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# PATENTS AS SIGNALS FOR STARTUP FINANCING*

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We examine the role of patents as signals used to reduce information asymmetries in entrepreneurial finance. A theoretical model gives conditions for a unique separating equilibrium in which startup founders file for patents to signal invention quality to investors, as well as appropriating value. The theory allows for heterogeneous investors and examines the optimal match of different types of startups, as defined by the quality of their technology, to investors who differ in the amount of non financial capital they provide. The empirical analysis is consistent with the model's predictions using a novel dataset of Israeli startups that received external funding during the period 1994–2011.

## I. INTRODUCTION

By construction, a patent is an informational mechanism. It publicly discloses the scope and specification of an invention. But it also creates an exclusionary property right which, in principle, allows the assignee(s) to capture or appropriate rents from the invention. The trade off between disclosure and appropriability has been extensively studied, going back to Arrow [1962].[1] One of the enduring questions to come out of this work is why firms invest in patents when their appropriability value is low (Cohen *et al*. [2000]). Particularly puzzling is the fact that small, capital constrained

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[1] Thursby and Thursby [2008] provide a review of research on the associated *ex ante* incentive to invent and *ex post* incentive to disclose.

firms have a higher propensity to patent than larger firms (Lerner *et al.* [2002]). One answer lies in the financial role of patents; and, indeed, the Berkeley Patent Survey finds that one of the most important reasons for startups to patent is to secure financing (Graham *et al.* [2009]). A patent is an asset that can be used as collateral in debt financing. Moreover, because a patent with misinformation can be invalidated, it provides a means to *credibly* convey information in situations of asymmetric information (Long [2002]).[2] One such situation is entrepreneurial finance where high technology startups with little or no track record face the problem of financing costly development of new inventions.

We construct a theoretical model that allows us to examine the patent choices of startup founders who seek development funds for an invention of uncertain quality in a setting with heterogeneous investors. Using a novel dataset of Israeli startups with external funding from 1994–2011, we test the proposition that patents are used as signals to attract new investors. Moreover, we provide evidence that startups with better technologies affiliate with investors who can add high value to the startup.

In the model, the founders of a startup need external capital to develop an invention of quality that is known only to them. In order to signal this quality, the founders can file for patents, which also add appropriability value to the firm. We incorporate the fact that investors are not homogeneous with respect to the value they add to a startup (Hochberg *et al.* [2010], and Bottazzi *et al.* [2008]) and that startups are willing to incur costs to affiliate with investors who add high value (Hsu [2004]). In our model, a continuum of external investors differ in the amount of non financial capital they can provide, and the startup bears a cost associated with adjustments required by the investor. This cost is increasing in the amount of non financial capital provided by the investor, and decreasing in the quality of the invention. Under these conditions, there exists a signaling equilibrium characterized by a positive match of startup invention quality and external investor non financial capital.

The empirical analysis uses a dataset of 787 Israeli startups provided by the Israel 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 startup founders, patents filed in each year and rounds of financing, including the amounts invested, by whom, and by stage of investment. If patents are used as signals, the number of patents filed and external investment are endogenously determined. This simultaneity is likely to be an issue primarily for new investors in a round. Moreover, our prior is that

[2] See also Burk [2008] on the role of patents in the codification of tacit knowledge. In entrepreneurial finance, firm patents ensure that knowledge invention knowledge remains in the event of managerial turnover.

simultaneity occurs only for rounds subsequent to the first, to the extent that startups are formed based on an initial set of patents associated with its founders. In addition to simultaneity, there is an issue of unobserved heterogeneity because we cannot fully control for all aspects of a startup's technology. Thus our empirical analysis estimates a series of instrumental variable (IV) models.

We separately consider the initial round of funding from subsequent rounds, and we consider several analyses of investors. In particular, we find that the number of patents filed prior to the first round of funding is not endogenous to the round. However, for rounds subsequent to the first, we find that patents are endogenous. In this setting, we distinguish new and old investors, and find that new and old investors are jointly endogenous but old investors do not significantly affect patents. We also distinguish venture capitalists from private investors in an attempt to capture differential services among types of investors. To the extent that venture capitalists provide greater non financial capital than private investors (Brav and Gompers [1997]; Graham *et al.* [2009]), our theory would suggest such a distinction. Indeed, we find that venture capitalists are endogenous to the process but private investors are not. Overall, our results are consistent with our theory.

Our analysis contributes to the theoretical literature on the role of signals in entrepreneurial finance. This literature goes back to Leland and Pyle's [1976] analysis of equity to signal entrepreneurial commitment. Subsequent generalizations include the use of managerial incentive schemes (Ross [1977]), dividends (Bhattacharya [1979]), as well as underpricing and timing of initial public offerings (Grinblatt and Hwang [1989]). To our knowledge, only Long [2002] and Conti *et al.* [2013] consider patents as a signal. Long [2002] provides a legal theory of patents as a mechanism to reduce asymmetries of information, and Conti *et al.* [2013] provide a model in which patents signal invention quality while own investment signals founder commitment.[3] In this paper, we consider heterogeneous external investors, which allows us to predict the matching of high quality startups with investor types, as defined by the amount of non financial capital they can provide.[4] This aspect of the theory is essential to frame an empirical analysis of the matching of investor and startup types.

We also contribute to the empirical literature on entrepreneurial finance that has examined both venture capital funding as a determinant of innovation, as measured by patents (Kortum and Lerner [2000]), and patents as a signals of technology quality to investors (Haeussler *et al.* [2009], Hsu and

[3] In Horstmann *et al.* [1985] patents signal value to potential imitators so that in equilibrium innovating firms file for fewer patents than in a situation of symmetric information. The contrasting result comes from the fact that our signal is sent to potential investors.

[4] For signaling combined with matching in a more general context, see Hoppe *et al.* [2009].

Ziedonis [2013] and Conti *et al*. [2013]). Haeussler *et al*. [2009] and Hsu and Ziedonis [2013] consider the effect of patents on venture funding. While they discuss patents as costly signals, they abstract from the endogeneity problem inherent in the fact that these signals are simultaneously determined by investor and startup choices. Conti *et al*. [2013] examine the role of patents in venture capital and business angel funding, taking this endogeneity into account, but their focus is quite different from ours. They focus on the choice of the type of signal but they do not examine the differential impact of new versus old investors on founders' patent investment, nor can they distinguish among rounds of investment or analyze matching. Our paper differs from all of these papers by focusing on the estimation of the patent signals as function of funding.

The paper proceeds as follows. Section II presents the theoretical model. Sections III, IV, and V provide a description of the data, econometric methodology and results, respectively. Section VI give concluding remarks.

## II. A THEORETICAL MODEL OF PATENTS AS SIGNALS

Consider the problem of a startup whose founders have an invention that requires further development to be commercially viable. While the founders have access to their own funds and those raised from friends and family ($M$), they need to approach external investors to obtain the capital, $K$, for further development. Development of the invention will ensure a return which is increasing in the quality of the invention, $\theta$. The distribution of $\theta$ is continuous and has support $[\underline{\theta}, \overline{\theta}]$.

### II(i). *Model Setup*

The founders have private information about $\theta$ which they need to convey to external investors. They consider patents as a signal, and they choose the number of patents to file, $p \in [0, \overline{p}]$, which is treated as a continuous variable.[5] While an invention can give rise to multiple patents, there is a maximum number of patents, $\overline{p}$, the founders can file for a given invention. In addition to signaling, patents intrinsically provide value for the company by excluding others from practicing the invention and/or by facilitating licensing and other negotiations (Arora and Ceccagnoli [2006]; and Graham *et al*. [2009]). Thus patents are a productive signal, and in this regard our model is similar to Spence's [1974] model of productive educa-

[5] In assuming that patents are a signal for the quality of the invention, we follow Conti *et al*. [2013]. While the legal literature suggests that patents signal management quality (Long [2002]; Graham *et al*. [2009]), studies in entrepreneurial finance have shown that external investors tend to replace the management team (Hellmann and Puri [2002]). These results suggest that management quality is not as relevant for our purposes as invention quality.

tion. The value of the startup is a function of patents and the quality of the invention, $V(p, \theta)$, where $V$ is strictly increasing in both arguments, and $V_{p\theta}(p, \theta) \geq 0$.[6] The assumption that $V_p > 0$ implies that the appropriability value of patents is positive.

Filing for patents involves a total cost, $c(p, \theta)$, which is clearly strictly increasing in $p$ with $c(0, \theta) = 0$. Moreover, we assume that this cost is decreasing in invention quality. To be patented in most countries, an invention must be useful, novel, and non-obvious to someone practiced in the art. We assume that the effort, and hence the cost, required to show that an invention meets these criteria is a decreasing function of quality so that $c_\theta(p, \theta) < 0$. The rationale is that the lower the quality of the invention, the more effort and rounds of revisions are likely to be required for a patent to be granted.[7] Moreover, the marginal cost of patenting is decreasing in invention quality or $c_{p\theta}(p, \theta) < 0$. This condition ensures that the single crossing property for founder expected utility holds.[8]

The game is played in three periods. The founders are risk neutral so that they maximize their expected wealth in the second period. We assume a unitary discount factor. In period 0, the founders choose the number of patents to file, which they finance by own, family, and friends' money, $M$, where $M \geqslant c(\overline{p}, \theta)$ and $K > M > 0$. As such we are assuming that $M$ can be used to finance patents but not the entire project. Contingent on the number of patents filed by the startup, an investor forms an estimate of the startup's value which we represent as $\hat{V}(p, \hat{\theta}(p))$ where $\hat{\theta}(p)$ is the perceived quality of the invention.

In addition to 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 $S \in [\underline{S}, \infty)$. We further assume that by employing these services, the startup's value becomes $\upsilon(S)\ V(p, \theta)$, where $\upsilon(\underline{S}) \geq 1$ and $\upsilon(S)$ 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 increases the startup's value by $\upsilon(S)$. In order to secure services and capital from an investor, the startup must relinquish a share of the company as equity. In addition, the external investor is likely to require management adjustments which are costly. Consistent with Hsu [2004], the cost of managerial adjustments, $\varsigma(S, \theta)$, is convex and increasing in the non financial services provided by the external investor, i.e.,

[6] Throughout, we use $f_x$ to denote the partial derivative of a function $f$ with respect to the variable $x$.

[7] We make this assumption based on discussions with patent attorneys in the United States, who emphasized that marginal inventions were more likely to require filing Requests for Continued Examination, which are quite costly. Less original inventions also tend to have more costly initial prior art searches.

[8] See Mailath [1987] on the meaning and importance of single crossing for signaling games.

$\varsigma_S(S, \theta) > 0$. Moreover, we assume that the marginal cost of making managerial adjustments is decreasing in the quality of the invention, or $\varsigma_{S\theta}(S, \theta) < 0$. Given this setup, the startup's budget constraint in period 1 is:

$$M + \upsilon(S)\hat{V}^{EI}(p, \hat{\theta}(p)) = c(p, \theta) + K + \varsigma(S, \theta) \tag{1}$$

where $\upsilon(S)\hat{V}^{EI}(p, \hat{\theta}(p))$ represents the amount the external investor is willing to invest in the startup given his perception, $\hat{\theta}(p)$. This amount is increasing in the amount of non financial capital, $S$, provided by the external investor. We make the standard assumption from finance that the market for external investment is perfectly competitive, so that in equilibrium the expected return of the investors is zero.

The value of the invention, $\theta$, is realized in period 2. Given this realization, the period 2 expected wealth of the startup founders, can be expressed as:

$$E(W) = \upsilon(S)V^{SU}(p, \theta) - M$$

where we define $V^{SU}(p, \theta) = V(p, \theta) - V^{EI}(p, \theta)$.

Substituting for $M$ from condition (1), we can rewrite the expression for expected wealth as follows:

$$E(W) = \upsilon(S)[V^{SU}(p, \theta) + \hat{V}^{EI}(p, \hat{\theta}(p))] - c(p, \theta) - K - \varsigma(S, \theta) \tag{2}$$

## II(ii). *Model Solution*

The founders choose $p$ to maximize their expected wealth in the last period, as given by (2). In a Perfect Bayesian Equilibrium, the external investors' beliefs about the quality of the invention must be correct, or

$$\theta = \hat{\theta}(p^*(\theta)) \tag{3}$$

where $p^*(\theta)$ is the number of patents that maximizes the founders' period 2 expected wealth. If $\theta < \hat{\theta}(p^*(\theta))$, then the investors who invest in the startup could do better by deviating from the amount they pay to the startup in the second period. If $\theta > \hat{\theta}(p^*(\theta))$, then investors would make excess returns.

The first order necessary condition for such an equilibrium is:

$$E_p(W) = \upsilon(S)[V_p(p, \theta) + \hat{V}_{\hat{\theta}}^{EI}(p, \hat{\theta}(p))\hat{\theta}_p] - c_p(p, \theta) = 0 \tag{4}$$

where we have used the fact that $V^{SU}(p, \theta) = V(p, \theta) - V^{EI}(p, \theta)$ and the Perfect Bayesian Equilibrium condition (3). As we show in the appendix, there is a unique $p^*$ which maximizes founder expected wealth in the second period. The assumptions $V_{p\theta}(p, \theta) > 0$ and $c_{p\theta}(p, \theta) < 0$ ensure $E_{p\theta}(W) > 0$ This implies that if $E_p(W) = 0$ for a particular $p$ (say $p^*$), then if we raise $p$, the maximum occurs at a higher value of $p$.

Moreover, in equilibrium, investor beliefs must be consistent with the founders' equilibrium strategy, or $\theta = \hat{\theta}(p^*(\theta))$, which allows us to rewrite (4) as:

$$\text{(5)} \qquad \hat{\theta}_{p^*} = \frac{c_p(p^*, \hat{\theta}(p^*)) - \upsilon(S)\hat{V}_p(p^*, \hat{\theta}(p^*))}{\upsilon(S)[\hat{V}^{EI}_{\hat{\theta}}(p^*, \hat{\theta}(p^*)]}.$$

This is a first order ordinary differential equation which is strictly increasing in $p^*$ if the founder's marginal cost of investing in patents, $c_p(p^*, \hat{\theta}(p^*))$, is greater than the marginal value patents intrinsically add to the startup, given the quality of the invention as perceived by the investors, $\upsilon(S)\hat{V}_p(p^*, \hat{\theta}(p^*))$. Intuitively, if patents are to be used as a signal, their marginal cost in equilibrium must exceed the marginal value they intrinsically add to the startup for a given belief on the part of external investors. In the appendix we show that the unique maximum occurs within the range of values of $p$ such that (5) is positive.

*Proposition 1.* There exists a unique separating, signaling equilibrium in which the signaling schedule is strictly increasing in the number of patents if and only if $c_p(p^*, \hat{\theta}(p^*)) > \upsilon(S)\hat{V}_p(p^*, \hat{\theta}(p^*))$, and the founders of a startup find it optimal to file $p^*$ patents, which is greater than the number filed under symmetric information.

### II(iii). *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, $\theta$. Additionally, we allow for a continuum of external investor types. The distribution of external investor types across startups has mixed joint density $f(S, y(\theta))$ where $y(\theta)$ is the number of external investors per value of $\theta$ and we assume that $y(\theta) \geq 2$. The condition $y(\theta) \geq 2$ ensures that the external investors' market is competitive. For simplicity, we assume that a single external investor invests in the startup.

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:

$$\text{(6)} \qquad E_S(W(p^*)) = \upsilon_S(S)V(p^*, \theta) - \varsigma_S(S, \theta) = 0.$$

Further $E_{SS}(W(p^*)) < 0$ from the optimality of the assignment. Note that the first term in equation (6) represents the marginal contribution of external investor services to the value of the startup and the second term is the marginal cost of implementing adjustments required by the investor.

If we totally differentiate the expression in (6) at the equilibrium, we find:

$$\frac{dE(W(p^*))}{dS} = E_{SS}(W(p^*)) + E_{S\theta}(W(p^*))\frac{d\theta}{dS} = 0 \tag{7}$$

which gives us:

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

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

$$\upsilon_S(S)V_\theta(p^*, \theta) - \varsigma_{S\theta}(S, \theta)$$

This expression is greater than zero, giving us the following proposition.

*Proposition 2.* The signaling equilibrium is characterized by positive matching of startup founders with invention value, $\theta$, and external investors with non financial capital amount, $S$.

This positive matching comes from the fact that the adjustment cost in equation (6) is increasing in $S$, decreasing in $\theta$, and $\varsigma_{S\theta}(S, \theta) < 0$.

## III. THE DATA

We empirically examine the model's implications using detailed information on patents and financing rounds for a sample of 787 startups based in Israel. We use data on Israeli startups compiled by the Israel 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 as of June, 2011, 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]). A recent article in *The Economist*[9] 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

[9] 'What Next for the Start-Up Nation?' *The Economist*, January 21st, 2012.

June, 2011. This amounts to 1,154 startups. We then add to this set of firms a random sample of 1,000 companies out of 2,912 companies that had ceased to operate (failed) during the period 2000–2011. From this set of 2,154 firms we retained only those that i) had at least a round of financing recorded by IVC,[10] 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 2,126 financing rounds.

The firms operated primarily in the IT and software sectors (25.0%), communications (22.0%), the internet sector (10.8%), semiconductors (7.0%), life sciences (9.7%) and medical devices (13.6%). The sector composition of our startups reflects Israel's comparative advantage in Information and Communications Technologies. Sixteen per cent of the startups spent time in a technology incubator, and the majority (85%) were founded between 1993 and 2005. Forty-three per cent 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 seed stage (30%), R&D stage (44%), initial revenue stage (20%), or revenue growth stage (6%).

There are 1968 investors classified according to whether they are venture capital companies, private investors, angel investment groups or 'other.' Private investors are identified by a 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 category '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 per cent 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% 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.

[10] 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.

Table I
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 I provides the distribution according to investor type and the total number of startups each investor invested in over our sample period. For example, 1,447 of the investors invested in only one of the 787 startups in our sample and 206 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 startups invested in by private investors is one. This is not the case for venture capitalists. Of the investors who invested in only one startup, 43.9% are private investors, whereas 12.4% are venture capitalists.

In Table II is the distribution of investors by investment round 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 invested in the first round, 34.1% are private investors and 28.8% are venture capitalists. For subsequent rounds, 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 1.1. Of course, all investors in the first round of financing are new investors.

The average amount raised per round (in constant U.S. dollars) is \$3.6 million, ranging from a minimum of \$0.01 million to a maximum of \$72

Table II
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 | 1,679 | 59.32 | 10.13 | 30.55 |

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 2.2), 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 typically 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[11], 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 grant is usually awarded to technology startups in a very early stage to develop their technology.

Finally, using Delphion, we collected information on U.S. granted patents for the startups. For each startup, we collected all patents granted that had either the name of the startup in the assignee field or the name of at least one of the founders in the inventor field. Because it is not uncommon for startups to change names, in our patent search we used 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 U.S. 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 of keeping 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 6.3 with a minimum of 1 and a maximum of 86. In IT and software 75 of the 198 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

[11] 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.

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.

## IV. ECONOMETRIC METHODOLOGY

The two results in Proposition 1 jointly imply that under asymmetric information, the founders of a startup *strategically* use patents to convey information about the value of their inventions, *given that* external investors judge the quality of these inventions *based on* the patents they observe. Hence, the founders' choice of the number of patents to file is an endogenous one.

Because asymmetric information is likely to be more of a problem for new investors, we expect more patents 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. Similarly, asymmetric information is less likely to be a concern for investors that had previously invested in the startup. Hence, we would expect either the number of previous investors not to be endogenous or its impact on founders' patents to be weaker than that of new investors.

Further, funding can either be secured from existing investors or new ones. Thus, funds raised in a round are also expected to be simultaneously determined. Unfortunately, our data do not differentiate additional funds raised by new *versus* existing investors.

We estimate the following equation for patents:

$$\Delta P_{it} = \beta_0 + \beta_1 n_{it} + \beta_2 V_{it} + X_{it}'\gamma + \varepsilon_{it} \tag{8}$$

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 $t - 1$. For firm $i$, $n_{it}$ 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. $X_{it}$ is a matrix of controls and includes the total number of rounds the startup experiences (*Tot. # of rounds*), whether a startup had failed as of June, 2011 (*Ceased*), the number of startups the founders had founded in the past (*# Startups founded in the past*), whether the startup was located in an incubator (*Incubator*), whether at least one of the founders is a university professor (*University professor*), the number of founders with a PhD who are not university professors (*# Founders with PhD*), whether the startup had received a grant from Israel's Office of the Chief Scientist (*Chief Scientist grant*), company age (*Age*), the number of days since the prior funding round (*Elapsed Days*), indicators for the industry sector (IT and software, communications, internet, semiconductors, life sciences, medical devices, and miscellaneous) 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 *Tot. # of rounds, Ceased*, and *# Startups founded in the past* are used as proxies for the quality of a startup. The variables *University professor, # Founders with PhD*, *Incubator*, and the industry sector dummies are meant to capture characteristics of the startup's underlying technology that is commercialized by a startup. In particular, *University professor* and *# Founders with PhD* are proxies for the degree of 'basicness' of a technology. Israeli incubators play a fundamental role in providing initial financial support and equipment to startups whose technologies require more time to reach the market. Finally, the variable *Chief Scientist grant* might capture some aspects of the quality of a startup as well as some characteristics of a startup's 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 III.

Our central hypothesis is that if patents have a signaling value, then patents, the number of new investors and amount raised are simultaneously determined. That is, in the equation above, $n_{it}$ and $V_{it}$ are endogenous. An additional source of endogeneity comes from the fact that, despite our controls, we could still be omitting characteristics of a startup's technology that might be correlated both with the willingness of the investors to invest in a startup and the patents filed by the founders. Hence, in our choice of instruments, we need to choose instruments that are correlated with the number of new investors and the total amount invested per round, but which are not correlated with omitted aspects of the founders' technology.

The preferred econometric approach is an instrumental variable (IV) counts model. 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. 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% 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 one or more patents (0, otherwise)[12]. 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.

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

Table III
Summary Statistics

| Variable | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|
| $\Delta P_t$ | 1.042 | 2.978 | 0.000 | 69.000 |
| $V_t$ | 3.614 | 5.089 | 0.006 | 72.000 |
| $n_t$ | 1.062 | 1.648 | 0.000 | 13.000 |
| $o_t$ | 2.074 | 2.043 | 0.000 | 21.000 |
| $n_t\_VC$ | 0.497 | 0.951 | 0.000 | 10.000 |
| $n_t\_PrivateInvestors$ | 0.136 | 0.571 | 0.000 | 11.000 |
| Tot. # of rounds | 3.807 | 2.137 | 1.000 | 13.000 |
| Ceased | 0.303 | 0.460 | 0.000 | 1.000 |
| # Startups founded in the past | 1.493 | 2.487 | 0.000 | 34.000 |
| Incubator | 0.190 | 0.393 | 0.000 | 1.000 |
| Age | 3.151 | 3.452 | 0.000 | 32.000 |
| University professor | 0.114 | 0.318 | 0.000 | 1.000 |
| # Founders with PhD | 0.416 | 0.662 | 0.000 | 3.000 |
| Elapsed_Days | 390.830 | 490.809 | 0.000 | 5658.000 |
| Seed | 0.303 | 0.460 | 0.000 | 1.000 |
| R&D | 0.444 | 0.497 | 0.000 | 1.000 |
| Initial Revenue | 0.202 | 0.401 | 0.000 | 1.000 |
| Revenue Growth | 0.052 | 0.222 | 0.000 | 1.000 |
| Semiconductors | 0.087 | 0.282 | 0.000 | 1.000 |
| Misc | 0.066 | 0.248 | 0.000 | 1.000 |
| Med Dev | 0.142 | 0.349 | 0.000 | 1.000 |
| Life Science | 0.108 | 0.310 | 0.000 | 1.000 |
| Internet | 0.084 | 0.278 | 0.000 | 1.000 |
| IT Software | 0.257 | 0.437 | 0.000 | 1.000 |
| Communications | 0.224 | 0.417 | 0.000 | 1.000 |
| CleanTech | 0.030 | 0.170 | 0.000 | 1.000 |
| Chief Scientist grant | 0.194 | 0.395 | 0.000 | 1.000 |
| US VC investment, by stage (constant USD Millions) | 6309.585 | 5896.546 | 634.756 | 41053.000 |
| # of US VC deals (by investment stage) | 1328.542 | 526.394 | 358.667 | 2895.667 |
| Ratio of US VC deals, by investment stage, to total # of deals | 0.315 | 0.067 | 0.096 | 0.504 |
| Yearly growth in the # of US VC deals (by investment stage) | 0.094 | 0.362 | –0.546 | 0.696 |
| Tel Aviv District | 0.342 | 0.474 | 0.000 | 1.000 |
| Jerusalem District | 0.069 | 0.254 | 0.000 | 1.000 |
| Center & North District | 0.501 | 0.500 | 0.000 | 1.000 |
| Haifa District | 0.088 | 0.283 | 0.000 | 1.000 |
| # of founders | 2.189 | 1.078 | 1.000 | 7.000 |
| # casualties, by district | 8.544 | 14.907 | 0.000 | 75.000 |
| Israeli GDP (constant Israeli shekels) | 560.472 | 80.152 | 0.000 | 737.000 |
| N | | 2126 | | |

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 startup 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.

We use as instruments (i) the three-year average *number* of deals done by U.S. venture capital companies by stage of investment (seed, early stage, expansion, later stage), (ii) the three-year average *amount* invested (in constant U.S. dollars) by stage of investment,[13] (iii) the *ratio* of the three-year average number of U.S. venture capital deals by stage of investment to the three-year average total number of U.S. venture capital deals, and (iv) the yearly *growth* in the number of U.S. venture capital deals by stage of investment. The data are from the U.S. National Venture Capital Association 2012 *Yearbook*. The variables just described are proxies for the availability of external financing in the U.S. (see, for example, Bottazzi *et al.* [2008]). However, to the extent that the U.S. and the Israeli VC markets are strongly interconnected, then these measures are also correlated with the supply of VC capital in Israel.[14] Consequently, we expect them also to be correlated with the total amount received by a startup in a given round and the number of investors in a round. These measures should impact the founders' patent decision only via the type of investors investing in a given round or the total amount invested. Moreover, they are unlikely to be correlated with aspects of a startup's technology.

Additionally, we include four dummies for the different Israeli districts in which the startups are located. In particular, we include a dummy for whether a startup is located in the Tel Aviv district, one for whether the startup is located in the Jerusalem district, another if it is located in the Haifa district, and a last dummy for whether the startup is located either in the North or in the Center district. These measures are likely to have an impact on the external investors' decisions to invest in a given round because the distribution of local investors (especially private investors) might vary across districts. They could be correlated with the error term if there were geographical clusters in which the know-how about given technologies is embedded. However, given the small size of Israel, it is unlikely that the know-how related to certain technologies is embedded in only a few of the districts. Policy makers and startup founders in Israel with whom we had discussions tended to consider Israel as a unique geographical cluster, in which information about new technologies is diffused from one district to another within a short span of time.[15,16] Finally, we also include the number of a startup's founders. This last instrument is likely to be uncorrelated with the error term given that we already control in our

[13] We use a three-year average to smooth out noise. The three years we consider in the average are $t$, $t-1$, and $t-2$. Year $t$ is the year at which a given round occurs.

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

[15] As an example, almost all policy makers we interviewed mentioned to us the 2009 book *Start-up Nation: The Story of Israel's Economic Miracle*, by Dan Senor and Saul Singer, which, as the title suggests, supports the thesis that the nation of Israel as such is a cluster of new technologies.

[16] In robustness checks (not reported here, but available upon request) we provide empirical results regarding the possibility of clustering in Israel. The evidence for clustering is weak.

regressions for characteristics of the founders that might capture some aspects of the founders' technology (*# Startups founded in the past*, *University professor*, *# Founders with PhD*). Yet this variable is likely to be correlated with the amount invested in a round and the number of investors if we posit that the founders' network of contacts is positively related with the probability of attracting funds in a given round.

In all regressions we proceed by first including the full set of instruments. However, standard checks for weakness of instruments reveal that not all instruments are significant. Thus the regression results presented are based only on instruments revealed not to be weak. That is, the regression results presented use varying subsets of instruments. However, our results are invariant with respect to using the full set of instruments as opposed to a subset.

A stronger set of instruments would be one that includes project or technology specific instruments. What we have are instruments that are time varying, but only vary cross-sectionally by district and stage of development of the company; thus, there are cases in which we use the same instrument values for multiple observations. While not an ideal set of instruments, this should not affect the validity of the instruments, though it will, of course, reduce efficiency. Finding project-specific instruments is very difficult because anything project specific arguably belongs as a control in the regression. The primary candidate for omitted variables are characteristics of the technology or project that would affect patenting directly.

Based on our prior that asymmetry of information should be more problematic for new investors *as opposed to old investors*, we estimate a variant of equation 8, which distinguishes between the number of new and old investors for the rounds subsequent to the first. Thus the equation we estimate is:

$$(9) \qquad \Delta P_{it} = \beta_0 + \beta_1 n_{it} + \beta_2 o_{it} + X_{it}'\gamma + \varepsilon_{it}$$

where $o_{it}$ is the number of investors that 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 number of patents is weaker than that of $n_{it}$. We use equation 9 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, as we show in the regression tables, is also not statistically significant). The matrix $X_{it}$ includes the same controls as the one used for the earlier regressions. 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.

In the regressions we present, the number of new patents is the number of startup patents whose priority year is after the year of the previous round and before (or in) the same year as the current round. The decision to consider the priority year is justified as follows. Having treated the number of patents as a signal in the economic sense, then it has to be that investment in patents is costly for a startup and is observed by external investors. Having defined patent cost in terms of the resources founders use 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 few U.S. patent applications fail to be granted (Quillen *et al.* [2002]), then the size of the bias should be limited.

## V. RESULTS

### V(i). *Initial Round*

As we noted above, we expect first round estimates to be different from subsequent round estimates to the extent the founders file for their first patents prior to the decision to found a startup. If this is the case we cannot regard the number of patents filed prior to the first round as being affected by the perspective of attracting external investors. We use as instruments the three-year average number of deals done by U.S. venture capital companies by stage of investment, and the three-year average amount invested (in constant U.S. dollars) by stage of investment.[17] We also include a squared term to account for nonlinearities in the relationship between these measures and the endogenous variables. Additionally, we include four dummies for the different districts in which the startups are located.

In the continuous and in the linear probability models, to test for endogeneity, we use a Hausman specification test which (jointly) tests for the endogeneity of $n_{it}$ and $V_{it}$. For both models, the efficient estimator—under the null hypothesis that the specified endogenous regressors are exogenous—is the ordinary least square estimator. For the Tobit model we use an alternative approach, based on Smith and Blundell [1986] and analogous to the Rivers-Vuong method described in 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

[17] We use a three-year average to smooth out noise. The three years we consider in the average are $t$, $t-1$, and $t-2$. Year $t$ is the year at which a given round occurs.

the second, we regress the patent count 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.

Our tests fail to reject the null hypothesis that $n_{it}$ and $V_{it}$ are exogenous, with p-values of 0.62 (continuous variable model), 0.41 (Tobit model), and 0.58 (linear probability model). The Sargan-Hansen test of overidentifying restrictions fails to reject the joint null hypothesis that the instruments are uncorrelated with the error term and that the excluded instruments are correctly excluded from the estimated equation, with a p-value greater than 0.29. The test results are consistent with our prior that the number of patents filed before the first round are not designed as a signal to attract external investors. They also suggest that, at least for the first round of investment, the problem of omitting aspects of a startup's technology which might be correlated with the decision of the founders to invest in patents should be minor.

In checking for the weakness of the instruments in this case we find that the F-statistics on excluded instruments is 7.69 for the total amount invested per round, and 3.00 for the number of new investors. While these figures are below the standard threshold of 10, they are significant with a p-value of 0.00.

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 $\Delta P_{it}$. Our interest lies primarily in the endogenous response of founder patents to the perspective of receiving external funds which does not seem to be the case for first round financing.

### V(ii). *Rounds Subsequent to the First Round*

Here we concentrate on rounds subsequent to the first (that is, when $t > 1$). We begin by estimating equation 8, which relates the impact of new investors and the amount received in a given round to a startup's number of patents. We use as instruments i) the three-year average number of deals done by U.S. venture capital companies by stage of investment (expressed in the natural logarithm), ii) the ratio of the three-year average number of U.S. venture capital deals by stage of investment to the three-year average number deals, iii) the Israeli district dummies, and iv) the number of a startup's founders.

For the IV continuous variable model and the IV linear probability model, a Hausman specification test to (jointly) test for the endogeneity of $n_{it}$ and $V_{it}$ accepts the hypothesis of endogeneity (p-value = 0.00). For the IV Tobit model, we again fail to reject the null hypothesis that $n_{it}$ and $V_{it}$

are (jointly) endogenous (p-value = 0.00).[18] These tests are consistent with the hypothesis that patents have a signaling value. In checking for the weakness of the instruments we find that the F-statistic is 3.22 for $V_{it}$ and 4.77 for $n_{it}$ (p-values = 0.00). Finally, we perform Sargan-Hansen tests of overidentifying restrictions which fail to reject the joint null hypothesis that the instruments are uncorrelated with the error term and that the excluded instruments are correctly excluded from the estimated equation with p-values greater than 0.60.

The IV results are presented in the last columns of Table IV.[19] As a reference, we include the non-IV estimates in the first three columns. We report average partial effects for all models.[20] Note that in a number of cases the estimated coefficients as well as the associated t-statistics are very different between the IV and the non-IV estimators. In particular, the coefficients of the endogenous variables, $n_{it}$ and $V_{it}$, are very different after correcting for endogeneity. We note that, when there is more than one endogenous variable and/or endogeneity is due to omitted variables as well as to simultaneity, it is not possible to determine *a priori* the direction of the bias (see for example, Mayston [2009]).

For each of our three IV estimators the coefficient of $n_{it}$ is positive, as expected, and significantly different from zero. The coefficient of $V_{it}$ is not statistically significantly different from zero in any of the models. This variable includes funds from new investors—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 support the endogeneity of $n_{it}$ (p-value = 0.00), but not the endogeneity of $V_{it}$ (p-value > 0.8).

As for the other variables in the model, the total number of rounds a startup received prior to an exit is positive and statistically significant in all cases. Consistent with our priors, whether a startup had ceased its operations is negatively correlated with the number of patents a startup has filed, although the coefficient is not significantly different from zero. Startups that had spent time in an incubator tend to file fewer patents than other startups. The characteristics of a technology play an important role in explaining a startup's decision to file for patents. The coefficient of # *Founders with PhD* is positive and statistically significant. The one for *Incubator* is negative and significant. Moreover, a test of joint significance

[18] We reiterate that our results are also unchanged when we use the full set of instruments described earlier.

[19] First-stage regressions for the IV estimators are available upon request.

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

TABLE IV
REGRESSION RESULTS FOR THE IMPACT OF THE NUMBER OF NEW INVESTORS AT ROUND $T$ ON THE NUMBER OF PATENTS FILED BY THE FOUNDERS

| | *Models that do not account for endogeneity* | | | *IV Models* | | |
|---|---|---|---|---|---|---|
| | Continuous Model | Tobit Model | Linear Probability Model | IV Continuous Model | IV Tobit Model | IV Linear Probability Model |
| Δpt | *Marg. Eff.* | *Marg. Eff.* | *Marg. Eff.* | *Marg. Eff.* | *Marg. Eff.* | *Marg. Eff.* |
| Vt | 0.004*** | 0.011*** | 0.017*** | –0.064 | –0.066 | –0.094 |
| | (0.124) | (0.434) | (0.012) | (1.889) | (4.965) | (0.182) |
| nt | 0.002*** | 0.003** | 0.007** | 0.085*** | 0.093*** | 0.121*** |
| | (0.082) | (0.222) | (0.008) | (1.260) | (3.315) | (0.121) |
| Tot. # of rounds | 0.002*** | 0.006*** | 0.013*** | 0.011*** | 0.013*** | 0.016*** |
| | (0.086) | (0.229) | (0.008) | (0.140) | (0.345) | (0.013) |
| Ceased | –0.003 | –0.010 | –0.018 | –0.008 | –0.014 | –0.012 |
| | (0.343) | (1.142) | (0.033) | (0.682) | (1.692) | (0.066) |
| # Startups founded in the past | 0.000* | 0.001 | 0.002 | 0.003 | 0.003 | 0.004 |
| | (0.029) | (0.096) | (0.003) | (0.070) | (0.191) | (0.007) |
| Incubator | –0.013** | –0.035 | –0.067** | –0.071*** | –0.088** | –0.106*** |
| | (0.823) | (4.512) | (0.082) | (1.139) | (4.254) | (0.112) |
| Age | –0.001*** | –0.004*** | –0.007*** | 0.000 | 0.000 | 0.000 |
| | (0.053) | (0.185) | (0.005) | (0.099) | (0.292) | (0.010) |
| University professor | 0.007** | 0.018*** | 0.038** | 0.016 | 0.022 | 0.025 |
| | (0.447) | (1.170) | (0.044) | (0.660) | (1.557) | (0.064) |
| # Founders with PhD | 0.003* | 0.007 | 0.015* | 0.022** | 0.023** | 0.030** |
| | (0.251) | (0.709) | (0.024) | (0.415) | (1.066) | (0.040) |
| Elapsed days | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.001) | (0.000) | (0.001) | (0.001) | (0.000) |
| Chief Scientist grant | 0.003 | 0.008 | 0.017 | –0.022 | –0.022 | –0.032 |
| | (0.447) | (1.289) | (0.043) | (0.932) | (2.365) | (0.090) |
| Seed | 0.006 | 0.010 | 0.029 | –0.067 | –0.078 | –0.098 |
| | (0.629) | (2.213) | (0.062) | (2.530) | (6.655) | (0.244) |
| Initial Revenue | 0.000 | –0.003 | –0.003 | 0.012 | 0.008 | 0.017 |
| | (0.315) | (0.999) | (0.031) | (0.614) | (1.539) | (0.059) |
| Revenue Growth | 0.012*** | 0.025** | 0.059*** | 0.070** | 0.069** | 0.101** |
| | (0.621) | (1.790) | (0.061) | (1.408) | (3.291) | (0.136) |
| Constant | –0.066*** | –0.133*** | 0.013 | –0.342*** | –0.371*** | –0.175** |
| | (0.822) | (2.660) | (0.081) | (2.559) | (6.880) | (0.247) |
| Sector Dummies | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| N | 1,339 | 1,339 | 1,339 | 1,339 | 1,339 | 1,339 |
| F-Test for weak instru. (Vt) | | | | 3.220*** | | |
| F-Test for weak instru. (nt) | | | | 4.770*** | | |

*Notes*: ***p < 0.01, **p < 0.05, *p < 0.10. Clustered standard errors (by firm) are reported in parenthesis. For the Tobit models, standard errors are bootstrapped using 500 replications and accounting for firm clusters in re-sampling. For the IV models we use the following instruments: i) the log of the 3-year-average number of U.S. venture capital deals by stage of investment; ii) the ratio of the 3-year-average number of U.S. venture capital deals, by stage of investment, to the 3-year-average total number of U.S. venture capital deals; iii) Israeli district dummies; iv) the number of a startup's founders.

of industry sector dummies rejects the null hypothesis that these are (jointly) equal to zero with a p-value of 0.00 in all regression specifications.

Table V presents the results on the coefficients of primary interest for the following three robustness checks. First, we estimate our IV models using

TABLE V
REGRESSION RESULTS FOR THE IMPACT OF THE NUMBER OF NEW INVESTORS AT ROUND $T$ ON THE NUMBER OF PATENTS FILED BY THE FOUNDERS (ROBUSTNESS ANALYSES)

| Δpt | IV Continuous Model *Marg. Eff.* | IV Tobit Model *Marg. Eff.* | IV Linear Probability Model *Marg. Eff.* |
|---|---|---|---|
| | *Panel A: The total amount invested at round t is used as a control* | | |
| nt | 0.069*** | 0.084*** | 0.112*** |
| | (1.047) | (2.780) | (0.101) |
| | *Panel B: A dummy for whether a startup is located in the city of Tel Aviv is included* | | |
| Vt | –0.074 | –0.080 | –0.101 |
| | (1.854) | (4.884) | (0.177) |
| nt | 0.093*** | 0.107*** | 0.124*** |
| | (1.282) | (3.273) | (0.123) |
| | *Panel C: District dummies, used as instruments, only include a dummy for the Jerusalem district and one for the Haifa district* | | |
| Vt | –0.055 | –0.052 | –0.085 |
| | (1.883) | (5.380) | (0.182) |
| nt | 0.082*** | 0.083*** | 0.122*** |
| | (1.249) | (3.580) | (0.120) |

*Notes*: See Table IV notes. We use the same instruments as in Table IV with the exception of the regression results in Panel C, in which we exclude the dummies for the districts of Tel Aviv and Center/North. Controls are the same as in the baseline regressions presented in Table IV except for Panel A, in which we include the total amount invested per round.

the total amount invested per round as a control rather than as an instrument. The results on the number of new investors per round remain invariant. Second, we estimate the models using as a control a dummy variable that takes a value equal to 1 if a startup is located in the city of Tel Aviv.[21] If there is any technology cluster in Israel, then this is likely to be in the city of Tel Aviv. In fact, by hosting 114 of our 787 startups, it represents the largest geographical concentration of startups in our sample. Having introduced this variable, our results on the total amount invested per round and the number of new investors do not change. As a last robustness check, we estimate the models including as instruments district dummies for Jerusalem and Haifa only. We do so because these two district dummies are the only ones significantly correlated with our endogenous regressors.[22] As a result, the F-statistics on excluded instruments increases to 3.80 for $V_{it}$ and to 5.55 for $n_{it}$. Moreover, the results on both the total amount invested per round and the number of new investors remain invariant.

In our data we not only have the number of new investors in a round, but also the number of old investors (that is investors who had invested in prior rounds for this startup). Our prior is that the signal value of a patent is more important for new investors than for old investors. In Table VI we

[21] For each startup, we have information on the city in which it is located as well as the district.

[22] Including instruments that are weakly correlated with the endogenous regressors can affect the quality of the IV estimator (Stock and Yogo [2003]; and Angrist and Pischke [2009]).

TABLE VI
REGRESSION RESULTS FOR THE IMPACT OF THE NUMBER OF NEW INVESTORS AT ROUND *T* AS WELL AS THE *NUMBER OF OLD INVESTORS*, ON THE NUMBER OF PATENTS FILED BY THE FOUNDERS

| | *Models that do not account for endogeneity* | | | *IV Models* | | |
|---|---|---|---|---|---|---|
| | Continuous Model | Tobit Model | Linear Probability Model | IV Continuous Model | IV Tobit Model | IV Linear Probability Model |
| Δpt | *Marg. Eff.* | *Marg. Eff.* | *Marg. Eff.* | *Marg. Eff.* | *Marg. Eff.* | *Marg. Eff.* |
| ot | 0.001*** | 0.002*** | 0.006*** | –0.036 | –0.040 | –0.048* |
| | (0.061) | (0.169) | (0.006) | (0.832) | (2.346) | (0.082) |
| nt | 0.002*** | 0.005*** | 0.012*** | 0.057*** | 0.082*** | 0.068*** |
| | (0.076) | (0.199) | (0.008) | (0.741) | (2.166) | (0.073) |
| Controls | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| N | 1,339 | 1,339 | 1,339 | 1,339 | 1,339 | 1,339 |
| F-Test for weak instru. (ot) | | | | 2.260*** | | |
| F-Test for weak instru. (nt) | | | | 4.340*** | | |

*Notes*: See Table IV notes. For the IV we use the following instruments: i) the log of the 3-year-average number of U.S. venture capital deals, by stage of investment; ii) the ratio of the 3-year-average number of U.S. venture capital deals, by stage of investment, to the 3-year-average total number of U.S. venture capital deals; iii) the yearly growth of the U.S. VC number of deals, by stage of investment; iv) Israeli district dummies; and v) the number of a startup's founders. We use the same controls as in Table IV.

examine the impact of the number of new and old investors on founder number of patents by estimating equation 9. This regression excludes $V_{it}$. This should not be a serious concern given that we found the coefficient of $V_{it}$ to be statistically insignificant in the previous regressions. We use as instruments i) the three-year average number of deals done by U.S. venture capital companies by stage of investment (this time expressed in the natural logarithm), ii) the ratio of the three-year average number of U.S. venture capital deals by stage of investment to the three-year average number deals, iii) the yearly growth in the number of U.S. venture capital deals, by stage of investment, iv) the Israeli district dummies, and v) the number of a startup's founders.

Our endogeneity tests fail to reject the null hypothesis of joint endogeneity of $n_{it}$ and $o_{it}$ (p-value = 0.00). The coefficient for the number of new investors per round is positive and significant, as expected. The coefficient for the number of old investors is negative, but significant only in the IV linear probability model. The sign of the coefficients is consistent with our prior that patents are used primarily to attract new investors rather than old ones. 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 0.00, regardless of the estimator. Moreover, a test of the equality of these coefficients rejects the null hypothesis that the coefficients are equal with a p-value of 0.00 for all specifications.

Overall, our results suggest that patents are used by startups as a signal and not simply as an input in the startup's value function. Moreover, they suggest that patents are used to attract new investors as opposed to old investors. Note, however, that while our results are consistent with signaling, they should be interpreted with caution because our instruments are not project or technology specific.

### V(iii). *The Matching of Investor Types and Startup Quality*

In this section, we consider Proposition 2 which predicts that investors who can provide a startup with 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, the value of an invention is defined by the number of patents a startup has filed. Hence, *ceteris paribus*, we should observe a positive relationship between the patents filed by a startup and the number of new investors that are relatively well endowed with non financial capital.

One way to operationalize this would be to differentiate among venture capital investors, based on their experience, the latter being a proxy for the parameter $S$. Unfortunately, even though we have information on the year in which venture capital companies are founded, 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 since factors that affect more experienced venture capitalists are also likely to affect less experienced ones.

We know, however, that venture capitalists provide more services and greater reputational capital than do private investors, given that many of the private investors are friends and family (Brav and Gompers [1997]). Further, results from the Berkeley Patent Survey (Graham *et al.* [2009]) provide evidence that private investors respond positively to founder patent filings because they view it as a signal of their technology's quality. In light of these considerations, we modify equation 8 to distinguish new investors who are venture capitalists (inclusive of the number of corporate venture capitalists) versus private investors. Hence, we replace $n_{it}$ with two regressors: the number of new venture capitalists and the number of new private investors. We exclude other categories of new investors because we do not have enough strong instruments to identify additional equations.

The results are in Table VII. As in Table IV, these results are for rounds subsequent to the first. The underlying regression specifications are the same as in Table IV, with the following exceptions. First, we exclude the total amount invested per round from the regressions, given that it is not

TABLE VII
REGRESSION RESULTS FOR THE IMPACT OF THE NUMBER OF NEW VENTURE CAPITALISTS AND PRIVATE INVESTORS AT ROUND $T$ ON THE NUMBER OF PATENTS FILED BY THE FOUNDERS

| | *Models that do not account for endogeneity* | | | *IV Models* | | |
|---|---|---|---|---|---|---|
| | Continuous Model | Tobit Model | Linear Probability Model | IV Continuous Model | IV Tobit Model | IV Linear Probability Model |
| Δpt | *Marg. Eff.* | *Marg. Eff.* | *Marg. Eff.* | *Marg. Eff.* | *Marg. Eff.* | *Marg. Eff.* |
| nt_VC | 0.003*** | 0.007*** | 0.017*** | 0.083*** | 0.099*** | 0.120*** |
| | (0.114) | (0.291) | (0.011) | (1.115) | (3.527) | (0.109) |
| nt_Private Investors | 0.000 | 0.001 | 0.001 | 0.015 | 0.036 | 0.020 |
| | (0.190) | (0.631) | (0.019) | (1.774) | (6.960) | (0.174) |
| Controls | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| N | 1,339 | 1,339 | 1,339 | 1,339 | 1,339 | 1,339 |
| F-Test for weak instru. (nt_VC) | | | | 2.000*** | | |
| F-Test for weak instru. (nt_Private Investors) | | | | 2.000*** | | |

*Notes*: See Table IV notes. For the IV models we use the following instruments: i) the log of the 3-year-average number of U.S. venture capital deals, by stage of investment; ii) the ratio of the 3-year-average number of U.S. venture capital deals, by stage of investment, to the 3-year-average total number of U.S. venture capital deals; iii) the number of casualties by terrorist attacks, per district; iv) Israeli district dummies; v) interactions between district dummies and Israel's GDP; and iv) number of a startup's founders. We use the same controls as in Table IV.

significant in previous regressions. Second, we modify the set of instruments to include predictors of the number of new private investors. Because the majority of private investors are Israeli, the most appropriate instruments would be regional macroeconomic indicators which are likely to affect their willingness to pay. Unfortunately, these measures are not publicly available. We use instead the yearly number of casualties from terrorist attacks, by district, and interactions between our district dummies and Israel's yearly gross domestic product (in constant Israeli shekels[23]).[24]

We believe that the conjectures expressed in Section V(ii) on the validity of the Israeli district instruments also apply to the number of casualties from terrorist attacks and the interactions between the Israeli district dummies and yearly gross domestic product. In support of these conjectures, Sargan-Hansen tests of overidentifying restrictions fail to reject the joint null hypothesis that the instruments are uncorrelated with the error term and that the excluded instruments are correctly excluded from the estimated equation (p-value > 0.15). In checking for the weakness of the instruments, we find that the F-statistic on excluded instruments is only

[23] The data is available from the International Monetary Fund.
[24] First-stage regressions are available upon request.

statistically significant at the five per cent level. This suggests that caution should be used when interpreting the results reported in this section. In robustness checks (not presented here) we only include as district indicators a dummy for the Jerusalem district and for the Haifa district, as well as their interaction with the Israeli yearly gross domestic product.[25] With this specification, the F-statistic becomes significant at the one per cent level and the results on the sign and the significance of the coefficients remain invariant.

A Hausman specification test to (jointly) test for the endogeneity of $n_{it}$*_VC* and $n_{it}$*_Private Investors* accepts the hypothesis of endogeneity with a p-value of 0.00. For the IV Tobit model, we again fail to reject the null hypothesis that $n_{it}$*_VC* and $n_{it}$*_Private Investors* are (jointly) endogenous. However, when we separately test for the endogeneity of $n_{it}$*_VC* and $n_{it}$*_Private Investors*, we fail to reject the null hypothesis of exogeneity of new private investors (p-value > 0.8). This last result might be due to the fact that our tests for endogeneity are not powerful enough to detect minimum levels of endogeneity; for that reason we report instrumental variable estimates for the coefficient of new private investors.

Consistent with Proposition 2, the results in Table VII show that in all regression specifications the number of new venture capital companies per round has a positive and statistically significant impact on a startup's number of patents (p-value ≤ 0.01 in all regression specifications). 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 (p-value = 0.00, regardless of the estimator). Moreover, a test of the equality of these coefficients rejects the null hypothesis that the coefficients are equal (p-value < 0.09).

In Table VIII are the results of several robustness checks. For the sake of brevity we only present the results for our variables of interest. For instance, in the first row, 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 hands-on role in the deals in which they participate and provide entrepreneurs with advice and contacts to potential business partners. The results are similar to those in Table VII. In particular, the number of new venture capitalists and business angel groups that participate in round *t* has a positive impact on the founders' number of patents while the impact of the number of new private investors is not significantly different from zero. In the second row, we attempt to disentangle business angel investors who are not organized in investment groups from friends and family, within the category of private investors. We define business angel investors (not organized in investment

[25] These robustness checks are available upon request.

TABLE VIII
REGRESSION RESULTS FOR THE IMPACT OF THE NUMBER OF NEW VENTURE CAPITALISTS AND PRIVATE INVESTORS AT ROUND *T* ON THE NUMBER OF PATENTS FILED BY THE FOUNDERS (ROBUSTNESS ANALYSES)

| Δpt | IV Continuous Model *Marg. Eff.* | IV Tobit Model *Marg. Eff.* | IV Linear Probability Model *Marg. Eff.* |
|---|---|---|---|
| | *Number of new venture capitalists includes angel syndicates* | | |
| nt_VC | 0.082*** | 0.097*** | 0.114*** |
| | (1.020) | (3.404) | (0.170) |
| nt_Private Investors | 0.009 | 0.030 | 0.010 |
| | (1.730) | (6.991) | (0.100) |
| | *Number of new venture capitalists includes angel syndicates and other angel investors* | | |
| nt_VC | 0.072*** | 0.095*** | 0.108*** |
| | (0.993) | (3.430) | (0.097) |
| nt_Private Investors | 0.029 | 0.065 | 0.045 |
| | (1.863) | (7.364) | (0.182) |
| | *Number of new private investors includes angel syndicates* | | |
| nt_VC | 0.086*** | 0.104*** | 0.121*** |
| | (1.092) | (3.511) | (0.107) |
| nt_Private Investors | 0.004 | 0.015 | 0.002 |
| | (1.624) | (6.451) | (0.159) |
| | *Number of new venture capitalists includes private equity firms or firms specializing in startup investment* | | |
| nt_VC | 0.049*** | 0.071*** | 0.077*** |
| | (0.673) | (2.257) | (0.066) |
| nt_Private Investors | –0.003 | 0.011 | –0.007 |
| | (1.714) | (6.875) | (0.170) |

*Notes*: See Table IV notes. We use the same controls as well as the same set of instruments as in Table VII.

groups) as those individuals that have invested in more than four startups in our sample. By imposing this cutoff we exclude those friends and family members who have invested in multiple startups, i.e., serial entrepreneurs. Having done so, we add the number of new angel investors (whether organized in groups or not) to the number of new venture capitalists that have participated in round *t*. The number of new venture capitalists and business angel investors continues to have a positive and significant impact on the number of patents filed, whereas the impact of the number of private investors is not significantly different from zero. In the third row, we add the number of new business angel investment groups to the number of private investors involved in round *t*. The rationale is that business angel groups could value the patents filed by a startup in the same way as the business angel investors who are not organized in groups. The redefinition of the categories of venture capitalists and private investors does not change our main findings. Finally, in the last rows, 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). These firms might value the quality of a startup technology at least as much as venture capitalists do. Again, the results do not change.

The results in Table VII are consistent with Proposition 2. However, they should be interpreted with caution since investment in patents could be larger for new venture capitalists simply because the asymmetry of information is more severe for them than for new private investors. While we cannot rule out this possibility, we note that the category of new private investors includes friends and family members who are likely to be less able to evaluate new technologies than venture capitalists.

## VI. CONCLUDING REMARKS

Of the many roles that patents serve, one that has eluded careful study is the reduction of asymmetries of information in entrepreneurial finance. Our study makes several important contributions to understanding this role.

First, we provide a theoretical model in which technology startups use the number of patents they file for as a signal for external investors. Our result on the conditions under which startup founders file for more patents than they would in situations of symmetric information provides new insight to the empirical puzzle that small, entrepreneurial firms have a higher propensity to patent than do large firms. Moreover, we provide a theoretical explanation for positive matching of startup founders with a given invention value and external investors with a certain amount of non financial capital. The reason is that the marginal costs of implementing management adjustments required by an external investor are decreasing in the founders' value of their invention.

Second, we test the theoretical predictions using a dataset of Israeli technology startups, giving careful attention to the fact that such estimation is subject to endogeneity not only because of omitted variables but also because patents are strategically chosen variables. Consistent with the model, we find that patents are endogenously chosen to attract new investors, which, all else equal, one would expect to be more affected by asymmetry of information. However, we also find that in the first round of funding, patents are not endogenous which is in line with the view that the decision to form a startup follows the filing of an important patent or set of patents. When we distinguish among types of external investors, we find that venture capitalists are endogenous to the process but private investors are not. This finding is consistent with the idea that startups with better technologies, as measured by the number of patents filed, use patents to attract venture capitalists but not private investors.

As we noted earlier, our instrument set is not ideal in that we do not have project or technology specific instruments; our instrument set is one that varies by time and to some extent by cross-section. Thus, a note of caution is in order on the strength of our evidence regarding the simultaneity of patents and new investors. On the other hand, we find evidence of endogeneity only for rounds of financing subsequent to the first round and significance only for new investors in rounds subsequent to the first. If omitted variables are the cause of endogeneity, then our prior is that endogeneity should be a problem with both the first round and rounds subsequent to the first, as well as for new and old investors. Our finding of no endogeneity in the first round and the insignificance of old investors in subsequent rounds, coupled with the finding of endogeneity in other rounds and significance only for new investors, is at least consistent with our prior of what we would find with simultaneity.

This paper only scratches the surface of the use of patents as signals in this context. Two directions for extension are immediately clear. First, we do not address the welfare implications of costly signaling. As noted by Spence [1974], productive signaling may or may not be welfare improving. In fact, Hoppe *et al.* [2009] provide a model of signaling and matching in which assortative matching improves welfare. Consideration of the welfare implications is well beyond our scope, but the fact that our matching proposition allows sorting according to quality suggests the possibility of designing welfare improving mechanisms.

Second, in the empirical analysis, we treat venture capitalists as a homogeneous category of investors. However, they clearly differ in the amount of expertise, market knowledge, information network, or reputation they have. As a topic for future research, it would be interesting to test whether a match similar to the one we examine holds with data that distinguish among venture capitalists.

## APPENDIX

*Proof of Proposition 1*

*Proposition 1.* There exists a unique separating, signaling equilibrium in which the signaling schedule is strictly increasing in the number of patents if and only if $c_p(p^*, \hat{\theta}(p^*)) > \upsilon(S)\hat{V}_p(p^*, \hat{\theta}(p^*))$ and the founders of a startup find it optimal to file $p^*$ patents, which is greater than the number filed under symmetric information.

*Proof.* In order to show that there exists a signaling equilibrium in which the founders of a startup find it profitable to file for a number of patents, $p^*$, that is greater than under symmetric information, we need to show that:

1. $p^*$ is a global maximum.
2. if $c_p(p^*, \hat{\theta}(p^*)) > \upsilon(S)\hat{V}_p(p^*, \hat{\theta}(p^*))$, $p^*$ is greater under asymmetric information than under symmetric information.

To show (1), we begin by noting that the second derivative of the expected wealth in the last period, $E(W)$, with respect to $p$ is:

(10) $$E_{pp}(W) = \upsilon(S)[V_{pp}(p,\theta) + \hat{V}_{\hat{\theta}}^{EI}(p,\hat{\theta}(p))\hat{\theta}_{pp} + \hat{V}_{\hat{\theta}\hat{\theta}}^{EI}(p,\hat{\theta}(p))(\hat{\theta}_p)^2] - c_{pp}(p,\theta)$$

This expression has to be negative over the relevant range of values for $p$, i.e., the range of values such that $c_p(p,\hat{\theta}(p)) > \upsilon(S)\hat{V}_p(p,\hat{\theta}(p))$.

Differentiating expression (5) in the text with respect to $p$, we obtain:

$$\begin{aligned}&\upsilon(S)[V_{pp}(p^*,\theta) + \hat{V}_{\hat{\theta}}^{EI}(p^*,\hat{\theta}(p^*))\hat{\theta}_{pp} + \hat{V}_{\hat{\theta}\hat{\theta}}^{EI}(p^*,\hat{\theta}(p^*))(\hat{\theta}_p)^2] - c_{pp}(p^*,\theta)\\ &\quad = [c_{p\theta}(p^*,\theta) - V_{p\theta}(p^*,\theta)]\hat{\theta}_{p^*} < 0\end{aligned}$$

Given that, by assumption, $c_{p\theta}(p, \theta) < 0$ and $V_{p\theta}(p, \theta) \geq 0$, expression (8) is negative iff $\hat{\theta}_{p^*} > 0$, that is iff $p^*$ lies in the interval of values of $p$ such that $c_p(p,\hat{\theta}(p)) > \upsilon(S)\hat{V}_p(p,\hat{\theta}(p))$.

To complete the second part of the proof, we define $\nu = -\hat{V}_{\hat{\theta}}^{EI}(p^*,\hat{\theta}(p^*))\hat{\theta}_p$ 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. $\nu = -\hat{V}_{\hat{\theta}}^{EI}(p^*,\hat{\theta}(p^*))\hat{\theta}_p$. Using standard comparative statics we derive that:

$$p_\nu^*(\nu) = -\frac{-1}{\upsilon(S)[V_{pp}(p^*,\theta) + \hat{V}_{\hat{\theta}}^{EI}(p^*,\hat{\theta}(p^*))\hat{\theta}_{pp} + \hat{V}_{\hat{\theta}\hat{\theta}}^{EI}(p^*,\hat{\theta}(p^*))(\hat{\theta}_{p^*})^2] - c_{pp}(p^*,\theta)}$$

$p_\nu^*(\nu) < 0$ iff $c_p(p^*,\hat{\theta}(p^*)) > \upsilon(S)\hat{V}_p(p^*,\hat{\theta}(p^*))$. This condition shows that the founders' number of patents increases when moving from symmetric to asymmetric information.

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