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SHOW ME THE RIGHT STUFF: SIGNALS FOR HIGH TECH STARTUPS

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Working Paper 17050
http://www.nber.org/papers/w17050

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2011

We are indebted to Jerry Thursby for insightful comments and suggestions. We also thank Thomas Astebro, David Beck, Victor Bergonzoli, Carolin Haeussler, Matt Higgins, David Hsu, David Ku, Josh Lerner, Laura Lindsey, William Oakes, Florin Paun, Carlos Serrano, Scott Shane, Rosemarie Ziedonis, and seminar participants at the 2010 NBER's Entrepreneurship Working Group Meeting for their valuable comments. Conti acknowledges support from the Hal and John Smith Chair in Entrepreneurship for support via a TI:GER Postdoctoral Fellowship and the Swiss National Foundation. Thursby acknowledges NSF Award #0221600, and Rothaermel acknowledges NSF SES 0545544. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 17050
May 2011, Revised February 2013
JEL No. G24

ABSTRACT

We present a theoretical model of startup signaling with multiple signals and potential differences in external investor preferences. For a novel sample of technology incubator startups, we empirically examine the use of patents and founder, friends, and family (FFF) money as such signals, finding that they are jointly endogenous to venture capital and business angel investment in the startups. For this sample, venture capitalists appear to value patents more highly than FFF money, while the reverse is true for business angels. Moreover, the impact of patents on venture capitalists is larger than the impact of FFF money on business angels.

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1 Introduction

One of the most important challenges facing entrepreneurs in technology startups is access to capital (Denis, 2004; Shane and Stuart, 2002). With little or no observable history of performance and uncertain technology, a major issue for these entrepreneurs is how to signal their company's value to potential investors. One such signal is an entrepreneur's own investment (Leland and Pyle, 1976). For technology startups, patents are also a potential signal. Indeed, the Berkeley Patent Survey finds that one of the most important reasons for startups to patent is to secure funds (Graham and Sichelman, 2008; Graham et al., 2009).[1] There is also empirical evidence that alliances (Stuart et al., 1999; Hsu, 2004), Nobel laureates as advisors (Higgins et al., 2011), and founder attributes (Burton et al., 2002) as well as patents (Hsu and Ziedonis, 2008, 2011; Haeussler et al., 2009) are correlated with startup value, suggesting they could serve as signals.

With multiple such mechanisms, how should managers choose signals? We address this topic in the context of two signals, patents and investment of founders, friends, and family (FFF) funds. We provide theoretical and empirical results on investment in these signals as a function of the cost of signaling and investor preferences. The theoretical model considers a situation of asymmetric information in which the founders of a startup have private information about the technology underlying their business. The value of the startup is a function of the probability of success of the technology, but also the founders' commitment. In seeking external investment, the founders consider using patents as a signal of the probability of success and FFF money as a signal of their commitment. In our model, both signals have other uses as well, and so they are productive signals in the sense of Spence (1974). The theory also incorporates the observation that different classes of investors (i.e., business angel and venture capitalists) vary in the extent to which they value startup characteristics (Osnabrugge and

[1] On average, "improving chances of obtaining financing" ranked second in importance among the seven reasons considered. Startups in the software sector also rated "enhancing the firm's reputation" more highly than firms in other sectors. Thus the authors interpret signaling as a primary reason for software patenting (Graham and Sichelman 2008, p. 161).

Robinson, 2000; Graham et al., 2009). Investor preferences are known to the founders when they choose their investment. Thus optimal investment is a function of both cost, which is well documented as important (Amit et al., 1990) and investor preferences. We then examine our predictions in the context of technology startups incubated in the Advanced Technology Development Center (ATDC) from 1998-2008.

We provide conditions under which it is worthwhile for startup founders whose technologies have a high probability of success to signal their company's "quality," and we characterize the investment in patents relative to FFF money in terms of their cost and investor preferences. Independent of investor preferences, founders of these startups (high quality startups hereafter) optimally invest more in patents and FFF money than they should in a situation of symmetric information. However, when a potential investor places more weight on the quality of the technology than founder commitment, high quality startups should invest more in patents than FFF money relative to the symmetric information case. Conversely, when a potential investor values founder commitment more highly, the startup should invest relatively more in FFF money. Finally, when the potential investor is indifferent between the two attributes, the signal ratio is inversely proportional to the ratio of their costs. Thus, what distinguishes our model from prior models of multiple signals (Milgrom and Roberts, 1986; Engers, 1987; Grinblatt and Hwang, 1989) is that the investment in the signals, in equilibrium, depends on the preferences of the external investors.

Empirically, we consider the impact of patents filed and FFF money on venture capitalist and business angel investments, respectively. To this scope we use novel data which builds on the startup database examined by Rothaermel and Thursby in their analysis of university ties and incubator startup performance (2005a, 2005b). These data include information on the investment of business angels and venture capitalists, the amount of FFF money invested in the firm, and the number of patents filed, which we augmented with information from the startup business plans and a survey of the founders.

Our empirical estimation addresses whether patents and FFF money are endogenously determined variables with regard to startup financing. Understanding this is important since otherwise patents and FFF money are simply attributes correlated with the value of a startup because of their productive value to the firm. In that case, they might be strategic choices with regard to output competition or other goals, but they would not be endogenous to the financing problem. One of our major findings is that, for this sample of firms, patents and FFF money are jointly endogenous to venture capital investment and business angel investment.

Accordingly, we estimate two structural equation models, one for each type of investor, which take this endogeneity into account. Having taken into account the costs of investing in the signals, the number of patents filed by a startup has a large, statistically significant effect on venture capitalist investment while FFF money is not statistically significant. In light of our theory, this suggests that venture capitalists care more about the quality of the technology of startups than founder commitment. In the case of business angels we find that FFF money has a positive statistically significant impact on investment while patents filed does not. Moreover, we find that the impact of patents on venture capitalists is stronger than the impact of FFF money on business angels: a 1% increase in the number of patents filed increases the likelihood of venture capital financing by 46%, while a 1% increase in FFF money increases the likelihood of business angel financing by 5%.

Both the theory and empirics contribute to the literature on entrepreneurial finance (see, for instance, Leland and Pyle, 1976; Grinblatt and Hwang, 1989; Denis, 2004; Shane and Stuart, 2002; Kaplan and Per Strömberg, 2004; Cumming, 2008; and Cumming and Johan, 2008), which with the exception of seminal work by Leland and Pyle (1976) and later that of Grinblatt and Hwang (1989), has abstracted from signaling choices by startup founders. While informational issues and quality variation among startups is well documented, much of the emphasis has been on the value added that venture capitalists provide in terms of selecting better quality startups in addition to their role in providing funds, advice, and contacts (Sahlman, 1990; Stuart et al., 1999; Hellmann and Puri, 2002; Hsu, 2004; Bottazzi, Da Rin and Hellmann, 2008). While Hsu (2004) shows that startups are willing to pay a price for venture capitalist certification in the form of equity discounts, he does not examine the startup's decision to invest in signals, *per se*.

More recently, Hsu and Ziedonis (2008, 2011) and Haeussler et al. (2009) have examined the relation between patents and firm valuation. Hsu and Ziedonis (2008, 2011) use a sample of US semiconductor firms and find that the greater the number of patents filed, the higher the pre-money valuation by venture capitalists. They interpret this result in terms of signaling since the effect of patents is greater in early financing rounds, as one would expect if patents worked as a signal. Haeussler et al. (2009) find similar results for a sample of German and British biotechnology companies. In their study, patent oppositions increase the likelihood of receiving venture capital, but ultimate grant decisions do not, presumably because they are anticipated. However, neither study examines patents as a costly signal nor accounts for the endogeneity of the signal.

We contribute to this literature in two ways– we endogenize the signaling decision and consider multiple signals. Our study is also one of the few to consider business angel investment. Kerr et al. (2010) is a notable exception which uses a regression discontinuity approach and finds a positive impact of business angel funding on startup survival and growth. Goldfarb et al. (2009) examines business angel and venture capitalist data to examine the relation between control rights and investor composition, finding that business angels exert weaker control rights. DeGennaro (2012) estimates expected returns on business angel investment and find that Angel investors earn similar returns to those earned by venture capitalists. Wong (2010) provides an agency model of funding in which business angels force the founders to hold a large stake in the firm to ensure the alignment of their interests with the firm. None of this work, however, examines startup decisions regarding signals.

2 Setup of the model

We build a simple model in which the founders of a startup company have private information about the probability of success of a technology as well as their own commitment to developing it. Potential investors observe these startup attributes only with noise. As in Leland and Pyle (1976), the asymmetry of information gives the founders an incentive to signal the company's type to potential investors, who for our purposes exclude friends and family members. We shall define the startup's type by whether its technology has a high or low probability of success.

We consider two potential signals which convey information about the quality of a company: number of patents filed and founders, friends and family money (hereafter "FFF money"). Patents reveal information on the quality of the firm's underlying technology, while FFF money reflects the founders' commitment to the startup. The model differs from other models with multiple signals (see for example Grinblatt and Hwang, 1989; and Milgrom and Roberts, 1986) by our inclusion of the preferences of external investors, which, in equilibrium, affect the founders' investment in the signals.

In line with the existing literature on family finance (Parker, 2009; Casson, 2003), our model assumes that family members and friends have private information about a startup given their proximity to the founders. Thus their investment can be used as a signal for external investors, who do not have private information on the startup's type. While we do not expect family members and friends to be informed about the technology, they are likely to have information about founder attributes, such as dedication, which affect the startup's value.

As in the case of signaling with productive education (Spence 1974), the number of patents filed and FFF money directly affect the value of a startup. In the case of patents, the Berkeley Patent Survey examined six reasons, in addition to attracting financing, for startups to patent their inventions (see Graham and Sichelman, 2008, p. 154). In general, patents generate value for firms by excluding competitors from practicing their inventions, facilitating licensing to interested parties or by increasing the startup's bargaining position in negotiations with other patent holders or established firms with complementary assets (Cohen et al., 2000; Arora and Ceccagnoli, 2006; and Gans et al., 2002). The role of FFF money is threefold.

In addition to signaling founder commitment, it generates value by increasing the startup's bargaining position in negotiations with other potential investors. Finally, it is a source of capital which complements the funds provided by other investors (Agrawal et al., 2011; Parker, 2009; Cumming and Johan, 2009).

2.1 Basic assumptions

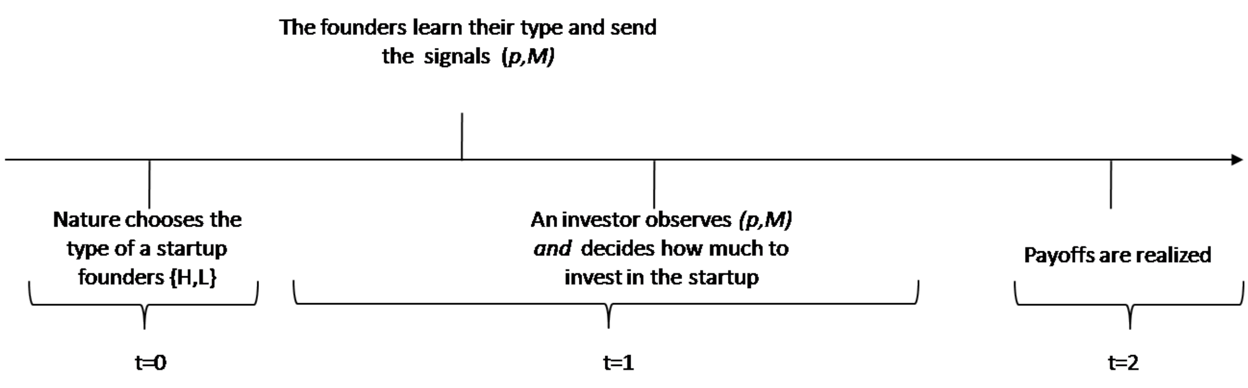
The game is played in three periods. In the first period, Nature chooses each startup's type, H or L, depending on whether its underlying technology has a high or low probability of success, respectively, θ_H or θ_L, with $\theta_H > \theta_L$. Each type of startup generates a value, $V(p, M; \theta)$, which depends on the founders' investment in patents, p, the investment by the founders, their friends and families in the startup, M, given the probability of success, θ, of the underlying technology. As discussed above, patents and FFF money are "productive" in the sense that they are inputs to a startup's value function. A startup with a high probability of success θ_H generates a greater value for any given p and M, thus $V_\theta(p, M; \theta) > 0$. In addition to contributing to the value of a startup, the investments in p and in M convey information about the quality of the technology and the founders' commitment to the technology, respectively. We assume that $V(p, M; \theta)$ is an increasing strictly concave function of p and M. For each value of p and M, the derivatives of $V(p, M; \theta)$ with respect to these signals are the same and do not vary across types. Moreover, p and M are complements in the realization of $V(p, M; \theta)$, thus, $V_{Mp}(p, M; \theta) > 0$, where $V_{Mp}(\cdot)$ is a cross-partial derivative.

In the second period, the founders learn their type and choose the amounts p and M to send as signals, incurring a cost $c(p, M; \theta)$, which we assume is an additive function of the costs of patents and FFF money, $r(p)$ and $q(M)$ respectively. Importantly, $r(p)$ is the opportunity cost of the effort necessary to develop a patentable invention. This definition of cost is not only more reflective of the true cost of patenting, but also for a patent to provide a signal in the economic sense, it must be more costly for L-type founders than for H-type founders. Indeed, the fee to file for a patent does not depend on startup type, but the opportunity cost does. Hence, we assume that for H-type founders $r(p)$ is a linear function of the investment in patents, $b_H \times p$, where $b_H > 0$ is the marginal cost of effort, while for L-type founders, $r(p)$ is $k \times b_H \times p$, with $k > 1$. This specification ensures that both the total and marginal costs of making a patentable invention are higher for L- than for H-type founders.

There are two components of $q(M)$. The first, ρM, with $\rho > 0$, is the opportunity cost of investing M in a startup, which we assume is the same for both type of founders. Thus, ρM can be viewed as the forgone returns from investing M in projects other than the startup. The second is the risk premium required for each dollar of FFF money obtained. Our assumption is that friends and family have private information about the startup type. Thus, we represent the premium as zero for a high quality startup and $g_L > 0$ for a low quality startup.

Based on the amount of each signal observed, an investor decides an amount to invest in the startup. We assume there are at least two investors potentially interested in financing the startup, but that only one eventually makes the investment. Finally, in the third period, the value of the startup is realized and both the founders and the investor receive their payoffs. All players are risk neutral and have a unitary discount rate.

Figure 1: **Time Line**



Investor's j utility is equal to $\alpha V(p, M; \theta) - F$, where $\alpha \in (0, 1)$ is the fraction of equity retained by investor j and F is the amount paid to the founders for retaining α. Because there are at least two investors potentially interested in financing the startup, F is equal to $\alpha V^j(p, M; \theta)$, where V^j is investor j's expectation of the value of a startup with productivity

θ and it coincides with that of the other potential investors.

Founder utility is a function of wealth in $t = 1$ and in $t = 2$, net of the costs of investing in M and in p[2]:

$$U_i = W_1(p, M; \theta) + W_2(p, M; \theta) - c(p, M; \theta)$$

Wealth in $t = 1$ is equal to:

$$W_1(p, M; \theta) = \alpha V^j(p, M; \theta) + M$$

$M \geq \underline{M} \geq 0$, is FFF investment in the startup, which is at least equal to a minimum amount $\underline{M}$ required to start the business. $W_1(p, M; \theta)$ is the sum of the amount received by the founders from external investors, after selling a portion α of their equity, and the amount M lent by friends and families or diverted by the founders to the startup, from alternative uses. W_1 is used to finance part of the venture, including the fees required to file a patent.

The founders' expected wealth in $t = 2$ is equal to:

$$W_2(p, M; \theta) = (1 - \alpha)V(p, M; \theta) - M$$

That is $W_2(p, M; \theta)$ is the return to equity, after the value of the startup is realized, net of the debt repayment to friends, families and to the founders themselves, who can now reassign to alternative uses the amount they had initially subtracted.

3 Solution of the game

We are interested in a separating equilibrium of this game. In order to find such an equilibrium, we need to define the system of beliefs and strategies of a potential investor. We allow the system of beliefs to depend on an investor's preferences over two startup attributes:

[2]A very similar objective function is by Bhattacharya (1979) and Leland and Pyle (1976).

the quality of a technology being commercialized and the commitment of the founders. We assume that investor preferences are known by the founders. In this setting, if an investor values the quality of a technology more highly than founder commitment, she will believe that the founders are type H if the ratio of patent investment to FFF money is greater or equal than k, with $k > 0$. The reverse occurs, if an investor values founder commitment. Then, the investor will believe that the founders are type H if $p/M < k$. If the external investor is indifferent between the two aspects of a startup, then she will believe that the founders are type H either if $p/M \geq k$ or if $p/M < k$.

The corresponding investor's strategy will be to invest an amount $\alpha V^j(M_H^*, p_H^*; \theta_H)$ if she believes that the founders are type H and an amount $\alpha V^j(M_L^*, p_L^*; \theta_L)$ otherwise. M_H^* and p_H^* are the amounts that solve H-type founders' constrained maximization problem. Similarly, M_L^* and p_L^* solve the L-type founders' maximization problem.

Given the beliefs' and strategies of an investor, the H-type maximization problem is as follows:

$$\underset{M,p}{Max}\ V(M, p; \theta_H) - b_H p - \rho M$$

s.t.:

(i) $U^H \geq 0$

(ii) $\alpha V(M_H, p_H; \theta_H) + (1-\alpha)V(M_H, p_H; \theta_L) - kb_H p_H - (\rho + g_L)M_H \geq V(M_L^*, p_L^*; \theta_L) - kb_H p_L^* - (\rho + g_L)M_L^*$

(iii) $V(M_H, p_H; \theta_H) - b_H p_H - \rho M_H \geq \alpha V(M_L^*, p_L^*; \theta_L) + (1-\alpha)V(M_L^*, p_L^*; \theta_H) - b_H p_L^* - \rho M_L^*$

(iv) $\overline{M} > M_H^* \geq 0$

(v) $\overline{p} > p_H^* \geq 0$

The first constraint is the participation constraint of H-type founders. The second is the incentive compatibility constraint (IC constraint) for L-type founders, while the third is the

IC constraint for H-type founders. The IC constraints show that a type of founder can mimic the other type only in $t = 1$ because, in $t = 2$, the true type will be revealed. We assume that with asymmetric information, L-type founders find it profitable to mimic H-type founders. This implies that the equity share, α, retained by an investor has to be high enough in order for L-type founders to find it profitable to invest an amount of p and M equivalent to that which maximizes H-type founders utility. This "envy" condition is crucial for the signaling game, because, if this were not the case, H-type founders would not need to differentiate themselves from L-type founders.

In any separating equilibrium, the expected value of a startup, $V^j(M, p; \theta)$, must equal its actual value $V(M, p; \theta)$. Indeed, the IC conditions require the utility of both types of founders being maximized, subject to the market correctly believing that each startup's value equals its true value. The upper bound on M embodies the assumption that the founders, their family and friends are wealth constrained. The upper bound on p stems from the fact that the founders of a startup can only dedicate a limited amount of effort to the production of patentable inventions. We assume that $\min\{|V_{pp}(p, M; \theta)|\,, |V_{MM}(p, M; \theta)|\} > V_{Mp}(p, M; \theta)$, where p and M are evaluated at $\{M_H^*\,, p_H^*\}$. This ensures that while an additional investment in one of the two signals affects the impact of the other signal on $V(p, M; \theta)$, this effect is not too strong.

We restrict our attention to interior solutions of the game and examine how the different structures of an investor's belief affect these solutions.

Proposition 1. *Given the system of beliefs and strategies of an investor, the following separating equilibria arise:*

(i) If an external investor values the quality of a startup's technology relatively more than founder commitment, then the founders' investment in p *and* M *will be such that* $p/M = k$.

(ii) If the external investor values the founder commitment relatively more than quality of a startup's technology, then the founders' investment in p and M will be such that $p/M = z$, with $z < k$.

(iii) If the external investor is indifferent between the quality of a startup's technology and founder commitment, then the founders' investment in p and M will be either $p/M = k$ or $p/M = z$, depending on the values of b_H and ρ.

All of these equilibria are characterized by the external investor investing $\alpha V(M_H^*, p_H^*; \theta_H)$, if a startup is of high value, and $\alpha V(M_L^*, p_L^*; \theta_L) < \alpha V(M_H^*, p_H^*; \theta_H)$, if a startup is of low value. Moreover, a startup of type θ_H invests greater amounts of both M and p than in symmetric information.

Proof. The proof of Proposition 1 is available in the appendix. □

If external investors place more weight on the quality of the founders' technology, then k is equal to the ratio of patent investment, p, which is derived from the IC constraint of L-type founders holding with equality and the investment in FFF money, M, which is derived from the first order condition of the founders' maximization problem. Intuitively, if an external investor places more weight on p than on M, the founders will use their investment in p to distinguish themselves from the low-type founders, thus leading to over-investment in p relative to symmetric information. Because $V_{Mp}(p, M; \theta) > 0$, and therefore, $\frac{dM}{dp} > 0$, an increase in p relative to the optimal amount under symmetric information leads M to be greater than the optimal amount under symmetric information. However, the upper bound on $V_{Mp}(p, M; \theta)$, ensures that the increase in M relative to a situation of symmetric information is lower than that of p.

If external investors value the commitment of the founders more highly, then the reverse occurs. The ratio of p over M will be equal to a constant z, with $z < k$. Intuitively, if external investors place more weight on M than on p, then the increase in M relative to a situation of symmetric information, in which the optimal investments in p and in M are independent of the investors' preferences, will be more pronounced than the increase in p. Because, the reverse occurs if the external investors place more weight on the quality of the founders' technology, then z has to be less than k. Finally, if the investors' beliefs are such that the investors are indifferent to combinations of M and p as long as the IC constraint for L-type founders is met, then H-type founders will choose to invest relatively more in the signal that costs the least in order to signal their type.

As we show in the Appendix, the application of the intuitive criterion proposed by Cho and Kreps (1987) leads to the elimination of all pooling equilibria. To provide intuition, under every configuration of an investor's preferences, a candidate pooling equilibrium could be one in which the founders invest amounts of p and/or M that are smaller than those invested by H-type founders in the separating equilibrium we have outlined. However, such candidate pooling equilibrium would be subject to profitable deviations by H-type founders. Having observed the amounts of p and M invested by the founders, the investor would place a probability of zero on the founders being H types since with constraint (iii) holding with equality, H-type founders would be better off by deviating and providing the equilibrium amounts of p and M. A similar argument can be made for candidate pooling equilibria in which the founders invest amounts of p and/or M that are larger than those invested by H-type founders in our separating equilibrium.

In some instances an external investor might place a relatively high weight on technology value, but at the same time require the founders to invest a positive amount of own money as a signal that they believe in their own venture (Dushnitsky, 2010a; Dushnitsky, 2010b; Lowe and Ziedonis, 2006). In this case, there exists a separating equilibrium such that $p/M' = k'$. Patent investment, p, is still be derived from the IC constraint of L-type founders holding with equality, but this time the investment in FFF money, M, is equal to an amount $M\prime$ set by an external investor as a guarantee that the founders are not behaving opportunistically. Hence, $M\prime$ will be greater than the amount that maximizes the founders' value function. The opposite conclusion is reached if the external investor attaches relatively more importance to founder commitment but requires a positive investment in patents as a guarantee that the startup's technology complies with a minimum standard. In this case, M is still derived from the IC-constraint of L-type founders, while p is equal to an amount $p\prime$ set by the external investor.

Two final points bear mention before turning to estimation. First, when external investors have different preferences over startup attributes, then the founders need to choose which external investors they intend to target with their signals, and, then, the amounts of M and p consistent with the investor's preferences, as in the separating equilibria depicted in Proposition 1. The founders' choice relative to the category of investors would depend on the fraction of equity α, and the founders' costs of investing in patents and FFF money. Second, while we have focused on FFF money and patents, the logic of Proposition 1 can clearly be extended to other signals, such as sweat equity to signal commitment rather than FFF money. If for instance, founder commitment could be signaled by either FFF money or sweat equity and the external investors have no specific preference regarding which signal the founders should use, then the founders of a startup should pick the signal that costs the least. If, instead, the external investors have specific preferences regarding which signal can better convey information on the commitment of the founders, then the latter should pick that signal.

4 Empirical estimation

In this section, we empirically examine the implications of Proposition 1: namely that the founders of high quality technology startups consider patents and FFF money as signals of their company's value and (i) when they use these mechanisms to signal, the number of patents they file is larger (smaller) than the investment in FFF money according to the investor's preferences for high quality technology relative to founder commitment, and (ii) the amount provided by an external investor will be larger the greater the founders' investment in the signal the investor values relatively more. We exploit detailed information available on technology startups located in the Advanced Technology Development Center (ATDC) of the Georgia Institute of Technology. Specifically, we use information on startup investment in patents and FFF money as well as the funds provided by business angels and venture capitalists.

Section 4.1 describes the data, 4.2 explains the empirical models which take into account endogeneity of FFF money and patents, 4.3 gives summary statistics, and 4.4 gives the results.

4.1 Dataset

The ATDC is a technology incubator sponsored by the Georgia Institute of Technology. Founded in 1981, it has hosted a total 226 startups during the period 1998-2008. In addition to ensuring incubation space on entrepreneur-friendly terms, the ATDC has an important role in providing strategic entrepreneurial advice and key business connections to the member companies. To this scope, it employs a staff of approximately 20 experienced managers. Additionally, ATDC makes equity investments in the member companies alongside angel investors and venture capitalists. Although this incubator is located on the campus of the Georgia Institute of Technology, the member companies need not be spinoffs from the university. Indeed, only 40% of those in our sample are university startups. For admission, applicant companies must pass a two-stage review by ATDC managers and only between 10% and 20% are eventually admitted (Rothaermel and Thursby, 2005b). As admission criteria, a company has to be located in Georgia, commercialize a technology which is proprietary in nature, and must have the potential for employing a large number of employees. The majority of the member companies in our sample, 79%, were admitted within the first five years after founding, 11% were admitted within their fifth and their tenth year, while the remaining joined ATDC more than ten years after founding. The majority of the companies, 54%, were active in the information technology sector, while only a small minority (about 5%) were in life sciences.

The ATDC provided information on the 226 startups which they gathered from an annual compulsory survey of member companies. This survey asks information on the company links with the university (e.g., such as commercializing a university technology, employee contracts with university students, informal contacts with the university's faculty), the amount of money they received from business angels and venture capitalists, the amount of FFF money invested by the founders, the number of patents they filed and the number of patents they were awarded. For 80 startups we integrated the information from this survey with information from their business plans submitted to the ATDC at the time of their entry to the incubator. The business plans contain information on the founders, including their age, whether they have family connections, the year and the university at which they obtained either their bachelor and/or master and/or PhD degree. They also include a detailed description of a startup's technology, including the industry sectors in which it should be commercialized. In cases where the business plans were unavailable, we sent a survey to at least one of the founders asking questions on their education background, the stage of their technology at the time of entry in the incubator and the sectors in which their technology was to be commercialized. The response rate was 25%, with 37 responses. The remaining information was obtained from founder web sites or linkedin profiles.

We exclude from the sample those companies joining ATDC more than ten years after founding, since for these companies information was incomplete. This, plus eliminating startups for which we had neither business plans nor survey responses, gave a sample of 117 startups and a total of 471 firm-year observations. The startups in our sample spent at least a year in the incubator during the period 1998-2008. On average a company spent 4.5 years, with a minimum of 1 and a maximum of 8 years. More than half of the startups in the sample had at least one founder who had studied either at the Georgia Institute of Technology or Emory University.

4.2 Estimation Models

To examine the impact of FFF money and patents on venture capital and business angel investment, we estimate two structural models one for each type of investor in which we relate external investment to the startup's investment in patents and FFF money:

$$VC\ BINARY_{it} = \delta_0 + \delta_1 FILED\ PAT_{it} + \delta_2 FFF\ MONEY_{it} + X'_{it}\xi + \epsilon_{it} \quad (1)$$

$$ANGEL\ BINARY_{it} = \varphi_0 + \varphi_1 FILED\ PAT_{it} + \varphi_2 FFF\ MONEY_{it} + X'_{it}\gamma + \eta_{it} \quad (2)$$

VC BINARY$_{it}$ is a dummy which takes the value 1 if the startup i received venture capital funding in year t. Similarly, ANGEL BINARY$_{it}$ is a dummy that takes the value 1 if the startup i received business angel funding in year t. FILED PAT$_{it}$ is the amount of patents filed (in log) in year t. FFF MONEY$_{it}$ is the amount invested in a startup by the founders, their friends, and families in year t (in logs).[3] We also estimate similar equations to those above, using as dependent variables the amount (in logs) invested in year t by venture capitalists in startup i (VC$_{it}$ FUNDS) and the amount (in logs)[4] invested in year t by business angels in startup i (ANGEL$_{it}$ FUNDS).

As discussed in the theory section, FFF money is an alternative to external funding from either type of investor. If this were its only role, then we should expect a negative impact of FFF money on external founding. In contrast, if FFF money were to have a signaling role, and this role were to outweigh the importance of FFF money as a source of funding, then we should expect FFF to have a positive impact on external investment.

With regard to the patent variable, we use the number of patents filed rather than the

[3] Although we only have yearly data and, thus, cannot determine whether, on a given year, the amount of patents or FFF money invested by the founders occurs before or after the investment of the external investors, we feel confident that either investment by the founders occurs just before or simultaneously with the investment of the external investors, and not after. In fact, discussions with ATDC staff as well as with startup founders revealed that external investors require that the founders commit their effort, be it in the form of FFF money or patents or other types of investment, before they invest.

[4] We add 1 to every variable in log. All the nominal variables were converted into real terms by dividing for the yearly consumer price index.

number of patents awarded because the latter would conflate founder use of patents as a productive signal with decision-making on the part of the patent office. In actuality, however, there should be little difference in the results from the two measures since 95% of US PTO patents filed are eventually granted (Quillen et al. 2002). We should also note that while we cannot empirically separate the signaling value of patents from their productive contribution, to the extent that the majority of the startups in our sample operate in the software sector, recent studies point to the importance of the signaling role of patent in this sector. For example, Bessen and Hunt (2007) find that patents as a means to increase a firm's bargaining position is less important for small firms than for large ones, and more to the point, the Berkeley survey finds that for software startups the most important reason to patent is as a reputational signal for external investors (Graham *et al.*, 2009).

X_{it} is a matrix of controls. It includes the variable AV WORK YS, defined as the average number of years the founders worked prior to founding the startup. This variable controls for founder work experience, as well as the founders' "pocket size" since the more years worked the more years of possible savings to invest. The dummy STARTUP EXP controls for whether the founders founded *successful* startups in the past. Serial founders are likely to have developed managerial and technical skills, and built a network of contacts of use in seeking external funds (McGrath and MacMillan, 2000; Shane, 2000). We consider only serial founders of successful startups as Gompers et al. (2010) suggest that unsuccessful serial entrepreneurs have substantially lower chances than successful ones of succeeding in the next venture, and, moreover, the chances of the first category of entrepreneurs are similar to those of first time entrepreneurs. To build the dummy, STARTUP EXP, we collected information from the founders' and the ATDC's websites on the name of the startups the founders had founded in the past and, through extensive web searches. We retained only those startups which either had a successful exit event or as of the time of estimation had a website with updated information on their activities. We include a count, N MASTER, of the founders who had obtained a master's degree in science or engineering, as a measure of founder quality.

We measure the size of a startup with the number of full time employees, FT_{it}.

The control READY FOR MKT bears special mention. It is a dummy which takes the value of one if a technology was ready to be commercialized or was at a manufacturing feasibility stage at the time the startup joined ATDC. To construct this variable, we employed two master's students with engineering backgrounds to independently code the stage of the startups' technology based on the technology description provided in the business plans. The students could choose among the following options: i) proof of concept; ii) prototype; iii) manufacturing feasibility; or iv) ready for the market.[5] For the startups with missing business plans, we used the founder assessment from the survey mentioned above, in which we asked the founder to choose among one of these four options to describe their technology's stage at the time of entry to ATDC. To reduce noise, we combined the four options into the binary alternative ready/not ready for the market.

To control for sector fixed effects, we use a dummy, SOFTWARE, which takes the value of one if a startup were to commercialize a software product. This dummy controls for the fact that 45% of the startups in our sample were offering software products. We also include a dummy, TIME TO ATDC, that controls for whether a startup had joined the incubator within the first five years after foundation. Discussions with startup founders revealed that, holding constant sector effects, one of the most important reasons for early year startups to join ATDC is seeking access to external investment. This factor decreases in importance for startups who join ATDC in their later years, relative to factors such as reaching new markets or making contacts. We include a dummy, GT LINK, which takes the value of one if a startup is commercializing proprietary knowledge of the Georgia Institute of Technology based on an exclusive license. As in Rothaermel and Thursby (2005b), we argue that an incubator firm founded to commercialize a technology from the sponsoring university might have greater incentive to exert effort to ensure the success of the venture than a firm with no such commitment. Finally, we include year dummies to control for time effects.

[5] Where the initial student assessments differed, we engaged the students in a discussion to determine a consistent assessment.

Our central hypothesis is that if FFF money and patents are used as a signal for external investors, then their investment is endogenous to the system. In this case, FFF money and patents are caused by external funding as well as being caused by external funding. This is because the founders of a startup choose their investment in FFF and patents *taking into account* external investors' beliefs and their corresponding investment strategies, and external investors make their investment decisions *based* on the signals they observe. To take the endogeneity of the signals into account we estimate two-stage least squares models. In the case in which the investment by venture capitalists and business angels is treated as a binary outcome we estimate a two-stage least squares linear probability model, which delivers consistent estimates of the average partial effects (Wooldridge, 2002).

Our instruments are measures of the opportunity costs of investing in the signals. Specifically, we include a count variable, CLOSENESS, which takes the value of three if the founders had family connections, two if they were in the same class during either their master or PhD, one if they studied at the same university but not in the same class, and zero otherwise. CLOSENESS is a measure for the opportunity costs of investing a dollar of FFF money (the parameter ρ in our theoretical model), in the sense that the closer are the relational ties among the founders, the less costly it is for them to risk invest their own money[6].

As a proxy for the opportunity cost of a unit of effort devoted to making a patentable invention (the parameter b_H in our theoretical model), we use a variable, PHD,which is defined as the number of founders with a PhD in science or engineering. The underlying logic is that, with a PhD in science or engineering, the founders acquire a knowledge background that reduces the costs of making a patentable invention. This instrument might be correlated to the unobserved quality of the founders and, thus, might not be exogenous. However, discussion with founders as well as with external investors revealed in many instances that

[6] There might be downsides to CLOSENESS as doing business with family and friends could sometimes endanger a close relationship (see for instance Noam Wasserman in://founderresearch.blogspot.com/2005/12/thanksgiving-dinner-with-your.html). However, given that information asymmetries are much lower when relational ties are close, a reasonable assumption is that the costs from endangering a close relationship are still less important than the opportunity costs of investing FFF money when the founders do not know each other well.

good quality technologies are as likely to come from founders with a master's degree -which we account for with our control- as from founders with a PhD's degree. What makes a PhD attractive from the standpoint of producing inventions is that by having access to their laboratory's equipment, PhD students can produce inventions at a lower cost than founders who need to buy the equipment themselves. In our sample, all founders with a PhD degree had founded their startup towards the end of their PhD study, which leads us to conclude that in our case having a PhD degree should principally translate into lower costs of making a patentable invention. Holding a PhD might also mean better access to a network of external investors interested in commercializing university technology, which might affect the likelihood of obtaining external investment. However, to the extent that we observe external investment only for the period in which the startup was located at the incubator and the majority of founders with a PhD had obtained their degree from the Georgia Institute of Technology, then our variable GT LINK is a good control for their network size.

Finally, we include a discrete variable, CYCLE, that takes increasing values the longer the time spent at ATDC and which we use to measure the extent of asymmetric information between startup founders and external investors. The rationale is that, having controlled for the stage of a technology to be commercialized and time effects, the length of time spent at ATDC affects external investors' willingness to finance a startup only indirectly, through the signaling investment decision of the founders.

4.3 Descriptive statistics

The descriptive statistics are given in Table 1. The average business angel and venture capital investment in our startups during their tenure in the incubator are $87,498 and $454,419, respectively[7]. Moreover, 54% of the startups in our sample received no business angel funding, while 57% of them received no venture capital funding. Consistent with DeGennaro (2010) and Shane (2009), only 20% of the startups in our sample received funding from both venture

[7] All figures are expressed in real terms.

capitalists and business angels. Further, with regard to funds raised, our sample of firms is not random. For the period we examine, the business angel and venture capital investments of the average ATDC startup are 24,000 USD and 143,633 USD, respectively. These means are statistically different from the average in our sample at the 1% level.

The average number of patents filed each year by the startups in our sample is 0.65 and the average number of patents granted during the period in question is 0.38. 44% of the companies made no patent applications while in ATDC and 28% were awarded at least one patent. Moreover, 37% of the startups in our sample received at least one round of investment by their founders, and the average amount invested was 27,890 USD.

Software was the most prevalent sector for the startups in our sample (44%) with the remainder in communication (32%), commercialization of hardware products (8%), pharmaceutical, biotechnology, or medical devices (9%), and finally microelectronic products (7%). One hundred and five companies joined ATDC within the first five years from inception. For 32% of the companies, their technology was ready for commercialization or manufacturing feasibility was known when they joined the incubator.

The average number of founders is 2, and 35% of the startups have at least one serial founder. For 7 of the startups, the founders were connected by family links. Nine startups had founders who had been in the same class during their masters and/or PhD studies. Finally, for 12 startups, the founders had been in the same university but not in the same class. The average number of working years prior to founding a startup is 13.6. On average, 1.36 founders had at least a masters in science or engineering and 0.69 had a PhD in these fields[8].

⟨ Insert Table 1 about here ⟩

[8]In Appendix B we present a correlation table.

4.4 Results

The first two columns of Table 2 present the results of endogeneity tests for the number of patents filed and the amount of FFF money invested by the founders, having estimated a regression for the likelihood of receiving venture capital funds and one for the total amount of venture capital funds (in logs). As discussed above, we use as instruments the variables CLOSENESS, PHD, and CYCLE. The endogeneity test rejects the null hypothesis that the regressors are exogenous with a p-value of 0.06, in both the regression for the likelihood of receiving venture capital funds and in that for the total amount of venture capital funds. As reported in the table, the F-statistic for the significance of the instruments is larger than ten in both the equation for FFF money (F-test =14.74) and that for the number of patents filed (F-test =16.57), suggesting that the instruments are not weak. Finally, the results for the Hansen's J test provide an indication that the instruments are valid. Indeed, the results for this test reveal that we cannot reject the null hypothesis that the instruments are valid with and a p-value of 0.57, in the regression for the likelihood of receiving venture capital funds, and a p-value of 0.60, in the regression for the total amount of venture capital funds. Taken together, these findings provide a first indication that, for the startups in our sample, patents and FFF are endogenously determined and might serve as signals to attract venture capital investment.

In Table 3 we present the regression results for the impact of FFF money and patents on venture capital investment. The first two columns report the regression results for the equation in which the dependent variable is the binary outcome, VC BINARY, equal to one if a startup had received a positive amount of venture capital funds on a given year. The last two columns report the regression results for the equation in which the dependent variable is the total amount of funds invested by venture capitalists (in logs).[9] The standard errors we report are clustered by company[10].

[9] The results of the first stage regressions are reported in Appendix C.

[10] We attempted to cluster standard errors by company and year. However, the estimated covariance matrix was not of full rank. As a robustness check we proceeded to partialing out the time dummies as suggested by Baum et al. (2007) and obtained the same qualitative results as if we had clustered standard errors by

The main result that emerges from Table 3 is that the number of patents filed by the founders has a positive and statistically significant impact on both the likelihood of receiving venture capital funding and the amount of funds received. A 1% increase in the number of patents filed increases the probability of venture capital funding by 46%. Moreover, the elasticity of venture capital funding with respect to the founders' investment in patents is 6.7, suggesting a high sensitivity of VC investment to patent investment. The high value of the elasticity should not be surprising given that so many companies in our sample had never filed for a patent, and very few had filed for more than one patent. The investment in FFF does not have a statistically significant impact on venture capital funding. Taken together, the results on the number of patents filed and that on FFF money suggest that venture capitalists care relatively more about the quality of a technology than about the commitment of the founders.

As for the other controls, having founded successful startups in the past has a statistically significant impact on venture capital investment. The magnitude of the coefficients reveal that having founded at least one successful startup in the past increases the likelihood of receiving venture capital funds by 14% and the the elasticity of the amount of funds relative to the investment in patents is 1.9. This result is in line with Gompers et al. (2010) as well as with anecdotal evidence that venture capitalists attach a high value to the past experience of the founders in assessing the quality of a venture. The number of full time employees is positively associated with funding from external investors. This result implies that either larger size startups require more funds from external investors, or, if size is positively correlated with the value of a startup, then higher value startups are positively associated with the investment provided by venture capitalists. Finally, startups that commercialize proprietary knowledge of the Georgia Institute of Technology, via an exclusive licence, have a higher likelihood of receiving venture capital funds and receive a greater amount. This could be due either to the fact that these companies are better quality on average or that they have better access than other startups to the network of venture capitalists.

company only.

Returning to Table 2, the last two columns present the results of endogeneity tests for the number of patents filed and the amount of FFF money invested by the founders, having estimated a regression for the likelihood of receiving business angel funds and one for the total amount of business angels funds (in logs). As before, we use as instruments the variables CLOSENESS, PHD, and CYCLE. The endogeneity test of FFF money rejects the null hypothesis that the regressors are exogenous with a p-value of 0.001 in the regression for the likelihood of receiving business angel funds, and with a p-value of 0.002 in the regression for the amount of funds invested. As before, the results for the Hansen's J test provide an indication that the instruments are valid: we cannot reject the null hypothesis that the instruments are valid with and a p-value of 0.55 in the regression for the likelihood of receiving business angel funds, and a p-value of 0.24 in the regression for the total amount of venture capital funds. Again, our findings suggest that FFF money and the investment in patents are endogenously determined.

In Table 4 we present the regression results for the impact of FFF money and patents on business angel investment. The first two columns of the table report the regression results for the equation in which the dependent variable is the binary outcome, ANGEL BINARY, equal to one if a startup had received a positive amount of venture capital funds on a given year. The last two columns report the regression results for the equation in which the dependent variable is the total amount of funds invested by business angels (in log)[11]. Again, the standard errors we report are clustered by company. Clearly, the main message from Table 4 is that FFF money has a positive impact both on the likelihood and on the amount of business angel funding. The magnitude of the coefficients suggests that an increase by 1% in the amount of FFF money increases the likelihood of business angel funding by 5%, while the elasticity of the total amount of business angel funding with respect to FFF money is 0.50. If the role of FFF money were simply to complement business angel funding then we should have observed a negative coefficient. Having found a positive coefficient suggests that FFF money have some

[11]The results of the first stage regressions are reported in Appendix C.

signaling value for business angels, while the investment in patents does not.

These findings are in line with survey evidence provided by Van Osnabrugge and Robinson (2000) and DeGennaro (2010), and our own interviews of startup founders. In particular, Van Osnabrugge and Robinson (2000) and DeGennaro (2010) show that business angels tend to consider characteristics such as commitment, trust and enthusiasm more than do venture capitalists. Our interviews point to similar conclusions. One of the founders we interviewed argued that business angels are not willing to risk their own money if the founders do not invest any funds of their own, that is unless the founders have some "skin in the game." Finally, other founders pointed to the importance of founder commitment for business angels. As for the other controls, contrary to our results for venture capital investment, neither commercializing proprietary knowledge from the Georgia Institute of Technology nor having past experience as a successful entrepreneur has a statistically significant impact on business angel investment.

Overall, the results in Tables 3 and 4 provide an indication that patents are chosen by the startup founders in our sample to attract venture capital investment but not business angel investment. By contrast, FFF money is used to attract business angel investment but not venture capital investment. More importantly, we find that the impact of patent investment on venture capital investment is very strong and stronger than the impact of FFF money on business angel investment. In the light of our theory, this result suggests that venture capitalists care more about the quality of a startup's technology than business angels care about the commitment of the founders.

⟨ Insert Table 2 about here ⟩

⟨ Insert Table 3 about here ⟩

⟨ Insert Table 4 about here ⟩

4.5 Robustness checks

As a robustness check, we estimate the same models as in Tables 3 and 4 excluding those startups whose external investment (either venture capital or business angel) falls within the 99th percentile. We present the results in Tables 5 and 6.

The results are quite similar. As found in Table 3, the larger the number of patents filed by the founders, the greater the likelihood that startups receive funding from venture capitalists, and the larger the amount received. Moreover, in line with the results in Table 4, the amount invested by the founders, their friends, and their families, is positively associated with business angel investment. In fact, the coefficient of FFF money is positive and statistically significant at the 1% level in the regression for the amount invested by business angels as well as the likelihood that business angel investment occurs. These results confirm an impact of patents on venture capital investment which is larger than the impact of FFF money on business angel investment.

⟨ Insert Table 5 about here ⟩

⟨ Insert Table 6 about here ⟩

5 Concluding remarks

This paper provides a simple model which can be used to frame the problem faced by founders of a high-tech startup who need to signal the company's value to potential investors. We consider the use of patents and FFF money as signals of the quality of the technology and founder commitment, respectively. We find that if an investor values relatively more (less) the quality of a technology being commercialized, then there exists a separating equilibrium where the founders of a high quality startup will make an investment in the number of patents filed that is larger (smaller) than that in FFF money, and the amount invested by the investor will be larger the greater the founders' investment in the signal it values relatively more. If an investor is indifferent between the two attributes of a startup, there exists a separating equilibrium where the optimal proportion with which the two signals are combined will depend on the costs incurred by the high quality startup's founders of investing in each signal. The results of our model can extend to the case of multiple signals. To the extent that the investors' preferences over the different aspects of a startups can be ordered, then the founders of a startup will, in general, invest relatively more in those signals that convey information about the aspect the investors value more highly.

We also provide an empirical analysis using a novel database on technology startups in the incubator of the Georgia Institute of Technology. To evaluate the impact of FFF money and patents on external investment we estimate two structural equation models, which take into the account the endogeneity of the signals. We find that while patents and FFF money are endogenous to venture capital investment, venture capitalists appear to value patents more highly. By contrast, FFF money is strategically used by the founders to attract business angel investment but not venture capital investment. Moreover, we also find that the impact of the number of patents filed on venture capital investment is larger than the impact of FFF money on business angel investment. This result provides an indication that venture capitalists value more the quality of a startup's technology than business angels value the commitment of the founders.

Our empirical results are consistent with evidence found by Hellmann and Puri (2002) that venture backed startups are more likely and faster to bring in outsiders as CEOs, this event often coinciding with the departure of the founders. Therefore, if the founders are to be substituted in case of venture capital financing, then the commitment of the founders should be relatively less important for venture capitalists. Moreover, they are consistent with our discussions with startup founders at ATDC who claimed that business angels often require the founders to have some "skin in the game" as evidenced by FFF money. Finally, they are in line with findings by Cosh et al. (2009) that there are systematic differences in the characteristics of startups that seek capital from venture capitalists and startups that seek capital from banks. Indeed, their findings provide evidence that the preferences of venture capitalists are well defined and distinct from those of other categories of investors.

Taken together our theory and empirics have two important implications for founders or managers of technology startups. The first is that, because investing in signals is costly, it is important to control for the cost of the signals in order to correctly assess their impact on the investment made by external investors. Our empirical model considers the costs of making a patentable invention and the opportunity costs of investing FFF in a startup. Once we take into account these costs, we find that FFF money has a positive impact on business angel investment and that patents have a signaling value for venture capitalists. The second implication is that the founders of a startup, when deciding which signal to invest in and how much to invest, need to consider the preferences of the investors they want to target. Our results, in fact, seem to suggest that patents have a signaling value for venture capitalists but not for business angels, while FFF investment serves as a signal for business angels but not for venture capitalists.

A few caveats are in order. First, the information available from the ATDC incubator does not allow us to assess how investor characteristics affect their preferences. Except for the distinction between venture capitalists and business angels, we do not have information on investors' characteristics such as sectors of specialization, reputation, and education background. These and other characteristics are likely to affect the preferences of external investors as well as their interpretation of the signals they receive. Extending the analysis to include investors' characteristics and the latter's influence on their preferences remains a subject for future research. Second, our data do not allow us to distinguish founders from family and friends investment. The two categories of investment might signal different degrees of commitment to external investors.

Our results are conditional on startups being located at an incubator. We know from previous studies (Colombo and Delmastro, 2002; Cumming and Fischer, 2012) that being member of an incubator is not a random event and member startups have different characteristics from the non-members. In our case, we believe that the distinguishing features of the member startups are their willingness to commercialize technology that is proprietary in nature, their concentration in the information technology sector, and their ties -formal and informal- with the Georgia Institute of Technology. Thus, these results may not generalize to startups located outside of an incubator or to incubators at other academic institutions. Extending the analysis to other university incubators and to a larger sample of startups in general is a venue for future research.

Moreover, for the startups in our sample we observe that they tend to receive either venture capital funding or business angel funding but not both. While this is not a specific feature of our startups (DeGennaro, 2010; Shane, 2009), we believe that it is in part due to the fact that the majority of our startups operate in the information technology sector and, hence, their financial needs are likely to be less stringent than those of startups operating in other sectors, such as life science. We have suggested in our theory that in the case of sequential investment, the founders of a startup would find it profitable to choose the external investors in such a way that they share the same preferences over the attributes of the startup. In fact, this choice would minimize their investment in the signals since the amount invested by the intermediate investor is considered as "credible" signal by the late stage investors. A last clarification on our results is in order. Van Osnabrugge and Robinson (2000) and Shane (2009) have argued that sometimes it is not easy for the founders of a startup to distinguish between friends' and family's money on the one side, and business angel's money on the other. Our own experience by interviewing a sample of startup founders revealed that they considered any investment from friends or family, no matter how wealthy, as FFF money rather than business angel investment.

References

[1] Agrawal A., C. Catalini, and A. Goldfarb. 2011. The Geography of Crowdfunding. SSRN Working Paper Series.

[2] Amit R., L. Glosten, and E. Muller. 1990. Entrepreneurial Ability, Venture Investments, and Risk Sharing. *Management Science*, 36(10): 1232-1245.

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

[4] Baum C. F., M. E. Schaffer, and S. Stillman. 2007. Enhanced routines for instrumental variables/generalized method of moments estimation and testing, The Stata Journal, 7(4): 465-506.

[5] Bessen J., and R. M. Hunt. 2007. An Empirical Look at Software Patents. *Journal of Economics & Management Strategy*, 16(1): 157-189.

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

[7] 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.

[8] Burton M.D., Sorensen J., Beckman, C. 2002. Coming from good stock: career histories and new venture formation. *Research in the Sociology of Organizations*, 19: 229262.

[9] Casson M.. 2003. The Entrepreneur: An Economic Theory. Second Edition, Cheltenham, Edward Elgar.

[10] Cho I.K., and D.M. Kreps. 1987. Signaling Games and Stable Equilibria. *The Quarterly Journal of Economics*, 102: 179-221.

[11] 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.

[12] Colombo, M. G., and M. Delmastro. 2002. How effective are technology incubators? Evidence from Italy. *Research Policy*, 31: 1103-1122.

[13] Cosh A., D. J. Cumming, and A., Hughes. 2009. Outside Entrepreneurial Capital. *Economic Journal*, 119: 1494-1533.

[14] Cumming D. J., and E. Fischer. 2012. Publicly Funded Business Advisory Services and Entrepreneurial Outcomes. *Research Policy*, forthcoming.

[15] Cumming D. J., and S. A. Johan. 2009. Venture Capital and Private Equity Contracting: An International Perspective. Academic Press.

[16] Cumming D. J., and S. A. Johan. 2008. Preplanned Exit Strategies in Venture Capital. *European Economic Review*, 52: 1209-1241.

[17] Cumming D. J.. Contracts and Exits in Venture capital Finance. *Review of Financial Studies*, 21: 1947-1982.

[18] DeGennaro, R. P.. 2012. Angel Investors and their Investments, in D. J. Comming, ed., Oxford Handbook of Entrepreneurial Finance, Oxford University Press, Chapter 13: 392-423.

[19] DeGennaro, R. P.. 2010. Angel Investors: Who They Are and What They Do. Can I Be One, Too?. *Journal of Wealth Management*, 13(2): 55-60.

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

[21] Dushnitsky G.. 2010a. Entrepreneurial Optimism and Venture Capital Valuations. Druid Working Paper Series.

[22] Dushnitsky G.. 2010b. Entrepreneurial Optimism in the Market for Technological Inventions. *Organization Science*, 21(1):150-167.

[23] Engers M.. 1987. Signalling with Many Signals. *Econometrica*, 55: 425-440.

[24] 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.

[25] Goldfarb B., G. Hoberg, D. Kirsch, and A. Triantis. 2009. Does Angel Participation Matter? An Analysis of Early Venture Financing. Working Paper.

[26] Gompers, P. A., J. Lerner, D. Scharfstein, and A. Kovner. 2010. Performance Persistence in Entrepreneurship and Venture Capital. *Journal of Financial Economics*, 96(1): 18-32.

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

[28] 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.

[29] Grinblatt M., and C. Y. Hwang. 1989. Signalling and the pricing of new issues. *Journal of Finance*, 44: 393-420.

[30] 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.

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

[32] Higgins, M.J., P. Stephan, and J. Thursby. 2011. Conveying quality and value in emerging industries: star scientists and the role of learning in biotechnology. Research Policy 40(4): 605-617.

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

[34] Hsu D., and R.H. Ziedonis. 2008. Patents as Quality Signals for Entrepreneurial Ventures. Academy of Management Best Papers Proceedings.

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

[36] Kaplan S. N., and P. Strömberg. 2004. Characteristics, Contracts, and Actions: Evidence from Venture Capitalist Analyses. *Journal of Finance*, 59: 2177-2210.

[37] 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.

[38] Lowe R., and R.H. Ziedonis. 2006. Overoptimism and the Performance of Entrepreneurial Firms. *Managemenr Science*, 52: 173:186.

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

[40] McGrath R.G., and I. Macmillan. 2000. The Entrepreneurial Mindset. Harvard Business School Press: Boston, MA.

[41] Milgrom P., and J. Roberts. 1986. Price and Advertising Signals of Product Quality. *Journal of Political Economy*. 94(4): 796-821.

[42] Parker S. C.. 2009. The Economics of Entrepreneurship. Cambridge University Press.

[43] 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.

[44] Rothaermel F., and M. Thursby. 2005a. University–Incubator Firm Knowledge Flows: Assessing Their Impact on Incubator Firm Performance. *Research Policy*, 34: 305-320.

[45] Rothaermel F., and M. Thursby. 2005b. Incubator Firm Failure or Graduation? The Role of University Linkages. *Research Policy*, 34: 1076-1090 .

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

[47] Shane S. A.. 2000. Prior knowledge and the Discovery of Entrepreneurial Opportunities. *Organization Science*, 11: 448-469.

[48] Shane S. A., and T. Stuart. 2002. Organizational Endowments and the Performance of University Start-ups. *Management Science*, 48: 154 - 170.

[49] Shane S. A.. 2009. Fool's Gold? The Truth Behind Angel Investing in America. Oxford University Press. New York.

[50] Sorensen M.. 2007. How Smart is the Smart Money? A Two-sided Matching Model of Venture Capital. *Journal of Finance,* 62: 2725-2762.

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

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

[53] Stuart T., E. H. Hoang, and R. Hybels. 1999. Interorganizational Endorsements and the Performance of Entrepreneurial Ventures. *Administrative Science Quarterly*, 44: 315-349.

[54] Van Osnabrugge M, and R. J. Robinson. 2000. Angel Investing: Matching Start-Up Funds with Start-Up Companies. Jossey-Bass. San Francisco.

[55] Wong A.. 2010. Angel Finance: The Other Venture Capital, in D. D. Cumming, ed., Venture Capital: Investment Strategies, Structures and Policies, Wiley Press, Chapter 5:71-110.

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

Table1: Variable definition and summary statistics

Variable	Description	Mean	Std. Dev.	N
VC FUNDS	Amount of venture capital funds received by startup *i* in year *t*	454,419	1,608,483	471
VC BINARY	Dummy =1 if startup *i* received venture capital funds in year *t*	0.189	0.392	471
ANGEL FUNDS	Amount of business angel funds received by startup *i* in year *t*	87,498	348,511	471
ANGEL BINARY	Dummy =1 if startup *i* received business angel funds in year *t*	0.166	0.372	471
FILED PAT	Number of patents filed in year *t* by startup *i*	0.654	2.677	471
FFF MONEY	Amount of FFF money invested by startup *i* in year *t*	27,890	155,968	471
MASTER	Number of founders that hold a master's degree in science or engineering	1.361	1.254	471
AV WORK YS	Average number of years the founders worked prior to founding the startup	13.577	7.832	471
STARTUP EXP	Dummy =1 if the founders had founded successful startups in the past	0.306	0.461	471
FT	Number of full time employees in year *t*	16.831	25.029	471
GT LINK	Dummy =1 if a startup is commercializing proprietary knowledge of GeorgiaTech based on an exclusive license	0.202	0.402	471
READY FOR MKT	Dummy =1 if a technology was ready to be commercialized or was at a manufacturing feasibility stage, when startup *i* joined ATDC	0.340	0.474	471
TIME TO ATDC	Dummy =1 if startup *i* had joined the incubator within the first five years after foundation	0.860	0.347	471
SOFTWARE	Dummy =1 if startup *i* were to commercialize a software product	0.418	0.494	471
CLOSENESS	Variable =3 if the founders had family connections, =2 if they were in the same class during either their master or PhD, =1 if they studied at the same university but not in the same class, and =0 otherwise	0.380	0.768	471
PHD	Number of founders with a PhD in science or engineering	0.687	1.098	471
CYCLE	Takes increasing values the longer the time spent at ATDC	3.285	2.082	471

The sample comprises 117 startups that joined the GeorgiaTech's incubator during the period 1998-2008.

Table 2: Endogeneity tests, F-tests of excluded instruments, and tests of overidentifying restrictions

	Likelihood of obtaining venture capital funds		Amount of venture capital funds obtained		Likelihood of obtaining business angel funds		Amount of business angel funds obtained	
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
Endogeneity test	5.720	0.057	5.654	0.059	14.379	0.001	12.862	0.002
F-test of excl. instr. (FFF MONEY)	14.740	0.000	14.740	0.000	14.740	0.000	14.740	0.000
F-test of excl. instr. (FILED PAT)	16.570	0.000	16.570	0.000	16.570	0.000	16.570	0.000
Test of overidentifying restrictions	0.318	0.573	0.271	0.603	0.361	0.548	1.390	0.238

Note : The endogeneity test is an Hausman's specification test which tests for the (joint) endogeneity of FFF MONEY and FILED PAT. The null hypothesis is that the specified endogenous regressors can actually be treated as exogenous.

Table 3: Impact of FFF money and the number of patents filed on venture capital investment

	VC BINARY			VC FUNDS		
	coef.		se	coef.		se
FILED PAT	0.457	***	[0.125]	6.660	***	[1.809]
FFF MONEY	-0.006		[0.017]	-0.114		[0.251]
MASTER	-0.050		[0.049]	-0.763		[0.692]
AVG WORK YS	-0.005		[0.026]	-0.025		[0.366]
STARTUP EXP	0.136	***	[0.050]	1.902	***	[0.691]
FT	0.051	***	[0.016]	0.762	***	[0.227]
READY FOR MKT	-0.053		[0.048]	-0.777		[0.670]
TIME TO ATDC	0.038		[0.050]	0.600		[0.708]
GT LINK	0.099	*	[0.051]	1.337	*	[0.702]
SOFTWARE	0.061		[0.051]	0.861		[0.720]
CONSTANT	0.057		[0.057]	0.715		[1.939]
YEAR fixed effects	YES			YES		
Observations	471			471		
R-squared	0.318			0.327		

Notes: The sample consists of 117 startups with 471 observations. Columns I and II report the results of the IV regression of VC BINARY on the endogenous variables, FILED PAT and FFF MONEY, and other exogenous regressors. Columns III and IV report the results of the IV regression of VC FUNDS on the endogenous variables, FILED PAT and FFF MONEY, and other exogenous regressors. VC BINARY takes the value of 1 if a startup had received venture capital funds. VC FUNDS is defined as the log of the total amount (in real USD) invested in a startup by venture capitalists. FILED PAT is defined as the log of the number of patents filed by the founders of a startup. FFF MONEY is defined as the log of the total amount (in real USD) invested in a startup by its founders, their friends, or their family. As instruments we use the variables CLOSENESS, PHD and CYCLE. CLOSENESS takes the value of 3 if the founders had family connections, 2 if they were in the same class during either their bachelor, master or PhD, 1 if they studied at the same university but not in the same class, 0 otherwise. PHD is defined as the log of the number of founders with at PhD degree in science or enginering. CYCLE takes increasing values the longer the time spent at ATDC. The other exogenous covariates are MASTER, AVG WORK YS, STARTUP EXP, FT, READY FOR MKT, TIME TO ATDC, GT LINK. All regressions include the sector dummy, SOFTWARE, and year dummies.
Standard errors are clustered at the company level. They are reported in brackets next to the coefficient estimates.
***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4: Impact of FFF money and the number of patents filed on business angel investment

	ANGEL BINARY			ANGEL FUNDS		
	coef.		se	coef.		se
FILED PAT	0.251		[0.128]	3.360		[1.583]
FFF MONEY	0.045	***	[0.017]	0.499	**	[0.211]
MASTER	-0.044		[0.052]	-0.550		[0.673]
AVG WORK YS	-0.041		[0.031]	-0.422		[0.386]
STARTUP EXP	0.024		[0.048]	0.275		[0.609]
FT	0.013	*	[0.012]	0.167	*	[0.154]
READY FOR MKT	-0.027		[0.049]	-0.260		[0.619]
TIME TO ATDC	0.030		[0.049]	0.404		[0.632]
GT LINK	-0.031		[0.050]	-0.343		[0.643]
SOFTWARE	0.016		[0.047]	0.150		[0.590]
CONSTANT	0.202		[0.128]	2.159		[1.625]
YEAR fixed effects	YES			YES		
Observations	417			417		
R-squared	0.136			0.146		

Notes: The sample consists of 117 startups with 471 observations. Columns I and II report the results of the IV regression of ANGEL BINARY on the endogenous variables, FILED PAT and FFF MONEY, and other exogenous regressors. Columns III and IV report the results of the IV regression of ANGEL FUNDS on the endogenous variables, FILED PAT and FFF MONEY, and other exogenous regressors. ANGEL BINARY takes the value of 1 if a startup had received business angel funds. ANGEL FUNDS is defined as the log of the total amount (in real USD) invested in a startup by business angels. FILED PAT is defined as the log of the number of patents filed by the founders of a startup. FFF MONEY is defined as the log of the total amount (in real USD) invested in a startup by its founders, their friends, or their family. As instruments we use the variables CLOSENESS, PHD and CYCLE. CLOSENESS takes the value of 3 if the founders had family connections, 2 if they were in the same class during either their bachelor, master or PhD, 1 if they studied at the same university but not in the same class, 0 otherwise. PHD is defined as the log of the number of founders with at PhD degree in science or enginering. CYCLE takes increasing values the longer the time spent at ATDC. The other exogenous covariates are MASTER, AVG WORK YS, STARTUP EXP, FT, READY FOR MKT, TIME TO ATDC, GT LINK. All regressions include the sector dummy, SOFTWARE, and year dummies.

Standard errors are clustered at the company level. They are reported in brackets next to the coefficient estimates.

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5: Impact of FFF money and the number of patents filed on venture capital investment: Excluding startups whose venture capital investment falls within the 99th percentile.

	VC BINARY			VC FUNDS		
	coef.		se	coef.		se
FILED PAT	0.469	***	[0.129]	6.771	***	[1.873]
FFF MONEY	-0.006		[0.018]	-0.093		[0.256]
MASTER	-0.055		[0.050]	-0.816		[0.708]
AVG WORK YS	0.001		[0.026]	0.037		[0.372]
STARTUP EXP	0.132	**	[0.052]	1.855	***	[0.718]
FT	0.053	***	[0.016]	0.774	***	[0.223]
READY FOR MKT	-0.055		[0.048]	-0.842		[0.667]
TIME TO ATDC	0.045		[0.050]	0.679		[0.710]
GT LINK	0.102	**	[0.052]	1.334	*	[0.718]
SOFTWARE	0.055		[0.051]	0.769		[0.715]
CONSTANT	0.066		[0.139]	0.856		[1.951]
YEAR fixed effects	YES			YES		
Observations	458			458		
R-squared	0.309			0.314		

Notes: The sample consists of 114 startups with 458 observations. Columns I and II report the results of the IV regression of VC BINARY on the endogenous variables, FILED PAT and FFF MONEY, and other exogenous regressors. Columns III and IV report the results of the IV regression of VC FUNDS on the endogenous variables, FILED PAT and FFF MONEY, and other exogenous regressors. VC BINARY takes the value of 1 if a startup had received venture capital funds. VC FUNDS is defined as the log of the total amount (in real USD) invested in a startup by venture capitalists. FILED PAT is defined as the log of the number of patents filed by the founders of a startup. FFF MONEY is defined as the log of the total amount (in real USD) invested in a startup by its founders, their friends, or their family. As instruments we use the variables CLOSENESS, PHD and CYCLE. CLOSENESS takes the value of 3 if the founders had family connections, 2 if they were in the same class during either their bachelor, master or PhD, 1 if they studied at the same university but not in the same class, 0 otherwise. PHD is defined as the log of the number of founders with at PhD degree in science or enginering. CYCLE takes increasing values the longer the time spent at ATDC. The other exogenous covariates are MASTER, AVG WORK YS, STARTUP EXP, FT, READY FOR MKT, TIME TO ATDC, GT LINK. All regressions include the sector dummy, SOFTWARE, and year dummies.

Standard errors are clustered at the company level. They are reported in brackets next to the coefficient estimates.

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6: Impact of FFF money and the number of patents filed on business angel investment: Excluding startups whose business angel investment falls within the 99th percentile.

	ANGEL BINARY			ANGEL FUNDS		
	coef.		se	coef.		se
FILED PAT	0.215		[0.160]	2.735		[1.959]
FFF MONEY	0.045	***	[0.017]	0.806	**	[0.212]
MASTER	-0.086	**	[0.086]	-1.075	**	[0.503]
AVG WORK YS	-0.063	**	[0.063]	-0.725	**	[0.363]
STARTUP EXP	0.010		[0.010]	0.102		[0.551]
FT	0.015		[0.015]	0.195		[0.164]
READY FOR MKT	-0.054		[0.043]	-0.623		[0.526]
TIME TO ATDC	0.013		[0.046]	0.139		[0.566]
GT LINK	-0.011		[0.056]	-0.037		[0.695]
SOFTWARE	0.042		[0.042]	0.516		[0.534]
CONSTANT	0.309		[0.122]	3.651	**	[1.504]
YEAR fixed effects	YES			YES		
Observations	417			417		
R-squared	0.120			0.020		

Notes: The sample consists of 112 startups with 446 observations. Columns I and II report the results of the IV regression of ANGEL BINARY on the endogenous variables, FILED PAT and FFF MONEY, and other exogenous regressors. Columns III and IV report the results of the IV regression of ANGEL FUNDS on the endogenous variables, FILED PAT and FFF MONEY, and other exogenous regressors. ANGEL BINARY takes the value of 1 if a startup had received business angel funds. ANGEL FUNDS is defined as the log of the total amount (in real USD) invested in a startup by business angels. FILED PAT is defined as the log of the number of patents filed by the founders of a startup. FFF MONEY is defined as the log of the total amount (in real USD) invested in a startup by its founders, their friends, or their family. As instruments we use the variables CLOSENESS, PHD and CYCLE. CLOSENESS takes the value of 3 if the founders had family connections, 2 if they were in the same class during either their bachelor, master or PhD, 1 if they studied at the same university but not in the same class, 0 otherwise. PHD is defined as the log of the number of founders with at PhD degree in science or enginering. CYCLE takes increasing values the longer the time spent at ATDC. The other exogenous covariates are MASTER, AVG WORK YS, STARTUP EXP, FT, READY FOR MKT, TIME TO ATDC, GT LINK. All regressions include the sector dummy, SOFTWARE, and year dummies.

Standard errors are clustered at the company level. They are reported in brackets next to the coefficient estimates.

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Appendix A: Proof of Propositions 1

We begin by proving Proposition 1 (i).

The utility maximization problem of H-type founders is defined in page 9 of the main text. Given the preferences of the investors, a candidate for a separating equilibrium is one in which p_H^* is derived from condition ii) of the maximization problem being binding and M_H^* is derived from the first order condition for M_H. Thus in this case $p_H^*/M_H^* = k$. This amounts to reducing the problem to a utility maximization in one variable, M_H, while allowing p_H to be derived from condition ii). As mentioned in the paper, we will only consider interior solutions for p_H and M_H. We need to show that a) the solution to M is a maximum; b) H-type participation constraint is satisfied; c) H-type IC constraint is satisfied; d) p_H^* and M_H^* are greater than the corresponding amounts under symmetric information and $\Delta p \geq \Delta M$; and e) the solution to this maximization problem delivers a separating equilibrium that rules out all pooling equilibria and all other separating Nash equilibria that are equilibrium-dominated, *given the beliefs of the investors.*

a) The proposed solution for M is indeed a maximum because $\frac{\partial^2 V(M_H^*,p_H^*;\theta_H)}{\partial M_H^2} < 0$.

b) H-type participation constraint is met. In fact:

$V(M_H^*, p_H^*; \theta_H) - b_H p_H^* - \rho M_H^* >$

$\alpha V(M_H^*, p_H^*; \theta_H) + (1-\alpha)V(M_H^*, p_H^*; \theta_L) - kb_H p_H^* - (\rho + g_L)M_H^* = \overline{U}_L^* > 0$

c) H-type IC constraint is met.

In fact, from 2 we have

$\alpha V(M_L^*, p_L^*; \theta_L) + (1-\alpha)V(M_L^*, p_L^*; \theta_L) - kb_H p_L^* - (\rho + g_L)M_L^* = \alpha V(M_H^*, p_H^*; \theta_H) + (1-\alpha)V(M_H^*, p_H^*; \theta_L) - kb_H p_H^* - (\rho + g_L)M_H^*$

Rewriting we obtain:

$\alpha V(M_L^*, p_L^*; \theta_L) = -(1-\alpha)V(M_L^*, p_L^*; \theta_L) + kb_H p_L^* + (\rho + g_L)M_L^* + \alpha V(M_H^*, p_H^*; \theta_H) + (1-\alpha)V(M_H^*, p_H^*; \theta_L) - kb_H p_H^* - (\rho + g_L)M_H^*$

Inserting this expression into condition 3 and rearranging, we obtain:

$\alpha V(M_H^*, p_H^*; \theta_H) + (1-\alpha)V(M_H^*, p_H^*; \theta_H) - b_H p_H^* - \rho M_H^* \geq$

$\geq -(1-\alpha)V(M_L^*, p_L^*; \theta_L) + kb_H p_L^* + (\rho + g_L)M_L^* + \alpha V(M_H^*, p_H^*; \theta_H) + (1-\alpha)V(M_H^*, p_H^*; \theta_L) - kb_H p_H^* - (\rho + g_L)M_H^* + (1-\alpha)V(M_L^*, p_L^*; \theta_H) - b_H p_L^* - \rho M_L^*$

The expression above can be rewritten as:

$(1-\alpha)[V(M_H^*, p_H^*; \theta_H) - V(M_H^*, p_H^*; \theta_L)] + [b_H(kp_H^* - p_H^*) + g_L M_H^*] \geq$

$\geq (1-\alpha)[V(M_L^*, p_L^*; \theta_H) - V(M_L^*, p_L^*; \theta_L)] + [b_H(kp_L^* - p_L^*) + g_L)M_L^*]$

This condition holds as a strict inequality. In fact:

$[b_H(kp_H^* - p_H^*) + g_L M_H^*] > [b_H(kp_L^* - p_L^*) + g_L M_L^*]$

And:

$[V(M_H^*, p_H^*; \theta_H) - V(M_H^*, p_H^*; \theta_L)] - [V(M_L^*, p_L^*; \theta_H) - V(M_L^*, p_L^*; \theta_L)] = 0$

d) The amounts M_H^* and p_H^* are greater than those under symmetric information p_H^+, M_H^+. Under symmetric information, the "envy" condition in the model ensures that L-type founders find it profitable to cheat and invest the same amounts of M and p as H-types would invest. Therefore, H-types need to invest a greater amount of at least one of the two signals, M and p, relative to a situation of symmetric information in order to differentiate from L-type founders. We will show that both signals are provided in greater quantities but that $\Delta p \geq \Delta M$.

Deriving the IC constraint for the L-type founders with respect to p, we obtain:

$$\alpha \frac{\partial V(M, p; \theta_H)}{\partial p} + (1-\alpha)\frac{V(M, p; \theta_L)}{\partial p} - kb_H = 0 \tag{1}$$

Under symmetric information, the first order condition implies that $\alpha \frac{\partial V(M,p;\theta_H)}{\partial p} + (1-\alpha)\frac{V(M,p;\theta_L)}{\partial p} = b_H$. Using result (1) into the first order condition, we obtain:

$kb_H - b_H \neq 0$

Thus, at the amount of p that meets (1) the first order condition under symmetric information is greater than zero, for $M = M_H^+$, (1). Because $kb_H - b_H > 0$, this implies that $p_H^* > p_H^+$.

As for M, the first order condition derived from the H-type maximization problem yields:

$\frac{\partial V(M,p;\theta_H)}{\partial M} - \rho = 0$

Deriving this expression with respect to p, at $\{M_H^*,\ \mathrm{p}_H^*\}$, we obtain:

$$\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial M^2}\frac{dM}{dp} + \frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial M \partial p} = 0$$

Solving for $\frac{dp}{dM}$, we obtain:

$$\frac{dM}{dp} = -\frac{\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial M \partial p}}{\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial M^2}} > 0$$

This implies that relative to the optimal quantities under symmetric information, an increase in p_H^* leads to an increase of M_H^*. Thus, $M_H^* > M_H^+$. However, because $\min\{|V_{pp}(p, M; \theta), V_{MM}(p, M; \theta$ $V_{Mp}(p, M; \theta)$, then $\left|\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial p^2}\right| > \frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial M \partial p}$. This implies that a unit increase in p causes M to increase by less than a unit.

e) The solution to this maximization problem delivers a separating equilibrium that rules out all pooling equilibria and all other separating Nash equilibria that are equilibrium-dominated, *given the beliefs of the investors*. We apply the intuitive criterion proposed by Cho and Kreps (1987). An equilibrium is said to violate the intuitive criterion if there are some founders of type $i \in \{H, L\}$ who have a deviation that yields a greater payoff than the equilibrium payoff, provided that the investors do not assign a positive probability to the deviation having being made by the other type of founders, for whom this action is equilibrium dominated. Under this criterion, if H-type founders were to invest any amount of p and M greater than the equilibrium amounts, they would still successfully differentiate themselves from L-type founders but they would not earn a greater payoff. Because, M and p are costly to provide, any amount of p and M greater than the equilibrium amounts would yield a lower utility to H-type founders. Moreover, any amounts of p and M smaller than the equilibrium amounts would yield a lower payoff to H-type founders because it would lead the investors to believe that the founders are of type L. Finally, given the preferences of the investors and the lower bound on α, any equilibrium amount of M and p respectively obtained from the IC constraint of L-types and the first order condition for p, would yield a lower payoff to H-type founders because it would lead the investors to believe that the founders are of type L. As for L-type founders, any positive amounts of p and M lower than the equilibrium amounts M_H^* and p_H^* would not change an investor's belief that the founders are of type L. Because the signals are costly, L-type founders' best strategy is to provide the same amounts as under symmetric information: M_L^* and p_L^*. Moreover it is not profitable for L-type founders to provide amounts of p and M greater than the equilibrium amounts. Finally, this criterion also eliminates all possible pooling equilibria. Any pooling equilibrium with p and M smaller than the equilibrium amounts would be subject to deviations by H-type founders. Similarly, any pooling equilibrium with p and M greater than the equilibrium amounts would be subject to deviations by L-type founders. Finally, any equilibrium amount of p and M respectively obtained from the IC constraint of L-types and the first order condition for M, would be subject to deviations by L- and H-type founders.

Proof of Proposition 1 (ii) The proof that, when the preferences of the external investors are such that they believe the startup is an H-type if $p/M < k$, $p_H^*/M_H^* = z$, where M_H^* is derived from condition 2 being binding and p_H^* is derived from the first order condition for p_H, is the same as the proof of Proposition 1 (i). However, we still need to prove that $z < k$. Mimicking the proof of Proposition 1 (i), point d), we find that the increase in p relative to a situation of symmetric information, when external investors value relative more the founders' commitment, is less than the increase, when the external investors value relative more the value of the founders' technology. Similarly we find that the increase in M relative to a situation of symmetric information, when external investors value relative more the founders' commitment, is greater than the increase, when the external investors value relative more the value of the founders' technology. Because, in symmetric information the optimal investments in p and in M do not depend on the preferences of the external investors, thus we conclude that $z < k$.

Proof of Proposition 1 (iii) Same as Proof of Proposition 1 (i).

Appendix B: Correlation Table

⟨ Insert Table B1 about here ⟩

Appendix C: First-Stage Regressions

Table C1 presents the regression results for the impact of the instruments on the number of patents filed and FFF money, adjusting for the exogenous covariates. We use, as instruments, the variables CLOSENESS, PHD and CYCLE. The first two columns report the regression results for the number of patents filed. The last two columns report the regression results for FFF money.

⟨ Insert Table C1 about here ⟩

Table B1: Correlation table

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
(1) VC FUNDS	1.000																
(2) VC BINARY	0.586	1.000															
(3) ANGEL FUNDS	0.049	0.039	1.000														
(4) ANGEL BINARY	0.031	0.062	0.564	1.000													
(5) FILED PAT	0.424	0.251	0.081	0.085	1.000												
(6) FFF MONEY	-0.015	-0.007	0.047	0.061	0.070	1.000											
(7) MASTER	0.100	0.142	0.137	0.059	0.130	-0.048	1.000										
(8) AV WORK YS	0.068	-0.011	0.021	-0.043	0.046	0.076	-0.128	1.000									
(9) STARTUP EXP	0.125	0.245	0.038	0.039	0.010	-0.052	0.085	0.161	1.000								
(10) FT	0.118	0.052	-0.036	-0.103	0.058	-0.067	-0.050	0.128	0.244	1.000							
(11) GT LINK	0.080	0.163	0.077	-0.010	0.031	-0.023	0.282	-0.173	-0.069	-0.083	1.000						
(12) READY FOR MKT	-0.095	-0.117	-0.029	0.006	-0.075	-0.002	-0.021	-0.048	-0.048	0.047	-0.148	1.000					
(13) TIME TO ATDC	0.093	0.132	0.067	0.130	-0.009	0.067	0.107	-0.179	0.029	-0.196	0.172	-0.059	1.000				
(14) SOFTWARE	-0.064	-0.035	-0.084	0.028	-0.106	-0.014	-0.155	-0.083	0.101	-0.033	-0.255	0.201	0.218	1.000			
(15) CYCLE	-0.079	-0.019	-0.059	-0.033	-0.145	-0.144	-0.067	-0.028	-0.093	0.167	0.023	0.031	-0.154	-0.085	1.000		
(16) PHD	0.162	0.154	0.138	0.059	0.202	-0.010	0.682	-0.034	0.049	0.004	0.325	-0.061	-0.002	-0.139	-0.051	1.000	
(17) CLOSENESS	-0.019	-0.020	0.016	0.019	0.107	0.108	0.233	-0.302	-0.185	0.017	0.020	0.112	-0.111	-0.100	-0.003	0.151	1.000

Table C1: First-stage regressions for the number of patents filed and the amount of FFF money invested by a startup's founders

	FILED PAT			**FFF MONEY**		
	coef.		se	coef.		se
MASTER	0.086		[0.056]	-0.566		[0.442]
AVG WORKING YS	-0.022		[0.036]	0.487	*	[0.274]
STARTUP EXPERIENCE	0.008		[0.067]	-0.034		[0.449]
FT	0.041	*	[0.022]	-0.112	**	[0.112]
READY FOR MKT	-0.070		[0.055]	0.473	**	[0.473]
TIME TO ATDC	0.113		[0.085]	0.443		[0.505]
GT LINK	0.060		[0.099]	-0.589		[0.494]
SOFTWARE	-0.092	*	[0.054]	0.437		[0.437]
CLOSENESS	0.039		[0.034]	0.752	***	[0.266]
PHD	0.177	**	[0.084]	-1.373	***	[0.449]
CYCLE	-0.069	***	[0.012]	-0.631	***	[0.120]
CONSTANT	0.432	*	[0.201]	2.338		[1.423]
YEAR fixed effects	YES			YES		
Observations	471			471		
R-squared	0.333			0.342		

Notes: The sample consists of 117 startups with 471 observations. Columns I and II report the results of the regression of FILED PAT on the intruments, CLOSENESS, PHD and CYCLE, as well as other exogenous covariates. Columns III and IV report the results of the regression of FFF MONEY on the instruments, CLOSENESS, PHD and CYCLE, and the other exogenous covariates. All regressions include year dummies.

Standard errors are clustered at the company level. They are reported in brackets next to the coefficient estimates.

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table B1: Correlation table

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
(1) VC FUNDS	1.000																
(2) VC BINARY	0.586	1.000															
(3) ANGEL FUNDS	0.049	0.039	1.000														
(4) ANGEL BINARY	0.031	0.062	0.564	1.000													
(5) FILED PAT	0.424	0.251	0.081	0.085	1.000												
(6) FFF MONEY	-0.015	-0.007	0.047	0.061	0.070	1.000											
(7) MASTER	0.100	0.142	0.137	0.059	0.130	-0.048	1.000										
(8) AV WORK YS	0.068	-0.011	0.021	-0.043	0.046	0.076	-0.128	1.000									
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