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ABSTRACT

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 these predictions empirically and find evidence in support of this proposition. 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).

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1 Introduction

One of the most important issues facing technology startups is access to capital (Denis, 2004). Because such startups have little or no observable history of performance and there is uncertainty about their technology, attracting funds from external investors is not easy (Shane and Stuart, 2002). Thus a major issue for the managers of technology startups is finding signals of their value for potential investors. However, investment in signals is costly and not all startups can afford it (Amit *et al*, 1990). Indeed, the Berkeley Patent Survey shows that while securing funds is one of the most important reasons for startup patenting, the associated cost is the most common reason for not patenting (Graham and Sichelman 2008, Graham *et al.* 2009) Moreover, different classes of investors (e.g. business angels and venture capitalists) reputedly vary in the extent to which they value different startup characteristics (Osnabrugge and Robinson 2000, Graham *et al.* 2009).

In this paper, we revisit a central topic in entrepreneurial finance, namely the signals technology startups send to external investors to convey information about their quality. We provide both theoretical and empirical results on investment in signals in relation to the cost of signaling and investor preferences. In the theory, 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 then examine our predictions in the context of technology startups incubated in the Advanced Technology Development Center (ATDC) from 1998-2008.

The theory applies the insights of Leland and Pyle (1976) and 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.

We conduct two empirical exercises. First, we relate the number of signals in which a startup's founders invest to the external investment received. We 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.

Second, we consider the impact of patents filed and FFF on venture capitalist and business angel investments, respectively. We find that patents are positively associated with venture capitalist investment, while the impact of FFF is not statistically significant. In the case of business angel investment, we estimate a structural model that takes into account the possibility that FFF money and business angel investment are simultaneously determined. The structural model relates FFF money to the cost of investing in this signal, and the investment in FFF money and patents to the financing provided by business angels. We find evidence that, having taken into account the opportunity cost of investing in FFF money, the latter has a positive impact on the financing provided by business angels, while the impact of filing patents is not statistically significant. These results suggest that 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.

While informational issues and quality variation among startups is well documented in the literature on entrepreneurial finance, 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, *per se*.

More recently, Hsu and Ziedonis (2008) and Haeussler et al. (2009) have concentrated on the signaling value of patents. 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. Moreover, the signaling value of patents is greater in early financing rounds and when funds are secured from prominent investors. Haeussler et al. (2009) find similar results for a sample of German and British biotechnology companies. In their study, patent oppositions increase the likelihood of receiving venture capital, but ultimate grant decisions do not, presumably because they are anticipated. However, both studies focus on patents as signals in the 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 build a simple model in which the founders of a startup company have private information about the probability of success of a technology as well as their own commitment to developing it. Potential investors observe these startup attributes only with noise. As in Leland and Pyle (1976), the asymmetry of information gives the founders an incentive to signal the company's type to potential investors, who for our purposes exclude friends and family members. We shall define the startup's type by whether its technology has a high or low probability of success.

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 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 $r(p)$ 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

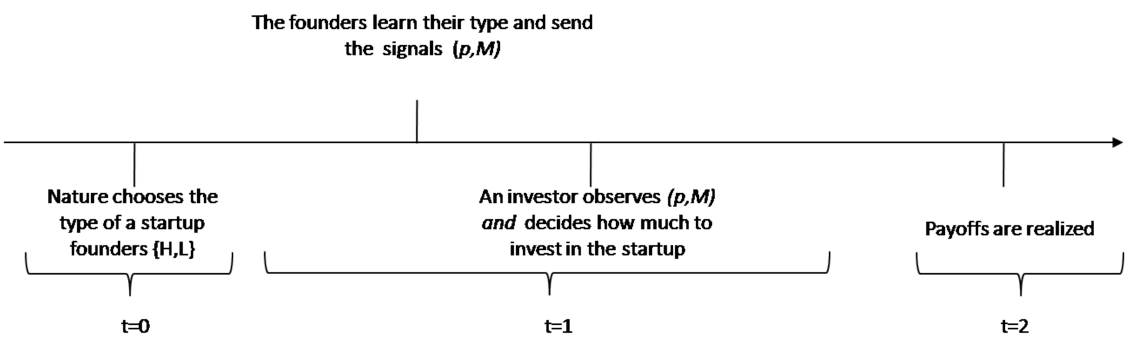
[1] θ_H and θ_L are also referred in the text as high quality and low quality startups, respectively.

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. 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 decides an amount to invest in the startup. We assume there are at least two investors potentially interested in financing the startup, but that only one eventually makes the investment.

Finally, in the third period, the value of the startup is realized and both the founders and the investor receive their payoffs. All players are risk neutral and have a unitary discount rate.

Figure 1: **Time Line**



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

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

Wealth in $t = 1$ is equal to:

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

[2] An objective function that takes into account present and future values of a firm is used, for instance, by Bhattacharya (1979).

where $\alpha \in (0,1)$ is the fraction of equity retained by investor j, V^j is investor $j's$ expectation of the value of startup with productivity θ. $M \geq \underline{M} \geq 0$, is FFF investment in the startup, which is at least equal to a minimum amount $\underline{M}$ required to start the business.

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

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

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 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 are characterized by θ_H investing greater amounts of both M and p than in symmetric information. In addition, 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 an on-line appendix. □

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.

Regardless of investor preferences H-type founders invest more in both signals than they would in the absence of asymmetric information, and the investment in both signals decreases with an increase in any of the cost parameters.

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 an on-line 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 extends to a situation in which there is more than one category of investors which differ in their preferences over the 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 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 one of the signals, 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 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, ORD_SIGNALS, 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 structural equation model which takes into consideration the endogeneity between FFF money and one type of external funding, namely funding by business angels. That is, it is possible for FFF money to both be caused by external funding and for it to cause external funding. This is because, contrary to venture capitalists, business angels invest their own money in startups. Therefore, in order for business angels to risk their money they require the founders to have some "skin in the game" and match business angel investment with own funds. Clearly, this problem does not extend to patents since patents are not caused by external funding.

The structural equation model relates (i) the founders' signaling decision, as measured by the ordinal outcome variable, ORDER_SIGNAL, to the founders' costs of investing in the signals, and then (ii) relates the decision to financing provided by venture capitalists and business angels.

A preferred estimation specification would have consisted in assessing the impact on total financing of three different dummies: the first indicating whether the founders had invested in patents, the second indicating whether the founders had invested in FFF money, and the third defined as the interaction between the first two dummies. However, due to the endogeneity concerns expressed above, this would have implied estimating a system of three equations, one for total financing, and the other two for the FFF money dummy and its interaction with the patent dummy (Wooldridge, 2002). Due to limited sample size, we opted for a structural system made of two equations, using the ordinal outcome ORDER_SIGNAL, rather three separate dummies.

As shown in equation one below, the regression for the ordinal outcome variable, ORDER_SIGNAL includes as a regressor a count variable, CLOSENESS, that takes the value of three if the founders had family connections, two if they were in the same class during either their master or PhD, one if they studied at the same university but not in the same class, and zero otherwise. CLOSENESS is a measure for the opportunity costs of investing founders, friends and family money in the sense that the closer are the relational ties among the founders, the less costly it is for them to risk invest their own money[3]. As a proxy for the opportunity cost of effort devoted to making a patentable invention, we use a variable, PHD, that is defined as the number of founders with a PhD in science or engineering. The underlying logic is that, with a PhD in science or engineering, the founders acquire a knowledge background that reduces the costs of making a patentable invention. We control for the "pocket size" of the founders with a variable defined as the average number of years the founders worked prior to founding the startup, AV_WORK_YS. Hence, the greater is the average number of years the founders have been working after their graduation, the greater the amount of money available to invest in the company. We also include three dummies that control for the time interval between the foundation year and the entry year at ATDC. The first, D_NO_LAG, is equal to one if the year of foundation and that of entry in the incubator coincide. The second dummy, D_2_5, is equal to 1 if a startup joined the incubator between the second and the fifth after foundation. The third dummy, D_6_10, is equal to one if a startup joined the incubator between the sixth and the tenth year after foundation. Moreover, we control for the life cycle of a startup starting from the entry year at ATDC, with a discrete variable, CYCLE, that takes increasing values the longer the time spent at ATDC. Our prior is that investment in signals occurs early in the startups' tenure in ATDC when the uncertainty over the value of a startup is greater. Therefore, investment in signals should be greater early in the startup's tenure, provided that the time lag between the foundation year and the year of entry in ATDC is short enough. Moreover, we measure the size of a startup with the number of full time employees, FT, and we proxy its quality with a

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

dummy, TIME AT ATDC, that takes the value of one if a startup remained at the incubator for more than six years. The time spent at the incubator is likely to be correlated to the time interval between a startup's creation and either exit event, IPO or acquisition. Carter *et al.* (1998), Clarck (2002), and Loughran and Ritter (2004) have found a negative relationship between the age of a startup and its IPO performance. Consistent with these studies, we use TIME AT ATDC as a proxy for a firm technology's quality. Controlling for this last aspect is fundamental because technology quality is likely to affect both the propensity of founders to invest in signals and that of external investors to provide funds. It is even more fundamental in our case, since we cannot include firms' fixed effects in our regression specifications, and therefore, we cannot control for time-invariant unobservables[4]. The dummy STARTUP EXP controls for whether the founders had founded other startups in the past. In fact, serial founders might 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). Moreover, we use a dummy variable, COM_ROUND, to control for whether external investment in a given year has been provided jointly by business angels and venture capitalists. Finally, we control for time as well as industry effects. 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 softwares are intended for the healthcare industry; a dummy, TELECOM, that takes the value of one if its softwares are intended for the telecommunication industry; a dummy, OTHER SOFTWARE, that takes the value if its softwares are 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 include startups operating mainly in the manufacturing sector.

The second regression of the structural equation model estimates external investment made by venture capitalists and business angels[5] as a function of the estimated value of ORDER_SIGNAL, the size of a startup, the number of full time employees, the number of founders with a PhD in science or engineering, whether the founders had founded other startups in the past, the dummy TIME AT ATDC, industry and time dummies.

[4]The reason why we do not include firm-fixed effects is that some of our startups had only received one round of funding during the sample period.

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

$$
\begin{aligned}
ORDER\ SIGNAL_{it} &= \alpha + \alpha_1 COM\_ROUND_{it} + \alpha_2 STARTUP\ EXP_i + \alpha_3 PHD_i + \alpha_4 FT_{it} + \\
&+ \alpha_5 TIME\ AT\ ATDC_i + \alpha_6 CLOSENESS_i + \alpha_7 AV\_WORKING\_YS_i + \\
&+ \alpha_8 D\_NO\_LAG_i + \alpha_9 D\_2\_5_i + \alpha_{10} CYCLE_{it} + \alpha_{11} INDUSTRY\ D_i + \varepsilon_{it} \quad (1)
\end{aligned}
$$

$$
\begin{aligned}
TOT\ FUND &= \beta + \beta_1 \widehat{ORDER\ SIGNAL}_{it} + \beta_2 COM\_ROUND_{it} + \beta_3 STARTUP\ EXP_i + \\
& \beta_4 PHD_i + \beta_5 FT_{it} + \beta_6 TIME\ AT\ ATDC_i + \beta_7 INDUSTRY\ D_i + \xi_{it} \qquad (2)
\end{aligned}
$$

where $\widehat{ORDER\ SIGNAL}_{it}$ is the instrument for $ORDER\ SIGNAL_{it}$ and is obtained from regression (1).

4.2.2 Signals, venture capital, and business angel funding

To investigate differences in business angel and venture capitalist responsiveness to signals, we first analyze the impact of FFF money and the investment in filed patents on venture capital investment. As we argued, we do not expect investment in FFF money to raise the issue of endogeneity as in the case of business angel investment. Indeed, because venture capitalists are not risking their own money, there is no reason for them to require the founders to have some skin in the game, the latter being responsible for the reverse causality problem we discussed in the case of business angel investment.

In addition to the signals, we relate the investment made by venture capitalists to the employment size of a startup, the number of founders with a PhD in science or engineering, whether the founders had founded other startups in the past, the dummy TIME AT ATDC, time and industry dummies. Finally, because venture capital investment tends to follow the investment made by business angels (provided that the latter occurs), we also control for the cumulated investment made by business angels.

$$
\begin{aligned}
VC\ INV_{it} &= \nu_0 + \nu_1 FFF\ MONEY_{it} + \nu_2 FILED\ PAT_{it} + \nu_3 STARTUP\ EXP_i + \\
& \nu_4 PHD_i + \nu_5 FT_{it} + \nu_6 TIME\ AT\ ATDC_i + \nu_7 INDUSTRY\ D_i + \eta_{it} \qquad (3)
\end{aligned}
$$

When we investigate the impact of the signals on business angel investment, however, we again account for the endogeneity of FFF money and investment. In the first stage of this structural model we regress FFF money on the regressors which conceptually affect the founders' decision of investing FFF money. These are the count variable, CLOSENESS, the measure of the founders' "pocket size", AV_WORK_YS, the dummies D_NO_LAG, D_2_5, D_6_10, the variable CYCLE, the employment size of a startup, FT, the dummy TIME AT ATDC, whether the founders had founded other startups in the past, the number of founders with a PhD in science or engineering, the investment in patents filed and, finally, time dummies. In the second stage regression, we relate the investment made business angels, to the estimated amount of FFF money, the investment in patents filed, FT, TIME AT ATDC, PHD, STARTUP EXP, time and industry dummies.

$$\begin{aligned} FFF\ MONEY &= \gamma + \gamma_1 FILED\ PAT_{it} + \gamma_2 STARTUP\ EXP_i + \gamma_3 PHD_i + \gamma_4 FT_{it} + \\ &+ \gamma_5 TIME\ AT\ ATDC_i + \gamma_6 CLOSENESS_i + \gamma_7 AV\_WORKING\_YS_i + \\ &+ \gamma_8 D\_NO\_LAG_i + \gamma_9 D\_2\_5_i + \gamma_{10} CYCLE_{it} + \gamma_{11} INDUSTRY\ D_i + \phi_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} ANGEL\ INV_{it} &= \zeta + \zeta_1 FFF\ \widehat{MONEY}_{it} + \zeta_2 FILED\ PAT_{it} + \zeta_3 STARTUP\ EXP_i + \\ &\zeta_4 PHD_i + \zeta_5 FT_{it} + \zeta_6 TIME\ AT\ ATDC_i + \zeta_7 INDUSTRY\ D_i + \tau_{it} \end{aligned} \tag{5}$$

where $FFF\ \widehat{MONEY}_{it}$ is the instrument for $FFF\ MONEY$ and is obtained from regression (4).

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[6]. 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.

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 USD, and the average amount of venture capital investment is 143,633 USD. 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.

[6] All figures are expressed in real terms

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.

25% of the startups joined the incubator the same year they were founded, while 65% joined the ATDC within the first five years from creation, and the remaining 10% within the 6th and the 10th year. 37% of the companies had spent more than 6 years at the incubator.

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.

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, 0.68 founders had a PhD in science or engineering.

4.4 Results

We estimate our equations using a censored regression model[7]. This estimation method allows us to take into account the realistic case in which an investor finds it optimal not invest in a company (Wooldridge, 2002). Additionally, when we examine the impact of the signals on venture capitalist and business angel investment, we also estimate a probit model, where both external investment and investment in signals are measured as binary outcomes. This is justified on the ground that the distributions of venture capitalist and business angel investment, as well as the distributions of FFF money and the investment in patents, are highly skewed.

4.4.1 Impact of FFF money and patent investment on external investment

Table 2 presents the regression results for the impact of the estimated values of the ordinal outcome, $\widehat{ORDER\_SIGNAL}$, on external investment. All variables, except for $\widehat{ORDER\_SIGNAL}$, the dummies, and the CLOSENESS index, are expressed in logs. We report the results for the second equation only, because we are interested in testing the theoretical prediction that, regardless of

[7]Robustness checks are reported in an on-line appendix.

investor preferences, the founders of a high quality startup will invest greater amounts of patents and FFF money to secure external funding.

The coefficients are marginal effects for the unconditional expected values of the external investment[8] Having controlled for the endogeneity of the founders' signaling choice, the impact on external funds is positive and statistically significant at the 1% level. This result suggests that startups that invest in both FFF money and patents tend to 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. Moreover, the number of full time employees is positively associated with funding from external investors, venture capitalists and business angels. Startups which spent the longest time at the incubator received lower levels of external funding. The latter tend not to be sector specific, none of the industry dummies being statistically significant. As a robustness check, we report in column 2 the impact of $\widehat{ORDER\_SIGNAL}$ on external investment, *excluding* industry dummies. The estimated value of $ORDER\_SIGNAL$ has still a positive and highly significant impact on external investment.

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 column reports the impact of FFF money and patents, expressed as binary variable, thus reflecting the impact of investing at all on the likelihood of venture capital investment. Also, rather than including as regressor the cumulative amount invested by business angels, we use a dummy, HAD_ANGEL, which takes the value of one if business angels invested any amount in a startup. The second column presents results as a function of the amounts of FFF money and number of patents filed. The results are quite similar.

Having filed patents has a positive and statistically significant impact on the likelihood that a startup received venture capital funds, the coefficient of FILED PAT BINARY being positive and statistically significant at the 1% confidence level. Moreover, the larger the number of patents filed, the larger the amount invested by venture capitalists. An increase by 1% in the number of patents filed induces an increase by 0.87% in the unconditional expected value of venture capital investment. The impact of FFF money is not statistically significant, both when we consider binary outcomes and total amounts.

The number of full time employees (FT) has a positive and statistically significant coefficient in both equation specifications, indicating a positive relation between the size of a startup and the

[8]Marginal effects are evaluated at the regressors' means.

investment made by venture capitalists. This result implies that either larger size startups require more funds from external investors, or, if size is positively correlated to the value of a startup, then higher value startups are positively associated with the investment provided by venture capitalists. The dummy TIME AT ATDC has negative and highly significant impact on the likelihood of receiving venture capital funds and on the amount of venture capital investment obtained. If we posit that the startups that spent the longest period in an incubator are the low quality startups, then again this result suggests that lower quality startups are negatively associated with investment by venture capitalists. 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 those founders that had created successful startups and those that were involved in unsuccessful projects. 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, including venture capital financing. Moreover, having received business angel investment, as well has its stock, does not have a statistically significant impact on venture capital investment. Finally, the coefficients of the industry dummies are not statistically significant in both equation specifications. This seems to suggest that investment by venture capitalists is not concentrated in any of the sectors described by the dummies, relative to the category OTHER.

In columns 3 and 4 we report a robustness check analysis and we exclude industry dummies from the equations for VC BINARY and VC FUNDS. The main results hold and investment in patents has still a positive and highly significant impact on venture capital investment, while the impact of FFF money is not significantly different from zero. Having excluded industry dummies, the coefficient of PHD is now statistically significant, albeit only at 10%. To the extent that PHD might be correlated with characteristics of a startup's technology, such as its research content, then the positive coefficient provides some indication that technologies with a high research content tend to receive more venture capital funds.

The result on the positive impact of the number of patents filed on venture capital investment provides support to the signaling value of patents for venture capitalists. Since the majority of the startups in our sample are in the information technology sector, 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.

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. We take into account the endogeneity of FFF money, by implementing two structural equations models. In this case we report the regression results on FFF money, because we are interested in the impact of the variable CLOSENESS on the founders' decision to invest in this signal. In fact, as we already mentioned, CLOSENESS is a proxy for the opportunity costs of investing FFF money, which corresponds to the parameter ρ in our theoretical model.

The first equation of the model, reported in columns one and three, considers both signals as binary outcomes and analyzes their impact on the likelihood that business angels invest a startup. The second equation, reported in columns two and four, examines the impact of the amounts of FFF money and patents filed on the investment provided by business angels.

In columns one and three, FFF investment, measured as binary outcome and in amounts, is modeled as a function of our proxy for the opportunity costs of investing, CLOSENESS, the pockets' size of the investors, the discrete variable CYCLE and the dummies D_NO_LAG, D_2_5, D_6_10, the investment in filed patents, whether the founders had invested other startups in the past, as well as the regressors PHD, FT and TIME AT INCUBATOR. As expected, the coefficient of CLOSENESS is positive and statistically significant at the 1% level, in both equation specifications. The interpretation of this result is as follows. The closer the relational ties among the founders, the lower the opportunity costs of investing FFF money, and therefore, the higher likelihood that FFF money is provided[9]. Moreover, lower opportunity costs also affect positively the amount of FFF money invested. The coefficient for AV_WORK_YS is not statistically significant. This result might be explained by the fact that AV_WORK_YS is only a partial measure of the pockets' size of the founders. In fact, while it captures the flow of income earned by the founders, it does not control for the stock of wealth. This implies that we cannot distinguish, for instance, between a dollar invested by a university graduate student backed by a wealthy family and a graduate student that earns the same salary as the first, but who is not economically supported by her family. The coefficient of the variable CYCLE is negative and statistically significant at the 1% confidence level, in both equation specifications. This suggests that the likelihood that FFF investment occurs, and the amount invested, tend to be greater the shorter the time spent at ATDC.

[9] 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.

Having filed patents tends to be positively associated with having invested in FFF money, suggesting a complementarity between the two signals. The number of founders with a PhD in science or engineering has a negative and highly significant impact on the investment in FFF money, under both equation specifications. We have used the number of founders with a PhD in science or engineering as a proxy for the opportunity cost of effort devoted to making a patentable invention. Therefore, this result might suggest that, all else equal, the larger the amount of knowledge the founders have acquired with their PhD, the greater the relative costs of investing in FFF money. This in turn reduces the likelihood that the founders provide FFF money, as well as the amount they provide.

In column two and four, we report the regression results on business angel investment. Having instrumented FFF money, the latter has a positive and statistically significant impact on business angel investment, both when we consider binary outcomes and total amounts. Interestingly, patent investment does not have a statistically significant impact on business angel investment. As in the case for venture capital investment, startups with a large number of full-time employees tend to be positively associated with business angel investment. Moreover, startups that have spent a long time at ATDC, are negatively associated with business angel investment.

In table 5 we report a robustness check analysis and we exclude industry dummies from the equations for ANGEL BINARY and ANGEL FUNDS. The main results hold and FFF money has still a positive and highly significant impact on business angel investment.

The results on FFF money 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 findings also receive 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 results is in order. Van Osnabrugge and Robinson (2000) and Shane (2009) have argued that sometimes it is not easy for the founders of a startup to distinguish between friends' and family's money on the one side, and business angel's money on the other. Our own experience by interviewing a sample of startup founders revealed that they considered any investment from friends or family, no matter how wealthy, as FFF money rather than business angel investment.

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 unique database on technology startups in the incubator of the Georgia Institute of Technology. As implied by the theory, we find that investing in FFF money and patents has a greater impact on external investment than investing in only one of these signals. We then consider the impact of both signals on venture capitalists and business angels. We find that investment in patents has a signaling value for venture capitalists. Conversely, 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. Finally, 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 estimated a structural equation model that takes into account for the possibility that FFF money and business angel investment are simultaneously determined. We find that having controlled for the opportunity cost of investing in FFF money, the latter has a positive impact on business angel investment, while the impact of patents is not statistically significant. These results are consistent with our discussions with startup founders at ATDC who claimed that business angels often require the founders to have some "skin in the game" as evidenced by FFF money.

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

A few caveats are in order. First, the information available from the ATDC incubator does not allow us to assess how investor characteristics affect their preferences. Except for the distinction between venture capitalists and business angels, we do not have information on investors' characteristics such as sectors of specialization, reputation, and education background. These and other characteristics are likely to affect the preferences of external investors. 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

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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
FFF BINARY	0.121	0.326	0	1	471
FILED PAT	0.654	2.677	0	45	471
FILED PAT BINARY	0.231	0.422	0	1	471
COM_ROUND	0.040	0.197	0	1	471
CUM_ANGEL	279,483	711,612	1	5,337,553	471
CYCLE	3.285	2.082	0	8	471
STARTUP EXP	0.501	0.500	0	6	471
PHD	0.687	1.10	0	6	471
TIME AT ATDC	0.361	0.481	0	1	471
FT	16.831	25.029	0	150	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
CLOSENESS	0.380	0.768	0	3	471
AV_WORK_YS	13.577	7.832	1	33	471
D_NO_LAG	0.238	0.426	0	1	471
D_2_5	0.622	0.485	0	1	471

Table 2: Signals' impact on external investment

Mrg. eff.	TOT FUND *With ind. dum.*	TOT FUND *W/out ind. dum.*
$\widehat{ORDER\_SIGNAL}$	8.811***	7.299***
	[2.415]	[2.171]
COM_ROUND	0.526	0.885
	[2.018]	[1.888]
STARTUP EXP	0.029	0.146
	[0.760]	[0.704]
PHD	0.378	0.582
	[0.630]	[0.571]
FT	1.604***	1.425***
	[0.293]	[0.274]
TIME AT ATDC	-3.175***	-3.298***
	[1.055]	[0.905]
TELECOM	0.161	
	[1.413]	
HEALTHCARE	0.807	
	[2.423]	
OTHER SOFTWARE	1.005	
	[1.346]	
HARDWARE	0.752	
	[2.315]	
PHARMA_MDEVICES	2.592	
	[1.965]	
YEAR DUMMIES	YES	YES
Wald chi2	216.49***	183.06***
Wald Test. Exog.	10.98***	8.22***
Observations	471	471

Clustered standard errors by firm in brackets
Marginal effects are calculated for the unconditional expected value of y
*** p<0.01, ** p<0.05, * p<0.1

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

	VC BINARY	VC FUNDS	VC BINARY	VC FUNDS
Mrg. eff.	*With ind. dum.*	*With ind. dum.*	*W/out ind. dum.*	*W/out ind. dum.*
FFF BINARY/ FFF MONEY	-0.040	-0.025	-0.042	-0.029
	[0.030]	[0.034]	[0.031]	[0.036]
FILED PAT BINARY/ FILED PAT	0.200***	0.865***	0.205***	0.919***
	[0.053]	[0.237]	[0.055]	[0.251]
HAD_ANGEL/CUM_ANGEL	-0.004	0.003	-0.008	0.000
	[0.032]	[0.017]	[0.031]	[0.017]
STARTUP EXP	-0.009	0.049	-0.015	-0.010
	[0.028]	[0.282]	[0.030]	[0.306]
PHD	0.040	0.365	0.053*	0.497*
	[0.030]	[0.308]	[0.029]	[0.288]
FT	0.086***	0.811***	0.088***	0.841***
	[0.013]	[0.149]	[0.014]	[0.148]
TIME AT ATDC	-0.176***	-1.996***	-0.180***	-2.077
	[0.040]	[0.475]	[0.034]	[0 .387]
SOFTWARE	0.029	0.378		
	[0.057]	[0.636]		
TELECOM	0.074	0.817		
	[0.083]	[0.926]		
HARDWARE	0.110	1.411		
	[0.110]	[1.396]		
PHARMA_MDEVICES	0.100	1.231		
	[0.103]	[1.289]		
HEALTHCARE	0.012	0.175		
	[0.094]	[0.992]		
YEAR DUMMIES	YES	YES	YES	YES
Pseudo R2	0.31	0.13	0.30	
Observations	471	471	471	471

Clustered standard errors by firm in brackets; *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Tobit marginal effects are calculated for the unconditional expected value of y

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

Mrg. eff.	FFF BINARY	ANGEL BINARY	FFF MONEY	ANGEL FUNDS
$\widehat{FFFBINARY}/\widehat{FFFMONEY}$		0.757***		0.787***
		[0.124]		[0.293]
FILED PAT BINARY/FILED PAT	0.084*	0.037	0.416	0.394
	[0.047]	[0.053]	[0.390]	[0.562]
STARTUP EXP	0.018	-0.023	0.235	-0.282
	[0.035]	[0.040]	[0.422]	[0.599]
PHD	-0.088***	0.042	-0.994***	0.617
	[0.030]	[0.044]	[0.350]	[0.612]
FT	-0.018**	0.039***	-0.198**	0.569***
	[0.008]	[0.012]	[0.100]	[0.179]
TIME AT ATDC	0.002	-0.144***	0.023	-2.193***
	[0.039]	[0.045]	[0.452]	[0.724]
TELECOM		-0.065		-0.979
		[0.057]		[0.752]
HEALTHCARE		0.054		0.945
		[0.096]		[1.462]
OTHER SOFTWARE		-0.026		-0.378
		[0.064]		[0.875]
HARDWARE		-0.120**		-1.610**
		[0.048]		[0.647]
PHARMA_MDEVICES		-0.006		0.065
		[0.073]		[1.112]
CLOSENESS	0.061***		0.731***	
	[0.020]		[0.223]	
AV_WORK_YS	0.024		0.255	
	[0.023]		[0.280]	
D_NO_LAG	-0.006		0.158	
	[0.046]		[0.514]	
D_2_5	0.046		0.742*	
	[0.037]		[0.417]	
CYCLE	-0.047***		-0.562***	
	[0.011]		[0.133]	
YEAR DUMMIES	YES	YES	YES	YES
Wald chi2		172.46***		110.73***
Wald Test. Exog.		7.11***		6.13**
Observations	471	471	471	471

Clustered standard errors by firm in brackets; *** p<0.01, ** p<0.05, * p<0.1
Tobit marginal effects are calculated for the unconditional expected value of y

Table 5: Impact of FFF money and the number of patents filed on business angel investment (Excluding industry dummies)

	FFF BINARY	ANGEL BINARY	FFF MONEY	ANGEL FUNDS
		Mrg. eff.		*Mrg. eff.*
$FFF\widehat{BINARY}/FFF\widehat{MONEY}$		0.740***		0.712***
		[0.131]		[0.257]
FILED PAT BINARY/FILED PAT	0.085*	0.041	0.420	0.471
	[0.047]	[0.053]	[0.390]	[0.545]
STARTUP EXP	0.016	-0.011	0.208	-0.074
	[0.035]	[0.040]	[0 .423]	[0.560]
PHD	-0.089	0.044	-1.008***	0.624
	[0.030]	[0.042]	[0.348]	[0.571]
FT	-0.018**	0.032**	-0.200**	0.434**
	[0.008]	[0.013]	[0.099]	[0.176]
TIME AT ATDC	-0.002	-0.129***	-0.013	-1.933***
	[0.039]	[0.043]	[0.461]	[0.671]
CLOSENESS	0.062***		0 .740***	
	[0.020]		[0.227]	
AV_WORK_YS	0.027		0.301	
	[0.024]		[0.286]	
D_NO_LAG	-0.013		0.062	
	[0.045]		[0.514]	
D_2_5	0.040		0.656	
	[0.037]		[0.413]	
CYCLE	-0.047***		-0.562***	
	[0 .011]		[0 .132]	
Constant	0.193		2.320*	
	[0 .118]		[1.365]	
YEAR DUMMIES	YES	YES	YES	YES
Wald chi2		121.83***		83.64***
Wald Test. Exog.		7.13***		6.25**
Observations	471	471	471	471

Clustered standard errors by firm in brackets

Tobit marginal effects are calculated for the unconditional expected value of y

*** p<0.01, ** p<0.05, * p<0.1

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 $\frac{\partial^2 V(pM_H^*, p_H^*; \theta_H)}{\partial p_H^2} < 0$.

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

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

c) H-type IC constraint is met.

In fact, from (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 invests 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 M greater than the equilibrium amounts, they would still successfully differentiate themselves from L-type founders but they would not earn a greater payoff. Because, M and p are costly to provide, any amount of p and M greater than the equilibrium amounts would yield a lower utility to H-type founders. Moreover, any amounts of p and M smaller than the equilibrium amounts would yield a lower payoff to H-type founders because it would lead the investors to believe that the founders are of type L. Finally, given the preferences of the investors and the lower bound on α, any equilibrium amount of 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.

Finally, this criterion also eliminates all possible pooling equilibria. Any pooling equilibrium with p and M smaller than the equilibrium amounts would be subject to deviations by H-type founders. Similarly, any pooling equilibrium with p and M greater than the equilibrium amounts would be subject to deviations by L-type founders. Finally, any equilibrium amount of p and M respectively obtained from the IC constraint of L-types and the first order condition for M, would 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 two 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 the 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:

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

Deriving (2) with respect to ρ 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 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: Robustness check analysis

In this section we estimate, as a robustness check, the same models as in tables 2-5 having excluded those startups whose external investment (either venture capital or business angel) falls within the 99th percentile. Similar to what we found in table 2, having invested in both signals has a greater impact on external ivestment than having invested in only one of the two signals. Moreover, similar to what we found in tables 3-5 having invested in FFF money, as well as the amount of FFF money invested, have a positive and statistically significant impact on business angel investment but not on venture capital investment. Finally, having invested in patents, as well as the number of patents filed, have a positive and statistically significant impact on venture capital investment but not on business angel investment.

Table 1: Signals' impact on external investment: Excluding startups whose venture capital or business angel investment falls within the 99th percentile

	TOT FUND	TOT FUNDS
Mrg. eff.	*With ind. dum.*	*W/out ind. dum.*
$\widehat{ORDER\_SIGNAL}$	7.559***	6.454***
	[2.458]	[2.311]
COM_ROUND	0.502	0.912
	[1.970]	[1.893]
STARTUP EXP	-0.355	-0.199
	[0.720]	[0.671]
PHD	0.562	0.587
	[0.577]	[0.569]
FT	1.507***	1.362***
	[0.302]	[0.283]
TIME AT ATDC	-3.163***	-3.299***
	[1.012]	[0.890]
TELECOM	0.404	
	[1.592]	
HEALTHCARE	1.274	
	[2.453]	
OTHER SOFTWARE	1.200	
	[1.320]	
HARDWARE	0.928	
	[2.279]	
PHARMA_MDEV	2.164	
	[2.085]	
YEAR DUMMIES	YES	YES
Wald chi2	181.96***	167.35***
Wald Test. Exog.	8.13***	5.94**
Observations	433	433

Clustered standard errors by firm in brackets
Marginal effects are calculated for the unconditional expected value of y
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Impact of FFF money and the number of patents filed on venture capital investment: Excluding startups whose venture capital investment falls within the 99th percentile

	VC BINARY	VC FUNDS	VC BINARY	VC FUNDS
Mrg. eff.	*With ind. dum.*	*With ind. dum.*	*W/out ind. dum.*	*W/out ind. dum.*
FFF BINARY/ FFF MONEY	-0.033	-0.019	-0.037	-0.024
	[0.030]	[0.033]	[0.031]	[0.035]
FILED PAT BINARY/ FILED PAT	0.184***	0.887***	0.189***	0.956***
	[0.055]	[0.249]	[0.056]	[0.268]
HAD_ANGEL/ CUM_ANGEL	-0.007	-0.001	-0.012	-0.004
	[0.031]	[0.016]	[0.030]	[0.016]
STARTUP EXP	-0.014	-0.036	-0.017	-0.061
	[0.028]	[0.288]	[0.030]	[0.304]
PHD	0.038	0.335	0.051*	0.442
	[0.029]	[0.284]	[0.028]	[0.277]
FT	0.082***	0.777***	0.083***	0.798***
	[0.014]	[0.147]	[0.014]	[0.144]
TIME AT ATDC	-0.172***	-1.913***	-0.174***	-1.974***
	[0.041]	[0.479]	[0.035]	[0.389]
TELECOM	0.057	0.564		
	[0.082]	[0.877]		
HEALTHCARE	0.015	0.155		
	[0.092]	[0.931]		
OTHER SOFTWARE	0.027	0.297		
	[0.055]	[0.599]		
HARDWARE	0.103	1.151		
	[0.107]	[1.290]		
PHARMA_MDEV	0.111	1.180		
	[0.111]	[1.354]		
YEAR DUMMIES	YES	YES	YES	YES
Pseudo R2	0.29	0.13	0.28	0.12
Observations	458	458	458	458

Clustered standard errors by firm in brackets

Tobit Marginal effects are calculated for the unconditional expected value of y

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Impact of FFF money and the number of patents filed on business angel investment: Excluding startups whose business angel investment falls within the 99th percentile

Mrg. eff.	FFF BINARY	ANGEL BINARY	FFF MONEY	ANGEL FUNDS
$\widehat{FFFBINARY}/\widehat{FFFMONEY}$		0.797***		0.932***
		[0.105]		[0.358]
FILED PAT BINARY/ FILED PAT	0.110**	0.004	0.654	-0.082
	[0.049]	[0.057]	[0.413]	[0.639]
STARTUP EXP	0.051	-0.027	0.678*	-0.420
	[0.035]	[0.040]	[0.404]	[0.648]
PHD	-0.100***	0.055	-1.138***	0.967
	[0.034]	[0.046]	[0.385]	[0.687]
FT	-0.021**	0.036***	-0.246**	0.593***
	[0.009]	[0.012]	[0.101]	[0.196]
TIME AT ATDC	-0.010	-0.123***	-0.103	-2.029***
	[0.043]	[0.043]	[0.493]	[0.738]
TELECOM		0.034		0.539
		[0.069]		[1.049]
HEALTHCARE		0.165		3.060
		[0.109]		[2.020]
OTHER SOFTWARE		0.076		1.249
		[0.060]		[0.897]
HARDWARE		-0.051		-0.735
		[0.067]		[0.972]
PHARMA_MDEV		0.090		1.791
		[0.097]		[1.807]
CLOSENESS	0.068***		0.811***	
	[0.019]		[0.220]	
AV_WORK_YS	0.015		0.089	
	[0.025]		[0.282]	
D_NO_LAG	-0.030		-0.108	
	[0.050]		[0.547]	
D_2_5	0.031		0.539	
	[0.037]		[0.415]	
CYCLE	-0.044***		-0.517***	
	[0.012]		[0.138]	
YEAR DUMMIES	YES	YES	YES	YES
Wald chi2		172.61***		85.72***
Wald Test. Exog.		7.51***		6.65***
Observations	446	446	446	446

Clustered standard errors by firm in brackets; *** p<0.01, ** p<0.05, * p<0.1
Tobit Marginal effects are calculated for the unconditional expected value of y

Table 4: Impact of FFF money and the number of patents filed on business angel Investment: Excluding startups whose business angel investment falls within the 99th percentile. (No Industry Dummies)

	FFF BINARY	ANGEL BINARY	FFF MONEY	ANGEL FUNDS
		Mrg. eff.		*Mrg. eff.*
$\widehat{FFFBINARY}/\widehat{FFFMONEY}$		0.750***		0.728**
		[0.155]		[0.286]
FILED PAT BINARY/ FILED PAT	0 .110**	0.008	0.650	-0.037
	[0.049]	[0.053]	[0.412]	[0.530]
STARTUP EXP	0.047	-0.012	0.629	-0.133
	[0.035]	[0.039]	[0.403]	[0.552]
PHD	-0.100***	0.051	-1.138***	0.840
	[0.033]	[0.047]	[0 .384]	
FT	-0.021**	0.029**	-0.245**	0.423**
	[0.009]	[0.013]	[0 .101]	[0.183]
TIME AT ATDC	-0.008	-0.125***	-0.080	-1.875***
	[0.044]	[0.040]	[0.506]	[0.649]
CLOSENESS	0.066***		0.792***	
	[0.020]		[0.232]	
AV_WORK_YS	0.019		0.147	
	[0.027]		[0.308]	
D_NO_LAG	-0.033		-0.145	
	[0.029]		[0.570]	
D_2_5	0.029		0.515	
	[0.037]		[0 .417]	
CYCLE	-0.045***		-0.536***	
	[0.012]		[0.133]	
YEAR DUMMIES	YES	YES	YES	YES
Wald chi2		107.44***		73.53***
Wald Test. Exog.		5.97**		5.91**
Observations	446	446	446	446

Clustered standard errors by firm in brackets

Tobit Marginal effects are calculated for the unconditional expected value of y

*** p<0.01, ** p<0.05, * p<0.1