NBER WORKING PAPER SERIES

SHOW ME THE RIGHT STUFF: SIGNALS FOR HIGH TECH STARTUPS

Annamaria Conti
Marie C. Thursby
Frank Rothaermel

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 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.

Show Me the Right Stuff: Signals for High Tech Startups
Annamaria Conti, Marie C. Thursby, and Frank Rothaermel
NBER Working Paper No. 17050
May 2011, Revised July 2011
JEL No. G24

ABSTRACT

This paper revisits a central issue in entrepreneurial finance, namely the signals technology startups send to external investors to convey information about their quality. We examine the potential for technology startups to use patents and founders, friends and family money (FFF money) as signals to attract business angel and venture capital funds, patents reflect technology quality and FFF money reflects founder commitment. We find that if investors value technology quality more (less) than founder commitment, the optimal mix of signals is a relatively higher (lower) use of patents than FFF money. Regardless of investor preferences, high quality founders should invest more in both signals than in the absence of private information. This investment is inversely related to the opportunity cost of investing in the signals. We test our predictions empirically and find strong support for our theoretical view that FFF and patents are endogenously determined signals. Moreover, we find that startups who invest in both signals receive greater external funds. When we distinguish between venture capitalist and business angel investment, we find that patents serve as a signal for venture capitalists and FFF money is a signal for business angels (but not vice versa).

Annamaria Conti
Annamaria Conti
800 W. Peachtree St N.W.
Atlanta, GA 30308
annamaria.conti@mgt.gatech.edu

Marie C. Thursby
College of Management
Georgia Institute of Technology
800 West Peachtree Street, NW
Atlanta, GA 30308-1149
and NBER
marie.thursby@mgt.gatech.edu

Frank Rothaermel
Professor Frank Rothaermel
800 W. Peachtree St N.W.
Atlanta, GA 30308
frank.rothaermel@mgt.gatech.edu

1 Introduction

One of the most important issues facing entrepreneurs in technology startups is access to capital (Denis, 2004, Shane and Stuart 2002). With little or no observable history of performance and uncertainty about their technology, a major issue for these entrepreneurs is how to signal their value to potential investors. In the theory of entrepreneurial finance, Leland and Pyle (1976) demonstrate conditions for which entrepreneurs can signal value by their own investment in the startup. For technology startups, however, another potential signal is investment in patents. Indeed, the Berkeley Patent Survey found that securing funds was one of the most important reasons for startups to file for patents (Graham and Sichelman 2008, Graham et al. 2009). Several empirical studies in the management literature also suggest the value of patents as a signal (Hsu and Ziedonis 2008; Haeussler et al. 2009). There is, however, a notable lack of empirical analysis reflecting the fundamental insight from an economic analysis of signals - that the entrepreneur's strategy choice is endogenously determined and that costs are important factors affecting this choice. Indeed, the Berkeley Survey reports that costs are the reason most technology firms give for not patenting.

In addressing this issue we revisit a central issue in entrepreneurial finance, namely the signals technology startups send to external investors to convey information about their quality. We provide a theoretical model of startup investment in signals as the equilibrium outcome of a signaling game in order to frame an empirical analysis of startup signaling. In the theoretical model, startup founders have private information about the quality of the technology underlying their business and they consider two signals: patents as a reflection of the quality of their technology and investment of their own money, or that of their friends and family (FFF) designed to signal their commitment. The theory yields predictions on optimal investment in the two signals as a function of investor preferences and signaling costs. We introduce the notion of investor preferences, which we assume are known to the founders, to account for the fact that different classes of investors, such as business angels and venture capitalists, vary in the extent to which they value different startup characteristics (Osnabrugge and Robinson 2000, Graham et al. 2009). Our empirical analysis is based on data for technology startups housed in the Advanced Technology Development Center of the Georgia Institute of Technology. The analysis provides strong support for our theoretical view that FFF and patents are endogenously determined signals.

The theory applies the insights of Engers (1987) to the financing problem of a technology startup with two potential signals. We show the conditions under which it is worthwhile for startup founders whose technologies have a high probability of success to signal their "quality" as a function of the preferences of a potential investor and the costs of investing in each signal. 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 an investor is indifferent between the two attributes of a startup, the ratio of investment in the two signals will be inversely proportional to their relative cost. In each equilibrium, the optimal investment in patents and FFF money made by high quality startups is negatively affected by the cost of investing in the signals.

Our empirical analysis uses 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 rounds of business angel and venture capitalist funding, the amount of FFF 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.

Empirically we find that patents and FFF money, indeed, are endogenously determined. We therefore take into account the endogeneity of a founder's choice by estimating a structural model which relates the cost of the signals to the choice of signals, and the latter to the external investment. Consistent with the model's predictions, investing in both signals has a greater impact on external investment than investing in only one of the signals.

We also consider the impact of patents filed and FFF on venture capitalist and business angel investments, respectively. We estimate two structural equation models, one for each type of investor, which take into account the endogeneity of the signals. These models relate FFF money and patents to their investment costs, and the investment in FFF money and patents to the financing provided by venture capitalists and business angels, respectively. We find that, having taken into account the costs of investing in the signals, patents have a signaling value for venture capitalists but not business angels, while FFF money serves as a signal for business angels but not venture capitalists.

Informational issues and quality variation among startups is well documented in the literature on entrepreneurial finance, but 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 2001, Hsu 2004, and 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.

Although several recent studies in the literature on strategic management highlight the value of patents as signals, they abstract from the entrepreneur's decision problem. For example, Hsu and Ziedonis (2008) 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, with the signaling value being higher in earlier rounds and when funds are obtained from more prominent investors. Haeussler et al. (2009) find similar results for a sample of German and British biotechnology companies. They focus on patents as signals in the limited sense that they are positively correlated with performance.

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 (2009) estimates expected returns on business angel investment and find that Angel investors earn similar returns to those earned by venture capitalists. Wong (2002) 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.

The remainder of the paper is organized as follows. Section two introduces the model. Section three describes the solution of the signaling game. Section four presents an empirical estimation of the theory. Section five concludes.

2 Setup of the model

We construct 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 define the startup's type by whether its technology has a high or low probability of success.

As in Engers (1987) and Grinblatt and Hwang (1989), we consider two potential signals, each of which conveys information on different aspects of the firm's type. The two signals we consider are the number of patents filed (or granted) 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. 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 probability of success.

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 addition to allowing the startup to earn rents from its inventions, patents generate value by facilitating the sale of rights to interested parties or by increasing the startup's bargaining position in negotiations with other patent holders or established firms with complementary assets (Cohen, Nelson, and Walsh 2000, Arora and Ceccagnoli 2006, and Gans, Hsu, and Stern 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 $\theta_H > \theta_L$[1]. Each type generates a value, $V(p, M; \theta)$, which depends on the investment of the founders in patents, p, the amount the founders, their friends and families, invest in the startup, M, and the technology, θ. 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, respectively, about the quality of the technology and the founders' commitment to the startup.

We assume that $V(p, M; \theta)$ is an increasing strictly concave function of p and M. At each point, the derivatives of $V(p, M; \theta)$ with respect to p and M are the same for both 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 in 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. Note that $r(p)$ is the cost of a patented invention, inclusive of the opportunity cost of the effort made to develop the invention. For H-type founders

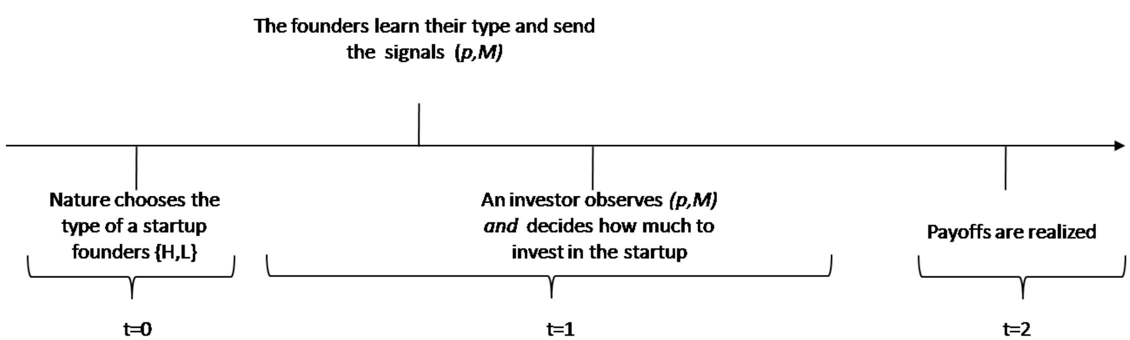
[1] θ_H and θ_L are also referred in the text as high quality and low quality startups, respectively.

$r(p)$ 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, $\rho > 0$, 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 foregone 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 can represent the premium as zero for high quality startup and $g_L > 0$ for a low quality startup.

Based on the amount of each signal observed, an investor chooses 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]:

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

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

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 family or diverted from alternative uses by the founders.

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

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

where $W_2(p, M; \theta)$ 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.

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: the quality of a technology being commercialized (QT) and the commitment of the founders (C). We assume that investor preferences are known by the founders, and we consider the case in which all external investors share the same preferences. In this setting, if an investor values QT more highly than C, she will believe that the founders are of type H if they invest more in p than a threshold p_s, which is is the level of p at which L-type founders are indifferent between mimicking an H-type and revealing their true type, for a given M. The reverse occurs, if an investor values C more highly. Then, the investor will believe that the founders are of type H if $M \geq M_s$, and the increment in M relative to a situation of symmetric information is at least equal to the increment in p. M_s is the investment which makes L-type founders are indifferent mimicking the H-type and revealing their true type, for a given p. and the increment in p (relative to a situation of symmetric information is at least equal to the increment in M). Finally, if an investor is indifferent between the two attributes, her beliefs will not be affected by the relative levels of M and p, as long as L-type founders do not find it profitable pretend they are of type H.

Hence, the investor's beliefs in and off the equilibrium path can be formalized as:

$$
\begin{aligned}
b(H \mid (M,p)) &= 1 \text{ if } M \geq M_s \text{ and } \Delta M \geq \Delta p, \text{ provided that } C \succ_I QT \\
&= 0 \text{ otherwise} \\
\\
&= 1 \text{ if } p \geq p_s \text{ and } \Delta M \leq \Delta p, \text{ provided that } C \prec_I QT \\
&= 0 \text{ otherwise} \\
\\
&= 1 \text{ if either } M \geq M_s \text{ or } p \geq p_s, \text{ provided that } C \sim_I QT \\
&= 0 \text{ otherwise}
\end{aligned}
$$

ΔM and Δp are the increments in M and in p, respectively, relative to a situation of symmetric information. 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 of 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^* are the amounts solving L-type founders' maximization problem.

Given the beliefs' and strategies of an investor, 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 founders 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 the investors, the following separating equilibria arise:*

(i) If $C \succ_I QT$, then H-type founders will choose M such that the IC constraint of type L-founders holds as equality and p such that the first order condition is satisfied.

(ii) If $C \prec_I QT$, then H-type founders will choose p such that the IC constraint of type L-founders holds as equality and M such that the first order condition is satisfied.

(iii) If $C \sim_I QT$, then H-type founders will choose M such that the IC constraint of type L-founders holds as equality and p such that the first order condition is satisfied, provided that $\Delta > 0$. Conversely, if $\Delta < 0$, then H-type founders will choose p such that the IC constraint of type L-founders holds as equality and M such that the first order condition is satisfied. Δ is the difference between the utility H-types would achieve if they were to choose p from the corresponding first order condition and M so as to satisfy the IC constraint of type L-founders and the utility they would achieve if they were two choose M from the corresponding first order condition and p so as to satisfy the IC constraint of type L-founders. Moreover, $\frac{\partial \Delta}{\partial b_H} < 0$ and $\frac{\partial \Delta}{\partial \rho} > 0$.

All these equilibria have the IC constraint of type H-founders hold as a strict inequality. Moreover, they survive the elimination of all separating Nash equilibria that are equilibrium-dominated and the elimination of all pooling equilibria.

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

Corollary 1. *All separating equilibria outlined in Proposition 1 are characterized by θ_H investing greater amounts of both M and p than in symmetric information.*

If an investor places more weight on founder commitment, then H-type founders will invest an amount of M such that the IC constraint of L-type founders holds with equality. As shown in the appendix, this amount is greater than that under symmetric information, and its increment relative to a situation of symmetric information is greater than that of p. The intuition is the following. Because $V_{Mp}(p, M; \theta) > 0$, and therefore, $\frac{dp}{dM} > 0$, an increase in M relative to the optimal amount under symmetric information leads p 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 p relative to a situation of symmetric information is lower than that of M. The rationale is that if an investor values founder commitment more highly, she will be inclined to believe that the founders are of type H provided that the latter invest relatively more in M in order to signal their quality. As is standard in signaling theory, amounts of M greater than M_s are not chosen by H-type founders because they are equilibrium dominated. If an investor values the quality of the technology more highly, then the reverse occurs. Finally if an investor's beliefs are such that he is 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 a 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 a candidate pooling equilibrium would be subject to profitable deviations by H-type founders. In fact, 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. Now, we know from condition condition (iii) holding as a strict inequality, that 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.

As we have mentioned above, the assumption $V_{Mp}(p, M; \theta) > 0$ ensures that, regardless of investor preferences, H-type founders invest more in both signals than they would in the absence of asymmetric information.

Proposition 2. *Provided the solutions of p and M are interior, then:*

(i) if $C \succ_I QT$: $\frac{\partial M_H^*}{\partial \rho} < 0$, $\frac{\partial p_H^*}{\partial b_H} < 0, \frac{\partial M_H^*}{\partial g_L} < 0$;

(ii) if $C \prec_I QT$: $\frac{\partial M_H^*}{\partial \rho} < 0, \frac{\partial p_H^*}{\partial b_H} < 0$, $\frac{\partial p_H^*}{\partial k} < 0$;

(iii) If $C \sim_I QT$ and $\Delta > 0$: $\frac{\partial M_H^*}{\partial \rho} < 0$, $\frac{\partial p_H^*}{\partial b_H} < 0, \frac{\partial M_H^*}{\partial g_L} < 0$. Conversely, if $C \sim_I QT$ and $\Delta < 0$:$\frac{\partial M_H^*}{\partial \rho} < 0, \frac{\partial p_H^*}{\partial b_H} < 0$, $\frac{\partial p_H^*}{\partial k} < 0$.

Proof. The proof of Proposition 2 is available in the appendix. □

In case (i), an increase in the opportunity cost, ρ, of investing in M and in the cost of investing in p, b_H, reduce the optimal amounts M_H^* and p_H^* H-types are willing to invest in the project. Moreover, an increase in the risk premium, g_L, L-type founders have to pay to their friends and families for each dollar they lend makes more onerous for L-type founders to mimic H-types. This, in turn, induces H-type founders to reduce the amount of M they provide as a signal. In case (ii), as before, an increase in ρ and b_H triggers a reduction in M_H^* and p_H^*, and an increase in k reduces the incentive for L-type founders to mimic H-types. Finally, case (iii) is identical to case (i) if $\Delta > 0$, and to case (ii) if $\Delta < 0$.

We have assumed that external investors share the same preferences over the two startup attributes. The results in Propositions 1 and 2 easily extend to a situation where investors differ in their preferences over startup attributes. With more than one category of investors, the founders would first need to choose the investor category they intend to target with their signals, and, then, the amounts of M and p consistent with an investor's preferences, as in the separating equilibria depicted in Proposition 1. The comparative statics in Proposition 2 would automatically follow. 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.

4 Empirical estimation

In this section, we examine the model's predictions in the context of technology startups in the Advanced Technology Development Center (ATDC) of the Georgia Institute of Technology. The analysis exploits the prediction in Corollary 1 that, regardless of investor preferences, signaling firms will invest relatively more in both patents and FFF money and their investments should be negatively related to the signals' costs. The availability of business angel and venture capital funding for the ATDC startups also allows us to explore the extent to which the two categories of investors view patent and FFF money as signals. 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 provided information on 226 startups that spent time in the incubator during the period 1998-2008. Although this incubator is located on the campus of the Georgia Institute of Technology, the member companies need not be spinoffs of the university. For admission, they must pass a two-stage review by ATDC managers (Rothaermel and Thursby 2005b). Every year, ATDC administers a compulsory survey which includes information on the amount of money they receive from business angels and venture capitalists, the amount of FFF money invested by the founders and the number of patents they filed.

For 80 startups we integrated the information from this survey with information from the business plans the companies submitted to the ATDC, at the time of entry in the incubator. These 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 available from founder web sites or linkedin profiles.

We excluded from the sample companies joining ATDC more than ten years after founding. This plus eliminating those startups for which we did not have a business plan or whose founders had not answered to our survey yields 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. Almost half of the startups in the sample had at least one founder who had studied either at the Georgia Institute of Technology or at Emory University.

4.2 Estimation Models

4.2.1 Signals and external investment

The theory predicts that in any separating equilibrium, H-type founders invest more in both signals than otherwise, regardless of investor preferences. To test this, we estimate the impact on external investment of an ordinal outcome variable, ORDER SIGNAL, which takes the value of zero if the founders invested in neither signal, one if they invested in only one, and two if they invested in both.

We estimate a simultaneous equation model which takes into account the endogeneity between the signals and external funding. That is, it is possible for FFF money and patents to be caused by external funding and for them to cause external funding. This is because in a signaling game 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.

The model relates (i) the financing provided by venture capitalists and business angels to the founders' signaling decision, as measured by the ordinal outcome variable, ORDER SIGNAL; and (ii) the founders' signaling decision to the founders' costs of investing in the signals. An alternative estimation specification would assess the impact on total financing of dummies indicating whether the founders invested in patents or FFF money and the interaction of these two dummies. Given the endogeneity concerns, this would entail a system of four equations, one for total financing, and the other three for the FFF money dummy, the patent dummy and the interaction between the two dummies (Wooldridge, 2002). This is not feasible given our sample size, hence we specify the ordinal outcome variable ORDER SIGNAL and the two equation structural system.

Equation one below relates external funding by venture capitalists and business angels[3], TOT FUND, to the endogenous variable, ORDER SIGNAL, as well as other exogenous covariates. In the latter category we include the variable AV WORK YS, which is defined as the average number of years the founders worked prior to founding the startup. This variable controls for the "pocket size" of the founders and, hence, the greater is the average number of years the founders have worked since graduation, the greater the amount of money available to invest in the company. This variable also controls for founder work experience. Moreover, we include the dummy STARTUP EXP to control for whether the founders had founded other startups in the past. In fact, serial founders are expected to have developed managerial and technical skills, and built a network of contacts, that will help them identify new business opportunities and obtain more easily external sources of funds (McGrath and MacMillan, 2000; Shane, 2000). We measure the size of a startup with the number of full time employees, FT.

We also include a dummy, READY FOR MKT, which takes the value of one if a technology was ready to be commercialized or was at a manufacturing feasibility stage, at the time a startup had joined ATDC. We constructed this variable with input from two MBA students with engineering backgrounds who separately coded the startup technology stage based on the technology description

[3]All the nominal variables were converted into real terms by dividing for the yearly consumer price index.

given in the business plan. The students could choose among the following options: i) proof of concept; ii) prototype; iii) manufacturing feasibility; or iv) ready for the market. For those startups without business plans, we asked the founders to choose among these to describe the technology stage at the time the startup joined ATDC. In order to reduce noise, we opted for combining the four options into the binary alternative ready/not ready for the market. The dummy variable, TIME TO ATDC, 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. Moreover, the dummy variable, COM ROUND controls for whether external investment in a given year has been provided jointly by business angels and venture capitalists.

Finally, we include year as well as industry dummies. Of the startups in our sample, 75% operated in the information technology sector, mainly offering software products. We therefore use a dummy, HEALTHCARE, that takes the value of one if a company's software is intended for the healthcare industry; a dummy, TELECOM, that takes the value of one if its software is intended for the telecommunication industry; a dummy, OTHER SOFTWARE, that takes the value of one if its software is destined to other industries than healthcare and telecommunications; a dummy, HARDWARE, that takes the value of one if a startup is intended to commercialize hardware products. We also include a dummy, PHARMA MDEV, that takes the value of one if its products are for the pharmaceutical, biotech and medical device sectors; and a dummy, OTHER, which is one for the remaining startups. The latter operate mainly in the manufacturing sector. The inclusion of industry dummies allows to capture technology differences across sectors, as well as other differences such as that in the effectiveness of patents as an appropriability mechanism for protecting profits derived from product innovation (Cohen et al., 2000).

As shown in equation two below, we instrument ORDER SIGNAL using the following variables: CLOSENESS, MASTER, and CYCLE. CLOSENESS is a count variable that takes the value of three if the founders had family connections, two if they were in the same class during either their bachelor or 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 founders, friends and family 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 investing their own money[4]. MASTER is defined as the number of founders with at least a master's degree in

[4]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,

science or engineering. This variable is a measure for the opportunity cost of a unit of effort devoted to making a patentable invention (the parameter b_H in our theoretical model). The underlying logic is that, with a masters in science or engineering, the founders acquire a knowledge background that reduces the costs of making a patentable invention. Finally, CYCLE is a discrete variable 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. Having controlled for the stage of a technology to be commercialized, which we expect to have a direct impact on external investors' funding decisions, the length of time spent at ATDC should affect external investors' willingness to finance a startup only through the signaling investment decision of the founders.

We estimate the simultaneous equation model using two-stage least squares.

$$\begin{aligned}
TOT\ FUND_{it} &= \beta + \beta_1 ORDER\ SIGNAL_{it} + \beta_2 AV\ WORK\ YS_i + \beta_3 STARTUP\ EXP_i + \\
&\quad + \beta_4 FT_{it} + \beta_5 TIME\ TO\ ATDC_i + + \beta_6 READY\ FOR\ MKT_i \\
&\quad + \beta_7 COM\ ROUND_{it} + \beta_8 INDUSTRY\ D_i + \beta_9 YR\ D_i + \xi_{it} \qquad (1)\\
ORDER\ SIGNAL_{it} &= \alpha + \alpha_1 AV\ WORK\ YS_i + \alpha_2 STARTUP\ EXP_i + \alpha_3 FT_{it} + \alpha_4 TIME\ TO\ ATDC_i + \\
&\quad + \alpha_5 READY\ FOR\ MKT_i + \alpha_6 COM\ ROUND_{it} + \alpha_7 CLOSENESS_i + \\
&\quad + \alpha_8 MASTER_i + \alpha_9 CYCLE_{it} + \alpha_{10} INDUSTRY\ D_i + \alpha_{11} YR\ D_i + \varepsilon_{it} \qquad (2)
\end{aligned}$$

Because the distribution of external funds is highly skewed we also present the regression results of a simultaneous equation model in which we measure external funds as a binary outcome (FUNDS BINARY). We use two-stage least squares which deliver consistent estimates of the average partial effects and require few distributional assumptions (Wooldridge, 2002).

4.2.2 Signals, venture capital, and business angel funding

To investigate differences in business angel and venture capitalist responsiveness to signals, we analyze the impact of FFF money and the investment in filed patents on venture capital and business angel investment, respectively (equation three below). As we argued, we expect investment in signals to raise the issue of endogeneity. This is because startup founders make their investment in FFF money and patents, taking into account the beliefs and investment strategies of venture capitalists and business angels, and, at the same time, venture capitalists and business angels make their investment decisions based on the signals they observe.

As reported in equations four and five, we use as instruments for the FFF money and patent equations the variables CLOSENESS, MASTER and CYCLE. The first two variables capture the

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.

opportunity cost of investing FFF money in a startup and the cost of making a patentable invention, respectively. The third measures the extent of asymmetric information between the founders and external investors. We relate each signal to both the opportunity cost of investing in FFF money and the cost of making a patentable invention because an increase in the cost of one of the signals might indirectly impact the investment in other signal by making it relatively cheaper. As exogenous covariates, in equations three to five, we use the average number of years the founders worked prior to founding the startup, whether the founders founded other startups in the past, the employment size of a startup, the stage of a technology, whether a startup had joined the incubator within the first five years since inception, industry and year dummies. We estimate the two systems of equations using two-stage least squares.

$$\begin{aligned}
FUNDS_{itj} &= \varphi + \varphi_1 FILED\ PAT_{it} + \varphi_2 FFF\ MONEY_{it} + \varphi_3 AV\ WORK\ YS_i + \\
&\quad + \varphi_4 STARTUP\ EXP_i + \varphi_5 FT_{it} + \varphi_6 TIME\ TO\ ATDC_i + \varphi_7 READY\ FOR\ MKT_i + \\
&\quad + \varphi_8 COM\ ROUND_{it} + \varphi_9 INDUSTRY\ D_i + \varphi_{10} YR\ D_i + \tau_{it} \qquad (3) \\
FILED\ PAT_{it} &= \gamma + \gamma_1 AV\ WORK\ YS_i + \gamma_2 STARTUP\ EXP_i + \gamma_3 FT_{it} + + \gamma_4 TIME\ TO\ ATDC_i \\
&\quad + \gamma_5 READY\ FOR\ MKT_i + \gamma_6 COM\ ROUND_{it} + + \gamma_7 CLOSENESS_i \\
&\quad + \gamma_8 MASTER_i + \gamma_9 CYCLE_{it} + \gamma_{10} INDUSTRY\ D_i + \gamma_{11} YR\ D_i + \eta_{it} \qquad (4) \\
FFF\ MONEY_{it} &= \delta + \delta_1 AV\ WORK\ YS_i + \delta_2 STARTUP\ EXP_i + \delta_3 FT_{it} + \delta_4 TIME\ TO\ ATDC_i \\
&\quad + \delta_5 READY\ FOR\ MKT_i + \delta_6 COM\ ROUND_{it} + + \delta_7 CLOSENESS_i \\
&\quad + \delta_8 MASTER_i + \delta_9 CYCLE_{it} + \delta_{10} INDUSTRY\ D_i + \delta_{11} YR\ D_i + \varsigma_{it} \qquad (5)
\end{aligned}$$

where j is either venture capital or business angel funds. Because venture capital and business angel investment are highly skewed we will also present the regression results of a simultaneous equation model in which we measure venture capital and business angel funds as binary outcomes (VC BINARY and ANGEL BINARY).

4.3 Descriptive statistics

Descriptive statistics are presented in Table 1. The average business angel and venture capital investment in our startups over their tenure in the incubator are \$87,498 and \$454,419, respectively[5]. 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's (2009), only 20% of the startups in our sample received funding from both venture capitalists and business angels.

[5] All figures are expressed in real terms

A test of significance of the means rejects at the 1% confidence level the null hypothesis that the startups in our sample received on average the same amount of business angel and venture capital funding as did the remaining startups housed at ATDC. Indeed, the average amount of business angel investment received by this second category of startups is only $24,000, and the average amount of venture capital investment is $143,633. This is a clear indication that our sample of 117 firms is not random with respect to all firms in ATDC in that they tend to be more successful at raising funds.

The average number of patents filed each year by a startup's founders in our sample during the time spent at the incubator is 0.65. 44% of the companies did not file any patent while at the ATDC. 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.

Of the total number of startups, 14% intended to provide software products for the telecommunication industry, 9% for healthcare industry, 44% for other sectors. Moreover, 8% of them were involved in commercializing hardware products, 9% operated in the pharmaceutical, biotechnology, and medical devices sectors, while the remaining were mainly operating in the manufacturing sector. One hundred and five companies joined ATDC within the first five years from inception. Thirty-two percent of the companies had their technology ready for commercialization or at the manufacturing feasibility stage when they had joined the incubator.

The average number of founders is 2, and 56% of the startups had at least a serial founder. In the case of 7 startups the founders were connected by family links. Nine startups had founders that had been in the same class during their master and/or PhD studies. Finally, in the case of 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 and, on average, 1.36 founders had at least a master in science or engineering.

⟨ Insert Table 1 about here ⟩

4.4 Results

We first present the regression results for the impact of FFF money and patents on total external investment. We then show the results for the impact of FFF money and patents on venture capital and business angel investment, separately. The standard errors we report are clustered by company.

4.4.1 Impact of FFF money and patent investment on external investment

Table 2 presents the regression results for the impact of the ordinal outcome, ORDER SIGNAL, on external investment, having taken the endogeneity of ORDER SIGNAL into account. All variables, except for ORDER SIGNAL, the dummies, and the CLOSENESS index, are expressed in logs. We report the results for equation one only, because we are interested in testing the theoretical prediction that, regardless of investor preferences, the founders of a high quality startup will invest greater amounts of patents and FFF money to secure external funding. The first two columns report the regression results for equation one where the dependent variable is the total amount of funds provided by external investors. The last two columns report the regression results for a similar equation where we use as a dependent variable the binary outcome, FUNDS BINARY, which is equal to one if a startup had received a positive amount of funds on a given year.

The endogeneity tests of ORDER SIGNAL, which we present at the bottom of Table 2 for each equation specification, reject the null hypothesis that ORDER SIGNAL is an exogenous regressor with a p-value of 0.00. In line with our expectations, this result suggests that endogeneity is indeed an issue. To check for weak instruments we use the standard rule-of-thumb that the F-statistic for joint significance of the instruments in the equation of the endogenous regressor on the instruments be larger than ten. As reported at the bottom of table 2, the F-statistic is 29.47, which leads us to conclude that our instruments for ORDER SIGNAL are not weak. Moreover, the Hansen's J statistics for overidentifying restrictions has a p-value of 0.91, in the equation with TOT FUNDS, and a p-value of 0.96, in the equation with FUNDS BINARY, which provides an indication that the instruments are valid.

Having controlled for the endogeneity of the founders' signaling choice, the impact on external funds is positive and statistically significant at the 1% level in both equation specifications. Thus, for this sample, startups that invest in both FFF money and patents have a higher likelihood of obtaining external investment and receive higher amounts than startups that either invest in only FFF money or patents, or those that do not make any investment.

Interestingly, having founded startups in the past does not have a statistically significant impact on venture capital investment. This result might be explained by the fact that we are not able to distinguish between the founders who created successful startups in the past and those with unsuccessful startups. Gompers et al. (2010) show that this distinction is indeed important, as unsuccessful serial entrepreneurs have substantially lower chances than successful ones of succeeding in the next venture, and, moreover, the changes of the first category of entrepreneurs are similar to those of first time entrepreneurs. While Gompers et al.'s focus is on ventures' probability of success, it is very likely that the same applies to the probability of obtaining external funds and to their total amount. The number of full time employees is positively associated with funding from external investors. Finally, external funds tend not to be sector specific, the industry dummies being statistically insignificant.

⟨ Insert Table 2 about here ⟩

4.4.2 Impact of FFF money and patents filed and on venture capital investment

Table 3 reports the regression results for the impact of FFF money and the investment in patents on venture capital funding. The first two columns report the regression results for equation three where the dependent variable is the total amount of funds invested by venture capitalists. The last two columns report the regression results for a similar equation where we use as a dependent variable the binary outcome, VC BINARY, which is equal to one if a startup had received a positive amount of venture capital funds on a given year[6].

The endogeneity test of FFF money and the number of filed patents rejects the null hypothesis that the regressors are exogenous at the 10% level, in both equation specifications. Again, this suggests that investment in patents and FFF money is endogenous to the system. Moreover, the F-statistic for joint significance of the instruments is larger than ten in both the equation for FFF money and that for the number of patents filed, suggesting that the instruments are not weak. Finally, the results for the Hansen's J test provide an indication that the instruments are valid.

The main results that emerge from Table 3 are that the number of patents have a positive and statistically significant impact on both the likelihood of receiving venture capital funding and the amount of funds received. Conversely the investment in FFF does not have a statistically significant impact on venture capital funding.

The result on the positive impact of the number of patents filed on venture capital investment, all else equal, provides support to the signaling value of patents for venture capitalists. Since the majority of the startups in our sample provide software products, our findings are consistent with the survey results reported by Graham and Sichelman (2008) and Graham et al. (2009) that patenting by information technology startups is mainly pursued for signaling purposes rather than for appropriability reasons. Moreover, the result of FFF money on venture capital financing is in line with the findings by Hellmann and Puri (2002) who show that venture backed startups are more likely and faster to bring in outsiders as CEOs, this latter event often coinciding with the departure of the founders. Therefore, if the founders are to be substituted in case of venture capital financing, then commitment by the founders is relatively less important for venture capitalists.

[6]The regressions results of FFF money and the number of filed patents on instruments and other exogenous covariates are reported in the appendix

⟨ Insert Table 3 about here ⟩

4.4.3 Impact of FFF money and patents filed and on business angel investment

Table 4 reports the regression results for the impact of FFF money and the investment in patents on business angel funding. As before, the first two columns report the regression results for equation three where the dependent variable is the amount of funds invested by business angels. The last two columns report the regression results for a similar equation in which the dependent variable is the binary outcome, ANGEL BINARY, equal to one if a startup had received a positive amount of business angel funds on a given year.

The endogeneity test of FFF money and the number of filed patents rejects the null hypothesis that the regressors are exogenous at the 1% level, in both equation specifications. As before, the results for the Hansen's J test provide an indication that the instruments used are valid.

Table 4 shows that the amount of FFF money invested has statistically significant impact, at the 1% level, on the likelihood of obtaining business angel funds, and at the 5% level, on the amount of funds received. These results could be the outcome of two factors. The first is the signaling value of FFF money. The second is the role of FFF money as a source of new capital. Cumming and Johan (2009) assert that "A part from the founding of entrepreneur's savings, family and friends [...] are a common source of capital for earliest-stage entrepreneurial firms." This role is likely to be more important in the case of investment by business angels. Indeed, the latter tend to invest in the early stages of a startup and they usually face greater financial constraints than venture capitalists. Therefore, the founders who opt for business angel investment are more likely to match it with their own money. Even though we are not able to distinguish between the two factors, the positive sign of the coefficient for the amount of FFF money indeed suggests that the latter has at least some signaling value. In fact, suppose the cost of a startup were x, and this cost were to be financed by either business angels or founders, friends, and family. Then, the larger the share of x financed by business angels, the lower the amount of FFF invested should be. Thus, if FFF money were uniquely to match business angel funds, then the sign of the coefficient for the amount of FFF money invested should be negative and not positive, as we observe.

Our finding also receives some support from 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 us 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 even invest a penny in their own startup. Another founder contended that business angels often require the founders to have some "skin in the game" and invest their own money in the startup. Finally, other founders pointed to the importance of founder commitment for business angels.

A last clarification on our result 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.

⟨ Insert Table 4 about here ⟩

4.5 Robustness check analysis

As robustness check, we estimate the same models as in Tables 2-4, having excluded those startups whose external investment (either venture capital or business angel) falls within the 99th percentile. As we did in the previous sections, we only report the regression results for equations 1 and 3, which relate the founders' signaling decision to total external investment, and to investment by either venture capitalists or business angels. The results are presented in Tables 5 to 7.

Similar to the results in Table 2, startups that have invested in both FFF money and patents receive higher levels of external investment than startups that either invest in only FFF money or patents, or those that do not make any investment. This time the dummy READY FOR MKT is statistically significant and has a negative sign. This result suggests that startups tend to receive greater external funds when their technology is either at the proof of concept or at the prototype stage rather than when their technology is about to be commercialized. Moreover, similar to the results 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. As before, investment in FFF money does not have a statistically significant impact on venture capital investment. Finally, 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 in that for the likelihood that business angel investment occurs. The impact of the average number of years the founders worked prior to founding the startup is negative and statistically significant. This result seems to suggest that the larger the "pocket size" of the founders, the lower the amount of business angel funds required by the founders.

⟨ Insert Table 5 about here ⟩

⟨ Insert Table 6 about here ⟩

⟨ Insert Table 7 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; both investments being greater than that under symmetric information. Moreover, the equilibrium investment in patents will be smaller, the greater the cost of making a patentable invention. Similarly, the equilibrium amount of FFF money will be lower the greater the investment's opportunity costs and the greater the cost for a low quality startup to mimic the investment in FFF money of a high quality startup. Finally, 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.

It is important to note that there is a large strand of the literature on founders' overoptimism which argues that the information on the probability of success of a technology, as revealed by founder investment in signals, might be confounded by the founders' overoptimism about future prospects of the startup (Dushnitsky, 2010; Lowe and Ziedonis, 2006). Our theoretical results are not in conflict with this literature since the private information we consider regards only the founders' commitment and technical aspects of the technology. It does not encompass information on the probability that a technology is successfully commercialized.

We also provide an empirical analysis using a novel database on technology startups in the incubator of the Georgia Institute of Technology. Consistent with our theoretical model, we find that patents and FFF money are endogenously determined. We therefore take into account the endogeneity of a founder's choice by estimating a structural model which relates the cost of the signals to the choice of signals, and the latter to the external investment. Consistent with the model's predictions, investing in both signals has a greater impact on external investment than investing in only one of the signals. We then consider the impact of both signals on venture capitalists and business angels, separately. We find that investment in patents has a signaling value for venture capitalists, whereas FFF money does not have a statistically significant impact on venture capital investment. This result is 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 it is not surprising that the commitment of the founders is relatively less important for venture capitalists. Moreover, this result is in line with survey results reported by Graham and Sichelman (2008) and Graham et al. (2009) that patenting by information technology startups is mainly pursued for signaling purposes rather than for appropriability reasons. In the case of business angel investment, we find that FFF money has a positive impact on business angel investment, while the impact of patents is not statistically significant. The result on FFF money is 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.

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. We thus cannot consider the possibility that startups with different attributes match with investors with different preferences towards these attributes. 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 distinguishing founders from family and friends investment. The two categories of investment might signal different degrees of commitment to external investors. Finally, our empirical analysis is based on data from a unique institution, the incubator of the Georgia Institute of Technology, and its startups are primarily concentrated in just one sector, information technology. Therefore, the results we found may not generalize to incubators at other academic institutions, as well as other industries. Extending the analysis to other university incubators and industries is a venue for future research

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

[5] 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.

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

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

[8] 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.

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

[10] DeGennaro, R. P.. 2009. Expected Returns to Angel Investors. Federal Reserve Bank of Atlanta Working Paper.

[11] 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.

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

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

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

[15] 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.

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

[17] 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.

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

[19] 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.

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

[21] 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.

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

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

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

[25] 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.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

[41] Wong A.. 2002. Angel Finance: The Other Venture Capital. Working Paper. University of Chicago.

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

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
VC FUNDS	454,418	1,608,483	0	23,463,160	471
VC BINARY	0.189	0.392	0	1	471
ANGEL FUNDS	87,498	348,511	0	4,473,386	471
ANGEL BINARY	0.166	0.372	0	1	471
FFF MONEY	27,890	155,968	0	2,673,797	471
FILED PAT	0.654	2.677	0	45	471
AV WORK YS	13.577	7.832	1	33	471
STARTUP EXP	0.501	0.500	0	6	471
FT	16.831	25.029	0	150	471
READY FOR MKT	0.34	0.474	0	1	471
TIME TO ATDC	0.86	0.347	0	1	471
TELECOM	0.176	0.381	0	1	471
HEALTHCARE	0.072	0.259	0	1	471
OTHER SOFTWARE	0.418	0.494	0	1	471
HARDWARE	0.055	0.229	0	1	471
PHARMA MDEV	0.104	0.306	0	1	471
OTHER	0.176	0.381	0	1	471
COMMON ROUND	0.040	0.197	0	1	471
CLOSENESS	0.380	0.768	0	3	471
MASTER	1.361	1.254	0	6	471
CYCLE	3.285	2.082	0	8	471

Table 2: Signals' impact on external investment

	TOT FUNDS		FUNDS BINARY	
	coef.	se	coef.	se
ORDER SIGNAL	11.524***	[2.479]	0.523***	[0.110]
AVG WORKING YS	0.014	[0.778]	-0.004	[0.035]
STARTUP EXPERIENCE	0.495	[1.219]	0.021	[0.055]
FT	1.685***	[0.389]	0.070***	[0.017]
READY FOR MKT	-2.043	[1.311]	-0.085	[0.059]
TIME TO ATDC	2.689	[1.926]	0.111	[0.084]
HEALTHCARE	-1.370	[2.823]	-0.052	[0.126]
TELECOM	-1.541	[2.023]	-0.070	[0.089]
OTHER SOFTWARE	0.335	[1.920]	0.018	[0.086]
HARDWARE	1.069	[2.748]	0.033	[0.126]
PHARMA MDEV	1.858	[1.963]	0.070	[0.086]
COM ROUND	9.311***	[2.707]	0.365***	[0.120]
CONSTANT	-3.330	[3.076]	0.278**	[0.136]
YEAR fixed effects	YES		YES	
Observations	471		471	
R-squared	0.175		0.150	
	Statistic	p-value	Statistic	p-value
Endogeneity test	11.673	0.001	12.168	0.001
F-test of excl. instr.	29.470	0.000	29.470	0.000
Test of overidentifying restrictions	0.193	0.908	0.085	0.958

Notes: The sample consists of 117 startups with 471 observations. Columns I and II report the results of the IV regression of TOT FUNDS on the endogenous variable, ORDER SIGNAL, and other exogenous regressors. Columns III and IV report the results of the IV regression of FUNDS BINARY on the endogenous variable, ORDER SIGNAL, and other exogenous regressors. TOT FUNDS is defined as the log of the total amount (in real USD) invested in a startup by external investors. FUNDS BINARY takes the value of 1 if a startup had received external funds. ORDER SIGNAL takes the value of 2 if a startup invested in both signals, 1 if it invested in either patents or FFF money, and 0 if it invested in neither signal. As instruments for ORDER SIGNAL we use the variables CLOSENESS, MASTER, 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. MASTER is defined as the log of the number of founders with at least a master's degree. CYCLE takes increasing values the longer the time spent at ATDC. The other exogenous covariates are AVG WORK YS, STARTUP EXP, FT, READY FOR MKT, TIME TO ATDC, and COM ROUND. All regressions include sector and year dummies. At the bottom of the table, we report a test of endogeneity, an F-test of excluded instruments, and the Hansen's J statistics for overidentifying restrictions. 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 3: Impact of FFF money and the number of patents filed on venture capital investment

	VC FUNDS		VC BINARY	
	coef.	se	coef.	se
FFF MONEY	-0.110	[0.273]	-0.008	[0.019]
FILED PAT	6.673***	[1.866]	0.471***	[0.130]
AVG WORKING YS	0.160	[0.390]	0.007	[0.029]
STARTUP EXPERIENCE	0.226	[0.619]	0.017	[0.045]
FT	0.855***	[0.236]	0.057***	[0.017]
READY FOR MKT	-0.995	[0.730]	-0.067	[0.052]
TIME TO ATDC	0.307	[0.807]	0.019	[0.058]
HEALTHCARE	0.205	[1.344]	0.022	[0.099]
TELECOM	1.426	[1.007]	0.099	[0.072]
OTHER SOFTWARE	1.763*	[0.998]	0.124*	[0.072]
HARDWARE	2.785**	[1.373]	0.187*	[0.101]
PHARMA MDEV	0.833	[1.272]	0.054	[0.092]
CONSTANT	-0.022	[1.875]	0.007	[0.134]
YEAR fixed effects	YES		YES	
Observations	471		471	
R-squared	0.151		0.126	
	Statistic	p-value	Statistic	p-value
Endogeneity test	5.295	0.070	5.662	0.059
F-test of excl. instr. (FFF MONEY)	14.080	0.000	14.080	0.000
F-test of excl. instr. (FILED PAT)	15.930	0.000	15.930	0.000
Test of overidentifying restrictions	0.894	0.344	0.950	0.330

Notes: The sample consists of 117 startups with 471 observations. Columns I and II report the results of the IV regression of VC FUNDS on the endogenous variables, FFF MONEY and FILED PAT, and other exogenous regressors. Columns III and IV report the results of the IV regression of VC BINARY on the endogenous variables, FFF MONEY and FILED PAT, and other exogenous regressors. VC FUNDS is defined as the log of the total amount (in real USD) invested in a startup by venture capitalists. VC BINARY takes the value of 1 if a startup had received venture capital funds. 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. FILED PAT is defined as the log of the number of patents filed by the founders of a startup. As instruments for both FFF MONEY and FILED PAT we use the variables CLOSENESS, MASTER, 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. MASTER is defined as the log of the number of founders with at least a master's degree. CYCLE takes increasing values the longer the time spent at ATDC. The other exogenous covariates are AVG WORK YS, STARTUP EXP, FT, READY FOR MKT, and TIME TO ATDC. All regressions include sector and year dummies. At the bottom of the table, we report a test of endogeneity, two F-tests of excluded instruments (one for each endogenous regressor), and the Hansen's J statistics for overidentifying restrictions. 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 FUNDS		**ANGEL BINARY**	
	coef.	se	coef.	se
FFF MONEY	0.629**	[0.261]	0.056***	[0.021]
FILED PAT	2.546	[2.059]	0.184	[0.164]
AVG WORKING YS	-0.506	[0.389]	-0.046	[0.031]
STARTUP EXPERIENCE	0.229	[0.649]	0.016	[0.051]
FT	0.290	[0.179]	0.023	[0.014]
READY FOR MKT	-0.390	[0.771]	-0.039	[0.060]
TIME TO ATDC	0.774	[0.853]	0.055	[0.067]
HEALTHCARE	0.352	[1.146]	0.030	[0.090]
TELECOM	-1.107	[1.036]	-0.079	[0.081]
OTHER SOFTWARE	-0.506	[0.920]	-0.031	[0.072]
HARDWARE	-2.226	[1.458]	-0.165	[0.117]
PHARMA MDEV	-0.199	[1.156]	-0.019	[0.089]
CONSTANT	2.349	[1.505]	0.215	[0.121]
YEAR fixed effects	YES		YES	
Observations	471		471	
R-squared	0.040		0.030	
	Statistic	p-value	Statistic	p-value
Endogeneity test	12.797	0.002	14.373	0.001
F-test of excl. instr. (FFF MONEY)	14.080	0.000	14.080	0.000
F-test of excl. instr. (FILED PAT)	15.930	0.000	15.930	0.000
Test of overidentifying restrictions	0.162	0.687	0.104	0.747

Notes: The sample consists of 117 startups with 471 observations. Columns I and II report the results of the IV regression of ANGEL FUNDS on the endogenous variables, FFF MONEY and FILED PAT, and other exogenous regressors. Columns III and IV report the results of the IV regression of ANGEL BINARY on the endogenous variables, FFF MONEY and FILED PAT, and other exogenous regressors. ANGEL FUNDS is defined as the log of the total amount (in real USD) invested in a startup by business angels. ANGEL BINARY takes the value of 1 if a startup had received business angel funds. 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. FILED PAT is defined as the log of the number of patents filed by the founders of a startup. As instruments for both FFF MONEY and FILED PAT we use the variables CLOSENESS, MASTER, 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. MASTER is defined as the log of the number of founders with at least a master's degree. CYCLE takes increasing values the longer the time spent at ATDC. The other exogenous covariates are AVG WORK YS, STARTUP EXP, FT, READY FOR MKT, and TIME TO ATDC. All regressions include sector and year dummies. At the bottom of the table, we report a test of endogeneity, two F-tests of excluded instruments (one for each endogenous regressor), and the Hansen's J statistics for overidentifying restrictions. 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: Signals' impact on external investment: Excluding startups whose venture capital or business angel investment falls within the 99th percentile.

	TOT FUNDS		**FUNDS BINARY**	
	coef.	se	coef.	se
ORDER SIGNAL	11.120***	[2.845]	0.508***	[0.128]
AVG WORKING YS	0.132	[0.850]	0.002	[0.039]
STARTUP EXPERIENCE	-0.544	[1.285]	-0.025	[0.058]
FT	1.737***	[0.426]	0.073***	[0.019]
READY FOR MKT	-2.618**	[1.316]	-0.112*	[0.059]
TIME TO ATDC	2.497	[2.030]	0.109	[0.089]
HEALTHCARE	-0.720	[2.925]	-0.029	[0.131]
TELECOM	-1.176	[2.206]	-0.058	[0.098]
OTHER SOFTWARE	0.975	[2.028]	0.040	[0.092]
HARDWARE	1.787	[2.852]	0.056	[0.131]
PHARMA MDEV	1.749	[2.255]	0.071	[0.099]
COM ROUND	9.916***	[2.878]	0.395***	[0.129]
CONSTANT	-3.910	[3.123]	0.253*	[0.139]
YEAR fixed effects	YES		YES	
Observations	433		433	
R-squared	0.165		0.145	
	Statistic	p-value	Statistic	p-value
Endogeneity test	9.711	0.002	9.897	0.002
F-test of excl. instr.	25.030	0.000	25.030	0.000
Test of overidentifying restrictions	0.118	0.943	0.214	0.898

Notes: The sample consists of 109 startups with 433 observations. Columns I and II report the results of the IV regression of TOT FUNDS on the endogenous variable, ORDER SIGNAL, and other exogenous regressors. Columns III and IV report the results of the IV regression of FUNDS BINARY on the endogenous variable, ORDER SIGNAL, and other exogenous regressors. TOT FUNDS is defined as the log of the total amount (in real USD) invested in a startup by external investors. FUNDS BINARY takes the value of 1 if a startup had received external funds. ORDER SIGNAL takes the value of 2 if a startup invested in both signals, 1 if it invested in either patents or FFF money, and 0 if it invested in neither signal. As instruments for ORDER SIGNAL we use the variables CLOSENESS, MASTER, 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. MASTER is defined as the log of the number of founders with at least a master's degree. CYCLE takes increasing values the longer the time spent at ATDC. The other exogenous covariates are AVG WORK YS, STARTUP EXP, FT, READY FOR MKT, TIME TO ATDC, and COM ROUND. All regressions include sector and year dummies. At the bottom of the table, we report a test of endogeneity, an F-test of excluded instruments, and the Hansen's J statistics for overidentifying restrictions. 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 venture capital investment: Excluding startups whose venture capital investment falls within the 99th percentile.

	VC FUNDS		**VC BINARY**	
	coef.	se	coef.	se
FFF MONEY	-0.079	[0.279]	-0.006	[0.019]
FILED PAT	6.572***	[1.957]	0.466***	[0.137]
AVG WORKING YS	0.248	[0.387]	0.015	[0.028]
STARTUP EXPERIENCE	0.072	[0.630]	0.003	[0.046]
FT	0.877***	[0.232]	0.060***	[0.016]
READY FOR MKT	-1.108	[0.704]	-0.076	[0.050]
TIME TO ATDC	0.432	[0.791]	0.031	[0.057]
HEALTHCARE	-0.014	[1.356]	0.004	[0.100]
TELECOM	1.182	[1.015]	0.080	[0.072]
OTHER SOFTWARE	1.516	[0.992]	0.104	[0.072]
HARDWARE	2.529*	[1.405]	0.164	[0.103]
PHARMA MDEV	0.542	[1.387]	0.033	[0.100]
CONSTANT	0.279	[1.839]	0.029	[0.131]
YEAR fixed effects	YES		YES	
Observations	458		458	
R-squared	0.152		0.136	
	Statistic	p-value	Statistic	p-value
Endogeneity test	4.689	0.095	4.876	0.087
F-test of excl. instr. (FFF MONEY)	13.220	0.000	13.220	0.000
F-test of excl. instr. (FILED PAT)	13.720	0.000	13.720	0.000
Test of overidentifying restrictions	1.086	0.297	1.222	0.269

Notes: The sample consists of 114 startups with 458 observations. Columns I and II report the results of the IV regression of VC FUNDS on the endogenous variables, FFF MONEY and FILED PAT, and other exogenous regressors. Columns III and IV report the results of the IV regression of VC BINARY on the endogenous variables, FFF MONEY and FILED PAT, and other exogenous regressors. VC FUNDS is defined as the log of the total amount (in real USD) invested in a startup by venture capitalists. VC BINARY takes the value of 1 if a startup had received venture capital funds. 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. FILED PAT is defined as the log of the number of patents filed by the founders of a startup. As instruments for both FFF MONEY and FILED PAT we use the variables CLOSENESS, MASTER, 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. MASTER is defined as the log of the number of founders with at least a master's degree. CYCLE takes increasing values the longer the time spent at ATDC. The other exogenous covariates are AVG WORK YS, STARTUP EXP, FT, READY FOR MKT, and TIME TO ATDC. All regressions include sector and year dummies. At the bottom of the table, we report a test of endogeneity, two F-tests of excluded instruments (one for each endogenous regressor), and the Hansen's J statistics for overidentifying restrictions. 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 7: Impact of FFF money and the number of patents filed on business angel investment: Excluding startups whose venture capital investment falls within the 99th percentile.

	ANGEL FUNDS		**ANGEL BINARY**	
	coef.	se	coef.	se
FFF MONEY	0.816***	[0.256]	0.070***	[0.021]
FILED PAT	0.096	[2.330]	0.001	[0.193]
AVG WORKING YS	-0.881**	[0.416]	-0.073**	[0.035]
STARTUP EXPERIENCE	0.014	[0.648]	-0.003	[0.053]
FT	0.394**	[0.190]	0.031**	[0.016]
READY FOR MKT	-1.027	[0.653]	-0.088	[0.054]
TIME TO ATDC	0.392	[0.913]	0.032	[0.073]
HEALTHCARE	1.217	[1.025]	0.090	[0.084]
TELECOM	-0.008	[0.953]	-0.004	[0.079]
OTHER SOFTWARE	0.393	[0.772]	0.031	[0.064]
HARDWARE	-0.913	[1.207]	-0.074	[0.101]
PHARMA MDEV	1.139	[1.239]	0.083	[0.099]
CONSTANT	3.857	[1.643]	0.325	[0.134]
YEAR fixed effects	YES		YES	
Observations	446		446	
R-squared	0.030		0.020	
	Statistic	p-value	Statistic	p-value
Endogeneity test	14.048	0.001	15.283	0.001
F-test of excl. instr. (FFF MONEY)	13.700	0.000	13.700	0.000
F-test of excl. instr. (FILED PAT)	11.780	0.000	11.780	0.000
Test of overidentifying restrictions	0.822	0.365	0.549	0.459

Notes: The sample consists of 112 startups with 446 observations. Columns I and II report the results of the IV regression of ANGEL FUNDS on the endogenous variables, FFF MONEY and FILED PAT, and other exogenous regressors. Columns III and IV report the results of the IV regression of ANGEL BINARY on the endogenous variables, FFF MONEY and FILED PAT, and other exogenous regressors. ANGEL FUNDS is defined as the log of the total amount (in real USD) invested in a startup by business angels. ANGEL BINARY takes the value of 1 if a startup had received business angel funds. 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. FILED PAT is defined as the log of the number of patents filed by the founders of a startup. As instruments for both FFF MONEY and FILED PAT we use the variables CLOSENESS, MASTER, 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. MASTER is defined as the log of the number of founders with at least a master's degree. CYCLE takes increasing values the longer the time spent at ATDC. The other exogenous covariates are AVG WORK YS, STARTUP EXP, FT, READY FOR MKT, and TIME TO ATDC. All regressions include sector and year dummies. At the bottom of the table, we report a test of endogeneity, two F-tests of excluded instruments (one for each endogenous regressor), and the Hansen's J statistics for overidentifying restrictions. 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 and 2

Proposition 1 (i): There exists a separating equilibrium whose characteristics are: if $C \succ_I QT$, H-type founders will choose M such that IC constraint of type L-founders hold as equality and p such that the first order condition is satisfied.

The utility maximization problem of H-type founders is defined as:

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

(i) $C \succ_I QT$

(ii) $U^H \geq 0$

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

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

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

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

Given the preferences of the investors, a candidate for a separating equilibrium is obtained as follows. M_H^* is derived from condition (iii) being binding and p_H^* is derived from the first order condition for p_H. This amounts to reducing the problem to a utility maximization in one variable, p_H, while allowing M_H to be derived from (iii). As mentioned in the the paper, we will only consider interior solutions for p_H and M_H. We need to show that a) this solution to p 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 $\Delta M \geq \Delta p$; 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 p is indeed a maximum because $\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial p_H^2} < 0$; $\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial M_H^2} < 0$; and $\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial M_H \partial p_H} > 0$.

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 (iii) 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 (iv) 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, the latter 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 indeed both signals are provided in greater quantities but that $\Delta M \geq \Delta p$.

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

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

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

$(\rho + g_L) - \rho = 0 \Longrightarrow g_L \neq 0$

Thus, at the amount of M that meets the first order condition under symmetric information, for $p = p_H^+$, (1) is not satisfied. Because, at this amount, the left-hand side of (1) is greater than zero, this implies that $M_H^* > M_H^+$.

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

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

Deriving this expression with respect to M, at $\{M_H^*,\ \mathrm{p}_H^*\}$, we obtain:
$\frac{\partial^2 V(M_H^*,p_H^*;\theta_H)}{\partial p^2}\frac{dp}{dM} + \frac{\partial^2 V(M_H^*,p_H^*;\theta_H)}{\partial p \partial M} = 0$

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

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

This implies that relative to the optimal quantities under symmetric information, an increase in M_H^* leads to an increase of p_H^*. Thus, $p_H^* > p_H^+$. However, because $\min\{|V_{pp}(p,M;\theta), V_{MM}(p,M;\theta)|\} > V_{Mp}(p,M;\theta)$, then $\left|\frac{\partial^2 V(M_H^*,p_H^*;\theta_H)}{\partial p^2}\right| > \frac{\partial^2 V(M_H^*,p_H^*;\theta_H)}{\partial p \partial M}$. This implies that a unit increase in M causes p 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/or 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/or M greater than the equilibrium amounts would yield a lower utility to H-type founders. Moreover, any amounts of p and/or 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 p and M respectively obtained from the IC constraint of L-types and the first order condition for M, 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 for H-type founders.

Finally, this criterion also eliminates all possible pooling equilibria. Any pooling equilibrium with p and M smaller than the equilibrium amounts for H-type founders would be subject to deviations by H-type founders. Similarly, any pooling equilibrium with p and M greater than the equilibrium amounts for H-type founders 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 would be subject to deviations by L- and H-type founders.

Proof of Proposition 1 (ii) Same as Proof of Proposition 1 (i)

Proof of Proposition 1 (iii) Same as Proof of Proposition 1 (i). In addition $\frac{\partial \Delta}{\partial b_H} < 0$ and $\frac{\partial \Delta}{\partial \rho} > 0$ are straightforwardly derived by comparing the utility H-types would achieve if they were to choose p from the corresponding first order condition and M so as to satisfy the IC constraint of type L-founders and the utility they would achieve if they were to choose M from the corresponding first order condition and p so as to satisfy the IC constraint of type L-founders.

Proof of Proposition 2 (i) If $C \succ_I QT$: $\frac{\partial M_H^*}{\partial \rho} < 0$, $\frac{\partial M_H^*}{\partial g_L} < 0$, $\frac{\partial p_H^*}{\partial b_H} < 0$;

$\frac{\partial M_H^*}{\partial \rho} < 0$:

Deriving the IC constraint for type L-founders with respect to M, at $\{M_H^*\ , p_H^*\}$, we obtain:

$$\alpha \frac{\partial V(M_H^*, p_H^*; \theta_H)}{\partial M} + (1-\alpha)\frac{\partial V(M, p; \theta_L)}{\partial M} - (\rho + g_L) = 0 \qquad (2)$$

Deriving (2) with respect to ρ, at $\{M_H^* \ , p_H^*\}$, and rearranging yields:

$\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial M^2} \frac{\partial M}{\partial \rho} - 1 = 0$

Solving for $\frac{\partial M}{\partial \rho}$, we obtain:

$\frac{\partial M}{\partial \rho} = \frac{1}{\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial M^2}} < 0$

$\frac{\partial M_H^*}{\partial g_L} < 0$:

Deriving (1) with respect to g_L, at $\{M_H^* \ , p_H^*\}$, and rearranging yields:

$\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial M^2} \frac{\partial M}{\partial g_L} - 1 = 0$

Solving for $\frac{\partial M}{\partial g_L}$, we obtain:

$\frac{\partial M}{\partial \rho} = \frac{1}{\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial M^2}} < 0$

$\frac{\partial p_H^*}{\partial b_H} < 0$:

Deriving the first order condition for p with respect to b_H, at $\{M_H^* \ , p_H^*\}$, yields:

$\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial^2 p_H^*} \frac{\partial p_H^*}{\partial b_H} - 1 = 0$

Solving for $\frac{\partial p_H^*}{\partial b_H}$, we obtain:

$\frac{\partial p_H^*}{\partial b_H} = \frac{1}{\frac{\partial^2 V(M_H^*, p_H^*; \theta_H)}{\partial^2 p_H^*}} < 0$

Proof of Proposition 2 (ii) Same as Proof of Proposition 2 (i)

Proof of Proposition 2 (iii) Same as Proof of Proposition 2 (i)

Appendix B: Estimation of equations 4 and 5

Table B1 presents the regression results for the impact of the instruments on the number of patents filed and FFF money, adjusting for the exogenous covariates. All variables, except for the CLOSENESS index and the dummies are expressed in logs. The first two columns report the regression results for the number of patens filed. The last two columns report the regression results for the amount invested by the founders, their friends and their families.

In the regression for the number of patents filed, the coefficients of MASTER is positive and statistically significant at the 1% level. Therefore, the larger the number of founders with a master in science and engineering, the larger the number of patents filed. Moreover, the coefficient of CYCLE is negative and statistically significant at the 1% level, indicating that investment in patents tends to occur in the first years a startup has joined ATDC.

In the regression for the amount invested by the founders, their friends and their families, the coefficient of CLOSENESS is positive and statistically significant at the 1% level. Hence, the closer the relational ties among the founders, the larger the amount of FFF money invested.[1]. As before, the coefficient of the variable CYCLE is negative and statistically significant at the 1% confidence level. Finally, the number of founders with a master in science or engineering has a negative and statistically significant impact on the investment in FFF money.

[1]In an alternative regression specification, we do not report here, we tested the impact on FFF money of three dummies that capture the three types of relational ties we have combined in the ordinal variable, CLOSENESS. The impact on FFF money of having the founders in the same class and that of having the founders in same university (but not in the same class) are both positive and statistically significant at the 5% confidence level.

Table B1: Estimation of Equations 4 and 5

	FILED PAT (Equation 4)		**FFF MONEY (Equation 5)**	
	coef.	se	coef.	se
AVG WORKING YS	0.011	[0.040]	0.349	[0.273]
STARTUP EXPERIENCE	-0.060	[0.069]	0.161	[0.452]
FT	0.048**	[0.021]	-0.219**	[0.109]
READY FOR MKT	-0.054	[0.062]	0.997*	[0.513]
TIME TO ATDC	0.197**	[0.080]	0.801	[0.589]
HEALTHCARE	-0.204**	[0.096]	-0.020	[0.757]
TELECOM	-0.158	[0.129]	-0.356	[0.646]
OTHER SOFTWARE	-0.204**	[0.096]	-0.381	[0.562]
HARDWARE	-0.144	[0.146]	-1.057	[0.850]
PHARMA MDEV	-0.008	[0.124]	-0.302	[0.774]
CLOSENESS	0.023	[0.038]	0.731***	[0.264]
MASTER	0.193***	[0.056]	-1.081**	[0.414]
CYCLE	-0.084***	[0.014]	-0.617***	[0.120]
CONSTANT	0.393*	[0.209]	2.664*	[1.478]
YEAR fixed effects	YES		YES	
Observations	471		471	
R-squared	0.227		0.324	

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, MASTER, and CYCLE, as well as other exogenous covariates. Columns III and IV report the results of the regression of FFF MONEY on the instruments and the other exogenous covariates. FILED PAT is defined as the log of the number of filed patents. FFF MONEY is defined as the log of the own, friends and family money. ORDER SIGNAL takes the value of 2 if a startup invested in both signals, 1 if it invested in either patents or FFF money, and 0 if it invested in neither signal. As instruments for ORDER SIGNAL we use the variables CLOSENESS, MASTER, 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. MASTER is defined as the log of the number of founders with at least a master's degree. CYCLE takes increasing values the longer the time spent at ATDC. The other exogenous covariates are AVG WORKING YS, STARTUP EXPERIENCE, FT, READY FOR MKT, and TIME TO ATDC. All regressions include the sector and year dummies.