a given technology type and year of application. Correspondingly, the instrument explains a large part of the variation in granted patents, which is reflected by the first stage F statistic of over 130, well in excess of the critical values for weak instruments tests.

[Insert table 3 about here]

[12]For the purpose of constructing these fixed effects, I used a finer grained definition of the technological sector, based upon VentureXpert classification. Specifically, the technological sector is one of the following: biotechnology, communications, computer hardware, computer software, internet specific, medical/health and semiconductor. Note that the art unit division at the USPTO corresponds to much finer grained classifications of the technological sector.

The fact that application outcomes are meaningfully impacted by examiners is in line with the prior qualitative and literature on examiners. In fact, this was the main point of the first paper on examiners by Cockburn, Kortum & Stern (2003). More recent studies such as Lemley & Sampat (2012) and Frakes & Wasserman (2014) find quantitatively that more senior examiners cite less prior art and are more likely to grant patents. A familiar analogy for patent examination may be scientific peer review where referees are prone to disagreement and some referees are systematically more generous than others (Welch 2014).

5.2 Instrument validity

The second identifying assumption is that examiner assignment is related to firm outcomes only through the granting of patents. This would be violated if examiner assignment was correlated with observable or unobservable determinants of firm outcomes (such as firm quality). While the validity of the instrument cannot be tested directly, I run two types of regressions to partially assess the validity of the examiner instrument. First, I regress predetermined characteristics of the firm on the examiner instrument. As reported in table 5, I find no significant association between the leniency of the examiner and (1) the amount raised in the first round, (2) the number of investors in the first round, (3) the age of the firm (4) the number of patent applications filed before the first VC round, (5) the prior success of investors (as proxied by prior IPOs) and (6) the prior experience of investors (as proxied as the sum of past investments to date).

[Insert table 5 about here]

A possible lingering concern is that better firms may find ways to get their patents assigned to more lenient examiners (perhaps by employing more skilled intellectual property counsel). To partially address this concern, I conduct the following falsification exercise. If better firms were consistently able to select more lenient examiners, we would expect firms that manage to get a lenient examiner in their first applications to also get a lenient examiner in subsequent applications. In the presence of such selection, we should observe a positive correlation between the leniency of the examiner for the first application of the firm and the leniency of the examiner in subsequent applications. It turns out there is no such correlation empirically (see table 4).[13]

[Insert table 4 about here]

6 Results

Effects of patents on firm success

The main results are shown in table 6. The dependent variable is firm success which is defined as having an IPO or being acquired for more than twice the amount raised from venture capitalists.[14] The variable of interest is the number of patents granted to the firm among the set of applications filed in the first 24 months since the firm has received venture capital funding. All specifications include fixed effects for the number of applications. The coefficient on patents can thus be interpreted as the effect of a (possibly additional) granted patent, holding the number of applications constant. All specifications use two stage least square estimation with mean examiner leniency (as defined previously) as an instrument for the number of granted patents.

[13] For the purpose of this exercise, I drop applications originating from the same company that have the same filing date.

[14] The coding of high acquisition follows Ewens & Marx (2014).

[Insert table 6 about here]

The first column of table 6 shows the result for the full sample. The point estimate of the effect of patents is positive but not significant. Splitting the sample between Life Sciences (column 2) and IT (column 5) reveals an interesting pattern: the point estimate is much larger, and significant at 5% in the Life Sciences sample, but insignificant and close to zero in the IT sample. Furthermore, I distinguish in each sample between more or less important inventions using whether the firm has filed for protection only in the US or also in Europe and Japan ('triadic patent applications'). Within the life science sample, the point estimate for triadic patents is larger still while the point estimate for non-triadic patents is negative and insignificant. Within the IT sample, none of the coefficients is significant but the point estimate are larger for triadic patents.

These results suggest a considerable heterogeneity in the effect of patent protection between sectors and types of inventions. Patents appear to have a large effect in the life science sector, but this is in turn driven by the subset of the (presumably more important) patents that have also been filed in Europe and Japan. Within the IT sector, the evidence about whether patents have any effect is inconclusive. However, it seems clear that patents matter more in the life science sector than in the IT sector.

[Insert table 7 about here]

In table (7), I take a closer look at how patents affect the types of exit, focusing on the life science and triadic patent application subsample. Specifically, I distinguish between (1) IPOs (2) 'high acquisitions' (being acquired for more than 200% of the VC investment)

(3) 'unknown acquisitions' (being acquired for an undisclosed sum[15]) (4) 'firesales' (being acquired for less than 100% of the VC investment) (5) being defunct, (6) being active as of the end of 2014. I find that patents increase the likelihood of IPO as well as of a high acquisition (though the latter is not significant). Patents appear to decrease the likelihood of firesales, being defunct and especially acquisitions for undisclosed sums. It is intrinsically difficult to interpret acquisitions for undisclosed sums as either positive or negative for the entrepreneurs. However, casual empiricism suggest that acquisitions for undisclosed sums are often effective firesales where the amount is not disclosed to avoid embarrassing the original investors.[16]

Ideally, I would want to use firm exit value as a dependent variable to quantify the value of patents for these firms. This is problematic since firm value exit is not directly observable for firms that have not exited yet or which were acquired for an undisclosed sum. In appendix B, I report on a quantification exercise where I use actual exit values when feasible and average exit values otherwise. I then construct the difference between the (partly imputed) exit value and the total investment (both in present values). Using this as a dependent variable, I obtain estimates the value of U.S. patent protection between 20 million and 35 millions (for life science firms and triadic applications).

6.1 Effects of patents on (re)financing

[Insert table 8 about here]

Next, I consider whether patents impact refinancing raised from venture capitalists.

[15]Acquisitions between 100% and 200% of the VC investment are also included in this category but they are only a small minority of cases.

[16]It is also worth noting that the disclosure of financial terms is mandatory when the acquiror is a public firm and the acquisition is expected to materially affect earnings.

It has often been suggested that patents help mitigate information asymmetries between entrepreneurs and investors and hence facilitate access to capital (see e.g. Hsu & Ziedonis 2013, Conti et al. 2013a, Conti et al. 2013b, Haeussler et al. 2014). If firms in my sample are capital constrained, perhaps patents could help firms success by alleviate this constraint. As reported in table 8, I find no evidence that patents have an effects on financing raised from venture capital in the first five years since the first round.[17] The coefficients for patents are not significant in any of the specification and the point estimates for the life science subsample are actually negative.

6.2 Effects of patents for non-VC backed firms

Finally, I study whether patents also help firms that have not yet raised venture capital. To do this, I reproduce my empirical methodology for two samples of firms: recipients of NIH Small Business Innovation Research (SBIR) grants and firms that file a form D to the SEC after raising some form of capital.[18] I consider four outcomes (1) Being acquired (2) Being acquired for more than USD 25 million, (3) Having an IPO and (4) Raising venture capital. When instrumenting for patents, I do not find significants effects of patents on any of these outcomes variables in either the SBIR recipients sample or the form D filers sample. Definitive conclusions are unwarranted given the small sample size of the SBIR sample and other limitations of the empirical methodology. However, the *prima facie* evidence is that patents are less useful to other startups in the pre-VC stage than in the VC stage. One potential explanation for the differential results may be that

[17]These regressions are run on the stable of firms that have no missing round amount in the first five years. I obtain qualitatively identical results when looking at capital raised after 6, 7 or 8 years.

[18]Filing a 'form D' enables privately held firms to sell securities without registering with the SEC. In both samples, I exclude firms that have already raised venture capital at the time of receiving the NIH/SBIR grant or filing a form D. Further details about are available in the data section

taking advantage of the legal protection in the form of patents require substantial capital expenditures or other resources which may be more readily available to VC-backed firms.

[Insert table 10 and 9 about here]

7 Discussion and Conclusion

This paper studies the impact of patents on entrepreneurial firms using a sample of U.S. venture-backed firms matched to their patent applications in a relatively short time window after the first round (24 months). I compare firms that filed the same number of patent applications at the USPTO, but had more or less success in converting these applications into granted patents due to differences in leniency across the patent examiners they got. This approach aims to identify the local average treatment effect (LATE) of patents for firms whose patenting outcomes were altered by examiner assignment. My first-stage regression suggests that examiners have considerable influence on examination outcomes, as previously found in prior studies on patent examiners (Cockburn, Kortum & Stern 2003, Lemley & Sampat 2012, Sampat& Williams 2015). However, firms appear to have little influence on the examiner their applications are assigned to. In my sample, examiner leniency (defined in terms of approval rates for other applications assigned to the same examiner in the same year) is uncorrelated with pre-determined firm characteristics such as proxies for the prior success of lead investors, the amount raised in the first round, firm age or the stock of pre-VC patent applications. The instrument appears to be both relevant and valid which suggest it might be a promising empirical strategy to understand the effect of patents on firms.

The analysis reveals considerable heterogeneity in the effect of patents on the success of entrepreneurial firms depending on the industry (life science versus IT), the stage of development (VC versus pre-VC) and whether the firm thought the inventions to be valuable enough to warrant incurring the costs of filing for protection in Europe and Japan. It is only in life science, for VC-backed firms and for applications also filed in Europe and Japan that I find a significant effect of patents on the likelihood of success defined as having an IPO or being acquired more than twice the VC investment. But the effect is economically considerable with a back of the envelope calculation suggesting that a patent may be worth between 20 and 30 million USD.

What drives the effects of patents on firm success for life science firms? Based on the literature on why firms patent, three candidate mechanisms seem plausible: access to capital, appropriation and patents as bargaining chip. Given that I find no evidence in my sample that patents help firms raise additional venture capital, I suggest that access to capital is unlikely to be the mechanism at play here. I cannot rule out that patents as bargaining chip could play a role but the literature on strategic patenting has focused on telecommunication and semiconductors industries, with much more limited evidence on the role that patents as bargaining chip may play in life science. Given that the prior survey evidence emphasizes the importance of patents for appropriation in pharmaceuticals and biotechnology, I suggest that this appropriation is the most plausible mechanism to explain the effect of patents on firm success observed here.

This paper also present several "null results": no effect of patents on firm success in the IT sector, no effect at the pre-VC stage, no effect for less important (non-triadic) patents even in the life science sector. I remain agnostic as to whether or not these null results reflect a true absence of effect for at least two reasons. First, the confidence intervals are too large to statistically rule out economically meaningful effects. Second, my definition of firm success (IPO or acquisition for more than twice the amount invested by venture capitalists) is blunt and imperfect. Larger samples or more fine-grained firm success data might overturn those null results and reveal effects not observed here.

I conclude by acknowledging several other limitations of this study. First, the empirical strategy identifies the local average treatment effect (LATE) of patents whose grant status was altered by examiner assignment. The LATE effect identified by an instrumented variable approach is not the only policy relevant effect. For instance, there may be patents applications that are so innovative that they would be granted irrespective of examiner assignment. The value of patent protection for these innovation may be highly relevant yet it would not be included in the LATE effect. Second, with venture capital data not much is known about the firms besides the timing and size of the investments. Using variation in examiner leniency with richer data on entrepreneurial firms could be a fruitful avenue for future research. In particular, observing sales or licensing revenues may shed more direct light on the role of patents in product markets while more detailed financial data could lead to better quantification of the value of patents. Third, examiners may affect firms not just by granting patents but also by the speed with which they grant patents or by the scope of the granted patents. If more lenient examiners grant faster and allow broader claims, the effects of patents identified here would be biased upwards. The dichotomy between granted versus not granted patent application may be a useful first step in understanding the causal effects of patents but a more nuanced view taking into account the breadth of the granted patent may ultimately be more accurate.

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Tables

Table 1: **Descriptive statistics on selected variables, VC firms sample**

Panel A: Industry	No of companies	As fraction
Information Technology	1,660	0.76
Life Science (*)	531	0.24
Panel B: Exit type	No of companies	As fraction
Success (Went Public or High acquisition)	418	19.1
Went Public	186	0.08
High acquisition	232	0.11
Unknown acquisition	599	0.27
Low acquisition	86	0.04
Defunct	219	0.10
Still active as of 2014	869	0.40
Panel C: Financing variables	Mean	S.D.
Year of first round	2002	2.2
First round amount (million USD)	8.56	19.4
First round number of investors	2.63	1.67
Time from founding to first round (years)	2.97	6.17
Total raised 5 years after the first round (million USD)	24.11	34.4
Panel D: Patent variables at patent level	Mean	S.D.
Granted	0.60	0.26
Difference between examiner grant rate and unit grant rate	0.0	0.14
Nr of applications assigned to same examiner in given year (**)	41.0	28.8
Panel E: Patent variables at firm level	Mean	S.D.
Patent applications	3.3	4.6
Granted patents	2.1	6.2
Triadic patent applications (***)	0.9	2.1
Triadic patents (****)	0.6	1.7

Notes: (*) The industry classification is based on VentureXpert "Company industry class". I relabel "Medical/Health/Life Science" as "Life Science" for conciseness.(**) Applications where the number of applications assigned to the same examiner in a given year is 5 or less are excluded from the sample as examiner leniency is imprecisely observed in those cases. (***) Triadic patent applications refer to US patent applications that were also filed in Europe and Japan. (****) Triadic patents refer to U.S. applications that were granted in the U.S. and filed in Europe and Japan (irrespective of whether they were granted or not in Japan and the U.S.

Table 2: **Descriptive statistics, pre-VC firms sample**

Panel A: SBIR recipients (n=396)	Mean	S.D.
Year of grant receipt	2001.5	1.8
Went Public	0.02	0.14
Acquired	0.19	0.40
Acquired for more than 25 mio USD	0.04	0.20
Subsequently received VC	0.15	0.36
Applications	2.8	3.7
Of which: granted	1.7	2.6

Panel B: Form D filers (n=1,761)	Mean	S.D.
Year of first form D filing	2003.2	1.2
Went Public	0.03	0.18
Acquired	0.16	0.36
Acquired for more than 25 mio USD	0.02	0.16
Subsequently received VC	0.17	0.37
Applications	2.3	2.2
Of which: granted	1.3	1.8

Notes: Panel A shows descriptive statistics for firms receiving a NIH SBIR grant and filing at least one patent application. Patent B shows descriptive statistics for firms filing a form D report to the SEC (as the results of raising some form of capital) and filing at least one patent application. Firms that already have raised venture capital by the time they receive their first SBIR grant of file their first form D report are excluded from the sample.

Table 3: **First stage of the instrumental variable regressions**

	(1) Patents
Mean examiner leniency (normalized)	0.217*** (0.019)
Observations	2191
Sector by 1st round year FE	Yes
Nr of applications FE	Yes
F-statistic	132
Mean of dependent variable	2.14
R2	0.97

Notes: Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: **Does examiner leniency in the first application predict subsequent applications or examiner leniency in subsequent applications?**

	Nr of subsequent applications (1)	Examiner leniency in subsequent applications (2)
Examiner leniency in first application (normalized)	-0.086 (0.162)	0.000 (0.005)
Observations	2191	991
Technological sector by year FE	Yes	Yes
Mean of dependent variable	2.30	-0.00

Notes: Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Examiner leniency in first application is normalized to have a standard deviation of 1. Subsequent patent applications up until two years from the first venture capital round. Firms that apply once do not appear in the second column, hence the lower number of observations.

Table 5: **Instrument and pre-determined firm characteristics**

	Nr of lead investors (1)	First round amount (log) (2)	Firm age (3)
Mean examiner leniency (normalized)	0.001 (0.032)	-0.008 (0.027)	0.036 (0.114)
Observations	2191	2050	1954
Mean of dependent variable	2.63	8.36	2.97
R2	0.06	0.10	0.10

	Pre-VC patent applications (4)	Lead investors prior IPOs (5)	Lead investors prior investments (log) (6)
Mean examiner leniency (normalized)	0.050 (0.090)	-0.041 (0.149)	-0.002 (0.117)
Observations	2191	2191	2191
Mean of dependent variable	1.44	4.23	9.26
R2	0.40	0.05	0.05

Notes: Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Mean examiner leniency is normalized to have a standard deviation of 1. All regressions include fixed effects for the number of applications and technological sector by first venture capital round year fixed effects. The number of observations is slightly lower in columns 2 and 3 due to missing values for first round amount and year of founding, respectively. Lead investors refer to all first VC round investors.

Table 6: **Patents and firm success**

		Life science			IT		
DV=success	All patents (1)	All patents (2)	Triadic patents (3)	Other patents (4)	All patents (5)	Triadic patents (6)	Other patents (7)
Patents	0.048	0.149**	0.244**	-0.034	0.017	0.103	-0.028
(instrumented)	(0.037)	(0.076)	(0.096)	(0.161)	(0.043)	(0.136)	(0.042)
Observations	2191	531	348	531	1660	415	1660
Mean of dep. variable	0.19	0.29	0.32	0.29	0.16	0.20	0.16

Notes: Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is firm success which is defined as having an IPO or being acquired for more than twice the amount raised from venture capitalists. The variable of interest is the number of patent granted to the firm among the set of applications filed in the first 24 months since the firm has received venture capital funding. All specifications use two stage least square estimation with mean examiner leniency as an instrument for the number of granted patents. In columns 2 and 5 the sample is restricted to life science and IT firms respectively. In columns 3 and 6 the sample is restricted to patent applications that were also filed in Europe and Japan (triadic patents), for life science and IT firms respectively. In columns 4 and 7 the sample is restricted to patent applications that were not filed in Europe and Japan. All specifications include fixed effects for the number of applications and technological sector by first venture capital round year fixed effects.

Table 7: **Patent and firm outcomes in the life science, triadic patents sample**

	IPO (1)	Acq-H (2)	Acq-U (3)	Acq-L (4)	Defunct (5)	Active (6)
Patents	0.130*	0.114	-0.161**	-0.033*	-0.065	0.015
(instrumented)	(0.076)	(0.071)	(0.082)	(0.019)	(0.049)	(0.096)
Observations	348	348	348	348	348	348
Mean of dep. variable	0.16	0.16	0.17	0.02	0.05	0.44

Notes: Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The sample corresponds to life science firms is limited to patent applications that were also filed in Europe and Japan (triadic applications). The dependent variable is having an IPO (column 1), being acquired for more than twice the amount raised from venture capitalists (column 2), being acquired for an undisclosed amount (column 3), being acquired for less than the amount raised from venture capitalists (column 4), being defunct (column 5), being active as of the end of 2014 (column 6). The variable of interest is the number of patents granted (in the US) to the firm among the set of applications filed in the first 24 months since the firm has received venture capital funding. All specifications use two stage least square estimation with mean examiner leniency as an instrument for the number of granted patents. All specifications include fixed effects for the number of applications and technological sector by first venture capital round year fixed effects.

Table 8: **Patents and refinancing**

		Life science			IT		
	All patents	All patents	Triadic patents	Other patents	All patents	Triadic patents	Other patents
DV=refinancing (log)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Patents	0.069	-0.108	-0.061	-0.172	0.132	-0.407	0.062
(instrumented)	(0.136)	(0.320)	(0.353)	(0.644)	(0.155)	(0.498)	(0.159)
Observations	1431	345	235	345	1086	294	1086
Mean of dep. variable	9.76	9.86	10.06	9.86	9.73	9.92	9.73

Notes: Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is venture capital raised in the first five years after the first VC round, in logs. The variable of interest is the number of patent granted to the firm among the set of applications filed in the first 24 months since the firm has received venture capital funding. The regressions are run on the stable panel of firms that have no missing round amount in the first five years since receiving venture capital. All specifications use two stage least square estimation with mean examiner leniency as an instrument for the number of granted patents. In columns 2 and 5 the sample is restricted to life science and IT firms respectively. In columns 3 and 6 the sample is restricted to patent applications that were also filed in Europe and Japan (triadic patents), for life science and IT firms respectively. In columns 4 and 7 the sample is restricted to patent applications that were not filed in Europe and Japan. All specifications include fixed effects for the number of applications and technological sector by first venture capital round year fixed effects.

Table 9: **Patents and firm success for non-VC firms- form D filers sample**

	Acquired	Acquired >25 million	IPO	VC
	(1)	(2)	(3)	(4)
Patents	0.037	0.007	-0.019	-0.036
(instrumented)	(0.049)	(0.021)	(0.025)	(0.050)
Observations	1761	1761	1761	1761
Mean of dep. variable	0.16	0.02	0.03	0.16

Notes: Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. These regressions are run on a sample of non-VC/pre-VC firms: firms that file a form D report to the SEC as the result of raising some form of capital. The dependent variables are having an IPO (column 1), being acquired (column 2), being acquired for more than 25 million USD (column 3), raising venture capital (column 4). The variable of interest is the number of patent granted to the firm among the set of applications filed in the first 2 years since filing the first form D. All specification use two stage least square estimation with mean examiner leniency as an instrument for the number of granted patents. All specifications include fixed effects for the number of applications, year (of first form D filing) fixed effects, and technological type fixed effects.

Table 10: **Patents and firm success for non-VC firms- NIH SBIR recipients sample**

	Acquired (1)	Acquired >25 million (2)	IPO (3)	VC (4)
Patents	0.032	-0.008	-0.074	0.029
(instrumented)	(0.098)	(0.033)	(0.048)	(0.092)
Observations	396	396	396	396
Mean of dep. variable	0.20	0.04	0.02	0.15

Notes: Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. These regressions are run on a sample of non-VC/pre-VC firms: firms that receive a Small Business Innovation Research (SBIR) from the NIH. The dependent variables are having an IPO (column 1), being acquired (column 2), being acquired for more than 25 million USD (column 3), raising venture capital (column 4). The variable of interest is the number of patent granted to the firm among the set of applications filed in the first 2 years since receiving the SBIR grant. All specifications use two stage least square estimation with mean examiner leniency as an instrument for the number of granted patents. All specifications include fixed effects for the number of applications, year (of SBIR grant receipt) fixed effects, and technological type fixed effects.

A Appendix: Data appendix

Data sources. Multiple sources were combined to produce the analysis data set. Data on venture-backed companies, including firm names, classification into industries, founding rounds, investor characteristics and current status came from Thomson Reuters' VentureXpert. Further details on acquisitions of VC-backed firms were collected manually from press releases and business press reports. Lists of NIH 'Small Business Innovation Research' recipients were downloaded using the NIH RePorter Tool. Lists of firms filing form Ds to the SEC (as a result of raising some form of capital) are available from the SEC website and were shared by Michael Ewens. SDC Global Issues database and Bureau van Dijk Zephir database were used to identify IPOs and acquisitions, respectively, for non VC firms. Data on patents applications and patents comes from the USPTO, either through the USPTO directly or through the 'USPTO bulk downloads' distributed by Google. The USPTO data contains data on the name of the examiner, date of filing, status of the application and the names of the assignees. In July, the USPTO released a 'Patent Assignment Dataset' in bulk format (described in Marco et al. 2015) which was used to measure subsequent patent application filing. To identify U.S. patent applications that were also filed in Europe and Japan, I relied on the OECD triadic patent families database (OECD 2015).

Data	Source
VC-backed firms	VentureExpert
Acquisition details (VC firms)	Press releases and Business press reports
Patent assignment data	USPTO website (assignment.ustpo.gov)
Examiner names	USPTO bulk data release (through Google)
Triadic patent families	OECD Triadic Patent Families database
NIH SBIR recipients	NIH Reporter
Form D data	SEC Website (through Michael Ewens)
IPO data (for non-VC firms)	SDC Global Issues database
Acquisition data (for non-VC firms)	Bureau van Dijk Zephir database

Patent application data. I collected data both from USPTO patent assignments record and from USPTO Patent Application Information Retrieval (PAIR). For assignments, I collected patent assignment data from from the USPTO website (http://assignment.uspto.gov/). I limited the collection to application numbers 9,800,000 to 11,800,000 which roughly correspond to patent applications filed between 2001 and 2007. For information on which patent applications are assigned to which examiners, I collected data from the USPTO PAIR system distributed through Google (http://www.google.com/googlebooks/uspto-patents-pair.html). I collected bibliographic patent application information, including patent examiner name and grant status for patent applications ranging from application numbers 9,800,000 to 11,800,000.

Matching procedure between patent applications and VC firms The matching procedure between companies and patent application assignment records is as follows. First, I selected assignments that are made no earlier than 7 days before the filing date, and no later than 90 days after the filing date.[19] Second, I used a name standardization procedure to standardize firm names in the assignment and in the venture capital data.

[19]The assignment data include both the initial assignment (if any) from the inventors to an assignee and subsequent re-assignments. The initial assignment date need not correspond to the filing date and while it is common for the initial assignment date to be the same as the file, it is also common for the assignment date to be after or just before the filing date.

The procedure followed closely that of the NBER patent data project.[20] Third, I matched assignment records to firm names if the standardized names match exactly. Since this may be failing to match firms names whose name has been misspelled, I also considered the set of possible matches that have a Levenshtein distance (a standard measure of distance between strings) of one. In this set, I inspected the matches manually to determine whether the match is correct. Fourth, I kept patent applications that were filed in the two years following the first venture capital round.

[20] http://sites.google.com/site/patentdataproject/Home/posts/namestandardizationroutinesuploaded

B Appendix: quantifying patent value using assumptions on net the present value of the firm at exit

In order to quantify the value of patents, I perform the following quantification exercise. Note that I do not seek to measure how patents influence returns to venture capital investment since the equity split between the venture capital investors and earlier investors, including founders, is not known. Rather, I attempt to provide a very rough dollar estimate for how much the granting of a patent increases firm value.

The calculation is based on comparing the net present value of the VC-backed firm at exit versus the net present value of VC investment. I use actual exit values when feasible and a number of assumptions about exit values when exit values are not directly observable. More specifically, for firms that are acquired, the value of the firm is set at the acquisition price (if disclosed). For firms that go public, the value of the firm is set as the share price times the number of share outstanding, as of the IPO. For seven firms that went public, share prices and number of shares outstanding could not be found; in those cases, I imputed firm value at exit as the sample average for firms going public. For firms that are coded as defunct in VenturXpert, I assume a firm value at exit of zero.

There are a substantial number of firms that were acquired with undisclosed terms. Since acquisitions with undisclosed terms may often (though not always) reflect firesales where the initial investors chose to not disclose their losses, my preferred estimate is based on taking the 25% centile (instead of the mean) of the sample distribution of acquisitions for which financial terms were disclosed (USD 75 million). I also have a sizeable number of firm as well had not exited by the end of 2014. In those cases, I input as firm value at exit as the sample mean value for firms that have already exited (USD 250 million).

Finally, I use a discount rate of 5%. With these assumptions, I am able to compute a net present value of the firm at exit.

I then use the difference between the net present value of the firm and the net present value of VC investment as a dependent variable in regressions using the same empirical methodology as the rest of the paper. I focus on the sample life science industry and patent applications filed in Europe and Japan (in addition to the U.S.). I report the results of these regressions in table 11. Under the preferred set of assumptions, the point estimate for the value of patent is around USD 36 million. Changing the assumption on the firm value at exit for firms that are still active by the end of 2014 from USD 250 million (the mean of the distribution of known firm exit values) to 64 million (the 25th centile of said distribution) has little impact on the point estimate (column 2). Assuming a discount rate of 10% instead of 5% reduces the point estimate to around 23 million (column 3). The point estimate is similarly sensitive to changing the assumption about the assumed value of undisclosed acquisitions from the 25th centile of the the sample distribution of acquisitions for which financial terms were disclosed (USD 75 million) to the sample mean of said distribution (USD 230 million). This is unsurprising since patents appear patents decreases the likelihood of an acquisition with undisclosed terms (table 7, column 2).

Table 11: **Estimating the value of a patent, life science VC-backed firms**

DV=NPV of firm at exit-NPV of VC investment	(1)	(2)	(3)	(4)
Patents	36.278**	33.886**	23.178*	22.141
(instrumented)	(16.059)	(17.146)	(12.056)	(14.560)
Observations	348	348	348	348

Notes: Robust standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The sample corresponds to life science firms and is limited to patent applications that were also filed in Europe and Japan (triadic applications). The variable of interest is the number of patents granted (in the U.S.) to the firm among the set of applications filed in the first 24 months since the firm has received venture capital funding. The dependent variable is the net present value of the firm at exit minus the net present value of VC investment under different assumptions. In column 1, the following set of assumption is made: the discount rate is assumed to be 5%, the acquisition price when not disclosed is assumed to be USD 75 millions (the 25th centile of disclosed acquisition prices) and the exit value for firms that have not exit yet is assumed to be USD 250 millions (the mean of known exit values). In column 2 the exit value for firms that have not exit yet is assumed to be 64 millions (the 25th centile of known exit values) instead of USD 250 millions. In column 3, the discount rate is assumed to be 10% instead of 5%. In column 4, the the acquisition price when not disclosed is assumed to be USD 230 millions (the mean of disclosed acquisition prices). The specifications use two stage least square estimation with mean examiner leniency as an instrument for the number of granted patents. All specifications include fixed effects for the number of applications and technological sector by first venture capital round year fixed effects.