Are Patents Endogenous or Exogenous to Startup Financing?*

Annamaria Conti †, Jerry Thursby ‡and Marie Thursby §

October 29, 2012

Abstract

We study the role of patents as signals sent by technology startups to external investors to convey information about the quality of their inventions. We provide a theoretical model of patents as a productive signal sent by startup founders to a continuum of external investors who differ in the amount of capital they can provide to the startup. This allows us to examine the optimal match of different types of startups, as defined by the quality of their technology, to external investors who differ in the amount of capital they can provide. To test the model we use a novel dataset of Israeli startups that received external funding during the period 1990-2011. The analysis provides strong support to our view that patents are used strategically by startups to attract new investors. Moreover, it provides evidence that startups with better technologies affiliate with investors who can add high value to the startup.

Preliminary: Please do not cite or quote without permission.

*We are indebted to William Kerr, Pierre Regibeau, Mark Schankerman, and participants at the Conference on Patents, Innovation, and Entrepreneurship in Washington D. C., May 2012. We also thank Haim Abramovich, Orna Berry, Shlomo Caine, Uri Gabai, Gad Levi, Shlomo Maital, Ayla Matalon, Ed Mlavsky, Mira Peled, Maura Rosenfeld, Eduardo Shoval, Yossi Smoller, Einat Spivak, Manuel Trajtenberg, Daniel Wasserteil, and Yuval Weiss. The views expressed herein are those of the authors.

†Scheller College of Business, Georgia Institute of Technology, GA 30308, Atlanta, USA, annamaria.conti@mgt.gatech.edu

‡Scheller College of Business, Georgia Institute of Technology, GA 30308, Atlanta, USA, jerry.thursby@mgt.gatech.edu

§Scheller College of Business, Georgia Institute of Technology, and NBER marie.thursby@mgt.gatech.edu

1 Introduction

Recent survey evidence suggests that securing funds is one of the most important reasons for startup patenting (Graham and Sichelman 2008; Graham et al. 2009). This adds to mounting evidence that patents signal value to external investors in startup companies (Haeussler et al. 2009; Conti et al. 2011; Hsu and Ziedonis 2011). More importantly, it suggests that startup patents are the result of conscious funding strategies, and in particular, are the equilibrium outcome of a signaling game much like that first observed in the education setting (Spence 1973). Increasing evidence also shows that external investors are not homogeneous with respect to the value they add to a startup (Sahlman 1990; Hsu, 2004; Hochberg et al., 2010; and Bottazzi et al. 2008), and that startups are willing to pay a price to affiliate with external investors that can potentially add high value (Hsu, 2004). This suggests that startups strategically choose the type of external investors to whom they will signal their value.

We construct and test a theoretical model that allows us to analyze the strategic decision of startup founders with regard to patents. Patents have a dual role: they are both an input to the startup's value function and a signal for external investors. In the model, we consider a continuum of external investors who differ in the amount of capital, be it expertise, market knowledge, information network, or reputation, they can provide to the startup. This allows us to examine the optimal match of different types of startups, as defined by the quality of their technology, to external investors who differ in the amount of capital they can provide. To test the model we use a novel dataset of Israeli startups that received external funding during the period 1990-2011. The analysis provides strong support to our view that patents are used strategically by startups to attract new investors. Moreover, it provides evidence that startups with better technologies affiliate with investors who can add high value to the startup.

The theory applies insights of Leland and Pyle (1977) to the financing problem of technology startups. In the model, the founders of a startup choose their patent investment to maximize their expected wealth which is a function of both the productive and signaling value of the patents on their invention. We examine the conditions under which a signaling equilibrium emerges in which the founders invest more than under symmetric information, as in Spence's (1973) model of education as a productive signal. The important modification we make in order to examine venture financing is that we consider a continuum of external investors which differ in the amount of capital they can provide. For the capital the startup receives it pays a price, which in equilibrium is equal to the external investors' share of the value their capital adds to the startup. We show that there exists a signaling equilibrium in which startups with high value technologies match with external investors that provide a large amount of capital. This result derives from the fact that the price startups pay for a unit of capital is decreasing in the quality of their technology, and the magnitude of the decrease is larger in a signaling equilibrium than under symmetric information. In fact, in a signaling equilibrium patent investment is more responsive to the underlying technology's quality than under symmetric information, and startups with better technologies file a larger number of patents. This in turn enhances the value of a startup and increases its bargaining position, thus reducing the price the startup pays to external investors for their capital.

The empirical analysis uses a rich dataset on 787 Israeli startups that was provided by Israel's Venture Capital Research Center (IVC). Israeli startups are particularly relevant for our setting given the innovative performance of the Israeli economy (Trajtenberg, 2000). For each startup we

have detailed information on their rounds of financing, including the amount they received, the external investors that invested, and the stage of the investment. We integrated this information with additional information on the founders and their patent investment.

We find that startup investment in patents prior to the first round of funding is not endogenous to this round. This result is consistent with the fact that startups are often formed based on an initial patent or set of patents associated with the founders. However, for rounds subsequent to the first, startups strategically use their investment in patents to attract new investors. They do not strategically use patents to have old investors investing in subsequent rounds. This is an interesting result since the problem of asymmetric information is likely to be more acute for external investors funding the startup for the first time than for old investors. Finally, having distinguished among types of external investors we find that startups with better technologies, as measured by their investment in patents, receive more funding from venture capitalists than from private investors. To the extent that venture capitalists provide greater capital, in terms of expertise, market knowledge, information network, or reputation, than private investors (Brav and Gompers, 1997; Field, 1996), then our findings suggest that startups with higher quality technologies tend to match with external investors who provide a larger amount of capital.

This study contributes to the literature on patents as signals for external financing which, with the exception of Conti et al. (2011), has not considered patents as endogenously determined strategic variables. For example, Haeussler et al. (2009) and Fischer and de Rassenfosse (2012) examine patents as predictors of venture capital funding and Hsu and Ziedonis (2011) examine the role of patents in IPO performance. By examining the endogeneity of patents, we provide evidence that patents are costly economic signals used to attract new investors, i.e., those most likely to be affected by the asymmetric information problem inherent in startup financing. While Conti et al. (2011) consider endogeneity, they focus on patents as one of several economic signals, and they are unable to identify either new investors or funding rounds.

An important contribution of the theoretical model is the consideration of heterogeneous external investors, which allows us to predict the matching of high quality startups with investor types, as defined by the amount of capital they can provide.[1] This aspect of the theory is essential to frame the empirical analysis of the matching of investor and startup types. While other empirical studies distinguish among investor types, they are unable to make the inference that the funding pattern is consistent with optimal matching (for example, Hsu 2004 and Conti et al. 2011).

The paper proceeds as follows. Section two introduces the model. Section three describes the solution to the signaling game. Section three extends the baseline model by allowing for a continuum of investors. Section four presents an empirical estimation of the theory. Section five concludes.

[1] For an example of signaling combined with matching in a more general context, see Hoppe et al. (2009).

2 Model Setup

We first consider the case in which there is one startup seeking external funding and at least two investors who are potentially interested in investing in the startup. The setup of the model is as follows. The founders of a startup have made an invention which they need to develop in order to translate it into a commercially viable product. Similarly to Leland and Pyle (1977) and to Grinblatt and Hwang (1989), the founders need to raise funds from external investors in order to obtain the capital, K, to cover the invention's development. The project will ensure a return $\theta + x$, where θ is the value of the invention. The distribution of θ is continuous and has support $(0, \overline{\theta})$; x is a random variable with mean zero and variance σ^2.

The founders have private information about θ which they need to convey to external investors, and they choose patents as a signal, $p \in (\underline{p}, \overline{p})$. We allow for the possibility that an invention can give rise to multiple patents, but there is a maximum number of patents, $\overline{p}$, the founders can file for a given invention. Patents can, of course, add value to the startup in a variety of ways (Cohen et al. 2000; Gans et al. 2002; Arora and Ceccagnoli 2006; and Graham et al. 2009). For simplicity, we assume that this intrinsic value plus the signaling value of the patents enter the value function additively, so that the total value the startup generates from patents is given by $\theta(p) + V(p)$, where $V(p)$ is strictly increasing and concave in p.

Patent investment involves a total cost, cp. We assume that the marginal cost of the patent investment, c, is a decreasing function in the quality of an invention, or $c_\theta < 0$, where c_θ denote the partial derivative of c with respect to θ[2]. Hence higher quality inventions require less investment by the founders to obtain patents than low quality inventions. This is because validating the novelty of a low quality invention takes more effort. Moreover, low quality inventions might go through a higher number of revision rounds than high quality patents. We assume the founders can finance cp using own's, friends' and family's money, M. This amount is limited and it is just enough to cover cp as well as other expenses, A, which are any expenses the founders incur to set up their project. Thus, M is not used to finance K, for which the founders can either seek equity financing or debt financing.

The game is played in three periods, and the players are risk neutral. In the first period, the founders make an invention and finance their patent investment, cp, as well as other setup expenses, A, using M. Thus, in the first period:

$$M = cp + A \tag{1}$$

In the second period, the founders of a startup seek equity and debt financing using their patent investment as a signal. In this period, their budget constraint is:

$$D + \alpha[\theta(p) + V(p) - D] = K \tag{2}$$

where D is the amount of the loan the founders can obtain from their bank. Without loss of insight we assume that it is raised at a riskless rate. In addition, $\alpha \in (0, 1)$ is the fraction of the equity in the startup that is retained by an external investor. Thus, $\alpha[\theta(p) + V(p) - D]$ is the amount the

[2]In the model we use f_x to denote the partial derivative of a function f with respect to the variable x.

founders of a startup receive in the second period after having sold a portion α of their equity. Even though there are multiple external investors who are potentially interested in investing, only one ends up investing. The fraction of the equity α must be high enough to guarantee the investor a return equal to the opportunity cost of investing in the startup, which we assume to be the same for all external investors. It cannot guarantee a greater return because otherwise other investors would invest in the startup for a lower return. At the same time, α must be large enough to guarantee that the founders' second period budget constraint holds.

In line with Hsu (2004), in addition to his funding, an external investor adds value, $\upsilon(S)$, to the startup from his stock of expertise, market knowledge, information network, and reputation. We denote the input provided by the investor as S and assume that $S \in (\underline{S}, \infty)$. We further impose that $\upsilon(S)$ is strictly increasing and concave in S. In the model, S is an intrinsic characteristic of the external investor rather than a choice, so that as he invests he automatically adds $\upsilon(S)$ to the startup's value. This investment is not free and the price the founders have to pay, once the value of a startup is realized, is equal to $\alpha\upsilon(S)$. Thus, the founders' expected wealth in the last period is equal to:

$$E(W) = (1-\alpha)[\theta + V(p) + \upsilon(S) - D] - M \tag{3}$$

If we substitute for M from the first period's budget constraint and for D from the second period budget constraint, we obtain:

$$E(W) = (1-\alpha)[\theta + V(p) + \upsilon(S)] + \alpha[\theta(p) + V(p)] - K - cp - A \tag{4}$$

Notice that we have assumed a unitary discount rate, so that the net expected return to an external investor is equal to:

$$E(r) = \alpha[\theta + V(p) + \upsilon(S) - D] - \alpha[\theta(p) + V(p) - D] - \varsigma S \tag{5}$$

where ς is the marginal cost of investing a unit of the investor's capital stock, S, in the startup. We assume that $\varsigma > \upsilon_S(\underline{S})$. This condition ensures that $\alpha_S > 0$, that is, the portion of the startup the founders are willing to give up is an increasing function of the amount of capital, S, they receive from an external investor. From expressions (2) and (5), we find that α is equal to:

$$\alpha = \frac{\varsigma S + K - D}{[\theta + V(p) + \upsilon(S) - D]} \tag{6}$$

As is clear from this expression, α is a decreasing function of the invention's value, θ, and of the number of patents filed. The rationale is that the greater the value of an invention the less likely the founders are willing to sell a portion of their startup.

3 Model Solution

Similar to the problems of Leland and Pyle (1977) and Grinblatt and Hwang (1989), the founders need to choose a value of p to maximize their expected wealth in the last period. Their maximization problem is

$$\underset{p}{Max}\ (1-\alpha)[\theta + V(p) + \upsilon(S)] + \alpha[\theta(p) + V(p)] - K - cp - A$$

subject to (1), (2) and (6). Moreover, in a perfect Bayesian equilibrium, the external investors' beliefs about the quality of the invention must be correct, or

$$\theta = \theta(p^*(\theta)) \tag{7}$$

where $p^*(\theta)$ is the value of p that maximizes the founders' last period expected wealth. This is a natural condition in a competitive capital market with more than one potential investor. If $\theta < \theta(p^*(\theta))$, then the investor which ends up investing in the startup could do better by deviating from the amount he pays to the startup in the second period. If $\theta > \theta(p^*(\theta))$, then excess returns would exist for other investors.

The first order necessary condition for such an equilibrium is

$$V_p(p) - \alpha_p(p, \theta, S)\upsilon(S) + \alpha\theta_p(p) - c = 0, \tag{8}$$

with the second order condition given by

$$V_{pp}(p) - \alpha_{pp}(p, \theta, S)\upsilon(S) + \alpha\theta_{pp}(p) + \alpha_p(p, \theta, S)\theta(p) < 0. \tag{9}$$

These two conditions lead to the following proposition about founder investment:

Proposition 1. *There exists a signaling equilibrium in which the founders of a startup find it optimal to invest an amount, p^*, that is greater than that under symmetric information and in which $\theta = \theta(p^*(\theta))$ and p and θ are complementary in the founders' last period wealth.*

Proof. See Appendix. □

The founders of a startup find it profitable to choose p as a signal for the value of their invention, provided that the assessment made by the founders of the invention's value, $\theta(p)$, is increasing in p. As we show in the appendix, $\theta(p)$ is an increasing function of p if p and θ are complementary in the founders' last period wealth function. If this condition holds, then the founders of high-value inventions find it optimal to invest in a larger number of patents, p, than under symmetric information.

4 A signaling equilibrium with optimal matching

We now allow for a continuum of startups which are ordered according to the expected value of their invention, θ. Additionally, we allow for a continuum of external investors' types. The distribution of external investors' types across startups has mixed joint density $f(S,\, y(\theta))$, with $\underline{S} < S < \varphi^{-1}(-c_\theta)$ and $y(\theta) \geq 2$. The upper bound of S follows from the condition $\varphi(S) = \alpha_{p\theta}(p, \theta, S)\upsilon(S) - \alpha_\theta(p, \theta, S)\theta_p(p^*) < -c_\theta$, which guarantees that p and θ are complementary in the founders' last period wealth. The function $\varphi(S)$ is strictly increasing in S, since $\alpha_{\,S} > 0$. Moreover, $y(\theta) \geq 2$ ensures that the external investors' market is competitive.

In order to find a matching equilibrium, we compute the partial derivative of the founders' optimized expected wealth with respect to S. Applying the envelope theorem, we obtain:Applying the envelope theorem, we obtain:

$$E_S(W) = (1 - \alpha)\upsilon_S(S) - \alpha_S(p, \theta, S)\upsilon(S) \tag{10}$$

which in equilibrium must equal zero. That is, the founders should not find it profitable to deviate from the external investor they have chosen. The condition we have imposed on the lower bound of ς ensures that $E_{SS}(W) < 0$, as required by the optimality of the assignment.

If we compute the full derivative of expression (10) at the equilibrium, we find

$$\frac{dE(W)}{dS} = E_{SS}(W) + E_{S\theta}(W)\frac{d\theta}{dS} = 0 \tag{11}$$

which gives us

$$\frac{d\theta}{dS} = -\frac{E_{SS}(W)}{E_{S\theta}(W)}$$

The sign of $\frac{d\theta}{dS}$ depends on the sign of $E_{S\theta}(W)$, given that by the second order condition $E_{SS}(W) < 0$. The expression for $E_{S\theta}(W)$ is:

$$-\upsilon_S(S)[\alpha_p(p,\theta,S)p_\theta(\theta) + \alpha_\theta(p,\theta,S)] - \upsilon(S)[\alpha_{Sp}(p,\theta,S)p_\theta(\theta) + \alpha_{S\theta}(p,\theta,S)]$$

As we show in the Appendix, this expression is greater than zero, giving us the following proposition about the matching of startups and investor types.

Proposition 2. *There exists a signaling equilibrium in which startup founders with an invention that has a high expected value, θ, find it profitable to match with external investors that provide the startup with a high S.*

Proof. See Appendix. □

The positive match between startups with high value inventions and external investors with a high S derives from the fact that α is a decreasing function of the expected value of an invention. Thus, for a given S, all startups derive the same benefit $\upsilon(S)$; however, the price that they have to pay in exchange of S, $\alpha\upsilon(S)$, is lower the greater the expected value of their invention. The discount founders with a high quality invention receive in the signaling equilibrium we have examined is greater than if the parties were equally informed about the technology value of the startup. In fact, from condition (7), optimal patent investment is more sensitive to the quality of the underlying technology than in the case of symmetric information, and therefore the decrease in α, due to an increase in θ, is larger.

5 Empirical Estimation

In the section we test the model's implications that i) there exists a signaling equilibrium in which startups use patent investment to attract external investors; and ii) startups with high-value inventions match with the types of external investors that provide high-value services. In our estimation we exploit detailed information available on patent investment and financing rounds for a sample of 787 startups based in Israel. Section 4.1 presents a description of the data. Section 4.2 describes the econometric methodology. Finally, section 4.3 presents the results.

5.1 Description of the dataset

We use data on Israeli startups compiled by Israel's IVC Research Center, which specializes in monitoring Israel's high-tech industry and collects extensive information on the population of Israeli startups. Included are data on financing rounds (amount received at each round, investors involved, and firm stage of development at the time of the round), whether startups ceased to operate, went IPO or were acquired, founder biographies and R&D grants awarded by the Israeli government and other foreign institutions. Israeli startups are particularly relevant for our setting given the innovative performance of the Israeli economy (Trajtenberg, 2000). An article recently appeared in The Economist[3] shows that Israel attracts far more venture capital per person than the United States: $170 in 2010 relative to America's $75.

In developing our data we began by selecting all startups that, according to IVC, had a successful exit event (IPO or acquisition) between 2000 and June 2011. This amounts to 1154 startups. We then add to this set of firms a random sample of 1000 companies out of 2912 companies that had ceased to operate (failed) during the period 2000-2011. From this set of 2154 firms we retained only those that i) had at least a round of financing recorded by IVC,[4] ii) had complete information on the typologies of external investors as well as on the total amount invested per round, and iii) had information on the identity of the founders. This final sample of 787 firms had experienced 2126 financing rounds.

The firms operated primarily in the IT and software sectors (25.5%), communications (22.0%), the internet sector (10.8%), semiconductors (7.0%), life sciences (9.7%) and medical devices (13.6%). Indeed, the sector composition of our startups reflects Israel's comparative advantage in Information and Communications Technologies (Trajtenberg, 2005). Sixteen percent of the startups spent time in a technology incubator. Eighty-five percent were founded between 1993 and 2005, 4.5% before 1993, and the remaining after 2005. Forty-three percent ceased to operate sometime during the period 2000-2011, while the remaining were either acquired or went public via an IPO.

The average number of financing rounds is 2.7; 227 startups had a single round of financing (the minimum in our sample), while 52 had more than 5 rounds. IVC classified the rounds as either seed stage (30%), R&D stage (44%), initial revenue stage (20%), or revenue growth stage (5%).

There are 1968 investors classified according to whether they are venture capital companies, private investors, angel investment groups or "other." Private investors are identified through listing in the IVC database with first and last name rather than by an investment group name. Private investors can be friends, family members or business angels. Business angels cannot be distinguished from friends and family unless the angels are organized in investment groups reported in the IVC database. The "other" investors includes primarily investment companies, private equity funds, pension funds and insurance companies. It is known whether an external investor operates from outside Israel; this includes foreign companies which do not have subsidiaries in Israel.

Twenty percent of the investors are venture capital companies, 37% are private investors, 3% are either incubators or universities, and 1% are business angel investment groups. The remaining 39%

[3] "What next for the start-up nation?" The Economist, January 21st, 2012.

[4] We excluded startups that did not receive any financing because discussions with IVC revealed that, instead of having received zero funding, many of these startups had received funding but that information had not been recorded by IVC.

are "other" investors. Of the 387 venture capital companies, 259 (67%) are non-Israeli. Moreover, 20% of the venture capital companies were founded before 1990, 63% were founded between 1990 and 2000, and 17% were founded after 2000. Fifty-one of the venture capital companies are corporate venture capitalists.

Table 1 provides the distribution according to investor type and the total number of start-ups each investor had invested in over our sample period. For example, 1447 of the investors had invested in only one of the 787 startups in our sample and 206 had invested in two startups. Consistent with the fact that many of the private investors are friends or family of the founder the modal number of start-ups invested in by private investors is one. This is not the case for venture capitalists. Of the investors who had only invested in only one startup, 43.88% are private investors, whereas only 12.37% are venture capitalists.

In Table 2 is the distribution of investors by investment round and and type of investor. Not surprisingly, private investors tend to invest more in the first funding round of a startup relative to venture capitalists. As shown in the table, of the investors who had invested in the first round, 34.05% are private investors and 28.83% are venture capitalists. For rounds greater than one the share of private investors progressively declines, whereas the share of venture capitalists increases.

The average number of investors participating in each round is 3.1, with a minimum of one and a maximum of 24. At each round, the average number of new investors, i.e. those investors who had not participated in any of the previous rounds, is 1.06. Of course, all investors in the first round of financing are new investors.

The average amount raised per round (in constant US dollars) is $3.61 million, ranging from a minimum of $0.01 million to a maximum of $72 million. Seed rounds (the earliest round) tend to receive the least funding, with an average amount of $1.1 million. Startups considered to be in a revenue growth round generally receive the greatest funding with an average amount of $7.07 million.

We also have information on startup founders and in particular on the number of founders (average of 2.19), the number of founders who are university professors, the number who hold a PhD degree, and the number of serial founders. Eighty-one startups have at least one professor founder, 267 startups have at least one founder with a PhD, while 428 startups have at least one serial founder. This last result is in line with discussions we had with policy makers in Israel which revealed that Israeli entrepreneurs are typycally involved in more than one venture. We have information on the number of R&D grants awarded by Israel's Office of the Chief Scientist[5], the European Commission, and other types of grants. Thirty-seven percent of the startups received at least one grant, and 29% of them had received a grant from Israel's Office of the Chief Scientist. This last type of grants is usually awarded to technology startups in their very early stage to develop their technology.

Finally, using Delphion we collected information on US granted patents for the startups. For each startup, we collected all patents granted that had either the name of the startup in the assignee

[5]Israel's Office of the Chief Scientist is an office, within the Ministry of Industry, Trade and Labor whose main mission is to promote industrial R&D.

field or the name of at least one of the founders in the inventor field. Because it is not uncommon that startups change their names, we used in our patent search information provided by IVC on startup name changes. In the case of patents whose priority year preceded the foundation year of a startup and whose inventor field included the name of at least a startup founder, we only retained those whose underlying technology had been used by the startup. In order to make this distinction, we went through the technology description provided by IVC for each startup. We excluded from our search patent applications that were not granted, for two reasons. First, before 2001 there was no requirement that a US patent application be published, so that information on patent applications is not systematically available in the Delphion database prior to this date. Second, even after this requirement was established, firms had the option to keep their applications from being published (Mann and Sager, 2007). Of the 787 startups, 433 were never granted a patent nor had their founders received a patent relevant to the startup. For those companies with at least one patent, the average number of patents is 6.26 with a minimum of 1 and a maximum of 86. In IT and software 14 of the 35 companies had at least one patent granted, in communication 73 of 173, in the internet sector 17 of 85, in semiconductors 36 of 55, in life sciences 42 of 76, in medical devices 65 of 107, in cleantech 14 of 35, and in the miscellaneous sector 32 out of 58. On average, 0.8 patents are filed before a seed stage, 1.1 before an R&D stage, 0.9 before an initial revenue stage, and 2.2 patents are filed before a revenue growth stage.

⟨ Insert Table 1 about here ⟩
⟨ Insert Table 2 about here ⟩

5.2 Econometric Methodology

Proposition 1 of our model predicts that *i*) there is a positive relationship between the value of a founders' invention and the number of patents in which they invest, and *ii*) patent investment is larger under asymmetric information than under symmetric information. These results jointly imply that under asymmetric information, the founders of a startup *strategically* use patent investment to convey information about the value of their inventions, *given that* external investors judge the value of these inventions *based on* the patent investment they observe. Since asymmetric information is likely to be stronger with new investors, we expect more patents (relative to symmetric information) when founders try to involve new investors in a round. Thus, the number of new investors in a round is expected to be simultaneously determined along with the number of patents obtained since the prior round. Because asymmetric information is likely to be less of a concern in the case of investors that had invested in the previous rounds of a startup, we also expect that either the number of previous investors is not endogenous or that its impact on the number of patents filed by a startup is weaker than that of new investors.

In a setting with multiple rounds of financing, additional funding can either be secured from existing investors (for second and succeeding rounds) or new ones (who are expected to be attracted by new patents). Thus, intuitively, funds raised in a round are also expected to be endogenous in our new patents regression. Unfortunately, our data do not differentiate additional funds raised by new *versus* existing investors.

We estimate three structural models for patents. The first model considers patents in the first round of funding, while the second and the third concentrate on the strategic use of patents in

attracting investors and funds in the rounds subsequent to the first round. The first and the subsequent rounds are estimated separately based on our prior that the first round is different from subsequent rounds. For example, it is likely that the decision to form a start-up follows from the filing of an important patent or set of patents. The implication is that patents in the first round of funding are not simultaneously determined along with the number of investors and the amount raised; that is, patents are possibly exogenous to the first round of funding. The third model considers the impact on the founders' patent investment of the number of new investors *as opposed to* the number of old ones (in the rounds subsequent to the first).

The equation we estimate in the *first* and in the *second* model is:

$$\Delta P_{it} = \beta_0 + \beta_1 n_{it} + \beta_2 V_{it} + X'_{it}\gamma + \varepsilon_{it} \tag{1}$$

Where i and t index firms and rounds, respectively. $\Delta P_{it} = P_{it} - P_{it-1}$ is the change in the number of patents between funding rounds t and $t-1$ (when t is the initial round $P_{it-1} = P_{i0} = 0$). n_{it} is the number of new investors added at round t, and V_{it} (measured in logs) is the amount raised in the t^{th} round. X_{it} are controls and include the total number of rounds the start-up experiences (N_Round), whether a startup had failed and hence ceased to operate as of June 2011 ($Ceased$), the number of founders with a PhD ($PhD_Founders$), company age (Age), the number of days since the prior funding round ($Elapsed\ Days$), indicators for the industry sector and for the life cycle stage (seed, R&D, initial revenue or revenue growth) of the startup in round t, as well as year dummies. The variables N_Round and $Ceased$ are used as proxies for the intrinsic quality of a startup. Age captures the experience of a startup. $PhD_Founders$, together with the industry sector dummies, are meant to capture some characteristics of the underlying technology that is commercialized by a startup. In particular, $PhD_Founders$ is a proxy for the degree of "basicness" of a technology. It is important to control for technology characteristics, given that some technologies might be intrinsically more suitable for patent protection than others. Summary statistics are reported in Table 3.

Our central hypothesis is that if patents have a signaling value, then patents, number of new investors and amount raised are simultaneously determined. That is, in the equation above m_{it} and V_{it} are endogenous. Our approach is to use the above equation to test for their endogeneity. Because of a lack of instruments we are unable to directly estimate the equations explaining the total amount raised per round and the number of new investors.

The preferred econometric approach is an instrumental variable (IV) counts model which takes into account the fact that the dependent variable is a count variable. We attempted to estimate an IV Poisson model using the Stata command -ivpois- but the model did not converge. In its place we use three alternative estimation techniques. First, we use an IV model which treats the investment in patents as a continuous variable. Second, we use an IV Tobit procedure to account for the many zero values. Thus for both techniques, we use the log of $\Delta P_{it} + 0.0001$. Finally, we estimate an IV linear probability model given that that 81% percent of the observations take either the value of one or the value of zero. This model delivers consistent estimates of the average partial effects (Wooldridge, 2002). The dependent variable in this case is set to 1 if there are 1 or more patents (0, otherwise)[6].

[6]We do not estimate an IV probit model as the model did not converge.

In the first model, we include as instruments the number of deals done by US venture capital companies in a given year, by stage of investment, and the total amount invested (in constant US dollars). For this last measure we also include a squared term to account for nonlinearities in the relationship between this measure and the endogenous variables. The data were obtained from US National Venture Capital Association 2012 Yearbook. Both the number of venture capital deals and the amount invested are proxies for the supply of VC capital in the US and thus are a measure for the availability of external financing in this country (see, Berger et al., 2005; Hellmann et al., 2007; and Bottazzi et al. (2008). However, to the extent that the US and the Israeli VC market are strongly interconnected, then these measures are also correlated with the supply of VC capital in Israel[7]. Consequently, we expect them to be also correlated with the total amount received by a startup in a given round and the number of investors in a round. Additionally, we use as an instrument a count for the number of startups the founder had founded in the past (expressed in the natural logarithm). Discussions we had with Israeli startup founders revealed that being a serial entrepreneur helps a founder build a network of contacts with external investors that might potentially invest in the founder's subsequent startups. This is especially true in the case of Israel, given its small population size and the relatively small community of founders and external investors. Because we do not distinguish between whether the startups founded in the past had a successful exit event or not, it is unlikely that our measure will be correlated with the ability of founders of identifying successful technologies and thus be correlated with the error term.

In the second model, we use very similar instruments as in the first. Specifically, we include i) the number of deals done by US venture capital companies, by stage of investment, in a given year and ii) the total amount invested by venture capital companies located in the Silicon Valley region (in constant US dollars). Both measures are expressed in the natural logarithm. The reason why the second instrument focuses on the Silicon Valley region is that, for rounds subsequent to the first, the amount supplied by venture capital funds from this region has the strongest correlation with the amount a startup had received in given round as well as with the number of new investors. As before, we use the number of startups the founders had founded in the past. Moreover, we also include a dummy variable that takes the value of 1 if the startup had received a grant from the Israel's Office of the Chief Scientist. As we mentioned, this type of grant is awarded to startups in their very early stage, to develop their technology. Thus while such a grant might directly affect patent application prior to the first round, it is predetermined to patent investment in subsequent rounds. The constraint attached to this grant is that the founders are not allowed to export abroad the intellectual property generated from a technology, unless they pay up to seven times the amount they had originally received. Hence, our measure is likely to be correlated with the amount received in subsequent rounds and/or with the number of new investors, to the extent that it might deter foreign investors from investing in a startup[8].

In the continuous and in the linear probability models we use cluster standard errors where clustering is by company. In the Tobit model we use a two-step sequential estimator and compute standard errors using a cluster bootstrap with 500 replications.

[7]Several US venture capital companies have offices in Israel and many of the Israeli venture capital companies have offices in the US. Moreover, discussions with venture capitalists and policy makers in Israel confirmed Israeli venture capital companies have frequent contacts with venture capital companies in the US.

[8]We performed tests of overidentifying restrictions for all models and we rejected the null hypothesis that the instruments are correlated with the error term in all instances.

The *third* model we estimate distinguishes between the number of new and old investors, for the rounds subsequent to the first. Thus the equation we estimate is:

$$\Delta P_{it} = \beta_0 + \beta_1 n_{it} + \beta_2 o_{it} + X'_{it}\gamma + \varepsilon_{it} \quad (2)$$

Where o_{it} is the number of investors that had invested in the rounds prior to round t. As we mentioned, our hypothesis here is that either o_{it} is not endogenous or its impact on founder patent investment is weaker than that of n_{it}. We use equation 2 to test for endogeneity of o_{it} and n_{it}. Because of a lack of instruments we do not include the total amount raised at each round (which is also not statistically significant). The matrix X_{it} includes the same controls as the one used for the first and the second models. As before, we estimate: i) an IV model which treats the investment in patents as a continuous variable, ii) an IV Tobit model, and iii) an IV linear probability model. We use the same instruments as in the second model except for the amount of venture capital investment in the Silicon Valley region, which we exclude[9].

The number of new patents is the number of startup patents whose priority year is greater than the year of the previous round and smaller than or equal to the year of the current round. The decision to consider the priority year is justified as follows. Having treated patent investment as a signal, in the economic sense, then it has to be that this investment is costly for a startup and it is observed by external investors. Having defined patent cost in terms of the resources startup founders have to invest in order to convince the patent examiners of the novelty of their inventions, this cost is incurred before or at the time the first application is filed (the priority date). Hence, the resulting signal is observed by external investors at around the time of the first application and it is likely to trigger their response before a patent is granted. Of course, here we are underestimating the costly investment made by a startup because we only have information on patents which were eventually granted and not on patent applications in general. However, to the extent that the few US patent applications fail to be granted (Quillen et al., 2002), then the size of the bias should be limited.

⟨ Insert Table 3 about here ⟩

5.3 Results

5.3.1 Initial Round

As we noted above, we expect first round structural estimates to be different from subsequent round estimates to the extent that investment in the first patents precede the decision to found a startup. If this is the case we cannot regard the investment in patents which precede the first round as being affected by the perspective of attracting external investors. To test for endogeneity we use a Hausman specification test which (jointly) tests for the endogeneity of n_{it} and V_{it}. The test fails to reject the null hypothesis that n_{it} and V_{it} are exogenous, with a p-value of 0.55 (continuous

[9]The amount venture capital investment in the Silicon Valley region appears to be weakly correlated with the number of old investors, hence using it as an instrument might cause the IV estimator to be biased (Stock and Yogo, 2003; Newey, 2004; Chao and Swanson, 2005; and Angrist and Pischke, 2009).

variable model), 0.74 (Tobit model), 0.57 (linear probability model), respectively[10]. The results from the test confirm our prior that the number of patents filed prior to the first round are not a signal to external investors. These results should be regarded with some caution though since a check on the weakness of the instruments, using the standard rule-of-thumb that the F-statistic on excluded instruments in the equations of the endogenous variables be larger than ten, reveals that in the equation for the number of new investors the F-statistic on excluded instruments is only 4.92, although significant with a p-value of 0.000. Instrument weakness for the total amount invested appear to be less of a problem given that the F-statistic in this case is 9.26.

Since the results from the endogeneity tests support our prior that n_{it} and V_{it} are exogenous in the first round of funding, we do not present the detailed regression results for ΔP_{it}. Our interest lies primarily in the endogenous response of patent investment to the perspective of receiving external funds which does not seem to be the case for first round financing.

5.3.2 Rounds Subsequent to the First Round

Here we consider the structural model for rounds subsequent to the first (that is, when $t > 1$). We first estimate the second model, which considers the impact of new investors and the amount received in a given round on the founders investment in patents.

We begin by testing whether n_{it} and V_{it} are endogenous in equation 1. In checking for the weakness of the instruments in this case we find that the F-statistics is substantially larger than 10 for V_{it} and close to 10 for n_{it}; for V_{it} the F-statistic is 16.07 and for n_{it} it is 8.09.

A Hausman specification test to (jointly) test for the endogeneity of n_{it} and V_{it} accepts the hypothesis of endogeneity with a p-value of 0.000. This test supports the hypothesis that patents have a signaling value. The IV results are presented in the first three columns of Table 4[11]. We report average partial effects for all models[12]. For each of our three estimators the coefficient of n_{it} is significantly different from zero (p-value= 0.001 for the continuous and the linear probability models, and p-value=0.002 for the Tobit model). The coefficient of V_{it} is not statistically significantly different from zero for any of the estimators, suggesting that it does not belong in the equation. This variable includes funds from new investor - which are expected to be endogenous - as well as from old investors - which are not expected to be endogenous. The latter is because asymmetric information holds primarily for new investors. This might explain the insignificance of V_{it}. Because of this, we perform separate tests for endogeneity for n_{it} and V_{it}. As expected, the tests strongly support the endogeneity of n_{it} (p-value=0.000) but not the endogeneity of V_{it} (p-value> 0.2).

[10]The test in the continuous and in the linear probability models is conducted using a standard Hausman approach. For the Tobit model an alternative approach is necessary. For this we construct our endogeneity test based on a procedure suggested by Wooldridge (2002). This procedure consists of two steps. In the first, we regress the suspected endogenous regressors on the instruments indicated above and the other exogenous regressors, and we derive the residuals from each equation. In the second, we regress the investment in patents on the suspected endogenous regressors, the residuals from the previous step, and the other exogenous regressors. In this step we use a Tobit specification. If the coefficients of the residuals are not statistically significant, then this is evidence against the null hypothesis that our suspected variables are endogenous.

[11]First-stage regressions are reported in Table A1.

[12]The coefficients presented in all tables are average partial effects and were computed using the procedure suggested by Wooldridge (2002).

As for the other variables in the model, the total number of rounds a startup has received prior to an exit is positive and statistically significant at the 1% confidence level. Consistently, whether a startup had ceased its operations has a negative impact on the number of patents a startup has filed, although the coefficient is not significantly different from zero. The characteristics of a technology play an important role in explaining a startup's decision to file for patents. The coefficient of $PhD_Founders$ is positive and statistically significant at the 10% confidence level. Moreover, a test of joint significance of industry sector dummies rejects the null hypothesis that these are (jointly) equal to zero with a p-value of 0.000 in all regression specifications. Finally, test of joint significance of year dummies rejects the null hypothesis that these are (jointly) equal to zero with a p-value less than 0.05 in all regression specifications.

In the last three columns of Table 4 we examine the impact of the number of new and old investors on the patent investment made by the founders of a startup. To this scope we estimate equation 2, which excludes V_{it}. This should not be a serious concern given that we found the coefficient of V_{it} to be highly statistically insignificant in the previous regressions. We use the same instruments as in the previous models, except for the amount venture of capital investment in the Silicon Valley region, which we exclude. A Hausman specification test to (jointly) test for the endogeneity of n_{it} and o_{it} accepts the hypothesis of endogeneity with a p-value of 0.000. However, when we perform the test on o_{it} only, the test fails to accept the the null hypothesis of endogeneity. While this test should be interpreted with caution given that the F-statistic is equal to 4 (although statistically significant at the 1% level), nevertheless it provides some support to our hypothesis that patents are predominantly used as a strategic means of attracting new investors rather than old ones. This is because for new investors the problem of asymmetric information is more serious than for investors that have invested in previous rounds. In the regressions we present in Table 4, we include both old and new investors as endogenous regressors. As shown, while the coefficient for n_{it} remains highly statistically significant, that for o_{it} is not statistically different from zero. A test of joint significance of the coefficients of the number of new and old investors rejects the null hypothesis that the coefficients are jointly equal to zero with a p-value of 0.002 in the first and in the third models, and of 0.006 in the second model. Moreover, a test of the equality of these coefficients rejects the null hypothesis that the coefficients are equal with a p-value of 0.01 in the first and in the third models, and of 0.006 in the second model.

Overall, our results provide clear evidence that patents are used as a signal by the founders of a startup and they are not simply an input in the startup's value function. Moreover, they suggest that patents are used to attract new investors as opposed to old investors.

⟨ Insert Table 4 about here ⟩

5.3.3 Unveiling New Investors in Rounds Subsequent to the First Round

In the above we did not distinguish among the different types of investors (VC versus private investors). We simply used the aggregate number of new or old investors in estimating the number of new patents in a round. In this section, we consider Proposition 2 which predicts that investors, who can provide a startup with a large amount of high-value services, match with startups that have high value inventions. Because in a perfect Bayesian equilibrium the condition $\theta = \theta(p^*(\theta))$ has to hold at equilibrium, the value of an invention is defined by the number of patents a startup has filed. Unfortunately, even though we have information on the year in which venture capital

companies were founded, which would allow us to build some measure for their experience (and thus the parameter S), we cannot estimate a system of equations that includes one equation for the number of experienced venture capital companies and one for the number of less experienced venture capital companies. This is because we are unable to find suitable instruments for these two equations, given that what might affect more experienced venture capitalists is also likely to affect less experienced ones. However, past research has shown that venture capitalists provide more services and greater reputational capital to a startup than do private investors, given that many of the private investors are friends and family (Brav and Gompers, 1997; Field, 1996). Therefore, according to Proposition 2 we should observe that new venture capitalists have a greater effect on changes in patents than do private investors. We explore this venue and modify model 2 to consider, among the new investors at each round, the number of venture capitalists, inclusive of the number of corporate venture capitalists, and the number of private investors. We restrict our attention to these categories of new investors and exclude the remaining new investors because we do not have enough strong instruments that would allow us to identify all equations in the model. Given the results above that first round patents are not caused by a need for new investors or additional funds, we focus on those rounds subsequent to the first.

In the case of private investors we suspect that they are less responsive to patent investment than venture capitalists given their relatively limited capacity for assessing the characteristics of inventions. Indeed, when we test for the endogeneity of the number of new private investors in the continuous model, the Hausman specification test fails to reject the null hypothesis of endogeneity, with a p-value of 0.980. On the contrary, when we test for the endogeneity of the number of new venture capitalists that participate in round t, the test accepts the null hypothesis of endogeneity, with a p-value of 0.017[13]. This result is not at odds with our theoretical implications. In fact, it is very likely to be the case that our tests for endogeneity are powerful enough to detect minimum levels of endogeneity, which would still suggest that startup founders condition their patent investment, to a minimum extent, to the type of external investors, which in this case are private investors.

Based on the results of the endogeneity tests, we estimate an equation which relates the investment in patents to the total amount of financing received at round t, the number of new venture capitalist investors, which we treat as endogenous variables, as well as the number of new private investors and controls[14]. The instruments are the same as those used in model 2. They are i) the number of deals done by US venture capital companies, in a given year, by stage of investment, ii) the total amount invested by venture capital companies located in the Silicon Valley region (in constant US dollars), iii) the number of startups the founders had founded in the past, and iv) a dummy variable that takes the value of 1 if the startup had received a grant from the Israel's Office of the Chief Scientist.

The results are shown in the first three columns of Table 5. In the first column we present the results of the model in which patent investment is considered a continuous variable. Following that we present the results of a Tobit estimator and, finally, the results of a linear probability estimator.

[13]We use the same instruments as those used for model 2. The results should be taken with some caution as the F-statistic on excluded instruments in the equations of the number of new private investors is 2.5.

[14]If the controls *N_Round* and *Ceased* were to be proxies for the technology quality of a startup, then we should not include them in our equations. In fact, including them would amount to regressing the value of a startup's invention on some proxy for this value. Therefore, in regressions not presented here we excluded them to check whether our results would still hold. The results were unchanged, suggesting that these controls might be more accurate proxies for quality aspects of a startup other than the value of a technology.

In line with Proposition 2, in all regression specifications the number of new venture capital companies per round has a positive and statistically significant impact on the patent investment by the founders. The p-values are, respectively, 0.006 (continuous variable model and linear probability model), and 0.005 (Tobit model). On the contrary, the coefficient of number of new private investors, while positive, is not significantly different from zero. A test of joint significance of the coefficients of the number of new venture capitalists and the number of new private investors rejects the null hypothesis that the coefficients are jointly equal to zero with a p-value of 0.020 in the first and in the third models, and of 0.019 in the second model. Moreover, a test of the equality of these coefficients rejects the null hypothesis that the coefficients are equal with a p-value of 0.005 in the first and in the third models, and of 0.006 in the second model.

In the last three columns of Table 5 we estimate a version of equation 2, which differentiates between new and old venture capital investors. As before, we do not include in the equation the total amount the founders had received in a given round. Moreover, we use the same instruments as in the previous models, except for the amount of venture capital investment in the Silicon Valley region, which we exclude. The results confirm our prior that patents are used mainly to attract new venture capital investors. First, a test of endogeneity of the number of old venture capital investors fails to accept its endogeneity. Second, test of joint significance of the coefficients of the number of new and old venture capital investors rejects the null hypothesis that the coefficients are jointly equal to zero with a p-value of 0.000 in the first and in the third models, and of 0.002 in the second model. Third, a test of the equality of these coefficients rejects the null hypothesis that the coefficients are equal with a p-value of 0.06 in the first and in the third models, and of 0.006 in the second model.

⟨ Insert Table 5 about here ⟩

5.3.4 Robustness Check Analysis

In Tables 6 to 11 we perform some robustness checks. Tables 6 and 7 present the same regression results as in Tables 4 and 5, but including only those rounds that took place before 2009. This is because there is likely to be a problem of censoring, given that there is a lag between the priority date of a patent and the granting date. Indeed, it is possible that startups have filed patents in the latest years but we do not observe them because they have not been granted yet. Because it takes on average three years before a patent is granted by the US Patent Office (OECD, 2009), we exclude from our sample those rounds that occurred between 2009 and 2011. The results are robust to excluding these years. As before, the number of new investors per round has a positive and statistically significant impact on patent investment. When we examine the impact of both new and old investors on patent investment, we continue to find evidence that the impact of the number of old investors on founder patent investment is statistically insignificant. Moreover, the coefficient for the number of new venture capitalists is positive and statistically significant, while the coefficient for the number of new private investors is statistically insignificant. Finally, the number of old venture capitalists does not impact patent investment.

In Table 8 we add the number of business angel investment groups to the number of new venture capitalists that participated in round t. According to Kerr et al. (2010), business angel investment groups are similar to venture capital companies in that they adopt a very hands-on role in the

deals they participate in and provide entrepreneurs with advice and contacts to potential business partners. The results are very similar to the ones presented in Table 5, both in terms of the sign and the significance of the coefficients. The main result that emerges is that the number of new venture capitalists and business angel groups that participate in round t has a positive impact on the number of patents that are filed by a startup. The impact of the number of new private investors is not significantly different from zero. Moreover, when we consider both the number of new and old venture capitalists, the latter does not significantly affect patent investment.

In Table 9, we add the number of new business angel investment groups to the number of private investors that are involved in round t. The rationale for doing that is that that business angel groups might value the patent investment made by a startup in the same way as the business angel investors that are included in the category private investors. The redefinition of the categories of venture capitalists and private investors does not change our main findings.

In Table 10, we attempt to disentangle business angel investors that are not organized in investment groups from friends and families, within the category of private investors. To this scope we define business angel investors (not organized in investment groups) as those individuals that have invested in more that four startups in our sample. By imposing this cutoff we intend to exclude from our category those friends and families that have invested in multiple startups just because these were founded by serial entrepreneurs. Having done so, we add the number of new angel investors (organized in groups and not) to the number of new venture capitalists that have participated in round t. The number of new venture capitalists and business angel investors has a positive and significant impact on the patent investment by a startup, whereas the impact of number of private investors is not significantly different from zero. Moreover, we find confirmation that the impact of old investors on patent investment is statistically insignificant.

In Table 11 we add to the number of new venture capitalists those new investors that are either private equity firms or firms that specialize in startup investment (but do not use venture capital funds). The reason is that these firms might value the quality of a startup technology at least as much as venture capitalists do, and, therefore, startup investment in patents might be affected by the prospect of attracting these types of investors. The results indicate that the number of new investors, which belong to the category just defined, has a positive and statistically significant impact on patent investment. This impact is significantly larger than that of the number old investors, whose coefficient is not statistically significant.

Finally, in regressions not reported here (available upon request) we tried different combinations of the instruments. For example, if we exclude the amount of venture capital investment in the Silicon Valley region from the set of instruments used to estimate equation 2, for the rounds subsequent to the first, the results on the number of new investors remain unchanged. Moreover, if we replace in all models the number of deals done by US venture capital companies, by stage of investment, with the amount invested (measured in constant US dollars), the results on the significance of the coefficients do not change. If we exclude in all models the number of startup the founders had founded in the past, the results remain invariant.

⟨ Insert Table 6 about here ⟩
⟨ Insert Table 7 about here ⟩

⟨ Insert Table 8 about here ⟩
⟨ Insert Table 9 about here ⟩
⟨ Insert Table 10 about here ⟩
⟨ Insert Table 11 about here ⟩

6 Concluding Remarks

Our study makes two important contributions to understanding the actions technology startups take to convey private information to external investors on the value of their technology.

First, we construct a theoretical model in which technology startups use their investment in patents as a signal for external investors. The novelty of the model is not so much in showing that there is a signaling equilibrium in which the founders of a startup make an investment in patents that is greater than in a situation of symmetric information. Rather it is in showing that there exists a signaling equilibrium in which founders with high quality inventions match with external investors that offer a large amount of capital, in terms of expertise, information network, and reputation. The reason is that the price the founders have to pay for the capital offered by the external investors, which at equilibrium is equal to the investors' share of the value the capital adds to a startup, is decreasing in the quality of a technology. Thus, *ceteris paribus*, startups with high quality inventions can benefit more from matching with external investors that provide large capital than startups with low quality inventions.

Second, we test the theoretical predictions using a rich dataset of Israel's technology startups. We find that the investment in patents prior to the first round of funding is not endogenous to this round. The most likely reason is that the decision to form a startup follows the filing of an important patent or a set of patents. However, for rounds subsequent to the first, we find that startups strategically use patent investment as a signal for external investor that invest for the first time in the startup and for which the problem of asymmetric information is more serious. Moreover, once we distinguish among types of external investors we find that startups with better technologies, as measured by their investment in patents, tend to receive greater funding from venture capitalists than from private investors. To the extent that venture capitalists provide greater capital, be it expertise, market knowledge, information network, or reputation, than private investors then we take our finding as evidence that startups with higher quality technologies tend to match with external investors that provide a larger amount of capital. As an important topic for future research it would be interesting to test whether a similar type of match holds, once we distinguish between venture capitalists with different levels of expertise.

References

[1] Arora. A, and M. Ceccagnoli. 2006. Patent protection, complementary assets, and firms' incentives for technology licensing. *Management Science*, 52(2): 293-308.

[2] Angrist J.D., and J.-S Pischke. 2009. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton: Princeton University Press.

[3] Berger A, N. Miller, M. Petersen, R. Rajan, and J. Stein. 2005. Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks. *Journal of Financial Economics*, 76 (2): 23769.

[4] Bottazzi L., M. Da Rin, and T. Hellmann. 2008. Who are the Active Investors? Evidence from Venture Capital. *Journal of Financial Economics*, 89: 488-512.

[5] Brav, A., and P. A. Gompers. 1997. "Myth or reality": Long-run underperformance of initial public offerings; Evidence from venture capital and nonventure capital-backed IPOs. *Journal of Finance*, 52: 1791-1821.

[6] Chao, J. C., and N. R. Swanson. 2005. Consistent Estimation with a Large Number of Weak Instruments. *Econometrica*, 73: 16731692.

[7] Cohen W.M., R.R. Nelson, and J. Walsh. 2000. Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not). NBER Working Paper 7552.

[8] Conti A., M. Thursby, and F. T. Rothaermel. 2011. Show me the right stuff: Signals for high-tech startups. Mimeo.

[9] Field, L.C.. 1996. Is the institutional ownership of initial public offerings related to the long-run performance of these firms? Unpublished working paper, Pennsylvania State University, University Park, PA.

[10] Fischer T., and de Rassenfosse G., 2012. Venture debt financing: Determinants of lending decision. SSRN Working Paper.

[11] Frenkel A., D. Shefer, and M. Miller. 2005. Public vs. Private Technological Incubator Programs:Privatizing the Technological Incubators in Israel. Working Paper presented at the European Regional Science Association, 45th European Congress, Amsterdam, Holland.

[12] Gans J.S., D.H. Hsu, and S. Stern. 2002. When Does Start-up Innovation Spur the Gale of Creative Destruction?. *RAND Journal of Economics*, 33: 571-86.

[13] Graham S. J. H. and T. M. Sichelman. 2008. Why do Start-ups Patent?. *Berkeley Technology Law Journal*, 23(3):1063-1097.

[14] Graham S. J. H., R. P. Merges, P. Samuelson, and T. M. Sichelman. 2009. High Technology Entrepreneurs and the Patent System: Results of the 2008 Berkeley Patent Survey (June 30, 2009). *Berkeley Technology Law Journal*, 24(4): 255-327.

[15] Grinblatt M., and C. Y. Hwang. 1989. Signalling and the Pricing of New Issues. *Journal of Finance*, 44(2): 393-420.

[16] Haeussler C., D. Harhoff and E. Mueller. 2009. To Be Financed or Not... - The Role of Patents for Venture Capital Financing. CEPR Discussion Papers 7115.

[17] Hellmann T., and M. Puri. 2002. Venture Capital and the Professionalization of Start-Up Firms: Empirical Evidence. *Journal of Finance*, 57(1): 169-197.

[18] Hellmann T., L. Lindsey, and M. Puri. 2008. Building Relationships Early: Banks in Venture Capital. *Review of Financial Studies*, 21 (2): 513-541.

[19] Hochberg, Y., A. Ljungqvist, and Y. Lu (2010). Whom You Know Mat- ters: Venture Capital Networks and Investment Performance. *Journal of Finance*, 62 (1): 251302.

[20] Hoppe, H., D. Moldovanu, and A. Selu. 2009. The Theory of Assortative Matching Based on Costly Signals. *The Review of Economic Studies* 76, 253-281.

[21] Hsu D. 2004. What Do Entrepreneurs Pay for Venture Capital Affiliation?. *Journal of Finance*, 52: 1805-1844.

[22] Hsu D., and R.H. Ziedonis. 2011. The Dual Roles of Intangible Resources as Sources of Advantage: Evidence from Technology Startup Patents, mimeo.

[23] Kerr W. R., J. Lerner, and A. Schoar. 2010. The Consequences of Entrepreneurial Finance: A Regression Discontinuity Analysis. Harvard Business School Working Paper, 10-086.

[24] Leland H. E., and D. H. Pyle. 1976. Informational Asymmetries, Financial Structure, and Financial Intermediation. *Journal of Finance*, 32: 371:387.

[25] Lerner, J. 1995. "Venture Capitalists and the Oversight of Private Firms. J*ournal of Finance*, 50(1): 301-18.

[26] Mann R. J., and T. W. Sager. 2007. Patents, venture capital, and software start-ups. *Research Policy*, 36: 193-208.

[27] Modena V., and D. Shefer. 1998. Technological Incubators as Creators of New High Technology Firms in Israel. Working Paper presented at the European Regional Science Association, 38th European Congress, Vienna, Austria.

[28] Newey, W. K. 2004. Many Weak Moment Asymptotics for the Continuously Updated GMM Estimator. MIT Working Paper.

[29] OECD Patent Statistics Manual. 2009. Organisation for Economic Cooperation and Development.

[30] Quillen C. D., O. H. Webster, and R. Eichmann. 2002. Continuing Patent Applications and Performance of the U.S. Patent and Trademark Office - Extended. *The Federal Circuit Bar Journal*, 12(1): 35-55.

[31] Sahlman W.. 1990. The Structure and Governance of Venture Capital Organizations. *Journal of Financial Economics*, 2: 473-521.

[32] Spence M.. 1973. "Job Market Signaling". *Quarterly Journal of Economics*, 87: 355-374.

[33] Stock, J. H., and M. Yogo. 2003. Asymptotic Distributions of Instrumental Variables Statistics with Many Weak Instruments, in D. W. K. Andrews and J. H. Stock (editors), Identification and Inference for Econometric Models: Essays in Honor of Thomas J. Rothenberg, Cambridge, U.K.: Cambridge University Press.

[34] Trajtenberg M. 2000. R&D Policy in Israel: An Overview and Reassessment. NBER Working Paper 7930.

[35] Trajtenberg M. 2005. Innovation Policy for Development: an Overview. Paper prepared for the LAEBA 2005 second annual meeting, Buenos Aires, Argentina.

[36] Wooldridge, J. M. 2002. Econometric Analysis of Cross Section and Panel Data. The MIT Press, Cambridge MA.

Appendix A: Proof of Proposition 1 and 2

Proposition 1. There exists a signaling equilibrium in which the founders of a startup find it optimal to invest an amount, p^*, that is greater than that under symmetric information and in which $\theta = \theta(p^*(\theta))$ and p and θ are complementary in the founders' last period wealth function.

Proof. In order to show that there exists a signaling equilibrium in which the founders of a startup find it profitable to invest an amount of p that is greater than under symmetric information, we need to show:

1.The conditions under which $\theta(p^*)$, that is the assessment made by the external investors of an invention's value, is increasing in the optimal patent investment, p^*, made by the founders.

2. For the values of the parameters for which $\theta_p(p^*) > 0$, p^* is greater under asymmetric information than under symmetric information.

3. p^* is a global maximum.

We begin by noting that for a signaling equilibrium to be a Perfect Bayesian Equilibrium condition (7) has to hold. Differentiating (7) with respect to p we obtain: $1 = \theta_p(p^*)p^*_\theta(\theta)$. Thus, the sign of $\theta_p(p^*)$ depends on the sign of $p^*_\theta(\theta)$. Using standard comparative statics we derive that:

$$p^*_\theta(\theta) = -\frac{-\alpha_{p\theta}(p,\theta,S)\upsilon(S) + \alpha_\theta(p,\theta,S)\theta_p(p^*) - c_\theta}{V_{pp}(p) - \alpha_{pp}(p,\theta,S)\upsilon(S) + \alpha\theta_{pp}(p) + \alpha_p(p,\theta,S)\theta(p)}$$

Because the denominator if this expression is negative by the second order conditions, then $p^*_\theta(\theta) > 0$ if and only if the numerator is greater than zero, that is if p and θ are complementary in the founders last period wealth function. Thus, for $\theta_p(p^*) > 0$, then $E_{p\theta}(W) > 0$.

To complete the second part of the proof, we define $\nu = -\alpha\theta_p(p^*)$ where $p^* = p^*(\theta)$. Then, we note the following cases:

1. $\nu = 0$. In this case, the solution to the founders' maximization problem is equivalent to that under symmetric information.

2. $\nu = -\alpha\theta_p(p^*)$. Using standard comparative statics we derive that:

$$p^*_\nu(\nu) = -\frac{\nu}{V_{pp}(p) - \alpha_{pp}(p,\theta,S)\upsilon(S)}$$

$p^*_\nu(\nu) < 0$ iff p and θ are complementary in the founders' last period wealth function. This condition shows that the amount of patents provided by the founders increases when moving from symmetric to asymmetric information.

Finally, we note that because $\theta(p)$ is strictly increasing in p, and thus the expected last period wealth is strictly increasing in p, and given that p^* lies in the open interval $(\underline{p}, \overline{p})$, then p^* is a global maximum.

Proposition 2. There exists a signaling equilibrium in which startup founders with an invention that has a high expected value, θ, find it profitable to match with external investors that provide the startup with a high S.

Proof. In order to show that there exists a signaling equilibrium in which startup founders with an invention that has a high expected value, θ, find it profitable to match with external investors that provide the startup with a high S, we need to show that $\frac{d\theta}{dS} = -\frac{E_{SS}(W)}{E_{S\theta}(W)} > 0$.

We begin by showing that $E_{SS}(W) < 0$. We will then show that $E_{S\theta}(W) > 0$. The expression for $E_{SS}(W)$ is found by computing the derivative of expression (10) with respect to S. Thus:

$$E_{SS}(W) = (1-\alpha)\upsilon_{SS}(S) - \alpha_S(p,\theta,S)\upsilon(S) - \alpha_{SS}(p,\theta,S)\upsilon(S) - \alpha_S(p,\theta,S)\upsilon_S(S)$$

where:

$$\begin{aligned}
\alpha_S &= \frac{\varsigma}{[\theta + V(p) + \upsilon(S) - D]} - \frac{(\varsigma S + K - D)\upsilon_S(S)}{[\theta + V(p) + \upsilon(S) - D]^2} \\
\alpha_{SS} &= -\frac{2\varsigma\upsilon_S(S)}{[\theta + V(p) + \upsilon(S) - D]^2} - \frac{(\varsigma S + K - D)\upsilon_{SS}(S)}{[\theta + V(p) + \upsilon(S) - D]^2} - \frac{(\varsigma S + K - D)[\upsilon_S(S)]^2}{[\theta + V(p) + \upsilon(S) - D]^3}
\end{aligned}$$

By inspection, the expression above is negative, given that $\upsilon_{SS}(S) < 0$ and $\varsigma > \upsilon_S(\underline{S})$.

The next step is to show that $E_{S\theta}(W) > 0$. Computing the partial derivative of expression (10) with respect to θ, we find:

$$E_{S\theta}(W) = -\upsilon_S(S)[\alpha_p(p,\theta,S)p_\theta(\theta) + \alpha_\theta(p,\theta,S)] - \upsilon(S)[\alpha_{Sp}(p,\theta,S)p_\theta(\theta) + \alpha_{S\theta}(p,\theta,S)]$$

where:

$$\begin{aligned}
\alpha_p &= -\frac{(\varsigma S + K - D)V_p(p)}{[\theta + V(p) + \upsilon(S) - D]^2} \\
\alpha_\theta &= \frac{(\varsigma S + K - D)}{[\theta + V(p) + \upsilon(S) - D]^2} \\
\alpha_{Sp} &= -\frac{\varsigma V_p(p)}{[\theta + V(p) + \upsilon(S) - D]^2} - 2\frac{(\varsigma S + K - D)\upsilon_S(S)V_p(p)}{[\theta + V(p) + \upsilon(S) - D]^3} \\
\alpha_{S\theta} &= -\frac{\varsigma}{[\theta + V(p) + \upsilon(S) - D]^2} - 2\frac{(\varsigma S + K - D)\upsilon_S(S)}{[\theta + V(p) + \upsilon(S) - D]^3}
\end{aligned}$$

By inspection, because $\varsigma > \upsilon_S(\underline{S})$, the expression above is positive.

Appendix B: First Stage Regressions

⟨ Insert Table B1 about here ⟩

Table 1: Frequency of Investment

# Startups	# Investors	% Venture Capitalists	% Private Investors	% Other Investors
1	1,447	12.37%	43.88%	43.75%
2	206	31.07%	24.76%	44.17%
3	92	43.48%	18.48%	38.04%
4	59	38.98%	13.56%	47.46%
5	35	45.71%	8.57%	45.71%
6	26	46.15%	7.69%	46.15%
7	22	40.91%	9.09%	50.00%
8	19	52.63%	5.26%	42.11%
9	10	20.00%	20.00%	60.00%
10	8	50.00%	0.00%	50.00%
>10	44	63.64%	9.09%	27.27%

Table 2: Frequency of Investment Across Funding Rounds

Stages of Investment	# Investors	% Venture Capitalists	% Private Investors	% Other Investors
1st	1,859	28.83%	34.05%	37.12%
2nd	1,725	46.03%	19.94%	34.03%
3rd	1,304	51.23%	15.11%	33.67%
>3rd	1679	59.32%	10.13%	30.55%

Table 3: Summary statistics

Variable	**Mean**	**Std. Dev.**	**N**
ΔP_t	1.042	2.978	2126
V_t	3.614	5.089	2126
n_t	1.062	1.648	2126
o_t	2.074	2.043	2126
n_t_VC	0.497	0.951	2126
o_t_VC	0.958	1.361	2126
n_t_$PrivateInvestors$	0.136	0.571	2126
Age	3.151	3.452	2126
PhD_Founders	0.553	0.831	2126
Elapsed_Days	390.830	490.809	2126
N_Round	3.807	2.137	2126
Ceased	0.303	0.46	2126
Seed	0.303	0.46	2126
R&D	0.444	0.497	2126
Initial Revenue	0.202	0.401	2126
Revenue Growth	0.052	0.222	2126
Semiconductors	0.087	0.282	2126
Misc.	0.066	0.248	2126
Med Dev	0.142	0.349	2126
Life Science	0.108	0.31	2126
Internet	0.084	0.278	2126
IT Software	0.257	0.437	2126
Communications	0.224	0.417	2126
CleanTech	0.03	0.17	2126
US VC (N deals -by stage)	1342.777	723.773	2126
US VC (amount -by stage)	9166.694	8115.275	2126
Silicon V. VC (amount)	11942.27	8482.291	2126
N Past Startups	1.493	2.488	2126
Chief Scientist	0.286	0.452	2126

Table 4: Regression results for the impact of the number of new investors per round on the number of patents filed by the founders

Δpt	**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**			**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**		
	APE		se	APE		se	APE		se	APE		se	APE		se	APE		se
Vt	0.008		*1.033*	0.000		*0.101*	0.327		*3.221*									
nt	0.069	***	*0.923*	0.003	***	*0.090*	3.295	***	*2.997*	0.076	***	*0.994*	0.109	***	*0.096*	0.113	***	*3.219*
ot										0.007		*0.884*	0.000		*0.085*	0.008		*3.211*
Age	-0.001		*0.080*	0.000		*0.008*	-0.030		*0.282*	-0.001		*0.093*	-0.002		*0.009*	-0.002		*0.337*
PhD_Founders	0.011	*	*0.263*	0.000	*	*0.025*	0.463	*	*0.783*	0.010		*0.334*	0.013		*0.032*	0.015		*1.071*
Elapsed Days	0.000	***	*0.001*	0.000	***	*0.000*	0.002	***	*0.002*	0.000	***	*0.001*	0.000	***	*0.000*	0.000	***	*0.002*
N_Round	0.007	***	*0.111*	0.000	***	*0.011*	0.352	***	*0.343*	0.007	**	*0.142*	0.010	**	*0.014*	0.011	*	*0.507*
Ceased	0.010		*0.510*	0.000		*0.050*	0.341		*1.665*	0.012		*0.647*	0.013		*0.062*	0.016		*2.151*
Seed	0.023		*1.650*	0.001		*0.162*	0.715		*5.151*	0.018		*1.201*	0.019		*0.116*	0.024		*4.360*
Initial Revenue	0.000		*0.470*	0.000		*0.046*	-0.109		*1.437*	-0.001		*0.584*	-0.004		*0.056*	-0.001		*2.033*
Revenue Growth	0.027		*0.928*	0.001		*0.091*	0.954		*2.895*	0.023		*1.206*	0.027		*0.116*	0.038		*4.050*
Semiconductors	0.051	**	*1.114*	0.002	*	*0.109*	2.243	*	*3.540*	0.051	**	*1.110*	0.072	*	*0.107*	0.073	*	*3.745*
Misc	0.058	**	*1.072*	0.003	**	*0.105*	2.898	**	*3.540*	0.059	**	*1.221*	0.090	**	*0.117*	0.089	**	*3.994*
Med Dev	0.051	**	*0.859*	0.002	**	*0.085*	2.443	***	*2.667*	0.050	**	*0.941*	0.077	**	*0.091*	0.074	**	*3.142*
Internet	-0.037	*	*0.972*	-0.002		*0.097*	-2.175	*	*3.641*	-0.037		*1.098*	-0.070		*0.106*	-0.057		*4.550*
IT & Software	0.017		*1.062*	0.001		*0.105*	0.921		*3.474*	0.022		*1.026*	0.031		*0.100*	0.031		*3.421*
Communications	0.038		*1.121*	0.002		*0.111*	1.970		*3.609*	0.040	*	*1.071*	0.061		*0.104*	0.058		*3.686*
CleanTech	0.036		*1.229*	0.002		*0.121*	1.954		*3.849*	0.037		*1.319*	0.010		*0.128*	0.058		*4.433*
Constant	-15.431	***	*2.182*	-0.006	***	*0.214*	-15.356	***	*7.560*	-0.359	***	*2.657*	-0.485	**	*0.256*	-0.228	***	*8.596*
Year FE	YES			YES			YES			YES			YES			YES		
N	1,339			1,339			1,339			1,339			1,339			1,339		
F-Test on excl. coeff. (Vt)	16.070																	
F-Test on excl. coeff. (nt)	8.090									7.210	***							
F-Test on excl. coeff. (ot)										4.000	***							

*** p < 0.01, ** p < 0.05, * p < 0.10. The table reports average partial effects. Standard errors are in italics. They are clustered by firm. For the Tobit Model, standard errors are bootstrapped using 500 replications and accounting for firm clusters in re-sampling.

Table 5: Regression results for the impact of the number of new VCs and private investors at round *t* on the number of patents filed by the founders

Δpt	**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**			**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**		
	APE		se	APE		se	APE		se	APE		se	APE		se	APE		se
Vt	-0.024		*1.570*	-0.034		*4.559*	-0.035		*0.152*									
nt_VC	0.125	***	*1.909*	0.171	***	*5.902*	0.178	***	*0.184*	0.128	***	*1.125*	0.188	***	*3.633*	0.146	***	*0.109*
ot_VC										-0.037		*1.504*	-0.048		*6.178*	-0.046		*0.146*
nt_Private Investors	0.006		*0.293*	0.009		*0.973*	0.008		*0.029*	0.002		*0.267*	0.004		*0.969*	0.001		*0.026*
Age	0.001		*0.120*	0.003		*0.413*	0.002		*0.012*	0.002		*0.113*	0.002		*0.475*	0.001		*0.011*
PhD_Founders	0.013	*	*0.295*	0.016	*	*0.855*	0.018	*	*0.028*	0.018	**	*0.302*	0.025		*1.117*	0.021	**	*0.029*
Elapsed Days	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.002*	0.000	***	*0.000*
N_Round	0.004		*0.110*	0.006		*0.373*	0.006	*	*0.011*	0.010		*0.214*	0.014		*0.820*	0.012		*0.021*
Ceased	0.007		*0.471*	0.005		*1.587*	0.008		*0.046*	0.012		*0.528*	0.011		*1.874*	0.013		*0.051*
Seed	-0.014		*2.231*	-0.029		*6.522*	-0.023		*0.216*	0.003		*1.003*	0.000		*3.801*	0.001		*0.098*
Initial Revenue	-0.001		*0.499*	-0.004		*1.559*	-0.001		*0.049*	0.005		*0.575*	0.002		*2.291*	0.006		*0.056*
Revenue Growth	0.031		*1.084*	0.032		*3.211*	0.045		*0.105*	0.053		*1.286*	0.066		*4.547*	0.064		*0.125*
Semiconductors	0.010		*0.932*	0.009		*2.800*	0.010		*0.090*	0.042		*1.540*	0.053		*6.262*	0.046		*0.150*
Misc	0.009		*0.962*	0.017		*3.001*	0.012		*0.093*	0.033		*1.142*	0.051		*4.510*	0.039		*0.111*
Med Dev	0.017		*0.788*	0.025		*2.510*	0.023		*0.076*	0.043		*1.025*	0.066		*3.934*	0.050		*0.100*
Internet	-0.070	***	*0.985*	-0.108	***	*3.612*	-0.101	***	*0.097*	-0.048		*1.457*	-0.102		*5.969*	-0.055		*0.142*
IT & Software	-0.037	**	*0.731*	-0.049	*	*2.450*	-0.055	**	*0.072*	-0.015		*1.523*	-0.029		*5.944*	-0.016		*0.149*
Communications	-0.009		*0.788*	-0.007		*2.493*	-0.016		*0.078*	0.022		*1.738*	0.031		*7.062*	0.026		*0.169*
CleanTech	0.016		*1.007*	0.028		*3.562*	0.023		*0.100*	0.033		*1.059*	0.060		*3.631*	0.041		*0.106*
Constant	-0.278	***	*1.192*	-0.336	***	*4.093*	-0.077	*	*0.116*	-0.356	***	*1.778*	-0.481	***	*6.553*	-0.097		*0.172*
Year FE	YES			YES			YES			YES			YES			YES		
N	1,339			1,339			1,339			1,339			1,339			1,339		
F-Test on excl. coeff. (Vt)	16.080	***																
F-Test on excl. coeff. (nt_VC)	11.380	***								10.990	***							
F-Test on excl. coeff. (ot_VC)										3.000	**							

*** p < 0.01, ** p < 0.05, * p < 0.10. The table reports average partial effects. Standard errors are in italics. They are clustered by firm. For the Tobit Model, standard errors are bootstrapped using 500 replications and accounting for firm clusters in re-sampling.

Table 6: Regression results for the impact of the number of new investors per round on the number of patents filed by the founders (excluding rounds that occurred after 2008)

Δpt	**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**			**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**		
	APE		se	APE		se	APE		se	APE		se	APE		se	APE		se
Vt	0.019		*0.951*	0.018		*2.928*	0.024		*0.093*									
nt	0.069	***	*0.844*	0.078	***	*2.654*	0.093	***	*0.082*	0.084	***	*1.039*	0.120	***	*3.300*	0.116	***	*0.100*
ot										0.015		*0.878*	0.021		*3.325*	0.019		*0.084*
Age	-0.001		*0.075*	-0.001		*0.260*	-0.002		*0.007*	-0.001		*0.096*	-0.002		*0.333*	-0.001		*0.009*
PhD_Founders	0.009		*0.251*	0.009		*0.768*	0.012		*0.024*	0.007		*0.346*	0.009		*1.098*	0.009		*0.033*
Elapsed Days	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.000*	0.000	***	*0.000*	0.000	***	*0.002*	0.000	***	*0.000*
N_Round	0.008	***	*0.109*	0.009	***	*0.336*	0.011	***	*0.011*	0.006	*	*0.154*	0.010		*0.570*	0.009	*	*0.015*
Ceased	0.010		*0.509*	0.005		*1.667*	0.012		*0.050*	0.013		*0.670*	0.010		*2.314*	0.016		*0.064*
Seed	0.042		*1.544*	0.034		*4.892*	0.052		*0.152*	0.030		*1.170*	0.033		*4.363*	0.039		*0.113*
Initial Revenue	-0.005		*0.447*	-0.007		*1.422*	-0.007		*0.044*	-0.007		*0.577*	-0.011		*2.062*	-0.010		*0.056*
Revenue Growth	0.020		*0.906*	0.014		*2.741*	0.027		*0.089*	0.013		*1.242*	0.013		*4.410*	0.020		*0.119*
Semiconductors	0.048	*	*1.011*	0.051	*	*3.159*	0.059	*	*0.100*	0.048	*	*1.107*	0.070		*3.692*	0.062	*	*0.106*
Misc	0.055	**	*0.991*	0.068	**	*3.140*	0.073	**	*0.097*	0.059	**	*1.234*	0.094	*	*4.472*	0.081	**	*0.118*
Med Dev	0.054	**	*0.847*	0.062	***	*2.603*	0.070	**	*0.084*	0.054	**	*0.984*	0.084	**	*3.250*	0.073	**	*0.095*
Internet	-0.048	**	*0.939*	-0.060	*	*3.562*	-0.065	**	*0.094*	-0.051	*	*1.171*	-0.087		*4.515*	-0.072	*	*0.113*
IT & Software	0.013		*0.940*	0.019		*3.001*	0.016		*0.093*	0.020		*1.014*	0.031		*3.732*	0.026		*0.098*
Communications	0.032		*0.994*	0.041		*3.208*	0.041		*0.099*	0.036		*1.066*	0.056		*3.934*	0.047		*0.103*
CleanTech	0.046		*1.310*	0.060	*	*3.977*	0.064		*0.128*	0.052		*1.418*	0.090		*4.618*	0.073		*0.137*
Constant	-0.388	***	*1.911*	-0.390	***	*6.346*	-0.198	***	*0.187*	-0.401	***	*2.637*	-0.540	***	*9.187*	-0.241	***	*0.254*
Year FE	YES			YES			YES			YES			YES			YES		
N	1,278			1,278			1,278			1,278			1,278			1,278		
F-Test on excl. coeff. (Vt)	16.120	***																
F-Test on excl. coeff. (nt)	8.210	***								7.210	***							
F-Test on excl. coeff. (ot)										4.350	***							

*** p < 0.01, ** p < 0.05, * p < 0.10. The table reports average partial effects. Standard errors are in italics. They are clustered by firm. For the Tobit Model, standard errors are bootstrapped using 500 replications and accounting for firm clusters in re-sampling.

Table 7: Regression results for the impact of the number of new VCs and private investors at round t on the number of patents filed by the founders (excluding rounds that occurred after 2008)

Δpt	**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**			**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**		
	APE		se	APE		se	APE		se	APE		se	APE		se	APE		se
Vt	-0.016		*1.505*	-0.025		*4.314*	-0.025		*0.146*									
nt_VC	0.115	***	*1.810*	0.159	***	*5.542*	0.166	***	*0.174*	0.120	***	*1.115*	0.165	***	*3.631*	0.144	***	*0.108*
ot_VC										-0.029		*1.495*	-0.037		*5.311*	-0.038		*0.145*
nt_Private Investors	0.009		*0.315*	0.013		*1.010*	0.012		*0.031*	0.006		*0.288*	0.009		*0.954*	0.006		*0.028*
Age	0.002		*0.116*	0.003		*0.382*	0.002		*0.011*	0.002		*0.116*	0.002		*0.433*	0.002		*0.011*
PhD_Founders	0.012	*	*0.302*	0.016	*	*0.902*	0.018	*	*0.029*	0.016	*	*0.300*	0.021	*	*0.939*	0.020	*	*0.029*
Elapsed Days	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.002*	0.000	***	*0.000*
N_Round	0.004		*0.114*	0.005		*0.361*	0.006	*	*0.011*	0.009		*0.217*	0.012		*0.773*	0.012		*0.021*
Ceased	0.004		*0.462*	0.000		*1.586*	0.005		*0.045*	0.009		*0.526*	0.002		*1.720*	0.009		*0.051*
Seed	-0.003		*2.182*	-0.018		*6.288*	-0.007		*0.211*	0.008		*0.994*	0.003		*3.490*	0.007		*0.097*
Initial Revenue	-0.003		*0.503*	-0.005		*1.520*	-0.004		*0.049*	0.000		*0.548*	-0.002		*1.936*	0.001		*0.054*
Revenue Growth	0.022		*1.081*	0.020		*3.111*	0.032		*0.105*	0.038		*1.245*	0.043		*3.832*	0.048		*0.121*
Semiconductors	0.009		*0.898*	0.009		*2.707*	0.008		*0.087*	0.035		*1.586*	0.046		*5.541*	0.041		*0.154*
Misc	0.009		*0.937*	0.019		*2.869*	0.012		*0.090*	0.028		*1.188*	0.046		*3.725*	0.035		*0.115*
Med Dev	0.019		*0.775*	0.029		*2.331*	0.026		*0.074*	0.041		*1.110*	0.061		*3.654*	0.050		*0.109*
Internet	-0.070	***	*0.997*	-0.105	***	*3.451*	-0.102	***	*0.098*	-0.053		*1.508*	-0.093		*5.464*	-0.063		*0.147*
IT & Software	-0.035	**	*0.709*	-0.044	*	*2.263*	-0.052	**	*0.070*	-0.016		*1.566*	-0.024		*5.192*	-0.019		*0.153*
Communications	-0.010		*0.762*	-0.008		*2.274*	-0.018		*0.075*	0.015		*1.776*	0.023		*5.995*	0.019		*0.173*
CleanTech	0.023		*0.997*	0.042		*3.348*	0.035		*0.099*	0.037		*1.121*	0.066		*3.546*	0.048		*0.112*
Constant	-0.278	***	*1.100*	-0.336	***	*4.019*	-0.084	**	*0.107*	-0.345	***	*1.795*	-0.438	***	*6.328*	-0.104	*	*0.174*
Year FE	YES			YES			YES			YES			YES			YES		
N	1,278			1,278			1,278			1,278			1,278			1,278		
F-Test on excl. coeff. (Vt)	16.060	***																
F-Test on excl. coeff. (nt_VC)	11.450	***								11.040	***							
F-Test on excl. coeff. (nt_VC)										3.000	**							

*** p < 0.01, ** p < 0.05, * p < 0.10. The table reports average partial effects. Standard errors are in italics. They are clustered by firm. For the Tobit Model, standard errors are bootstrapped using 500 replications and accounting for firm clusters in re-sampling.

Table 8: Regression results for the impact of the number of new VCs (including Angel Syndicates) and private investors at round *t* on the number of patents filed by the founders

Δpt	**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability**			**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**		
	APE		se	APE		se	APE		se	APE		se	APE		se	APE		se
Vt	-0.019		*1.501*	-0.030		*4.936*	-0.029		*0.146*									
nt_VC	0.124	***	*1.884*	0.183	**	*7.797*	0.177	***	*0.182*	0.129	***	*1.159*	0.178	***	*3.840*	0.149	***	*0.112*
ot_VC										-0.030		*1.515*	-0.035		*6.704*	-0.039		*0.147*
nt_Private Investors	0.003		*0.264*	0.005		*0.934*	0.004		*0.026*	0.000		*0.256*	0.001		*0.950*	0.000		*0.025*
Age	0.002		*0.121*	0.003		*0.493*	0.002		*0.012*	0.002		*0.115*	0.002		*0.509*	0.002		*0.011*
PhD_Founders	0.012	*	*0.289*	0.015		*0.872*	0.016	*	*0.028*	0.017	*	*0.319*	0.021		*1.249*	0.020	*	*0.030*
Elapsed Days	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.000*	0.000	***	*0.001*	0.000	**	*0.002*	0.000	***	*0.000*
N_Round	0.004		*0.110*	0.006		*0.390*	0.006		*0.011*	0.009		*0.214*	0.012		*0.893*	0.011		*0.021*
Ceased	0.008		*0.475*	0.008		*1.721*	0.011		*0.046*	0.013		*0.540*	0.011		*1.895*	0.014		*0.052*
Seed	-0.006		*2.125*	-0.020		*6.691*	-0.013		*0.206*	0.007		*1.019*	0.005		*3.997*	0.005		*0.099*
Initial Revenue	0.000		*0.501*	-0.003		*1.580*	0.000		*0.049*	0.004		*0.582*	0.001		*2.439*	0.006		*0.057*
Revenue Growth	0.029		*1.078*	0.032		*3.228*	0.043		*0.104*	0.049		*1.294*	0.056		*4.690*	0.060		*0.126*
Semiconductors	0.011		*0.932*	0.010		*2.842*	0.010		*0.091*	0.037		*1.540*	0.043		*6.604*	0.041		*0.150*
Misc	0.011		*0.952*	0.021		*3.017*	0.014		*0.092*	0.030		*1.132*	0.044		*4.444*	0.036		*0.109*
Med Dev	0.019		*0.780*	0.029		*2.488*	0.026		*0.075*	0.040		*1.006*	0.057		*4.131*	0.047		*0.098*
Internet	-0.077	***	*1.049*	-0.129	***	*3.949*	-0.112	***	*0.103*	-0.064		*1.457*	-0.117		*6.122*	-0.072		*0.142*
IT & Software	-0.037	**	*0.732*	-0.051	*	*2.587*	-0.054	**	*0.072*	-0.020		*1.530*	-0.034		*6.197*	-0.022		*0.149*
Communications	-0.009		*0.785*	-0.008		*2.526*	-0.016		*0.077*	0.015		*1.741*	0.020		*7.418*	0.019		*0.170*
CleanTech	0.019		*1.002*	0.036		*3.721*	0.029		*0.099*	0.033		*1.048*	0.057		*3.753*	0.041		*0.105*
Constant	-0.279	***	*1.218*	-0.366	***	*5.348*	-0.082	**	*0.119*	-0.352	***	*1.774*	-0.445	***	*7.057*	-0.095		*0.172*
Year FE	YES			YES			YES			YES			YES			YES		
N	1,339			1,339			1,339			1,339			1,339			1,339		
F-Test on excl. coeff. (Vt)	16.080	***																
F-Test on excl. coeff. (nt_VC)	10.750	***								10.150	***							
F-Test on excl. coeff. (ot_VC)										2.990	**							

*** p < 0.01, ** p < 0.05, * p < 0.10. The table reports average partial effects. Standard errors are in italics. They are clustered by firm. For the Tobit Model, standard errors are bootstrapped using 500 replications and accounting for firm clusters in re-sampling.

Table 9: Regression results for the impact of the number of new VCs and private investors (including Angel Syndicates) at round *t* on the number of patents filed by the founders

Δpt	**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**			**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**		
	APE		se	APE		se	APE		se	APE		se	APE		se	APE		se
Vt	-0.023		*1.563*	-0.033		*4.528*	-0.034		*0.151*									
nt_VC	0.125	***	*1.908*	0.169	***	*5.870*	0.178	***	*0.184*	0.128	***	*1.127*	0.189	***	*3.643*	0.146	***	*0.109*
ot_VC										-0.037		*1.511*	-0.047		*6.246*	-0.045		*0.147*
nt_Private Investors	0.007		*0.291*	0.011		*0.934*	0.011		*0.028*	0.003		*0.267*	0.007		*0.952*	0.003		*0.026*
Age	0.001		*0.120*	0.003		*0.413*	0.002		*0.012*	0.002		*0.113*	0.002		*0.477*	0.002		*0.011*
PhD_Founders	0.013	*	*0.294*	0.015	*	*0.855*	0.018	*	*0.028*	0.018	**	*0.303*	0.024		*1.130*	0.021	**	*0.029*
Elapsed Days	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.000*	0.000	***	*0.001*	0.000	**	*0.002*	0.000	***	*0.000*
N_Round	0.004		*0.110*	0.006		*0.373*	0.006	*	*0.011*	0.010		*0.215*	0.014		*0.827*	0.012		*0.021*
Ceased	0.007		*0.472*	0.006		*1.589*	0.008		*0.046*	0.012		*0.528*	0.011		*1.876*	0.013		*0.051*
Seed	-0.013		*2.221*	-0.028		*6.488*	-0.022		*0.215*	0.004		*1.006*	0.000		*3.830*	0.001		*0.098*
Initial Revenue	-0.001		*0.499*	-0.004		*1.562*	-0.001		*0.049*	0.005		*0.576*	0.002		*2.309*	0.006		*0.056*
Revenue Growth	0.030		*1.083*	0.031		*3.213*	0.044		*0.105*	0.052		*1.290*	0.065		*4.576*	0.063		*0.125*
Semiconductors	0.011		*0.931*	0.009		*2.798*	0.010		*0.090*	0.042		*1.543*	0.053		*6.311*	0.046		*0.150*
Misc	0.010		*0.960*	0.018		*3.002*	0.013		*0.092*	0.034		*1.144*	0.051		*4.533*	0.040		*0.111*
Med Dev	0.018		*0.786*	0.025		*2.504*	0.024		*0.076*	0.043		*1.027*	0.066		*3.959*	0.050		*0.101*
Internet	-0.070	***	*0.988*	-0.107	***	*3.629*	-0.101	***	*0.097*	-0.049		*1.472*	-0.104		*6.051*	-0.055		*0.143*
IT & Software	-0.037	**	*0.730*	-0.047	*	*2.454*	-0.054	**	*0.072*	-0.015		*1.527*	-0.029		*5.981*	-0.016		*0.149*
Communications	-0.009		*0.788*	-0.007		*2.492*	-0.015		*0.077*	0.022		*1.743*	0.031		*7.121*	0.026		*0.170*
CleanTech	0.016		*1.005*	0.029		*3.540*	0.025		*0.100*	0.033		*1.058*	0.061		*3.629*	0.041		*0.106*
Constant	-0.279	***	*1.196*	-0.334	***	*4.104*	-0.080	*	*0.117*	-0.357	***	*1.778*	-0.483	***	*6.556*	-0.098		*0.173*
Year FE	YES			YES			YES			YES			YES			YES		
N	1,339			1,339			1,339			1,339			1,339			1,339		
F-Test on excl. coeff. (Vt)	16.080	***																
F-Test on excl. coeff. (nt_VC)	11.350	***								10.950	***							
F-Test on excl. coeff. (ot_VC)										2.970	**							

*** p < 0.01, ** p < 0.05, * p < 0.10. The table reports average partial effects. Standard errors are in italics. They are clustered by firm. For the Tobit Model, standard errors are bootstrapped using 500 replications and accounting for firm clusters in re-sampling.

Table 10: Regression results for the impact of the number of new VCs (including Angel Syndicates and other Angel Investors) and private investors at round *t* on the number of patents filed by the founders

Δpt	**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**			**IV Continuous Model**			**IV Tobit Model**			**IV Linear Probability Model**		
	APE		se	APE		se	APE		se	APE		se	APE		se	APE		se
Vt	-0.022		*1.541*	-0.011		*0.444*	-0.033		*0.150*									
nt_VC	0.126	***	*1.912*	0.058	***	*0.592*	0.180	***	*0.185*	0.131	***	*1.187*	0.258	***	*0.408*	0.150	***	*0.115*
ot_VC				0.000						-0.033		*1.542*	-0.059		*0.730*	-0.042		*0.150*
nt_Private Investors	0.004		*0.270*	0.002		*0.091*	0.006		*0.026*	0.000		*0.279*	0.001		*0.102*	-0.001		*0.027*
Age	0.002		*0.121*	0.001		*0.041*	0.002		*0.012*	0.002		*0.116*	0.003		*0.054*	0.002		*0.011*
PhD_Founders	0.012	*	*0.293*	0.005	*	*0.084*	0.017	*	*0.028*	0.017	*	*0.320*	0.032		*0.126*	0.020	*	*0.030*
Elapsed Days	0.000	***	*0.000*	0.000	***	*0.000*	0.000	***	*0.000*	0.000	***	*0.001*	0.000	**	*0.000*	0.000	***	*0.000*
N_Round	0.004	*	*0.110*	0.002		*0.037*	0.007	*	*0.011*	0.009		*0.217*	0.019		*0.098*	0.012		*0.021*
Ceased	0.008		*0.480*	0.002		*0.158*	0.010		*0.047*	0.013		*0.547*	0.015		*0.187*	0.014		*0.052*
Seed	-0.010		*2.179*	-0.008		*0.630*	-0.017		*0.212*	0.007		*1.028*	0.003		*0.408*	0.005		*0.100*
Initial Revenue	0.001		*0.512*	-0.001		*0.156*	0.001		*0.050*	0.005		*0.591*	0.004		*0.248*	0.007		*0.058*
Revenue Growth	0.031		*1.080*	0.011		*0.314*	0.045		*0.105*	0.050		*1.298*	0.087		*0.480*	0.061		*0.126*
Semiconductors	0.010		*0.943*	0.002		*0.283*	0.009		*0.092*	0.037		*1.555*	0.063		*0.692*	0.041		*0.151*
Misc	0.012		*0.951*	0.007		*0.295*	0.016		*0.092*	0.033		*1.130*	0.069		*0.447*	0.039		*0.110*
Med Dev	0.023		*0.777*	0.011		*0.242*	0.032		*0.075*	0.046		*1.042*	0.095		*0.465*	0.054		*0.102*
Internet	-0.076	***	*1.080*	-0.039	***	*0.393*	-0.111	***	*0.106*	-0.060		*1.477*	-0.158		*0.636*	-0.068		*0.144*
IT & Software	-0.034	*	*0.751*	-0.015	*	*0.250*	-0.050	*	*0.074*	-0.015		*1.547*	-0.038		*0.655*	-0.016		*0.151*
Communications	-0.006		*0.819*	-0.001		*0.251*	-0.010		*0.081*	0.021		*1.764*	0.041		*0.784*	0.025		*0.172*
CleanTech	0.024		*0.990*	0.014		*0.346*	0.036		*0.099*	0.039		*1.075*	0.097		*0.406*	0.048		*0.108*
Constant	-0.288	***	*1.327*	-0.085	***	*0.449*	-0.094	**	*0.129*	-0.362	***	*1.857*	-0.478	***	*0.805*	-0.108	*	*0.180*
Year FE	YES			YES			YES			YES			YES			YES		
N	1,339			1,339			1,339			1,339			1,339			1,339		
F-Test on excl. coeff. (Vt)	16.080	***																
F-Test on excl. coeff. (nt_VC)	11.350	***								9.740	***							
F-Test on excl. coeff. (ot_VC)										2.950	**							

*** p < 0.01, ** p < 0.05, * p < 0.10. The table reports average partial effects. Standard errors are in italics. They are clustered by firm. For the Tobit Model, standard errors are bootstrapped using 500 replications and accounting for firm clusters in re-sampling.

Table 11: Regression results for the impact of the number of new VCs (including private equity firms or firms that specialize in startup investment) and private investors at round *t* on the number of patents filed by the founders

Δpt	**IV Continuous Model**		**IV Tobit Model**		**IV Linear Probability Model**		**IV Continuous Model**		**IV Tobit Model**		**IV Linear Probability Model**	
	APE	se	APE	se	APE	se	APE	se	APE	se	APE	se
Vt	-0.005	*1.117*	-0.020	*0.345*	-0.009	*0.109*						
nt_VC	0.084 ***	*0.994*	0.231 ***	*0.329*	0.118 ***	*0.097*	0.079 ***	*0.738*	0.206 ***	*0.243*	0.108 ***	*0.072*
ot_VC							-0.006	*1.245*	-0.012	*0.539*	-0.012	*0.121*
nt_Private Investors	-0.002	*0.210*	-0.005	*0.078*	-0.003	*0.021*	-0.003	*0.244*	-0.006	*0.091*	-0.004	*0.024*
Age	-0.001	*0.071*	-0.002	*0.026*	-0.002	*0.007*	-0.001	*0.092*	-0.004	*0.047*	-0.002	*0.009*
PhD_Founders	0.012 *	*0.256*	0.028	*0.078*	0.016 *	*0.024*	0.013	*0.342*	0.030	*0.138*	0.018	*0.033*
Elapsed Days	0.000 ***	*0.000*	0.000 ***	*0.000*	0.000 ***	*0.000*	0.000 ***	*0.000*	0.000 ***	*0.000*	0.000 ***	*0.000*
N_Round	0.005 **	*0.096*	0.014 **	*0.032*	0.008 **	*0.009*	0.006	*0.221*	0.018	*0.085*	0.010	*0.022*
Ceased	0.004	*0.413*	0.001	*0.141*	0.004	*0.041*	0.004	*0.445*	-0.002	*0.158*	0.004	*0.043*
Seed	0.010	*1.642*	0.000	*0.520*	0.009	*0.161*	0.012	*0.964*	0.017	*0.388*	0.014	*0.095*
Initial Revenue	0.003	*0.439*	0.001	*0.139*	0.004	*0.043*	0.004	*0.539*	0.003	*0.217*	0.006	*0.053*
Revenue Growth	0.034	*0.918*	0.074	*0.284*	0.049	*0.089*	0.037	*1.195*	0.087	*0.421*	0.055	*0.116*
Semiconductors	0.029	*0.873*	0.064	*0.254*	0.035	*0.085*	0.032	*1.273*	0.077	*0.532*	0.042	*0.124*
Misc	0.013	*0.839*	0.045	*0.274*	0.018	*0.082*	0.016	*0.990*	0.050	*0.384*	0.023	*0.096*
Med Dev	0.030 *	*0.669*	0.082 *	*0.203*	0.040 *	*0.065*	0.032	*0.831*	0.093	*0.310*	0.044	*0.082*
Internet	-0.059 ***	*0.758*	-0.186 ***	*0.301*	-0.084 ***	*0.076*	-0.053 *	*1.272*	-0.179	*0.539*	-0.072	*0.124*
IT & Software	-0.027	*0.674*	-0.067	*0.224*	-0.039	*0.067*	-0.022	*1.374*	-0.063	*0.557*	-0.030	*0.134*
Communications	-0.007	*0.703*	-0.009	*0.228*	-0.012	*0.070*	-0.001	*1.637*	0.001	*0.672*	0.000	*0.160*
CleanTech	0.029	*1.112*	0.095	*0.366*	0.042	*0.110*	0.030	*1.108*	0.104	*0.364*	0.043	*0.110*
Constant	-0.288 ***	*1.026*	-0.494 ***	*0.383*	-0.078 **	*0.101*	-0.288 ***	*1.592*	-0.487 ***	*0.610*	-0.079	*0.155*
Year FE	YES		YES		YES		YES		YES		YES	
N	1,339		1,339		1,339		1,339		1,339		1,339	
F-Test on excl. coeff. (Vt)	16.080 ***											
F-Test on excl. coeff. (nt_VC)	15.630 ***						14.480 ***					
F-Test on excl. coeff. (ot_VC)							2.950 **					

*** p < 0.01, ** p < 0.05, * p < 0.10. The table reports average partial effects. Standard errors are in italics. They are clustered by firm. For the Tobit Model, standard errors are bootstrapped using 500 replications and accounting for firm clusters in re-sampling.

Table B1: First-Stage regressions

	Amount of external funding			**New investors per round**			**Old investors per round**			**New venture capital investors**			**Old venture capital investors**		
	Coeff.		se	Coeff.		se	Coeff.		se	Coeff.		se	Coeff.		se
US VC (N Deals)	3.582	***	*1.109*	4.861	*	*2.513*	0.651		*0.443*	2.441		*1.627*	-0.039		*0.298*
Silicon V. VC (amount)	-2.130	***	*0.544*	-3.048	***	*1.096*				-1.739	**	*0.693*			
N Past Startups	0.037	***	*0.007*	0.017	*	*0.009*	0.027	**	*0.014*	0.022	***	*0.006*	0.023	**	*0.010*
Chief Scientist	-0.224	***	*0.083*	0.130		*0.110*	-0.430	***	*0.161*	0.027		*0.071*	-0.190	*	*0.112*
Age	0.007		*0.013*	-0.045	**	*0.019*	0.060	**	*0.029*	-0.043	***	*0.012*	0.034		*0.021*
PhD_Founders	0.068		*0.046*	0.005	**	*0.063*	0.180	**	*0.083*	0.006		*0.042*	0.099		*0.066*
Elapsed Days	0.000		*0.000*	0.000		*0.000*	0.000	*	*0.000*	0.000		*0.000*	0.000	***	*0.000*
N_Round	0.025	***	*0.021*	-0.015		*0.030*	0.102	*	*0.057*	0.026		*0.022*	0.128	***	*0.039*
Ceased	-0.326	***	*0.094*	-0.317	***	*0.105*	-0.251	*	*0.149*	-0.235	***	*0.069*	0.009		*0.108*
Seed	-1.371	***	*0.167*	-0.247		*0.190*	-0.702	***	*0.166*	-0.201	*	*0.111*	-0.378	***	*0.119*
Initial Revenue	0.226	***	*0.078*	0.063		*0.117*	0.392	**	*0.152*	0.098		*0.071*	0.259	**	*0.105*
Revenue Growth	0.700	***	*0.141*	0.273		*0.213*	0.904	**	*0.370*	0.307	**	*0.154*	0.729	**	*0.311*
Semiconductors	0.223		*0.167*	-0.329		*0.256*	0.362		*0.391*	0.211		*0.148*	0.816	***	*0.242*
Misc	-0.321	*	*0.181*	-0.815	***	*0.234*	0.122		*0.404*	-0.140		*0.162*	0.448		*0.281*
Med Dev	-0.233	*	*0.141*	-0.470	**	*0.217*	0.155		*0.362*	-0.051		*0.114*	0.443	**	*0.176*
Internet	-0.110		*0.178*	0.090		*0.293*	-0.015		*0.422*	0.274		*0.172*	0.704	***	*0.258*
IT & Software	-0.083		*0.138*	-0.685	***	*0.220*	0.128		*0.384*	0.032		*0.123*	0.732	***	*0.187*
Communications	0.103		*0.149*	-0.614	***	*0.218*	0.441		*0.390*	0.071		*0.120*	0.934	***	*0.208*
CleanTech	-0.420		*0.358*	-0.347		*0.273*	-0.467		*0.409*	-0.112		*0.137*	0.141		*0.215*
nt_Private Investors										-0.029		*0.034*	-0.092		*0.041*
Constant	-5.313		*3.409*	-4.520		*8.171*	-3.974		*3.054*	-0.766		*5.443*	-0.105	**	*2.064*
Year FE	YES			YES			YES			YES			YES		
N	1,339			1,339			1,339			1,339			1,339		

*** p < 0.01, ** p < 0.05, * p < 0.10. Standard errors are in italics.