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Coaching or Selection? Venture Capital and Firms' Patenting Performance

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Abstract

In the process of new firm growth different types of capabilities are deployed in the pursuit of entrepreneurial opportunities. In this paper we investigate the role of coaching vs. selection capabilities of venture capitalists in the patenting performance of portfolio companies. We develop simultaneous models that predict the likelihood that firms attract venture capital, the likelihood that they patent and the number of patents applied for and granted. When estimating simple models with independent equations, we find evidence of a positive impact of venture capital on patenting; but if we account for endogeneity of venture capital investments, this effect becomes insignificant or negative. Our results show that venture capital follows patent signals to invest in companies with commercially viable know-how and that, as far as the patenting performance of firms is concerned, the selection function of venture capital is stronger than its coaching function.

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1. INTRODUCTION

New firms cannot typically rely on internal cash flow in the pursuit of emerging entrepreneurial opportunities. Among the sources of external finance available to entrepreneurs, venture capital has been identified as the most effective market-based solution that can jointly provide not only the required financial resources through its capacity to overcome information asymmetries at the screening and monitoring stages, but also an ability to enhance the design, development and performance of new firms (Lerner, 1995; Bergemann & Hege, 1998; Gompers and Lerner, 1999; Mayer, Schoorsb, & Yafeh, 2005; De Clercq, Fried, Lehtonen, & Sapienza, 2006; Schwienbacher, 2008).

A large body of research across the management, economics and finance disciplines has accumulated evidence that venture capital (VC) investors can contribute to portfolio companies in excess of the monetary value of their investment (Sahlman & Gorman, 1989; MacMillan, Kulow, & Khoylian, 1989; Sapienza, 1992). Venture capitalists can facilitate the introduction of superior managerial practices (Bygrave & Timmons, 1992; Kaplan & Strömberg, 2001; Hellmann & Puri, 2002; Wright Lockett, 2003); co-ordinate access to additional, including financial, resources (Lerner, 1995; Fried & Hirich, 1995; Hochberg, Ljungqvist, & Lu, 2007); and confer reputational advantages – a ‘certification effect’ – to newly established companies (Stuart, Hoang, & Hybels, 1999; Busenitz, Arthurs, Hoskisson, & Johnson, 2003; Davila, Foster, & Gupta, 2003; Hsu, 2004). Crucially, venture capitalists can also take an active role in shaping the companies’ strategic orientation and in implementing strategic decisions through formal board representation or informal interaction with entrepreneurial teams (Fried, Bruton, & Hisrich, 1998; Vanaelst, Clarysse, Wright, Lockett, Moray, & S'Jegers, 2006; Beckman & Burton, 2008).

Because of the growing connection between risk finance and new ventures, an important stream of contributions has emerged in the literature on the relationship between VC investments and innovation. Venture capital can improve the innovative performance of portfolio companies and this has been interpreted as evidence of the ‘coaching’ capabilities of venture capitalists, that is to say their skills at nurturing the development of portfolio companies (Kortum & Lerner, 2000; Ueda & Hirukawa, 2008; Bertoni, Croce, & D’Adda, 2010; Popov & Roosenboom, 2012). But is this really what VCs excel at? An alternative theoretical argument leads to a different interpretation: VC is exceptionally good at identifying the best ideas and the best teams, which will then turn into successful new products and fast-growing businesses. As a consequence, the most distinctive trait of VC, and the best explanation for the stronger performance of VC-backed firms relative to other firms, would be their superior 'selection' capabilities (Baum & Silverman, 2004; Engel & Keilbach, 2007).

This fundamental question about the selection and coaching capabilities of VC firms and innovation has a rich underlying structure, involves endogeneity and reverse causation between the two processes, and entails considerable technical obstacles in identifying causes and effects.[1] It poses a significant theoretical as well as empirical research challenge. Moreover, it has important implications not only for the management of the VC investment process, but also for the design of policy interventions based on the VC investment model.[2]

In this paper we model the relation between VC and innovation in a simultaneous equations setting where we take into account both the determinants of VC investments, including patents as signals of firm quality, and the effect of VC on firms' post-investment patenting performance, controlling for prior performance. Instead of relying on propensity score matching or comparable algorithms to identify a control group of non-VC backed firms, we can work with 'treatment' and 'control' data generated contemporaneously through a survey of US and UK small and medium-sized enterprises (SMEs). While prior studies are limited to the observation of firms obtaining or not obtaining VC investments, this survey enables us to identify firms that sought external finance and those among them that obtained risk finance. The explicit consideration of finance-seeking behaviors strengthens the quality of this sample and the precision or our results.

We work with a sample of 940 firms (513 in the US and 427 in the UK) that sought finance between the years 2002 and 2004. We match these firms' records with patent data extracted from the European Patent Office's Worldwide Patent Statistical Database (PatStat) for the periods concurrent to and following the survey years. First, controlling for other firm characteristics (e.g. size, age, R&D expenditure and market size), we estimate independent models for 1) the likelihood that firms' patenting activities predict VC investments and 2) the likelihood that VC leads to patenting in the following period. We then employ a bivariate recursive probit model and develop a simultaneous zero-inflated Poisson model for count data, which both control for the endogenous nature of the selection and coaching processes.

We show that we can reproduce prior findings on the relationship between VC and patenting when we estimate separate bivariate equations. However, we find that once we

[1] A similar question, with mixed empirical evidence, characterises studies of VC investments and the financial performance of portfolio companies. Confront, for example, Steier & Greenwood (1995) and Busenitz, Moesel, & Fiet (2004) with Fitza, Matusik, & Mosakowski (2009) and Matusik & Fitza (2012).

[2] See, for example, the recent volume by Lerner (2009) on VC-based innovation policy designs.

account for endogeneity, the effect of venture capital on the patenting behaviour of portfolio companies after investment is either negative or insignificant. These results support the view that venture capitalists positively react to patents as signals of companies with potentially valuable products, confirming the 'selection' capability hypothesis, whereas there is no evidence on the effects of 'coaching' on patenting performance. While it is perfectly plausible that VC will positively influence later stages in the life-cycle of the new products and services of portfolio companies (i.e. launch, marketing, or operations management), the involvement of VC does not increase the technological output of firms. In turn, the fact that the technological productivity of a firm may slow down after VC investment does not mean that the firm would be better off without VC. It means that the contribution of VC to innovation should not be looked for or measured at the level of the firm's patenting performance, as is often done in existing literature on this topic. Moreover, an insignificant or negative effect of VC on firm patenting can in fact indicate that the beneficial contribution of VC is to *rationalize* technological searches and *focus* the attention of firms on existing inventions that need to be commercialized as opposed to new inventions.

To sum up, this paper addresses the question of how VC contributes to innovation. It contributes to theory by connecting the capability framework with entrepreneurial finance and it advances the study of the innovation process by modelling and testing the relative importance of 'coaching' vs. 'selection' capabilities of VC in relation to the technological profile of portfolio companies at the time of and after investment. Finally, it develops an original methodology that can efficiently handle the endogenous nature of the relationship between VC and patenting, with potential for further uses in the treatment of similar underlying theoretical structures.

2. VC INVESTMENTS AND INNOVATION: THEORY AND EVIDENCE

Investments in small and medium-sized businesses, and in particular new technology-based firms, pose specific challenges to capital markets because they involve high risk and strong information asymmetries (Storey, 1994; Lerner, 1995; Hall, 2002). From an investors' viewpoint, the economic potential of these firms is difficult to assess given their short history, lack of external signals about their quality (e.g. audited financial statements, credit ratings) and lack of market feedback on new products and services at the time of investment (Sahlman, 1990; Gompers, 1995; Hellman, 1998, Gompers & Lerner, 1999, 2001; Kaplan & Strömberg, 2003, 2004). Only few investors are able and willing to back these businesses. They can do so with an expectation of satisfying returns by applying a specific set of capabilities, and often sector-specific business knowledge, that enable them to make better choices relative to competing investors, handle technological and market uncertainty, and actively influence the outcome of their investments. From the viewpoint of a resource-based theory of the firm (Penrose, 1956; Wernerfelt, 1984; Barney, 1986), these are the capabilities typically attributed to venture capitalists (Lerner, 1995; De Clercq et al., 2006).

Venture capital has played a key role in the development of several highly innovative, high-growth firms and it is no surprise that the literature has developed a keen interest, both theoretical and empirical, in the connection between VC and innovation. Two polarized views have emerged among scholars, which reflect the endogenous nature of this relationship. We refer to them as the 'coaching hypothesis' vs. the 'selection hypothesis'. The first posits that the fundamental contribution of VC rests in its ability to nurture the development and growth of portfolio companies through formal and informal decision-making and advice. In line with the literature on the value-adding function of VC (Gorman & Sahlman, 1989; Sapienza, 1992; Barney, Busenitz, Fiet, & Moesel, 1996; Busenitz et al. 2004; Colombo & Grilli, 2010; Park & Steensma, 2012) we can identify this set of activities as the 'coaching capabilities' of VC. The second hypothesis emphasizes, instead, the ability of VC to make superior choices – on a portfolio basis – among the investment options that are presented to them. What then generates above-average innovation performance is not their involvement in the management of investee firms but the quality of their initial decisions. If this is the case, the source of VC competitive advantage rests on their superior 'selection capabilities', defined as the ability to identify the portfolio companies with the highest growth potential (Dimov, Sheperd, & Sutcliffe, 2007; Yang, Narayanan, & Zahra, 2009, Fitza et al. 2009). In the following sections we review the arguments and evidence behind these two perspectives.

2.1 Coaching

The proposition that venture capitalists are able to increase firm value beyond the provision of financial resources has broad support in the literature (Gorman & Sahlman, 1989; Sahlman, 1990; MacMillan et al., 1989; Bygrave & Timmons, 1992; Tyebjee & Bruno, 1984; Lerner, 1995; Keuschnigg & Nielsen, 2004). This characteristic is especially clear when they are compared to banks, the most common alternative for the external financing of SMEs (Ueda, 2004). Venture capitalists take an active role in many aspects of the strategic and operational conduct of portfolio firms. They assist in the recruitment of key personnel through personal networks (Hellmann & Puri, 2002) and monitor the development of business plans, often on the basis of an in-depth knowledge of the industry (Fried et al., 1998). They can attenuate the founder's overconfidence (Kahneman & Lovallo, 1993) and direct information about firms' quality to future investors, who might also be venture capitalists (Hsu, 2004). They also assist in identifying opportunities for alliances and in supporting incumbents in mergers and acquisitions or the sale of the business (Sørensen, 2007).

Among the positive effects of VC, a link has been found between VC investments and the firms' innovation performance. One of the most prominent studies on this topic is Kortum and Lerner's (2000) empirical investigation of a patent production function. Aggregating patent numbers by industry, they find a positive and significant effect of VC financing on (log) patent grants.[3] Ueda and Hirukawa (2008) show that Kortum and Lerner's findings become even more significant during the venture capital boom in the late 1990's. They further estimate models of total factor productivity (TFP) growth, but do not find that VC investment affects total factor productivity growth. Popov and Roosenboom (2009) find similar, albeit weaker results for European countries and industries, and Hirukawa and Ueda (2008), who estimate autoregressive models for TFP growth and patent counts by industry, find that that TFP growth is positively related to future VC investment, and little evidence that VC investments precede an increase in patenting. On the contrary, lagged VC investments are often negatively related with both TFP growth and patent counts.

Firm-level studies on venture capital and patenting have appeared only recently. Lerner, Sørensen and Strömberg (2008) estimate various models, including Poisson and negative binomial models, for patents granted and patent citations in firms that experienced private equity-backed leveraged buyouts (LBOs). They find an increased number of citations for patents applications after the LBO and no decrease in patent originality and generality after the investments. Patent counts do not seem to change in a uniform direction. VC-funded firms apply for ten times as many patents as matched non-VC firms in a study by Engel and Keilbach (2007), where propensity score matching and balanced score matching are used to compare German venture-funded firms to non-VC ones with respect to innovation output and growth. However, this difference is only weakly significant. Caselli, Gatti and Perrini (2009) use a similar matching procedure to assess the difference in patenting and growth in venture-

[3] Both patenting and venture funding could be related to unobserved technological opportunities, thereby causing an upward bias in the coefficient on venture capital, but regressions that use information of a policy shift in venture fund legislation to construct an instrumental variable, also show a positive impact on patenting (Kortum & Lerner, 200).

backed IPOs of Italian firms. They find a higher average number of patents in the venture-backed firms than in their control group. They argue, however, that VCs might select firms based on patents rather than promote continued innovation after the investment. These results are compatible with Zhang's (2009): estimation of a log-linear tobit model of patents before and after an IPO shows that venture capital appears to be positively related to patents in the pre-IPO period, but not after.

The assumption of firms having at least one patent when taking logs may bias results. Bertoni, Croce and D'Adda (2010) address this methodological problem by estimating random effects logit models for the likelihood of observing one or more patents and random effects negative binomial models for the number of patents. Venture capital investment positively affects subsequent patent applications in their sample of Italian technology firms, in line with Arqué-Castells' (2012) results from Poisson and probit estimation of pooled panel data on Spanish firms.

2.2 Selection

The second hypothesis in contention to explain the correlation between VC and innovation is that venture capitalists have distinctive selection capabilities that are superior to those possessed by other equity investors. This implies a framework of analysis where the innovative profile of potential investee firms affects the probability that they receive VC investment. From this perspective, innovation indicators such as patents function as signals to investors about the quality of the firm (Macmillan, 1985; Lerner, 1994; Baum & Silverman, 2004; Mann & Sager, 2007; Hsu & Ziedonis, 2008; Häussler, Harhoff, & Müller, 2009).[4]

There are several dimensions to the VC investment evaluation process (Shepherd, 1999), but substantial empirical evidence on the technological determinants of venture capital financing has been collected only recently. Baum and Silverman (2004) authored the first contribution that includes VC financing, patent applications and granted patents. Their VC model suggests that the amount of VC finance obtained depends on lagged patents granted and applied for, R&D expenditures, R&D employees, government research assistance, the amount of sector-specific venture capital, horizontal and vertical alliances, and being a university spin-off. Age is negatively related to venture capital, as are net cash flow, diversification and industry concentration. Mann and Sager (2007) confirm the positive impact of patenting on VC-related performance variables, including the number of financing

[4] Spence (1973) is a classic reference in the more general literature on market signals.

rounds, total investment and exit status. Similarly, a start-up firm's prior patenting attracts larger amounts of VC funds in Cao and Hsu's (2011) study of venture-backed firms.

Two other relevant studies relate patents to outcome variables associated with venture funding: Häussler, Harhoff and Müller (2009) and Hsu and Ziedonis (2008). Häussler et al. use a proportional hazards model to estimate the time to VC financing and find a positive effect of patent applications on the hazard rate. They test various measures of patent quality, of which both the average number of citations and the share of opposed patents reduce the time until the first VC investment occurs. Results from Hsu and Ziedonis' (2008) study of VC-financed start-ups suggest that patent applications increase both the likelihood of obtaining initial capital from a prominent VC and of going public (for the semiconductor sector).

Other studies employ sets of binary models for the likelihood of obtaining venture capital. As part of their matching procedure, Engel and Keilbach (2007) estimate a probit model for VC involvement that predicts a positive association with patents as well as the founder's education. Colombo and Grilli (2010) show results for similar probit models, in which founders' managerial education and the firm's objective to exploit a technological opportunity help predict the likelihood of VC investments. Patenting, however, does not appear among their explanatory variables. Finally, Audretsch, Bönte and Mahagaonkar (2009) have results for separate probit models for venture capital and business angel investments. In both cases, patents predict VC financing if the company is at the prototyping stage in its life cycle.

2.3 The research challenge

Does venture capital positively contribute to the patenting performance of firms or is this a consequence of the ability of venture capitalists to identify the best companies at the time of investment? Results based on firm-level information are mixed and suggest that positive findings could be driven by venture firms' selecting companies on the basis of their current patent output instead of VC fostering technological output after investment. If we take into account the endogeneity of the relationship between venture capital and innovation, we will be able to shed light on the role of the coaching capabilities relative to the selection capabilities of VC.

We therefore formulate the following hypotheses:

Hypothesis 1: Venture capital has a positive effect on the patenting performance of portfolio companies after investment.

Hypothesis 2: The patenting performance of firms has a positive effect on the probability of investments.

We first test each hypothesis in separate models and then estimate the two hypotheses simultaneously to identify the effects of endogeneity and obtain unbiased results on the 'true' effect of VC investment.

3. DATA AND METHODOLOGY

This paper builds on a unique comparative survey of UK and US businesses jointly carried out by the [ANONYMIZED FOR SUBMISSION] and the [ANONYMIZED FOR SUBMISSION] in 2004-2005. The basis for the sampling was the Dun & Bradsheet (D&B) database, which contains company-specific information drawn from various sources, including Company House, Thomson Financial and press and trade journals. The sample covered manufacturing and business service sectors and was collected through a telephone survey between March and November 2004 (response rate: 18.7% for the US and 17.5% for the UK), which was followed by a postal survey of large firms in Spring 2005 leading to a total sample of 1,540 US firms and 2,129 UK firms.

The survey was addressed to businesses with up to 1000 employees. We restrict our sample to firms that sought finance during the two years prior to being interviewed. This generates a working sample of 940 firms, 513 in the US and 427 in the UK. We also run separate analyses on firms that did not become merger targets in the post-survey period. There are 888 firms in this sample, 486 in the US and 402 in the UK. The survey lists venture capital funds and business angels as a possible source of external finance. We incorporate this information as an endogenous binary variable in our models.[5] Firms answered the survey questions almost completely. Minor gaps in the data, however, would have prevented us from using about 10 percent of the survey responses. In order to avoid having to drop observations due to missing values, we impute missing values by random regression imputation (Gelman

[5] For simplicity we will refer to VC, instead of VC and business angels, in the reminder of the paper. While there are institutional differences between these types of investors, from a theoretically and empirical point of view these are not especially relevant for our research questions. In addition, robustness checks do not uncover any significant difference between these two sources of risk finance in our estimations.

& Hill, 2006). The number of imputations is generally very low and always below 2 percent per variable. If values are missing in our dependent variables, we drop these observations.

Patent data are taken from the European Patent Office's (EPO) Worldwide Patent Statistical Database (PatStat). It contains information on 68.5 million applications by 17.3 million assignees and inventors from 1790 to 2010, although the European Patent Office states that both numbers are likely to be smaller due to a large number of duplicate entries or entries for referential consistency of publications in the database. Since there are no firm identifiers available in PatStat, we match patent information to the survey data by firm name. To align patent data with the period addressed in the survey (three years), we count the number of patents applied for and granted within a three-year period prior to the interview and determine patenting status for each firm from this number. More specifically, we use application filing dates and publications dates that represent the first grant of an application to locate applications and grants in the time dimension. For our dependent variables, we count applications and grants for the whole post-survey period. This procedure captures long-term effects of venture capital and maximises the chance that firms with small, but positive, patenting rates produce at least one patent, which allows us to distinguish patenting from non-patenting firms. Three-year periods are calculated from exact survey response dates.

Insert Table 1 about here

Table 1 shows descriptive statistics for patenting activities and independent variables. In our sample, 147 firms applied for patents during the three-year survey period (t), while 170 firms filed patent applications in the next period ($t+1$). Patent grants can be identified in 116 and 144 firms, respectively. Ninety-four firms received venture capital or business angel financing with about equal proportions of these two types of early stage financing. A simple cross-tabulation of an indicator for VC financing and an indicator for patenting activity at t highlights the strong link between venture capital and patenting (see table 2). It shows that 44.8 percent of VC-financed firms were applying for patents whereas only 12.3 percent of those without VC involvement did so. This picture begins to look different already if we consider the time dimension. In the group of firms without VC involvement and without any patent applications at time t, 52 applied for patents at $t+1$, while 26 of those who were patenting at t did not show any patenting activities one period later. In the VC-financed group, firms that start to patent (11) balance those that discontinue patenting activities (11).

In our multivariate analyses, further control variables help extract the precise relationship between VC financing and patenting.

Insert Table 2 about here

We select explanatory variables based on the literature on venture capital and patenting. Prior studies often used a very limited number of explanatory variables, sometimes limited to R&D expenditures only. We extend the scope of relevant predictors for the propensity to patent. R&D intensity is a variable of first choice (Scherer, 1965a, 1965b, 1983; Pakes & Griliches, 1980; Pakes, 1981; Hausman et al., 1984; Hausman, Hall, & Griliches, 1984; Brouwer & Kleinknecht, 1999). Since prior research used various measures, including the log of R&D expenditures, R&D expenditures scaled by size variables, or the number of R&D employees, we choose a combination of these, which best suits our estimation equations: We first proxy for size by the logarithm of employment and control for R&D intensity by the percentage of R&D staff and a dummy indicating the presence of R&D expenditures. One advantage of this structure is that it avoids including multiple size-dependent measures, since variables enter the expected mean in Poisson specifications multiplicatively. Further variables control for age, country and whether a firm belongs to the manufacturing sector, defined as ISIC Rev. 3.1 codes 15–37. Similar to Scherer (1983), we use the amount of international sales to measure market size and control for industry concentration by the number of competitors. We measure CEO education by a dummy variable indicating whether the CEO has a university degree. Product development time enters our equations, since it might play a role in attracting VC financing (Hellman & Puri, 2000). Finally, we include lagged patent applications and grants as proxies for the part of a firm's knowledge stock that is used to produce new patents.[6]

3.1 Models and estimation

The structure of firms' patenting decisions presents several econometric challenges. Previous research shows that the vast majority of firms do not patent, which causes observations of zero patents in a large proportion of firms. This in turn leads to model instability and error distributions that do not meet the model's assumptions if these excess zeroes are not properly addressed (Bound, Cummins, Griliches, Hall, & Jaffe, 1984;

[6] Baum and Silverman (2004) also argue that lagged dependent variables help account for unobserved heterogeneity (Jacobson, 1990).

Hausman et al. 1984). At the same time, unobservable heterogeneity is highly likely to be correlated between VC investment and patenting performance. For example, firms might disclose patenting activities to prospective venture capital investors, which increases the likelihood that we observe venture capital investments in combination with more patenting in the future. When using VC investment to explain patenting, this endogeneity complicates model estimation, which can become analytically intractable.

We suspect that there might be a two-step process for patenting, in which firms first decide whether to patent at all and then produce patents according to a Poisson or similar distribution (see figure 1). We model patenting activity as a binary variable that depends on firm and industry characteristics as well as an endogenous binary variable that indicates whether or not a firm receives venture capital financing. This endogenous selection process is more general than ex post comparison of firms by propensity score matching.

Insert Figure 1 about here

After establishing baseline results for independent patenting and VC equations, we present two sets of simultaneous equations: In the first set comprising two probit equations for patenting and venture capital investments, we ignore information about the number of patents and treat firms' patenting behaviour as a binary outcome. The second set of equations reintroduces the number of patents in a zero-inflated Poisson model.

The patenting equation in the recursive bivariate system of equations is

$$Pat_{i,t+1} = I(X_{it}\gamma_0 + \gamma_1 Pat_{it} + \gamma_2 \ln(PatN_{it}) + \theta^1 VC_{it} + \varepsilon_{it} > 0)\,, \tag{1}$$

where Pat_{it} is a dummy variable indicating whether firm i applied for one or more patents or, depending on context, received at least one patent grant in period t. $PatN_{it}$ denotes the number of patent applications or patents granted. The indicator function $I(\cdot)$ equals one if the condition in parentheses holds and zero otherwise. Since patent applications and grants can be zero, and the natural logarithm would not exist in this case, we set $\ln(PatN_{it})$ to zero and use a dummy variable (Pat_{it}) to indicate patenting status. Endogenous venture capital investment is captured by an indicator variable (VC_{it}), and X_{it} represents exogenous variables. The simultaneously determined venture capital investment is

$$VC_{it} = I(Z_{it}\beta_0 + \beta_1 Pat_{it} + \beta_2 \ln(PatN_{it}) + \nu_{it} > 0)\,, \tag{2}$$

where Z_{it} is a vector of exogenous explanatory variables which can contain some or all of the elements in X_{it}. Endogeneity of venture capital financing is accounted for by allowing arbitrary correlation between the error terms. Since the error terms' variance is not identified in binary models, the error terms ε_{it} and ν_{it} are normalised to have a variance of unity.

A similar simultaneous model structure can be used to predict the number of patents. Since patent data show a large number of non-patenting firms, we model this empirical fact using a zero-inflated Poisson distribution. In this model, firms self-select into the patenting regime, and a third equation models the number of patent applications or grants produced according to a Poisson distribution. Similar to Lambert's (1992) zero-inflated Poisson model, the number of patents is distributed as

$$PatN_{it+1} = \begin{cases} 0 & \text{with probability } \mathrm{p_{it}} + (1-\mathrm{p_{it}})\mathrm{e}^{-\lambda_{it}} \\ k & \text{with probability } (1-\mathrm{p_{it}})\mathrm{e}^{-\lambda_{it}} \lambda_{it}^{\mathrm{k}} / \mathrm{k}!, k = 1, 2, \ldots \end{cases} \quad (3)$$

The likelihood that a firm chooses *not* to patent in the next period is

$$p_{it} = I(X_{it}\gamma_0 + \gamma_1 Pat_{it} + \gamma_2 \ln(PatN_{it}) + \theta^{1} VC_{it} + \varepsilon_{it}), \quad (4)$$

while the conditional mean of the Poisson process in the patenting state is

$$\lambda_{it} = exp\left(X_{it}\delta_0 + \delta_1 Pat_{it} + \delta_2 \ln(PatN_{it}) + \theta^{N} VC_{it} + \omega_{it} \right) \quad (5)$$

A novel feature of our model is that a firm's likelihood of obtaining venture capital is determined by an additional equation

$$VC_{it} = I(Z_{it}\beta_0 + \beta_1 Pat_{it} + \beta_2 \ln(PatN_{it}) + \nu_{it} > 0) \quad (6)$$

as in the bivariate Probit case above.

We allow for arbitrary contemporaneous correlation between ν_{it} and ε_{it} as well as between ν_{it} and ω_{it}, which are assumed to follow bivariate normal distributions. Specifying the model in this way allows for correlation between heterogeneity in expected means of patent counts, the decision to patent and VC financing. The variance of individual-level errors (ω_{it}) introduces a free parameter that accounts for overdispersion in Poisson models (Miranda & Rabe-Hesketh, 2006). Identification in semiparametric models of binary choice variables often relies on exclusion restrictions (Heckman, 1990; Taber, 2000). In our parametric case, however, the functional form is sufficient for identification. Imposing additional restrictions on our model can in fact cause spurious results, since variables included in the VC equation but excluded from the patenting equations would affect the outcome equation through VC_{it} if these variables are not truly independent from patenting. We therefore choose the exogenous variables in all equations to be identical ($X_{it} = Z_{it}$).

We report results for our models in four steps: First, single-equation probit models serve as (most likely biased) benchmarks against which to compare simultaneous models (equations (1) and (2) independently). Second, we estimate bivariate recursive probit models for VC financing and patenting (equations (1) and (2) simultaneously). Third, zero-inflated Poisson models using information about the number of patents are presented, but excluding simultaneous VC investment to establish baseline results for the next step, which adds a zero-inflated Poisson model to the system of equations (equations (3) to (6)). Estimation of this last simultaneous model is done by maximum simulated likelihood (Gouriéroux & Monfort, 1996; Train, 2009).[7] We use the subscript t to distinguish between the periods concurrent to and following the survey.

4. RESULTS

Correlations between venture capital investment and subsequent patenting are substantial and highly significant, ranging between 0.21 for (log) patent applications and 0.26 for a dummy variable measuring whether a firm was granted any number of patents after the VC investment. As we construct increasingly complete models for the relations between VC investment and patenting, this link disappears and even becomes negative in several models. The effect of endogenizing venture capital investments can best be seen from performing three sets of estimations. Tables 3 and 4 show results from separate regressions for the likelihood of obtaining VC finance and the likelihood to patent. Table 5 shows models with identical regressors but allowing for error correlation between the venture capital and patenting equations. Finally, tables 6 and 7 include an equation for the number of patents in addition to the equation that predicts firms' latent patenting status.

Insert Table 3 and 4 about here
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[7] We use 200 random draws in all models estimated by maximum simulated likelihood. Further estimation details including likelihood function and MSL methodology are available from the authors.

4.1 Independent equations – Patenting

If patenting activity is estimated in univariate probit regressions, venture capital strongly increases the likelihood of obtaining patent grants (see table 4). This effect is only second in magnitude to the effect of lagged patenting activity and about as strong a predictor as R&D efforts. This result is in line with prior research which often finds a contemporaneous effect of venture capital on patenting (Zhang, 2009; Bertoni et al., 2010, Kortum & Lerner, 2000). Moreover, this finding is expected if VC funds select portfolio companies based on the number of patents. Dropping VC investment from the equation decreases model fit significantly, which suggests that in a *univariate* setting venture capital predicts patenting.

We find a strong persistence in patenting, both in patents and grants. If firms patent in one period, they tend to do so in the next, with coefficients being stable across models. An indicator for prior-period patenting is significant in all specifications, while applying for or receiving a large number of patents in one period increases the likelihood of observing at least one patent in the next. These effects can be interpreted in two ways: On one hand, prior patenting can proxy for unobserved heterogeneity between firms in their ability to produce innovations. Other variables in our models might not capture all aspects of firms' internal processes and external market characteristics that lead to patenting behaviour. On the other hand, knowledge in the form of existing patents often is an input factor for new patents. Existing patents can signal the size of this otherwise difficult to measure knowledge stock. Since this stock of productive capacity depreciates over time, it is reasonable to assume that recent additions to the patent stock explain present and future patenting best, which is what we find in our results.

The percentage of R&D staff and the existence of R&D expenditures are two other ways of measuring knowledge-producing capacity in firms. Consistent with prior studies, we find evidence for productivity effects of R&D expenditures. Contrary to the findings by Hausman et al. (1984), the percentage of R&D staff does not seem to predict patenting. Since we only measure whether a firm produces any number of patents compared to no patents at all, our finding is plausible given that the intensity of R&D staff helps predict the intensity of patenting, as shown in our models for simultaneous equations. Human capital as measured by the CEO's education, however, does not increase the likelihood of producing one or more patents. In contrast to findings presented by Bertoni et al. (2010), the CEO's education has no effect in any of our model specifications, neither for applications nor for patents granted.

A company's age does not seem to change the likelihood of patenting much, although we observe a slightly significant effect on future applications. This negative finding is consistent with the literature (however, Baum and Silverman (2004) find a negative effect of age on patent applications and a positive one on grants). If patenting was to depend on firm age, we would expect a start-up effect early in the life of firms that are founded to exploit some technological opportunity. We tried a dummy variable indicating whether a firm was only founded during the sample period but found no influence on patenting activity. Employment yields different results for patent applications and grants. As in Bound et al.'s (1984) study, we find a positive effect on future applications, but none for grants. Other observed variables do not explain variation in patenting that size would explain if these variables were excluded. Collinearity in our models is low (variance inflation factors well below 5) and dropping significant variables from the models does not significantly change the effect of size.

Industry effects are negligible in all our independent patenting models. Manufacturing is sometimes associated with a higher tendency to patent than the service sector. However, many technology firms operate under SIC codes assigned to service industries, which could blur the boundaries between patenting and non-patenting industries. A more fine-grained decomposition of industries into additional—possibly high-tech—sectors might help discover effects for some of these. Unfortunately, our sample size does not admit adding individual two-digit SIC codes, and composing industry dummies based on the likelihood of patenting would defeat the purpose of estimating the likelihood to patent. However, more complex models that account for the number of patents (see below) show a higher number of patents in manufacturing firms as expected.

Firms based in the US exhibit a higher chance of success (grant) of applications than those located in the UK, an indication of known institutional differences between patenting regimes.[8] Patenting activity is strongly associated with product market characteristics. Firms that operate nationally or internationally are more likely to engage in patent production than local or regional firms. There is little difference between models future applications and grants. Products that need a long development time are more often protected by patents than those with a short time to market. Again, this is reasonable from a firm's perspective to protect its intellectual property. Protection from imitation should be most prominent in industries with many competitors. However, firms in concentrated markets could also try to

[8] At the application stage, the non-obviousness standard in US patent law has been weakened, leading to the grant of patents on an increasing number of trivial inventions (Barton, 2003; Gallini, 2002). Structural differences in patenting processes also affect patent opposition, re-examination and revocation rates, which are significantly higher for European and UK patents (Harhoff & Reitzig, 2004; Graham, Hall, Harhoff, & Mowery, 2002).

deter potential competitors from entering their market through strategic use of their patent stocks (Scherer, 1983). While Scherer (1983) finds evidence for a link between industry concentration and the number of patents only in models that do not control for sectors, Baum and Silverman (2004) find fewer patents in concentrated industries. The effect of competition in our models, however, is negative but insignificant.[9]

4.2 Independent equations – Venture capital investment

A firm's knowledge stock is similarly predictive for venture capital investment as it is for patenting activity as shown in table 3. R&D expenditures and R&D staff strongly predict VC investments, as does the CEO's education. Patenting attracts VC investments, although it is the fact that a company applies for patents, and not the number of applications or grants, that predicts VC investments. Patent grants do not predict venture capital investments, although they are often said to convey a stronger signal about firm quality than applications, which are often rejected by patent offices.

Venture capital involvement can be found in young firms, in line with prior research. Interestingly, venture capital funds appear to invest in larger firms more often than in small ones, a finding that needs to be interpreted bearing in mind that our sample contains firms with 10 to 1000 employees. We can expect that the majority of micro firms never need or obtain funding by VCs, whereas the proportion of VC-financed businesses is likely to be larger for medium-sized firms. There is no contradiction here with the view that VC funds primarily invest in young and small firms. Conditional on being a portfolio company, it is likely that a firm is young and small. From an unconditional perspective of a firm that may or may not attract venture capital, this does not need to be the case.

Venture funds predominantly target firms operating in industries with non-manufacturing SIC codes. Firms in international market with few competitors seem to be attractive investments, although coefficients for industry competitiveness do not become significant. Firms with a long product development time are neither more nor less likely to

[9] We also test the hypothesis that competition is more relevant if the firm operates internationally, but do not find significance for such an interaction. Prior studies found conflicting evidence on the impact of profitability on patenting. Bertoni et al. (2010) show a positive relation between net cash flow and patents, whereas Baum and Silverman (2004) report a negative one. We also tried a proxy for profitability constructed from pre-tax profits scaled by assets, but did not find significant results. Consequently, we decided to drop this variable from our models due to the large amount of missing values in survey responses on profits.

obtain venture capital.[10] Equations 4 to 6 address the concern that results might be driven by sample attrition due to firms being taken over. Although the business entity would still be producing patents after the merger, we would not be able to observe this activity if the firm is merged into its parent company. We therefore exclude all firms that are involved in mergers and acquisitions as targets of such transactions. Results for this reduced sample are virtually unchanged compared to the full sample in all univariate and bivariate models.

4.3 Simultaneous equations – Patenting and VC

Venture capital investments and patenting are unlikely to be determined in isolation due to the economic effects of signalling and selection in the relationship between firms and VC investors. Instead of predicting patenting behaviour and venture capital investments separately, we now turn to a set of equations that predicts both variables simultaneously. Results are presented in table 5. Allowing for potential endogeneity of VC investments in the patenting equations, we find largely unchanged results in the VC equation. Differences for patenting activities, however, are particularly striking for coefficients on endogenous venture capital investments.

Insert Table 5 and 6 about here

Venture capital does not seem to increase patenting activity and even decreases the likelihood of filing patent applications after the investment, in contrast to industry level studies (Kortum & Lerner, 2000; Ueda & Hirukawa, 2008, for TFP growth) and firm level studies (Bertoni et al., 2010; Arqué-Castells, 2012) that found a positive association. Future patent grants are not negatively affected by venture capital, however, but may decrease several years later when patent authorities decide about applications.

Estimation uncertainty might explain the diminished influence of venture capital, since there is one more parameter (the error correlation) to estimate in the simultaneous model compared to the separate models. However, estimated correlations are positive and significant. Wald tests of the joint significance of this correlation and the coefficient of venture capital on patenting are significant at the five percent level in all models in table 5. The impact of positive error correlations can be seen in the coefficients for venture capital,

[10] Although collinearity is not a problem in these models, there is some correlation between product development time and R&D efforts, which causes development time to become a significant predictor of VC investments if R&D variables are dropped from the regression.

which change considerably when estimated simultaneously. The negative sign of this change is what we would expect if the error correlation was positive. In such cases, coefficients for VC in univariate models would exhibit an upward bias, which would be reduced if we account for endogeneity of VC investments.

Introducing cross-equation correlation harmonises coefficients for some variables across models. Age is now insignificant in all models for patenting, while the importance of R&D increases. The strength of the positive effect on patent grants for US firms decreases, but it is still weakly significant. Firm size, however, increases its effect size, but only on future patent applications. Whether or not a firm obtains finance could have an impact on its ability to start or sustain patenting activities. Since we perform our regressions on a sample of firms that sought external finance and not only those that obtained it, we perform a set of robustness tests on this subsample. Results of separate regressions confirm our findings in table 5. Two small changes appear, however, in the patenting equations. First, the effect size of development time decreases slightly and loses its significance. Second, coefficients on product market competition all increase in magnitude, and the one predicting future applications becomes slightly significant. Estimating our models on the full dataset including those 96 firms that did not obtain external finance provides two advantages over the smaller sample. First, adding these observations increases statistical precision of our results. Second, our findings are conservative, that is, the effect of obtaining venture capital on patenting can be upward biased if it includes a (positive) effect of obtaining *any* kind of finance which would be ignored if firms not obtaining any finance were excluded. In this sense, the negative or insignificant coefficients for venture capital represent upper bounds for the true effect.

4.4 Two-stage patenting – Patent counts, patenting and venture capital

The large number of zeroes in patent counts suggests that patenting is a two-stage process, consisting of the binary decision to patent and the decision of how many patents to produce. Two popular methods to model the number of patents produced by such a process are based on a zero-inflated Poisson distribution or a zero-inflated negative binomial distribution. Results in table 6 are derived from zero-inflated Poisson models, as the overdispersion parameter introduced in negative binomial models turns out to be not necessary. Unlike the patenting process in tables 4 and 5 which measures whether the firms produces any positive number of patents, the patenting equation now represents a latent patenting state. Not being in this latent state accounts for excess zeroes which would otherwise be incompatible with a pure Poisson process.

When ignoring the potential endogeneity of venture capital in both patenting decisions, we find opposing effects of venture capital on the decision to patent and on the number of patents granted (see table 6, model 3). Similar to binary models that ignore endogeneity, VC exerts a strong and positive influence on the likelihood of being in the latent state of obtaining a patent grant (models 3 and 6). On the other hand, VC investments seem to decrease the number of patents granted. This result contradicts the usual notion of venture capitalists facilitating growth and development of firms, if VCs pursue an extremely selective strategy that encourages firms to patent only the most promising of their developments.

Insert Table 7 about here

A more consistent picture emerges if endogenously determined venture capital is added to the models (see table 7). The positive effect on firms' latent patenting state – which would be expected if venture capitalists performed a coaching function in their portfolio companies – disappears across models, while the negative effect on the number of granted patents remains. Moreover, and similar to the simultaneous binomial models for patenting, the number of patent applications appears to drop after VC investments. This result holds for the sample excluding merger targets (model 4), while there are no effects of VC on patent applications in the full sample.

If we look at the number of patents applied for or being granted, our results support the view that venture capital follows patent signals to invest in companies with commercially viable products instead of initiating patenting programmes. While the effect of venture capital on the existence of patenting programmes and the number of patents produced seems negligible, it has a negative impact on patent grants and applications in some models. Venture capitalists seem to be attracted by firms that produce patents, but contribute only to the exploitation of existing technology. Our findings are in line with results presented by Hsu (2006), who finds that VC-funded firms engage in commercialization through cooperative strategies, such as strategic alliances or technology licensing, more often than similar firms without VC involvement. Similarly, venture capital seems to reduce the time to market for new products (Hellmann & Puri, 2002). In the medium term, VC funded firms are likely to undergo a structural change that shifts resources from the production of new patent applications to the exploitation of existing knowledge.

Control variables for future patent counts behave mostly as expected and give additional insights into firms' patenting decision. While manufacturing firms and service firms appeared – counterintuitively – equally likely to patent, we can now see that being a manufacturing firm increases the number of patents. The estimation algorithm for three simultaneous equations picks the relevant equations for our two R&D variables: The existence of R&D programmes mainly predicts patenting in general, while the proportion of R&D staff explains the number of applications and grants produced. Contrary to results presented by Baum and Silverman (2004), we find no impact of competition on the number of patents or the decision to patent. However, firms tend to protect their position in the market by choosing to patent if their relevant market is large and have long product development times.

Estimated model parameters provide strong support for simultaneously modelling VC investment, patenting and the number of patents. In most of the models tested for patent applications and grants, error correlations between the first (VC) equation and the second and third are substantial and significant. External shocks leading to VC investment correlate with the likelihood to patent with the expected positive sign (negative sign for *not* patenting). Estimated error correlations between VC investment and patent numbers are similarly large and significant.[11] We also test model stability by checking influential observations and cross-tabulations for firms that start or stop their patenting activities depending on VC investment, but do not find any abnormalities. Nevertheless, future research efforts should focus on the generation of larger samples that reduce the importance of individual observations, particularly in the subset of firms obtaining venture capital financing.

5. CONCLUSION

The mechanisms by which firms signal their quality to investors through patents and how venture capital funds influence these firms' patenting behaviour have been studied extensively in the literature. Because firm's patenting activity might not be independent from venture capitalists' decisions to invest based on patent signals, these two decisions should be investigated at the same time instead of separately. We take causality problems in firm's patenting behaviour into account by explicitly allowing for endogeneity of VC investments. Incorporating the investor's decision to invest into a simultaneous model helps distinguish selection and coaching effects.

[11] Interestingly, error correlations are more consistent and significant in the subsample that excludes merger targets which suggests that merger targets add mostly noise to our models.

We find that the causal link from venture capital to patenting is weak, contrary to studies on aggregate patenting and venture capital investment (Kortum & Lerner, 2000). A positive effect can only be found if potential endogeneity of VC financing is ignored. Instead, venture capital even exerts a negative influence on future patent applications and grants. We argue that this is because VC works as a focussing device in the entrepreneurial process: by limiting the dispersion of inventive efforts, which often characterizes inexperienced firms, venture capitalists help portfolio companies to rationalize technology searches and to focus on the opportunities with the highest commercial potential.

Venture capital funds select portfolio companies based on the signalling function of patents. Interestingly, these investors are attracted to patent-active firms but show strong sensitivity to the number of patents, which might indicate a preference for focus instead of possibly over-dispersed search activities. Our results for additional determinants of patenting are broadly in line with prior research. Firm size is positively related to future patent applications and R&D efforts measured by the existence of R&D expenses and the percentage of R&D staff are highly significant. Where Baum and Silverman (2004) find mixed evidence for an age effect on applications and grants, we decompose this effect into a non-significant one on the likelihood to patent and a negative one for the number of applications. The proportion of scientific staff explains the number of patent applications and grants, while having an R&D programme determines whether a firm patents. Finally, the effect of industry competition on the intensity of patenting is insignificant, contrary to results by Baum and Silverman (2004) and Scherer (1983). We test two new variables, product development time and market size. Both predict patenting activity, which might explain why competition is not associated with patenting in our models.

Venture capital investment is reliably explained by the same set of variables across specifications. VC investment depends on whether a firm applies for patents, but not on patenting volume. Interestingly, patent grants predict venture capital investments about as well as patent applications, although theoretically they should convey a stronger signal about firm quality than applications. Venture capital funds invest in companies operating in non-manufacturing sectors in international markets, whose CEOs tend to have university degrees. Unexpectedly, within-industry competition does not change the likelihood of VC investments.

By modelling the VC's decision to invest and the portfolio company's patenting activity simultaneously, we are able to resolve the puzzle of what comes first, patents or VC investment, in favour of patenting. More specifically, having a positive number of patent applications or grants predicts venture capital investments, whereas obtaining venture capital investments is not informative about the future existence of patenting programmes. In terms of patent numbers, portfolio firms of venture funds seem to reduce patenting activities. If venture capitalists are performing a coaching function, their activities are most likely found in the commercialization of existing patents rather than firms' efforts to generate additional products through additional patents.

Our models greatly reduce the chances that selection by VCs might drive a change in observed patenting behaviour, because estimating the correlation between the error terms in both equations controls for unobserved simultaneous variance in VC financing and patenting. If VC firms react to some unobserved company characteristic that can be subsumed in the error term of the switching equation, this unobserved heterogeneity is taken into account when estimating the outcome model for patenting activity. Error correlations between the venture capital and patenting equations are significant and substantial, which supports our estimation strategy.

Further research could generate additional quantitative evidence on the effect of VC's coaching capabilities on different aspects – or stages – of the innovation process, while controlling for selection effects, and identify their implications for short and long-run firm performance.

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Table 1. Descriptive statistics

Variable	Mean	Median	Std. Dev.	Min	Max	Description
Patent applications in t+1	4.139	0	34.243	0	779	Number of patent applications by the firm in the period after the survey.
Patent grants in t+1	2.770	0	30.340	0	889	Number of patent grants to the firm in the period after the survey.
Patent applications in t	3.293	0	25.356	0	526	Number of patent applications by the firm in the period three years prior to the survey.
Patent grants in t	1.203	0	9.996	0	273	Number of patent grants to the firm in the period three years prior to the survey.
VC/BA investment	0.102	0	0.303	0	1	A venture capital fund or business angel invested in the firm over the three-year period prior to the survey.
Age (Log)	2.936	2.996	0.858	0.693	5.720	The natural logarithm of the firm's age in years.
Size (Log(Employees))	3.848	3.714	1.059	1.099	6.804	The natural logarithm of the number of employees in the most recent financial year.
US firm	0.546	1	0.498	0	1	The firm has its headquarters in the United States. Dummy variable.
Manufacturing sector	0.699	1	0.459	0	1	The firm is operating in the manufacturing sector. Dummy variable.
R&D expend. (yes/no)	0.732	1	0.443	0	1	The firm has R&D expenditures. Dummy variable.
R&D staff	0.074	0	0.176	0	1	Full-time R&D staff as a proportion of total staff.
CEO has a degree	0.635	1	0.482	0	1	The firm's Chief Executive or MD has a degree. Dummy variable.
Market size	1.747	2	0.911	0	3	Size of the firm's market. Coded as ordinal 0=local, 1=regional, 2=national, 3=international, treated as cardinal.
Competitors (Log)	1.990	1.792	1.002	0	6.909	Number of companies that the firm regards as serious competitors plus one, in logs.
Product dev. time	0.971	1	1.048	0	4	Average time it takes to develop a new product from conception to the market. Coded as ordinal 0=less than 6 months to 4=more than 5 years, treated as cardinal.

Table 2. Venture capital and patenting status

This table presents the number of firms in each present and future patenting status dependent on venture capital / business angel investment. Row entries are the number of firms with any number of patent applications at time t. Columns show the number of firms applying for or being granted any number of patents.

	No VC/BA: Applications in t+1		VC/BA: Applications in t+1		No VC/BA: Grants in t+1		VC/BA: Grants in t+1	
Applications in t	No	Yes	No	Yes	No	Yes	No	Yes
No	688	52	42	11	717	23	47	6
Yes	29	75	11	32	24	80	8	35

Table 3. Venture capital investment – independent equations

This table presents probit models for the likelihood of observing venture capital or business angel investments. Robust standard errors are in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	All observations			Excluding merger targets		
Model	1	2	3	4	5	6
Dependent variable	VC/BA investment	VC/BA investment	VC/BA investment	VC/BA investment	VC/BA investment	VC/BA investment
VC/BA investment						
Patent applications (Log)	-0.093(0.08)			-0.100(0.09)		
Patent applications >0	0.606(0.20)***			0.626(0.21)***		
Patent grants (Log)		-0.156(0.12)			-0.231(0.12)*	
Patent grants >0		0.389(0.23)*			0.421(0.24)*	
Age (Log)	-0.339(0.09)***	-0.351(0.09)***	-0.349(0.09)***	-0.307(0.10)***	-0.317(0.09)***	-0.314(0.09)***
Size (Log(Employees+1))	0.192(0.07)***	0.190(0.06)***	0.182(0.06)***	0.164(0.07)**	0.166(0.07)**	0.155(0.07)**
US firm	-0.323(0.14)**	-0.316(0.14)**	-0.318(0.14)**	-0.334(0.15)**	-0.321(0.15)**	-0.326(0.15)**
Manufacturing sector	-0.405(0.13)***	-0.372(0.13)***	-0.364(0.13)***	-0.391(0.14)***	-0.357(0.14)**	-0.351(0.14)**
R&D expend. (yes/no)	0.462(0.21)**	0.488(0.21)**	0.513(0.21)**	0.756(0.26)***	0.773(0.26)***	0.802(0.26)***
R&D staff (in %)	0.707(0.32)**	0.901(0.32)***	0.911(0.30)***	0.853(0.35)**	1.112(0.33)***	1.052(0.33)***
CEO has a degree	0.374(0.17)**	0.381(0.17)**	0.407(0.17)**	0.378(0.18)**	0.377(0.18)**	0.400(0.18)**
Market size	0.215(0.09)**	0.223(0.09)**	0.239(0.09)***	0.198(0.10)**	0.205(0.10)**	0.219(0.09)**
Product dev. time	0.057(0.07)	0.065(0.07)	0.071(0.07)	0.055(0.07)	0.066(0.07)	0.072(0.07)
Competitors (Log)	-0.056(0.07)	-0.071(0.07)	-0.074(0.07)	-0.018(0.08)	-0.037(0.08)	-0.037(0.08)
Intercept	-1.900(0.39)***	-1.855(0.38)***	-1.872(0.38)***	-2.248(0.45)***	-2.211(0.44)***	-2.219(0.43)***
Observations	940	940	940	888	888	888
Log-Likelihood	-237.2	-239.9	-241.6	-203.4	-205.2	-207.5
Chi-sq. test	104.5	107.6	96.2	92.0	94.6	85.6
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo- R^2	0.235	0.226	0.221	0.243	0.237	0.228

Table 4. Patenting activity – independent equations

This table presents probit models for the likelihood of observing any number of patent applications or grants, respectively. Robust standard errors are in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	Including VC/BA			Excluding merger targets		
Model	1	2	3	4	5	6
Dependent variable	Applications in t+1	Grants in t+1	Grants in t+1	Applications in t+1	Grants in t+1	Grants in t+1
Patenting (yes/no)						
VC/BA investment	0.217(0.20)	0.616(0.19)***	0.438(0.24)*	0.157(0.22)	0.722(0.20)***	0.510(0.25)**
Patent applications (Log)	0.505(0.12)***		0.645(0.14)***	0.687(0.13)***		0.581(0.14)***
Patent applications >0	0.984(0.22)***		1.579(0.23)***	0.896(0.23)***		1.595(0.23)***
Patent grants (Log)		0.583(0.15)***			0.599(0.17)***	
Patent grants >0		1.218(0.22)***			1.245(0.23)***	
Age (Log)	0.135(0.08)*	0.010(0.09)	0.077(0.10)	0.129(0.08)	0.061(0.10)	0.077(0.10)
Size (Log(Employees+1))	0.131(0.06)**	0.023(0.06)	-0.003(0.07)	0.125(0.06)**	0.039(0.07)	0.007(0.07)
US firm	0.139(0.14)	0.357(0.15)**	0.418(0.17)**	0.163(0.14)	0.349(0.15)**	0.396(0.17)**
Manufacturing sector	0.016(0.14)	0.172(0.16)	0.132(0.18)	0.066(0.15)	0.139(0.17)	0.115(0.18)
R&D expend. (yes/no)	0.454(0.18)**	0.370(0.19)*	0.525(0.21)**	0.481(0.20)**	0.368(0.20)*	0.487(0.21)**
R&D staff (in %)	0.103(0.35)	0.541(0.43)	-0.422(0.44)	0.382(0.38)	0.826(0.42)**	-0.203(0.46)
CEO has a degree	0.112(0.14)	-0.236(0.15)	-0.260(0.17)	0.101(0.15)	-0.292(0.16)*	-0.251(0.17)
Market size	0.232(0.09)***	0.315(0.09)***	0.262(0.10)**	0.243(0.09)***	0.278(0.10)***	0.261(0.10)**
Product dev. time	0.175(0.06)***	0.129(0.06)**	0.105(0.07)	0.172(0.06)***	0.140(0.06)**	0.102(0.07)
Competitors (Log)	-0.072(0.06)	-0.051(0.06)	-0.101(0.08)	-0.055(0.06)	-0.069(0.07)	-0.104(0.08)
Intercept	-3.365(0.34)***	-2.839(0.42)***	-3.059(0.49)***	-3.448(0.37)***	-2.938(0.44)***	-3.033(0.49)***
Observations	940	940	940	888	888	888
Log-Likelihood	-259.0	-227.6	-167.3	-233.0	-209.4	-160.3
Chi-sq. test	233.2	205.4	243.5	267.1	185.0	220.2
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo- R^2	0.417	0.435	0.584	0.427	0.426	0.560

Table 5. Patenting and VC investment – simultaneous equations

This table presents bivariate recursive probit models for patent applications, patent grants and for the likelihood of observing venture capital or business angel investments. Robust standard errors are in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	All observations			Excluding merger targets		
Model	1	2	3	4	5	6
Dependent variable in patenting equation	Applications in t+1	Grants in t+1	Grants in t+1	Applications in t+1	Grants in t+1	Grants in t+1
Patenting (yes/no)						
VC/BA investment	-0.810(0.32)**	-0.109(0.45)	-0.336(0.33)	-1.266(0.51)**	0.093(0.55)	-0.260(0.36)
Patent applications (Log)	0.436(0.11)***		0.598(0.13)***	0.539(0.16)***		0.540(0.13)***
Patent applications >0	1.072(0.20)***		1.627(0.22)***	0.988(0.20)***		1.643(0.22)***
Patent grants (Log)		0.538(0.15)***			0.553(0.17)***	
Patent grants >0		1.243(0.22)***			1.278(0.23)***	
Age (Log)	0.040(0.08)	-0.049(0.10)	0.013(0.10)	-0.008(0.11)	0.018(0.11)	0.023(0.10)
Size (Log(Employees+1))	0.165(0.06)***	0.049(0.06)	0.028(0.07)	0.160(0.06)***	0.056(0.07)	0.031(0.07)
US firm	0.050(0.13)	0.298(0.16)*	0.348(0.17)**	0.019(0.15)	0.303(0.16)*	0.331(0.17)*
Manufacturing sector	-0.097(0.13)	0.092(0.16)	0.042(0.17)	-0.107(0.17)	0.081(0.17)	0.037(0.17)
R&D expend. (yes/no)	0.506(0.17)***	0.410(0.19)**	0.558(0.20)***	0.603(0.19)***	0.410(0.21)**	0.535(0.20)***
R&D staff (in %)	0.322(0.34)	0.729(0.42)*	-0.220(0.43)	0.690(0.35)**	1.027(0.42)**	0.028(0.44)
CEO has a degree	0.188(0.14)	-0.176(0.16)	-0.195(0.17)	0.216(0.15)	-0.244(0.16)	-0.189(0.17)
Market size	0.260(0.08)***	0.335(0.09)***	0.284(0.10)***	0.266(0.08)***	0.293(0.09)***	0.278(0.10)***
Product dev. time	0.172(0.06)***	0.134(0.06)**	0.109(0.07)	0.164(0.06)***	0.145(0.06)**	0.107(0.07)
Competitors (Log)	-0.077(0.06)	-0.059(0.06)	-0.105(0.08)	-0.047(0.06)	-0.072(0.07)	-0.102(0.08)
Intercept	-3.083(0.37)***	-2.690(0.44)***	-2.891(0.49)***	-2.989(0.48)***	-2.840(0.46)***	-2.902(0.49)***
VC/BA investment						
Patent applications (Log)	-0.093(0.08)		-0.096(0.08)	-0.112(0.09)		-0.105(0.09)
Patent applications >0	0.648(0.20)***		0.646(0.20)***	0.709(0.21)***		0.675(0.22)***
Patent grants (Log)		-0.161(0.11)			-0.234(0.12)*	
Patent grants >0		0.433(0.23)*			0.459(0.24)*	
Age (Log)	-0.351(0.09)***	-0.350(0.09)***	-0.349(0.09)***	-0.315(0.10)***	-0.317(0.09)***	-0.320(0.10)***
Size (Log(Employees+1))	0.184(0.07)***	0.197(0.06)***	0.194(0.07)***	0.162(0.08)**	0.173(0.07)**	0.167(0.07)**
US firm	-0.332(0.14)**	-0.317(0.14)**	-0.327(0.14)**	-0.366(0.15)**	-0.319(0.15)**	-0.338(0.15)**
Manufacturing sector	-0.411(0.13)***	-0.390(0.13)***	-0.412(0.13)***	-0.412(0.14)***	-0.377(0.15)**	-0.402(0.14)***
R&D expend. (yes/no)	0.468(0.21)**	0.487(0.21)**	0.467(0.22)**	0.723(0.26)***	0.774(0.26)***	0.770(0.27)***
R&D staff (in %)	0.710(0.32)**	0.861(0.32)***	0.666(0.33)**	0.844(0.35)**	1.069(0.34)***	0.806(0.35)**
CEO has a degree	0.398(0.16)**	0.384(0.17)**	0.379(0.17)**	0.422(0.17)**	0.381(0.18)**	0.383(0.18)**
Market size	0.210(0.09)**	0.228(0.09)**	0.221(0.09)**	0.193(0.10)**	0.211(0.10)**	0.206(0.10)**
Product dev. time	0.052(0.07)	0.065(0.07)	0.056(0.07)	0.046(0.07)	0.066(0.07)	0.055(0.07)
Competitors (Log)	-0.060(0.07)	-0.066(0.07)	-0.051(0.07)	-0.038(0.08)	-0.032(0.08)	-0.014(0.08)
Intercept	-1.840(0.40)***	-1.900(0.38)***	-1.909(0.39)***	-2.152(0.48)***	-2.254(0.44)***	-2.265(0.45)***
Observations	940	940	940	888	888	888
Log-Likelihood	-494.7	-466.9	-403.5	-434.5	-414.2	-362.9
Chi-sq. test	343.3	304.8	343.3	333.6	267.9	308.3
P-value	0.000	0.000	0.000	0.000	0.000	0.000
$\rho(\nu_{it}, \varepsilon_{it})$	0.573	0.395	0.428	0.814	0.338	0.420
P-value for ρ (Wald test)	0.006	0.097	0.002	0.179	0.237	0.005
Pseudo- R^2	0.325	0.345	0.434	0.357	0.346	0.427

Table 6. Patenting and patent numbers – zero-inflated Poisson

This table presents zero-inflated Poisson models for patent applications and patent grants during the period after the survey period. The equation for excess zeroes ("Not patenting") includes the same variables as the equation for the number of patents. Note that when comparing coefficients from the patenting equation with prior models for the likelihood to patent, all signs must be reversed as the "patenting" equation in this table predicts the likelihood of *not* patenting. As a robustness test, we tried zero-inflated negative binomial models. Tests for overdispersion are all insignificant in these models, while Vuong tests against the alternative hypothesis of a standard Poisson process are highly significant. Robust standard errors are in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

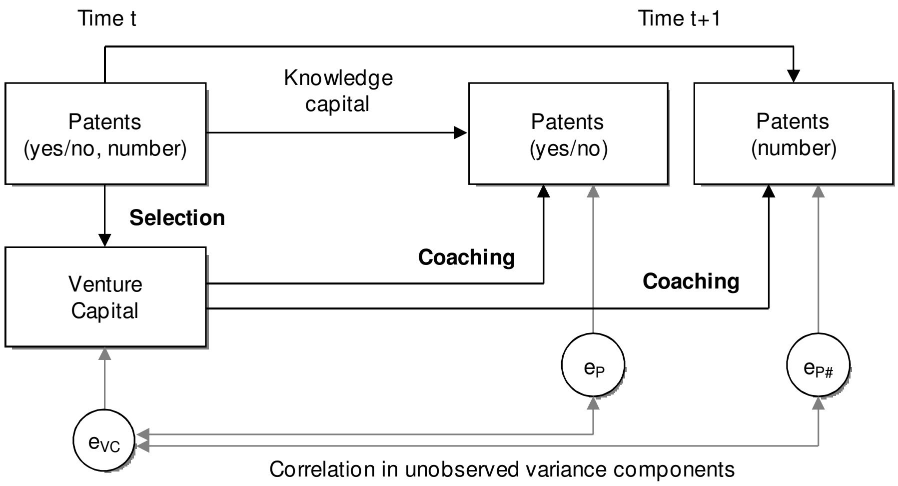
	All observations			Excluding merger targets		
Model	1	2	3	4	5	6
Dependent variable	Applications in t+1	Grants in t+1	Grants in t+1	Applications in t+1	Grants in t+1	Grants in t+1
Patents						
VC/BA investment	-0.348(0.25)	-0.285(0.22)	-0.525(0.21)**	-0.397(0.21)*	-0.233(0.23)	-0.314(0.14)**
Patent applications (Log)	0.827(0.10)***		0.989(0.10)***	0.856(0.10)***		1.034(0.09)***
Patent applications >0	-0.808(0.38)**		-1.120(0.56)**	-0.730(0.39)*		-1.291(0.51)**
Patent grants (Log)		0.700(0.12)***			0.601(0.08)***	
Patent grants >0		0.247(0.32)			0.521(0.27)**	
Age (Log)	-0.114(0.19)	-0.328(0.17)*	0.108(0.15)	-0.117(0.21)	-0.436(0.15)***	0.088(0.11)
Size (Log(Employees+1))	-0.110(0.13)	0.214(0.13)*	-0.096(0.13)	-0.156(0.19)	0.383(0.10)***	-0.065(0.08)
US firm	0.419(0.36)	0.563(0.25)**	0.132(0.18)	0.448(0.34)	0.609(0.20)***	0.238(0.17)
Manufacturing sector	-0.047(0.26)	-0.014(0.22)	0.233(0.18)	0.021(0.30)	-0.091(0.19)	0.260(0.18)
R&D expend. (yes/no)	0.329(0.36)	-0.255(0.53)	0.132(0.35)	0.383(0.32)	0.186(0.59)	0.317(0.35)
R&D staff (in %)	1.332(0.68)*	0.648(0.42)	1.493(0.43)***	1.350(0.73)*	0.510(0.43)	1.510(0.29)***
CEO has a degree	-0.124(0.29)	-0.277(0.31)	0.072(0.31)	-0.177(0.33)	-0.414(0.30)	-0.320(0.22)
Market size	0.200(0.28)	0.455(0.20)**	-0.094(0.18)	0.180(0.23)	0.532(0.18)***	-0.008(0.17)
Product dev. time	-0.244(0.09)***	-0.061(0.10)	-0.235(0.08)***	-0.279(0.13)**	0.082(0.08)	-0.146(0.07)**
Competitors (Log)	0.013(0.17)	-0.112(0.21)	-0.394(0.24)	0.090(0.20)	0.011(0.18)	-0.025(0.14)
Intercept	1.417(1.04)	0.292(0.91)	1.535(0.93)*	1.441(1.01)	-1.032(0.84)	0.551(0.77)
Not patenting (zero inflation)						
VC/BA investment	-0.281(0.22)	-0.710(0.22)***	-0.945(0.31)***	-0.262(0.25)	-0.823(0.23)***	-0.879(0.30)***
Patent applications (Log)	-0.436(0.13)***		-0.435(0.19)**	-0.604(0.14)***		-0.270(0.20)
Patent applications >0	-1.172(0.27)***		-2.461(0.45)***	-1.071(0.27)***		-2.767(0.52)***
Patent grants (Log)		-0.540(0.15)***			-0.556(0.17)***	
Patent grants >0		-1.229(0.23)***			-1.229(0.24)***	
Age (Log)	-0.145(0.08)*	-0.075(0.10)	0.026(0.14)	-0.139(0.09)	-0.164(0.11)	0.047(0.13)
Size (Log(Employees+1))	-0.158(0.07)**	0.012(0.07)	-0.011(0.10)	-0.159(0.08)*	0.029(0.07)	-0.017(0.09)
US firm	-0.089(0.15)	-0.281(0.15)*	-0.423(0.20)**	-0.115(0.16)	-0.251(0.16)	-0.351(0.20)*
Manufacturing sector	-0.025(0.14)	-0.182(0.17)	0.020(0.21)	-0.068(0.15)	-0.175(0.17)	-0.004(0.21)
R&D expend. (yes/no)	-0.453(0.19)**	-0.406(0.21)*	-0.640(0.26)**	-0.471(0.20)**	-0.337(0.26)	-0.588(0.26)**
R&D staff (in %)	0.037(0.36)	-0.455(0.44)	1.428(0.59)**	-0.243(0.40)	-0.785(0.43)*	1.258(0.59)**
CEO has a degree	-0.137(0.15)	0.194(0.17)	0.312(0.22)	-0.129(0.16)	0.226(0.18)	0.176(0.20)
Market size	-0.213(0.09)**	-0.257(0.10)***	-0.319(0.12)***	-0.224(0.09)**	-0.184(0.10)*	-0.296(0.12)**
Product dev. time	-0.212(0.07)***	-0.143(0.07)**	-0.238(0.10)**	-0.219(0.08)***	-0.128(0.07)*	-0.191(0.09)**
Competitors (Log)	0.069(0.06)	0.031(0.07)	-0.015(0.10)	0.062(0.07)	0.077(0.07)	0.094(0.08)
Intercept	3.469(0.38)***	2.761(0.45)***	3.165(0.59)***	3.557(0.41)***	2.609(0.49)***	2.839(0.56)***
Observations	940	940	940	888	888	888
Wald test	2552.4	407.3	473.3	2218.1	2469.9	2355.7
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Log likelihood	-1575.1	-1035.9	-881.7	-1441.0	-769.1	-581.8

Table 7. Patenting, patent numbers and VC investment

This table presents zero-inflated Poisson models for patent applications and patent grants during the period following the survey period, including an endogenous equation for venture capital investment. Robust standard errors (estimated using the sandwich estimator) are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	All observations			Excluding merger targets		
Model	1	2	3	4	5	6
Dependent variable in patenting equations	Applications in t+1	Grants in t+1	Grants in t+1	Applications in t+1	Grants in t+1	Grants in t+1
Patents						
VC/BA investment	-0.024(0.12)	0.278(0.41)	-1.154(0.22)***	-1.505(0.25)***	-0.606(0.27)**	-0.958(0.28)***
Patent applications (Log)	0.859(0.05)***		0.958(0.07)***	0.778(0.08)***		1.047(0.06)***
Patent applications >0	-0.276(0.21)		-0.158(0.30)	0.268(0.29)		-0.560(0.28)**
Patent grants (Log)		0.818(0.09)***			0.541(0.05)***	
Patent grants >0		0.411(0.27)			1.022(0.23)***	
Age (Log)	-0.004(0.08)	-0.399(0.15)***	-0.081(0.10)	-0.252(0.16)	-0.449(0.12)***	0.013(0.11)
Size (Log(Employees+1))	-0.111(0.06)*	0.155(0.11)	-0.018(0.09)	-0.140(0.13)	0.186(0.10)*	-0.103(0.10)
US firm	0.228(0.17)	0.077(0.22)	0.129(0.16)	-0.097(0.18)	0.006(0.17)	0.212(0.19)
Manufacturing sector	0.507(0.07)***	0.296(0.20)	0.361(0.16)**	0.496(0.13)***	0.308(0.14)**	0.270(0.23)
R&D expend. (yes/no)	-0.183(0.29)	-0.473(0.67)	0.346(0.25)	-0.039(0.37)	0.062(0.55)	0.539(0.37)
R&D staff (in %)	0.811(0.10)***	0.544(0.58)	1.266(0.29)***	1.338(0.27)***	1.294(0.44)***	1.383(0.38)***
CEO has a degree	-0.278(0.18)	-0.161(0.39)	0.072(0.19)	0.097(0.22)	0.057(0.27)	-0.111(0.20)
Market size	0.053(0.07)	0.348(0.17)**	-0.141(0.11)	0.000(0.13)	0.236(0.12)**	-0.117(0.12)
Product dev. time	-0.009(0.04)	-0.013(0.11)	-0.113(0.08)	-0.083(0.06)	-0.041(0.07)	-0.054(0.09)
Competitors (Log)	0.124(0.05)***	0.313(0.17)*	-0.035(0.09)	-0.070(0.14)	0.268(0.10)***	0.065(0.10)
Intercept	0.082(0.39)	-0.318(0.70)	-0.001(0.45)	1.312(0.79)*	-0.752(0.60)	-0.122(0.54)
Not patenting (zero inflation)						
VC/BA investment	-0.044(0.47)	-0.276(0.58)	-0.100(0.88)	-0.400(0.57)	0.106(0.77)	-0.281(0.64)
Patent applications (Log)	-0.281(0.19)		-0.397(0.25)	-0.530(0.18)***		-0.247(0.27)
Patent applications >0	-1.641(0.46)***		-2.859(0.73)***	-1.177(0.38)***		-3.030(0.79)***
Patent grants (Log)		-0.499(0.18)***			-0.541(0.23)**	
Patent grants >0		-1.366(0.30)***			-1.467(0.43)***	
Age (Log)	-0.142(0.11)	-0.104(0.13)	0.070(0.20)	-0.217(0.14)	-0.123(0.15)	0.113(0.18)
Size (Log(Employees+1))	-0.224(0.10)**	-0.013(0.09)	-0.033(0.12)	-0.235(0.11)**	-0.044(0.10)	-0.065(0.11)
US firm	-0.045(0.18)	-0.356(0.19)*	-0.394(0.26)	-0.191(0.19)	-0.360(0.21)*	-0.303(0.26)
Manufacturing sector	0.147(0.19)	-0.061(0.21)	0.255(0.26)	0.076(0.20)	0.036(0.22)	0.110(0.24)
R&D expend. (yes/no)	-0.623(0.21)***	-0.526(0.26)**	-0.785(0.37)**	-0.611(0.22)***	-0.580(0.33)*	-0.680(0.34)**
R&D staff (in %)	0.201(0.46)	-0.645(0.58)	1.410(0.64)**	-0.104(0.50)	-1.056(0.62)*	1.209(0.63)*
CEO has a degree	-0.273(0.19)	0.211(0.22)	0.243(0.24)	-0.133(0.19)	0.295(0.22)	0.164(0.23)
Market size	-0.272(0.12)**	-0.272(0.13)**	-0.457(0.14)***	-0.296(0.12)**	-0.310(0.14)**	-0.395(0.13)***
Product dev. time	-0.223(0.08)***	-0.181(0.11)*	-0.259(0.14)*	-0.255(0.09)***	-0.221(0.12)*	-0.208(0.12)*
Competitors (Log)	0.104(0.08)	0.146(0.08)*	0.105(0.09)	0.029(0.10)	0.167(0.08)**	0.134(0.10)
Intercept	3.611(0.51)***	2.690(0.54)***	3.113(0.72)***	4.106(0.61)***	3.010(0.70)***	2.867(0.64)***
VC/BA investment						
Patent applications (Log)	-0.091(0.08)		-0.119(0.08)	-0.045(0.07)		-0.107(0.09)
Patent applications >0	0.609(0.20)***		0.666(0.20)***	0.557(0.20)***		0.648(0.21)***
Patent grants (Log)		-0.168(0.11)			-0.203(0.14)	
Patent grants >0		0.432(0.22)*			0.440(0.27)*	
Age (Log)	-0.343(0.09)***	-0.353(0.09)***	-0.340(0.09)***	-0.302(0.10)***	-0.313(0.09)***	-0.318(0.10)***
Size (Log(Employees+1))	0.192(0.07)***	0.191(0.06)***	0.200(0.07)***	0.179(0.08)**	0.175(0.07)**	0.169(0.07)**
US firm	-0.325(0.14)**	-0.313(0.14)**	-0.316(0.14)**	-0.350(0.14)**	-0.324(0.15)**	-0.346(0.15)**
Manufacturing sector	-0.406(0.13)***	-0.387(0.13)***	-0.423(0.13)***	-0.398(0.13)***	-0.387(0.14)***	-0.398(0.14)***
R&D expend. (yes/no)	0.464(0.21)**	0.492(0.21)**	0.444(0.22)**	0.740(0.26)***	0.758(0.26)***	0.768(0.26)***
R&D staff (in %)	0.705(0.33)**	0.870(0.31)***	0.647(0.33)**	0.849(0.32)***	1.058(0.34)***	0.817(0.35)**
CEO has a degree	0.377(0.17)**	0.368(0.17)**	0.407(0.17)**	0.390(0.18)**	0.403(0.18)**	0.387(0.18)**
Market size	0.213(0.09)**	0.230(0.09)**	0.244(0.09)***	0.189(0.10)**	0.207(0.09)**	0.200(0.10)**
Product dev. time	0.057(0.07)	0.069(0.07)	0.063(0.07)	0.072(0.07)	0.066(0.07)	0.060(0.07)
Competitors (Log)	-0.056(0.07)	-0.069(0.07)	-0.074(0.08)	-0.017(0.08)	-0.030(0.08)	-0.018(0.08)
Intercept	-1.885(0.39)***	-1.867(0.38)***	-1.966(0.39)***	-2.311(0.44)***	-2.265(0.42)***	-2.257(0.44)***
$\mathrm{Var}(\omega_{it})$	1.163(0.10)***	0.775(0.14)***	0.661(0.12)***	1.689(0.18)***	0.666(0.13)***	0.513(0.12)***
$\rho(\nu_{it}, \varepsilon_{it})$	-0.132(0.18)	-0.285(0.22)*	-0.431(0.38)	0.104(0.24)	-0.494(0.31)*	-0.357(0.25)*
$\rho(\nu_{it}, \omega_{it})$	0.018(0.03)	-0.327(0.06)***	0.647(0.05)***	0.640(0.03)***	0.488(0.09)***	0.534(0.08)***
Observations	940	940	940	888	888	888
Wald test	3496.6	2017.4	1853.7	2752.2	1725.0	1766.5
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Log likelihood	-984.9	-866.4	-778.0	-878.3	-755.2	-681.3

Figure 1 – Model framework



Dependent variables are venture capital investment at time t and the number of patent applications or grants at time t+1. In the binary bivariate case, "Patents (yes/no)" measures whether we observe any number of patents for the firm at time t+1. In zero-inflated Poisson models that also include the number of patents at t+1, this variable indicates firms' latent patenting status.