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ABSTRACT

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 examine 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.

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1 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.[1] The trade off between disclosure and appropriability has been extensively studied, going back to Arrow (1962).[2] One of the enduring questions to come out of this work is why firms invest in patents when their appropriability value is low (Arora, 2006). Particularly puzzling is the fact that small, capital constrained firms have a higher propensity to patent than larger firms (Mansfield, 1986; Lerner, 2000). 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 and Sichelman, 2008; 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).[3] 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.

[1]These rents can be captured through licensing for revenue or cross-licensing as well as through monopoly returns from practice of the invention itself (Arora et al. 2001).

[2]Thursby and Thursby (2008) provide a review of research on the associated *ex ante* incentive to invent and *ex post* incentive to disclose. Reinganum (1983) and Eisenberg (1989) are notable examples in the context of perfect information. Horstmann et al. (1985) provides a model highlighting this trade off in the context of private information.

[3]See also Burk (2008) on the role of patents in the codification of tacit knowledge. In the entrepreneurial finance realm, the existence of patents ensures that knowledge about inventions remains with the firms in the event of managerial turnover.

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 (Sahlman, 1990; 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 should be endogenously determined. 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. This is consistent with our prior 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, we find that patents are endogenous. Specifically, the results for these rounds suggest that startups use patents to attract new investors, but not old investors. This finding is consistent with the intuition that asymmetric information is likely to be more of a problem for external investors funding the startup for the first time than for old investors. We also distinguish venture capitalists from private investors in an attempt to capture differential services among types of external investors. In this setting, 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. To the extent that venture capitalists provide greater non financial capital than private investors, our findings suggest that startups with higher quality technologies tend to match with external investors who provide a larger amount of capital (Field, 1996; Brav and Gompers, 1997; Graham *et al.*, 2009).

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; and Grenadier and Malenko, 2011). 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.[4] 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.[5] This aspect of the theory is essential to frame an empirical analysis of the matching of investor and startup types.

[4]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. This is in contrast to our model and that of Conti *et al.* (2013) where the signal is sent to potential investors.

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

We also contribute to the empirical literature on entrepreneurial finance which has examined a variety of issues related to patents and startup financing (Denis, 2004). This literature has examined both venture capital funding as a determinant of innovation, as measured by patents (Kortum and Lerner, 2000), and patents as a signal of technology quality to investors (Haeussler *et al.*, 2009, Hsu and Ziedonis, 2011, and Conti *et al.*, 2013). Haeussler *et al.* (2009) relate patents to venture capital funding and Hsu and Ziedonis (2011) examine patents in relation to IPO performance. These two papers abstract from the endogeneity problem inherent in the fact that "signals" are simultaneously determined by investor and startup choices. Conti *et al.* (2013) examine patents as endogenously determined signals, however, they cannot identify new investors or individual rounds, so they are unable to make the inference that the funding pattern is consistent with optimal matching. Although we are able to distinguish types of investors and rounds in this paper, our results should be interpreted with caution, because, as in Conti *et al.* (2013), our instruments are not technology specific.

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.

2 Model Setup

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, θ. The distribution of θ is continuous and has support $[\underline{\theta}, \overline{\theta}]$.

The founders have private information about θ 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.[6] 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 (Cohen *et al.* 2000; Gans *et al.* 2002; 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 education. 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 $V_{p\theta}(p, \theta) \geq 0$.[7] 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.[8] 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.[9]

[6] 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 and Sichelman, 2008), 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.

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

[8] We make this assumption based on discussions with patent attorneys in the United States, who emphasized that marginal inventions 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.

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

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 $\widehat{V}(p, \widehat{\theta}(p))$ where $\widehat{\theta}(p)$ 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 (Sahlman, 1990). 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 the 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., $\varsigma_S(S, \theta) > 0$. 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:

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

where $\upsilon(S)\widehat{V}^{EI}(p, \widehat{\theta}(p))$ represents the amount the external investor is willing to invest in the startup given his perception, $\widehat{\theta}(p)$. 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, θ, 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:

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

3 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

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

where $p^*(\theta)$ is the number of patents that maximizes the founders' period 2 expected wealth. If $\theta < \widehat{\theta}(p^*(\theta))$, 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 $\theta > \widehat{\theta}(p^*(\theta))$, then investors would make excess returns.

The first order necessary condition for such an equilibrium is

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

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 $\theta = \widehat{\theta}(p^*(\theta))$, which allows us to rewrite (4) as:

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

This is a first order ordinary differential equation which is strictly increasing in p^* if the founder's marginal cost of investing in patents, $c_p(p^*, \widehat{\theta}(p^*))$, is greater than the marginal value patents intrinsically add to the startup, given the quality of the invention as perceived by the investors, $\upsilon(S)\widehat{V}_p(p^*, \widehat{\theta}(p^*))$. The Appendix shows that the unique maximum occurs within the range of values of p such that (5) is positive. 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.

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 $c_p(p^*, \widehat{\theta}(p^*)) > \upsilon(S)\widehat{V}_p(p^*, \widehat{\theta}(p^*))$, and the founders of a startup find it optimal to file p^* patents, which is greater than the number filed under symmetric information.*

Proof. See Appendix. □

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 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 θ 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:

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

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, θ, 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 θ, and $\varsigma_{S\theta}(S, \theta) < 0$.

5 Empirical Estimation

In this section we empirically examine the model's implications that i) there exists a signaling equilibrium in which startups use patents 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 on patents 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, focusing on the sources of endogeneity in relation to founder patents and external funding. Finally, section 4.3 presents the results.

5.1 Description of the dataset

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*[10] 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

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

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,[11] 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 (25.0%), 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. The majority of the startups (85%) were founded between 1993 and 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 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

[11] 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.

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% 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 invested in over our sample period. For example, 1447 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 start-ups invested in by private investors is one. This is not the case for venture capitalists. Of the investors who only invested in only one startup, 43.9% are private investors, whereas only 12.4% are venture capitalists.

In Table 2 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 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 1.1. Of course, all investors in the first round of financing are new investors.

The average amount raised per round (in constant US dollars) is \$3.6 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 2.2), 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[12], 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 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 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,

[12] 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.

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 6.3 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 predicts that *i*) there is a positive relationship between the quality of a founders' invention and the number of patents filed, and *ii*) the number of patents filed is larger under asymmetric information than under symmetric information. These results 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.

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 simultaneously determined along with the number of patents. 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 $t-1$ (when t is the initial round $P_{it-1} = P_{i0} = 0$). 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 and hence ceased to operate 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 some aspects of the quality of a startup. *Age* captures the experience of a startup. The variables *University professor, # Founders with PhD*, and *Incubator*, together with the industry sector dummies, are meant to capture characteristics of the 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. Regarding Israeli incubators, they play a fundamental role in providing initial financial support and equipment to startups that deal with technologies that require a longer span of time to reach the market (Frenkel *et al.*, 2005). 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 3.

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 of investing 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 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 ΔP_{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 one or more patents (0, otherwise)[13]. 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.

We estimate the first and the subsequent rounds 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.

Ideally the instruments would be both technology and time variant. Unfortunately, such instruments are not available. Instead, we use as instruments the (i) three-year average *number* of deals done by US venture capital companies by stage of investment (seed, early stage, expansion, later stage), (ii) the three-year average *amount* invested (in constant US dollars) by stage of investment,[14] (iii) the *ratio* of the three-year average number of US venture capital deals by stage of investment to the three-year average total number of US venture capital deals, and (iv) the yearly *growth* in the number of US venture capital deals by stage of investment. The data were obtained from the US National Venture Capital Association 2012 *Yearbook*. The variables just described are proxies for the availability of external financing in the US (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 markets are strongly interconnected, then these

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

[14]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.

measures are also correlated with the supply of VC capital in Israel.[15] 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. 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.[16][17] 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 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

[15]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 that Israeli venture capital companies have frequent contacts with venture capital companies in the US.

[16]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.

[17]In Appendix C we provide empirical results regarding the possibility of clustering in Israel. The evidence for clustering is weak. In our robustness checks we examine this issue of clustering and we find that our main results do not change.

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, we note that the results are invariant with respect to using the full set of instruments as opposed to a subset.

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:

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

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 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 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 US venture capital companies by stage of investment, and the three-year average amount invested (in constant US dollars) by stage of investment.[18] 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

[18] 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.

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 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 prior to 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 ΔP_{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.

5.3.2 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 US venture capital companies by stage of investment (expressed in the natural logarithm), ii) the ratio of the three-year average number of US 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 with a p-value of 0.00. For the IV Tobit model, we use the same procedure as above and, once again, we fail to reject the null hypothesis that n_{it} and V_{it} are (jointly) endogenous with a p-value of 0.00.[19] 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-statistics is 3.22 for V_{it} and 4.77 for n_{it}, and the p-value is 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 4.[20] As a reference, we include the non-IV estimates in the first three columns. We report average partial effects for all models.[21] 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

[19] We reiterate that our results are also unchanged when we use the full set of instruments described earlier.
[20] First-stage regressions for the IV estimators are reported and explained in Appendix B (Table B1).
[21] The coefficients presented in all tables are average partial effects and were computed using the procedure suggested by Wooldridge (2002).

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, 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=0.00), 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 across the regression specifications. 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 the 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 statistically significant. 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 0.00 in all regression specifications.

Table 5 presents the results on the coefficients of primary interest for the following three robustness checks. First, we estimate our IV models using 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.[22] 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, as shown in Appendix B, these two district dummies are the only ones to be significantly correlated with our endogenous regressors while the Tel Aviv district dummy is not.[23] 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). As we mentioned, our prior is that the signal value of a patent is more important for new investors than for old investors. In Table 6 we examine the impact of the number of new and old investors on founder number of patents. To this scope we estimate equation 9, which 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 US venture capital companies by stage of investment (this time expressed in the natural logarithm), ii) the ratio of the three-year average number of US venture capital deals by stage of investment to the three-year average number deals, iii) the yearly growth in the number of US venture capital deals, by stage of investment, iv) the Israeli district dummies, and v) the number of a startup's founders.

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

[23]Including instruments that are weakly correlated with the endogenous regressors can affect the quality of the IV estimator (Stock and Yogo, 2003; Newey, 2004; Chao and Swanson, 2005; and Angrist and Pischke, 2009)

Our endogeneity tests fail to reject the null hypothesis of joint endogeneity of n_{it} and o_{it} with a p-value of 0.00. The coefficient for the number of new investors per round is positive and statistically 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 should be 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, independent of the regression specification. 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 technology specific.

⟨ Insert Table 4 about here ⟩

⟨ Insert Table 5 about here ⟩

⟨ Insert Table 6 about here ⟩

5.3.3 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, c*eteris 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, allowing us to build a measure of experience, 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; Field, 1996). Further, results from the Berkeley Patent Survey (Graham and Sichelman, 2008; 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 presented in Table 7. As in Table 4, these results are for rounds subsequent to the first. The underlying regression specifications are the same as in Table 4, with the following exceptions. First, we exclude the total amount invested per round from the regressions. 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. Second, we modify the set of instruments to include predictors of the number of new private investors.[24] 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,

[24]See Appendix B, Table B2.

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[25]).[26]

It is important that the additional instruments are uncorrelated with the error term. We believe that the conjectures expressed in section 5.2 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, with a p-value greater than 0.15. In checking for the weakness of the instruments, we find that the F-statistics on excluded instruments is only statistically significant at the five percent significance level. This suggests 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.[27] With this specification, the F-statistics becomes significant at the one percent 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 use the same procedure as above and, once again, we 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 the number of new venture capitalists and the number of new private investors, we fail to accept the hypothesis of endogeneity of new private investors, with a p-value greater than 0.8. This last result might be due to the fact that our tests for

[25]The data is available from the International Monetary Fund.
[26]First-stage regressions are reported and commented in Appendix B.
[27]These robustness checks are available upon request.

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 7 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 with a p-value of 0.00, regardless of the specification. Moreover, a test of the equality of these coefficients rejects the null hypothesis that the coefficients are equal with a p-value less than 0.09.

In Table 8 we report 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 the ones presented in Table 7, both in terms of the sign and the significance of the coefficients. 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 groups) as those individuals that have invested in more that 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 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 continues to have a positive and significant impact on the number patents filed by a startup, whereas the impact of 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 presented in Table 7 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.

⟨ Insert Table 7 about here ⟩

⟨ Insert Table 8 about here ⟩

6 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 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.

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 between venture capitalists.

References

[1] Akerlof. G. A.. 2006. The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *Quarterly Journal of Economics*, 84(3): 488-500.

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

[3] Arora, A., A. Fosfuri, and A. Gambardella. 2001. *Markets for Technology: Economics of Innovation and Corporate Strateg*y. Cambridge, MA: MIT Press.

[4] Arora A. and M. Ceccagnoli. 2006. Patent Protection, Complementary Assets, and Firms' Incentives for Technology Licensing. *Management Science*, 52(2): 293-308.

[5] Arrow K.1962. Economic Welfare and the Allocation of Resources for Invention, in *The Rate and Direction of Inventive Activity* edited by Richard Nelson. Princeton University Press, 609-625.

[6] Bhattacharya S. 1979. Imperfect Information, Dividend Policy, and "The Bird in the Hand" Fallacy. *The Bell Journal of Economics*, 10 (1): 259-270

[7] 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): 237-269.

[8] 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.

[9] Brav, A., and P. A. Gompers. 1997. "Myth or Reality": Long-Run Underperformance of Initial Oublic Offerings; Evidence from Venture Capital and Nonventure Capital-Backed IPOs. *Journal of Finance*, 52: 1791-1821.

[10] Burk, D. L. 2008. The Role of Patent Law in Knowledge Codification. *Berkeley Technology Law Journal* 23: 1009-1029.

[11] Chao, J. C., and N. R. Swanson. 2005. Consistent Estimation with a Large Number of Weak Instruments. *Econometrica*, 73: 1673-1692.

[12] 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.Eisenberg, R. S. (1989).

[13] Conti A., M. Thursby, and F. T. Rothaermel. 2013. Show Me the Right Stuff: Signals for High-Tech Startups. *Journal of Economics & Management Strategy,* 20(2).

[14] Denis, D. J. 2004. Entrepreneurial Finance: An Overview of the Issues and Evidence. *Journal of Corporate Finance*, 10: 301-326.

[15] Eisenberg, R. S. 1989. Patents and the Progress of Science - Exclusive Rights and Experimental Use. *University of Chicago Law Review*, 56 (3): 1017-1086.

[16] 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.

[17] Fischer T., and G. de Rassenfosse. 2012. Venture Debt Financing: Determinants of the Lending Decision. SSRN Working Paper.

[18] 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.

[19] 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.

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

[21] 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.

[22] Grenadier S. R., and A. Malenko. Real Options Signaling Games with Applications to Corporate Finance. *Review of Financial Studies,* 24(12): 3993-4036.

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

[24] 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.

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

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

[27] Hochberg, Y., A. Ljungqvist, and Y. Lu (2010). Whom You Know Matters: Venture Capital Networks and Investment Performance. *Journal of Finance*, 62 (1): 251-302.

[28] 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.

[29] Horstmann, I., G. MacDonald, and A. Slivinski. 1985. Patents as Information Transfer Mechanisms: To Patent or (Maybe) Not to Patent. *The Journal of Political Economy*

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

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

[32] 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.

[33] Kortum S., and J. Lerner. 2000. Assessing the Contribution of Venture Capital to Innovation. *RAND Journal of Economics*, 3(4): 674-692.

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

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

[36] _____. 2000. *Venture Capital and Private Equity: A Casebook.* John Wiley and Sons.

[37] Long, C. 2002. Patent Signals. *The University of Chicago Law Review*, 69(2): 625-679.

[38] Mann R. J., and T. W. Sager. 2007. Patents, Venture Capital, and Software Start-ups. *Research Policy*, 36: 193-208.

[39] Mailath, G. J. Incentive Compatibility in Signaling Games with a Continuum of Types. *Econometrica,* 55(6): 1349-1365.

[40] Mansfield E. 1986. Patents and Innovations: An Empirical Study. *Management Science*, 32 (2): 173-181.

[41] Mayston D. 2009. The Determinants of Cumulative Endogeneity Bias in Multivariate Analysis. *Journal of Multivariate Analysis*, 100(6): 1120-1136.

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

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

[44] 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.

[45] Reinganum, J. F. 1983. Uncertain Innovation and the Persistence of Monopoly. *American Economic Review,* 73: 741-748.

[46] Ross S.A. 1977. The Determination of Financial Structure: The Incentive Signaling Approach. *The Bell Journal of Economics*, 8(1): 259-270.

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

[48] Smith R., and R. Blundell. 1986. An Exogeneity Test for a Simultaneous Equation Tobit Model with an Application to Labor Supply. *Econometrica*, 54: 679-685.

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

[50] Spence M.. 1974. Competitive and Optimal Responses to Signals: An Analysis of Efficiency and Distribution. *Journal of Economic Theory*, 7: 296-332.

[51] 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.

[52] Thursby J., and M. Thursby. 2008. Knowledge Creation and Diffusion of Public Science with Intellectual Property Rights, in *Intellectual Property Rights and Technical Change, Frontiers in Economics*, Vol. 2, edited by Keith Maskus, Elsevier.

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

[54] Trajtenberg M. 2005. Innovation Policy for Development: an Overview. Paper prepared for the LAEBA 2005 Second Annual Meeting, Buenos Aires, Argentina.

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

Appendix A: 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 $c_p(p^*, \widehat{\theta}(p^*)) > \upsilon(S)\widehat{V}_p(p^*, \widehat{\theta}(p^*))$, 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 $c_p(p^*, \widehat{\theta}(p^*)) > \upsilon(S)\widehat{V}_p(p^*, \widehat{\theta}(p^*))$, 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:

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

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

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

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

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

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

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

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

Appendix B: First Stage Regressions

Table B1 presents the first-stage regression results for the models we have estimated in Tables 4 and 6. The coefficients of the three-year average of US venture capital deals by stage of investment and the ratio of the three-year average of US venture capital deals to the total number of deals are significantly different from zero. In the regressions for the total amount invested per round and for the number of new investors, the coefficient of the first variable is negative, while that of the second variable is positive. The negative sign of the first variable is likely to be explained by the fact that our variable cannot distinguish between the supply of funds by US venture capitalists and the demand for funds by technology startups. Hence our result might indicate that the larger is the amount of funds demanded by US startups, the fewer are the funds left for Israeli companies. Of the district dummies, the dummy for the Jerusalem district has a positive coefficient regardless of the regression specification, while the dummy for the Haifa district has a negative coefficient. The significance of these coefficients depends upon the regression specification used. Finally, the number of startup founders is positive and statistically significant in the regression for the total amount invested per round.

⟨ Insert Table B1 about here ⟩

Table B2 presents the first-stage regression results for the models in Table 7. The coefficients of the three-year average of US venture capital deals by stage of investment and the ratio of the three-year average of US venture capital deals to the total number of deals are significantly different from zero in the regressions for the number of new venture capitalists. As before, the coefficient of the first variable is negative, while that of the second variable is positive. The Jerusalem district dummy and its interaction with Israel's gross domestic product have highly significant coefficients. While the coefficient for the Jerusalem dummy is positive, its interaction with Israel's gross domestic product is negative. Finally, as expected, the number of yearly casualties by terrorist attacks (by district) is negatively correlated with the number of new private investors.

⟨ Insert Table B2 about here ⟩

7 Appendix C: Technology Clustering in Israel

In the main text we argue, based upon discussions with policy makers and the small size of Israel, that it is not appropriate to consider that there are technology clusters in Israel. Our sources claimed that know-how related to new technologies diffuses rapidly throughout Israel so that certain types of knowledge are not embedded in certain districts. However, even in the absence of clearly defined technology clusters, it might still be the case that Israeli startups locate next to universities or in incubators, for example.

In our regressions we include technology controls for whether a founder is a university professor, whether the firm had received funding from the Office of the Chief Scientist, the number of founders who hold a PhD, and whether a startup had spent at least some time in an incubator. If there is technology clustering in Israel, then, in a regression of location, we should observe that the above regressors are significant. We estimate a multinomial probit regression of location on all controls. In that regression we find that only 5 of the 24 coefficients associated with the above technology regressors are significant at conventional levels. This is only weak evidence of clustering in Israel.

In addition, we consider a series of probit regressions where the dependent is a dummy equal to one if a startup is located in a given district as compared to the other districts. We then calculate the number of correctly classified values using all controls versus the number of correctly classified values after excluding the above mentioned technology controls as well as the sector indicators. Results are in the following table.

⟨ Insert Table C1 about here ⟩

Knowledge of the technology controls provide little information about the region in which a startup is located, with the possible exception of location in the Center or North districts in which percentage of correctly classified observations changes from 54.6% to 62.6%.

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.	Min.	Max.
ΔP_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		

Table 4: 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*								
Δpt	**Continuous Model**			**Tobit Model**			**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	0.004	***	*0.124*	0.011	***	*0.434*	0.017	***	*0.012*	-0.064		*1.889*	-0.066		*4.965*	-0.094		*0.182*
nt	0.002	***	*0.082*	0.003	**	*0.222*	0.007	**	*0.008*	0.085	***	*1.260*	0.093	***	*3.315*	0.121	***	*0.121*
Tot. # of rounds	0.002	***	*0.086*	0.006	***	*0.229*	0.013	***	*0.008*	0.011	***	*0.140*	0.013	***	*0.345*	0.016	***	*0.013*
Ceased	-0.003		*0.343*	-0.010		*1.142*	-0.018		*0.033*	-0.008		*0.682*	-0.014		*1.692*	-0.012		*0.066*
# Startups founded in the past	0.000	*	*0.029*	0.001		*0.096*	0.002		*0.003*	0.003		*0.070*	0.003		*0.191*	0.004		*0.007*
Incubator	-0.013	**	*0.823*	-0.035		*4.512*	-0.067	**	*0.082*	-0.071	***	*1.139*	-0.088	**	*4.254*	-0.106	***	*0.112*
Age	-0.001	***	*0.053*	-0.004	***	*0.185*	-0.007	***	*0.005*	0.000		*0.099*	0.000		*0.292*	0.000		*0.010*
University professor	0.007	**	*0.447*	0.018	***	*1.170*	0.038	**	*0.044*	0.016		*0.660*	0.022		*1.557*	0.025		*0.064*
# Founders with PhD	0.003	*	*0.251*	0.007		*0.709*	0.015	*	*0.024*	0.022	**	*0.415*	0.023	**	*1.066*	0.030	**	*0.040*
Elapsed days	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.001*	0.000	***	*0.000*
Seed	0.006		*0.629*	0.010		*2.213*	0.029		*0.062*	-0.067		*2.530*	-0.078		*6.655*	-0.098		*0.244*
Initial Revenue	0.000		*0.315*	-0.003		*0.999*	-0.003		*0.031*	0.012		*0.614*	0.008		*1.539*	0.017		*0.059*
Revenue Growth	0.012	***	*0.621*	0.025	**	*1.790*	0.059	***	*0.061*	0.070	**	*1.408*	0.069	**	*3.291*	0.101	**	*0.136*
Semiconductors	0.010	*	*0.748*	0.021	*	*1.962*	0.041		*0.072*	0.067	**	*1.234*	0.075	**	*3.336*	0.090	**	*0.119*
Misc	0.002		*0.711*	0.007		*2.148*	0.009		*0.070*	0.047		*1.260*	0.056	*	*3.234*	0.065		*0.120*
Med Dev	0.006		*0.598*	0.017	*	*1.712*	0.030		*0.058*	0.037		*1.012*	0.048	*	*2.573*	0.051		*0.097*
Internet	-0.010	**	*0.660*	-0.034	**	*2.679*	-0.052	**	*0.067*	-0.044		*1.180*	-0.067	*	*3.547*	-0.065		*0.116*
IT & Software	-0.009	**	*0.594*	-0.022	*	*1.882*	-0.044	**	*0.059*	0.022		*1.157*	0.020		*3.137*	0.029		*0.112*
Communications	-0.001		*0.601*	-0.001		*1.867*	-0.007		*0.060*	0.054	*	*1.221*	0.062	*	*3.386*	0.074	*	*0.118*
CleanTech	0.005		*0.918*	0.017		*2.901*	0.026		*0.092*	0.006		*1.269*	0.020		*3.656*	0.010		*0.124*
Chief Scientist grant	0.003		*0.447*	0.008		*1.289*	0.017		*0.043*	-0.022		*0.932*	-0.022		*2.365*	-0.032		*0.090*
Constant	-0.066	***	*0.822*	-0.133	***	*2.660*	0.013		*0.081*	-0.342	***	*2.559*	-0.371	***	*6.880*	-0.175	**	*0.247*
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	***							

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The table reports average partial effects. Standard errors are in italics. They are clustered by firm. For the Tobit 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 US venture capital deals, by stage of investment; ii) the ratio of the 3-year-average number of US venture capital deals, by stage of investment, to the 3-year-average total number of US venture capital deals; iii) Israeli district dummies; iv) the number of a startup's founders.

Table 5: 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**			**IV Tobit Model**			**IV Linear Probability Model**		
	APE		se	APE		se	APE		se
	The total amount invested at round t is used as a control								
nt	0.069	***	*1.047*	0.084	***	*2.780*	0.112	***	*0.101*
	A dummy for whether a startup is located in the city of Tel Aviv is included								
Vt	-0.074		*1.854*	-0.080		*4.884*	-0.101		*0.177*
nt	0.093	***	*1.282*	0.107	***	*3.273*	0.124	***	*0.123*
	lummies, used as instruments, only include an indicator variable for the Jerusalem district and one for the Hai								
Vt	-0.055		*1.883*	-0.052		*5.380*	-0.085		*0.182*
nt	0.082	***	*1.249*	0.083	***	*3.580*	0.122	***	*0.120*

*** 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 IV Tobit model, standard errors are bootstrapped using 500 replications and accounting for firm clusters in re-sampling. The set of instruments includes: i) the log of the 3-year-average number of US venture capital deals, by stage of investment; ii) the ratio of the 3-year-average number of US venture capital deals, by stage of investment, to the 3-year-average total number of US venture capital deals; iii) Israeli district dummies; iv) the number of a startup's founders. In all regressions we include the following controls: the total number of rounds, whether a startup had ceased to operate as of June 2011, the number of startups the founders had founded in the past, whether the startup was located in an incubator, whether at least one of the founders is a university professor, whether the startup had received a grant from Israel's Office of the Chief Scientist, the number of founders with a PhD who are not university professors, company age, the number of days since the prior funding round, indicators for the industry sector and for the life cycle stage of the startup in round t, as well as year dummies.

Table 6: 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*								
Δpt	**Continuous Model**			**Tobit Model**			**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
ot	0.001	***	*0.061*	0.002	***	*0.169*	0.006	***	*0.006*	-0.036		*0.832*	-0.040		*2.346*	-0.048	*	*0.082*
nt	0.002	***	*0.076*	0.005	***	*0.199*	0.012	***	*0.008*	0.057	***	*0.741*	0.082	***	*2.166*	0.068	***	*0.073*
Tot. # of rounds	0.002	***	*0.086*	0.005	***	*0.234*	0.013	***	*0.008*	0.014	***	*0.147*	0.020	***	*0.414*	0.019	***	*0.015*
# Startups founded in the past	-0.004	**	*0.030*	0.001	**	*0.098*	0.002	**	*0.003*	0.002		*0.047*	0.003		*0.138*	0.002		*0.005*
Incubator	-0.012	**	*0.819*	-0.029		*4.496*	-0.066	**	*0.081*	-0.100	**	*1.488*	-0.137	*	*5.106*	-0.130	**	*0.149*
Age	-0.001	***	*0.053*	-0.003	***	*0.185*	-0.007	***	*0.005*	0.000		*0.086*	-0.001		*0.269*	0.000		*0.009*
University professor	0.006	*	*0.456*	0.014	**	*1.218*	0.034	**	*0.045*	0.042	**	*0.735*	0.057	**	*1.992*	0.056	**	*0.073*
# Founders with PhD	0.004	*	*0.255*	0.006		*0.725*	0.016	*	*0.024*	0.021	***	*0.290*	0.025	**	*0.847*	0.024	**	*0.028*
Elapsed days	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.001*	0.000	***	*0.000*
Seed	0.002		*0.603*	-0.001		*2.152*	0.010		*0.060*	-0.007		*0.879*	-0.016		*2.728*	-0.011		*0.087*
Initial Revenue	0.000		*0.316*	-0.002		*1.013*	-0.002		*0.031*	0.014		*0.540*	0.009		*1.499*	0.018		*0.053*
Revenue Growth	0.013	***	*0.626*	0.025	***	*1.821*	0.064	***	*0.061*	0.074	**	*1.073*	0.083	*	*3.065*	0.093	**	*0.106*
Semiconductors	0.010	*	*0.750*	0.020	*	*1.968*	0.043		*0.072*	0.063	**	*1.035*	0.089	**	*2.654*	0.072	**	*0.102*
Misc	0.001		*0.713*	0.005		*2.185*	0.006		*0.069*	0.046		*1.069*	0.072		*3.107*	0.054		*0.106*
Med Dev	0.006		*0.600*	0.015		*1.708*	0.027		*0.058*	0.046	*	*0.898*	0.076	**	*2.420*	0.055	*	*0.088*
Internet	-0.011	**	*0.659*	-0.030	**	*2.728*	-0.055	**	*0.067*	-0.040		*1.021*	-0.079		*3.391*	-0.050		*0.102*
IT & Software	-0.008	**	*0.587*	-0.018	*	*1.878*	-0.044	**	*0.059*	0.007		*1.019*	0.008		*2.835*	0.006		*0.101*
Communications	0.000		*0.596*	0.001		*1.842*	-0.005		*0.059*	0.046	*	*0.978*	0.067	*	*2.710*	0.052		*0.097*
CleanTech	0.004		*0.815*	0.014		*2.651*	0.023		*0.083*	0.008		*1.270*	0.033		*3.614*	0.008		*0.127*
Chief Scientist grant	0.003		*0.453*	0.005		*1.297*	0.014		*0.043*	-0.012		*0.650*	-0.013		*1.781*	-0.016		*0.063*
Constant	-0.064	***	*0.830*	-0.115	***	*2.674*	0.013		*0.082*	-0.343	***	*2.227*	-0.466	***	*6.420*	-0.098		*0.219*
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	***							

*** 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 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 US venture capital deals, by stage of investment; ii) the ratio of the 3-year-average number of US venture capital deals, by stage of investment, to the 3-year-average total number of US venture capital deals; iii) the yearly growth of the US VC number of deals, by stage of investment; iv) Israeli district dummies; and v) the number of a startup's founders.

Table 7: 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

Δpt	*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**		
	APE		se	APE		se	APE		se	APE		se	APE		se	APE		se
nt_VC	0.003	***	*0.114*	0.007	***	*0.291*	0.017	***	*0.011*	0.083	***	*1.115*	0.099	***	*3.527*	0.120	***	*0.109*
nt_Private Investors	0.000		*0.190*	0.001		*0.631*	0.001		*0.019*	0.015		*1.774*	0.036		*6.960*	0.020		*0.174*
Tot. # of rounds	0.002	***	*0.088*	0.006	***	*0.237*	0.012	***	*0.009*	0.005	**	*0.107*	0.007	**	*0.310*	0.008	**	*0.010*
Ceased	-0.004	*	*0.346*	-0.013	*	*1.149*	-0.022	*	*0.033*	0.005		*0.479*	0.001		*1.611*	0.006		*0.047*
# Startups founded in the past	0.000	**	*0.030*	0.001	**	*0.101*	0.002	*	*0.003*	0.000		*0.043*	0.000		*0.135*	0.000		*0.004*
Incubator	-0.012	**	*0.853*	-0.032		*4.630*	-0.066	**	*0.084*	-0.011		*0.825*	-0.022		*3.952*	-0.022		*0.081*
Age	-0.001	***	*0.052*	-0.003	***	*0.180*	-0.007	***	*0.005*	-0.001		*0.085*	-0.001		*0.303*	-0.001		*0.008*
University professor	0.007	**	*0.460*	0.017	**	*1.223*	0.037	**	*0.045*	0.018		*0.495*	0.024		*1.429*	0.029	*	*0.049*
# Founders with PhD	0.004	**	*0.255*	0.007	*	*0.726*	0.017	*	*0.024*	0.014	**	*0.277*	0.016	*	*0.819*	0.019	**	*0.026*
Elapsed days	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.000*	0.000	***	*0.000*	0.000	***	*0.001*	0.000	***	*0.000*
Seed	0.001		*0.623*	-0.002		*2.208*	0.005		*0.061*	0.014		*0.718*	0.007		*2.423*	0.019		*0.070*
Initial Revenue	0.000		*0.321*	-0.001		*1.021*	0.000		*0.032*	-0.003		*0.392*	-0.006		*1.142*	-0.004		*0.038*
Revenue Growth	0.014	***	*0.637*	0.028	***	*1.850*	0.068	***	*0.062*	0.027		*0.746*	0.025		*2.205*	0.040		*0.073*
Semiconductors	0.009		*0.759*	0.019	*	*2.006*	0.039		*0.073*	0.018		*0.851*	0.024		*2.576*	0.021		*0.083*
Misc	0.000		*0.717*	0.002		*2.216*	0.000		*0.070*	0.014		*0.871*	0.023		*2.929*	0.019		*0.083*
Med Dev	0.005		*0.605*	0.013		*1.751*	0.024		*0.059*	0.022		*0.668*	0.032		*2.099*	0.031		*0.064*
Internet	-0.011	**	*0.665*	-0.034	**	*2.683*	-0.057	**	*0.067*	-0.052	***	*0.812*	-0.076	**	*3.116*	-0.078	***	*0.080*
IT & Software	-0.010	**	*0.602*	-0.023	**	*1.929*	-0.051	**	*0.060*	-0.029		*0.763*	-0.033		*2.796*	-0.045	*	*0.076*
Communications	-0.001		*0.610*	-0.001		*1.897*	-0.010		*0.060*	-0.004		*0.818*	0.004		*2.983*	-0.010		*0.081*
CleanTech	0.003		*0.824*	0.012		*2.692*	0.018		*0.084*	0.022		*1.005*	0.039		*3.278*	0.033		*0.100*
Chief Scientist grant	0.002		*0.454*	0.005		*1.301*	0.013		*0.043*	0.003		*0.459*	0.003		*1.363*	0.005		*0.043*
Constant	-0.061	***	*0.832*	-0.12	***	*2.668*	0.0283		*0.082*	-0.270	***	*1.525*	-0.307	***	*6.388*	-0.071		*0.148*
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	**							

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The table reports average partial effects. Standard errors are in italics. They are clustered by firm. For the Tobit 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 US venture capital deals, by stage of investment; ii) the ratio of the 3-year-average number of US venture capital deals, by stage of investment, to the 3-year-average total number of US venture capital deals; iii) the number of casualties by terrosist attacks, per region; iv) Israeli district dummies; v) interactions between district dummies and Israel's GDP; and iv) number of a startup's founders.

Table 8: 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**			**IV Tobit Model**			**IV Linear Probability Model**		
	APE		se	APE		se	APE		se
	Number of new venture capitalists per round includes angel syndicates								
nt_VC	0.082	***	*1.020*	0.097	***	*3.404*	0.114	***	*0.170*
nt_Private Investors	0.009		*1.730*	0.030		*6.992*	0.010		*0.100*
	Number of new venture capitalists per round includes angel syndicates and other angel investors								
nt_VC	0.072	***	*0.993*	0.095	**	*3.430*	0.108	***	*0.097*
nt_Private Investors	0.029		*1.863*	0.065		*7.364*	0.045		*0.182*
	Number of new private investors includes angel syndicates								
nt_VC	0.086	***	*1.092*	0.104	***	*3.511*	0.121	***	*0.107*
nt_Private Investors	0.004		*1.624*	0.015		*6.451*	0.002		*0.159*
	of new venture capitalists per round includes includes private equity firms or firms that specialize in startup in								
nt_VC	0.049	***	*0.673*	0.071	***	*2.257*	0.077	***	*0.066*
nt_Private Investors	-0.003		*1.714*	0.011		*6.875*	-0.007		*0.170*

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The table reports average partial effects. Standard errors are in italics. They are clustered by firm. For the IV Tobit Model, standard errors are bootstrapped using 500 replications and accounting for firm clusters in re-sampling. The set of instruments includes: i) the log of the 3-year-average number of US venture capital deals, by stage of investment; ii) the ratio of the 3-year-average number of US venture capital deals, by stage of investment, to the 3-year-average total number of US venture capital deals; iii) the number of casualties by terrorist attacks, per region; iv) Israeli district dummies; v) interactions between district dummies and Israel's GDP; and vi) the number of a startup's founders. In all regressions we include the following controls: the total number of rounds, whether a startup had ceased to operate as of June 2011, the number of startups the founders had founded in the past, whether the startup was located in an incubator, whether at least one of the founders is a university professor, whether the startup had received a grant from Israel's Office of the Chief Scientist, the number of founders with a PhD who are not university professors, company age, the number of days since the prior funding round, indicators for the industry sector and for the life cycle stage of the startup in round *t*, as well as year dummies.

Table B1: First-stage regressions (total amount invested, number of new investors, number of old investors per round)

	Vt			nt			ot			nt		
	APE		se	APE		se	APE		se	APE		se
# of US VC deals (by investment stage)	-0.262	***	*0.338*	-0.293	***	*0.513*	0.161	***	*0.546*	-0.270	***	*0.505*
Ratio of US VC deals, by investment stage, to total # of deals	1.158	***	*1.617*	0.964	***	*1.851*	-0.450	*	*2.388*	0.892	***	*1.847*
Yearly growth in the # of US VC deals (by investment stage)							0.127		*0.729*	0.092		*0.437*
Tel Aviv District	-0.016		*0.085*	-0.010		*0.111*	-0.016		*0.147*	-0.010		*0.110*
Jerusalem District	0.065	*	*0.149*	0.001		*0.211*	0.029		*0.323*	0.003		*0.211*
Haifa District	-0.029		*0.122*	-0.040	**	*0.146*	-0.036	*	*0.191*	-0.040	**	*0.147*
Chief Scientist grant	-0.077	***	*0.101*	0.013		*0.116*	-0.039	**	*0.164*	0.013		*0.117*
# of founders	0.017	**	*0.036*	0.000		*0.044*	-0.004		*0.066*	0.000		*0.044*
Tot. # of rounds	0.007		*0.021*	-0.001		*0.029*	0.013	***	*0.046*	-0.001		*0.029*
Ceased	-0.075	***	*0.092*	-0.043	***	*0.104*	-0.022		*0.139*	-0.043	***	*0.105*
# Startups founded in the past	0.008	***	*0.007*	0.002	*	*0.009*	0.003	**	*0.014*	0.002	*	*0.009*
Incubator	-0.077	*	*0.176*	0.008		*0.273*	-0.130	***	*0.412*	0.008		*0.273*
Age	0.003		*0.013*	-0.006	**	*0.019*	0.006	**	*0.029*	-0.006	**	*0.018*
University professor	-0.017		*0.108*	0.008		*0.162*	0.060	**	*0.259*	0.008		*0.162*
# Founders with PhD	0.018		*0.062*	-0.004		*0.085*	0.013		*0.113*	-0.004		*0.085*
Elapsed days	0.000		*0.000*	0.000	**	*0.000*	0.000	*	*0.000*	0.000	**	*0.000*
Seed	-0.328	***	*0.161*	-0.030		*0.189*	-0.069	***	*0.192*	-0.030		*0.190*
Initial Revenue	-0.013		*0.146*	-0.016		*0.206*	0.046		*0.272*	-0.011		*0.206*
Revenue Growth	0.140	***	*0.151*	-0.001		*0.170*	0.102	**	*0.388*	-0.009		*0.171*
Semiconductors	0.033		*0.170*	-0.039		*0.257*	0.036		*0.373*	-0.038		*0.258*
Misc	-0.072	*	*0.183*	-0.107	***	*0.239*	0.008		*0.391*	-0.106	***	*0.239*
Med Dev	-0.054		*0.141*	-0.053	*	*0.221*	0.017		*0.347*	-0.053	*	*0.222*
Internet	-0.034		*0.175*	0.010		*0.294*	0.009		*0.389*	0.010		*0.294*
IT & Software	-0.023		*0.142*	-0.088	***	*0.223*	0.021		*0.363*	-0.087	***	*0.224*
Communications	0.016		*0.152*	-0.082	***	*0.220*	0.049		*0.375*	-0.081	***	*0.222*
CleanTech	-0.102		*0.381*	-0.038		*0.284*	-0.054		*0.421*	-0.040		*0.285*
Constant	1.624	***	*1.894*	2.055	***	*3.163*	-0.930	***	*3.343*	1.911	***	*3.113*
Year FE	YES			YES			YES			YES		
N	1,339			1,339			1,339			1,339		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The table reports average partial effects. Standard errors are in italics. The first two colums reports first-stage regression results for the IV regression models in Table 4. The last two colums report regression results for the IV regression models in Table 6.

Table B2: First-stage regressions (number of new venture capitalists and private investors per round)

	nt Private Investors			nt Venture Capitalists		
	APE		se	APE		se
# of US VC deals (by investment stage)	0.084		*0.214*	-0.359	***	*0.404*
Ratio of US VC deals, by investment stage, to total # of deals	0.048		*0.902*	0.930	**	*1.343*
# of founders	-0.007		*0.022*	0.009		*0.030*
Tel Aviv District	-0.115		*0.512*	0.108		*0.556*
Jerusalem District	0.435	***	*0.428*	0.219		*0.838*
Haifa District	0.020		*0.540*	-0.079		*0.658*
Tel Aviv District x Israel GDP	0.000		*0.001*	0.000		*0.001*
Jerusalem District x Israel GDP	-0.001	***	*0.001*	0.000		*0.001*
Haifa District x Israel GDP	0.000		*0.001*	0.000		*0.001*
# casualties, by district	-0.001	**	*0.001*	0.000		*0.004*
Chief Scientist grant	0.020		*0.066*	0.006		*0.069*
Tot. # of rounds	-0.007	*	*0.010*	0.011	*	*0.020*
Ceased	-0.022		*0.049*	-0.062	***	*0.069*
# Startups founded in the past	-0.001		*0.004*	0.007	***	*0.006*
Incubator	0.024		*0.100*	-0.116	***	*0.139*
Age	-0.005		*0.008*	-0.012	***	*0.012*
University professor	-0.003		*0.065*	0.013		*0.108*
# Founders with PhD	-0.014		*0.037*	-0.009		*0.054*
Elapsed days	0.000		*0.000*	0.000		*0.000*
Seed	0.014		*0.111*	-0.042		*0.114*
Initial Revenue	-0.048		*0.102*	0.024		*0.143*
Revenue Growth	0.020		*0.077*	0.014		*0.134*
Semiconductors	-0.072	*	*0.111*	0.052		*0.150*
Misc	-0.077	*	*0.117*	-0.043		*0.168*
Med Dev	-0.021		*0.121*	-0.017		*0.112*
Internet	-0.040		*0.162*	0.073		*0.175*
IT & Software	-0.088	**	*0.110*	0.001		*0.128*
Communications	-0.113	***	*0.110*	0.011		*0.125*
CleanTech	-0.073		*0.131*	-0.033		*0.149*
Constant	-0.361		*1.289*	2.425	***	*2.526*
Year FE	YES			YES		
N	1,339			1,339		

*** p < 0.01, ** p < 0.05, * p < 0.10. The table reports average partial effects. Standard errors are in italics. The first-stage regression results are for the IV regression models in Table 7.

Table C1: Percentage of correctly classified observations

	Correctly Classified Observations	
Districts	Including All Controls	Controls Excluding Technology Variables
Center/North	62.50%	54.60%
Tel Aviv	68.40%	66.40%
Jerusalem	93.40%	93.40%
Haifa	90.70%	91.00%