Coaching or Selection? Venture Capital and Firms' Patenting Performance[*]

Henry Lahr[†]
h.lahr@cbr.cam.ac.uk

Andrea Mina
a.mina@cbr.cam.ac.uk

Centre for Business Research and UK~IRC,
Judge Business School, University of Cambridge,
Trumpington Street, Cambridge,
CB2 1AG, UK.

(Version: May 2012)

[*] An earlier version of this paper was circulated under the title "Patenting performance in SMEs with endogenous venture capital financing".
[†] Contact author

Acknowledgments: The authors gratefully acknowledge funding from the European Community's Seventh Framework Programme (FP7/2007-2013) under Socio-economic Sciences and Humanities grant agreement n° 217466.

Abstract

Empirical evidence on the effect of venture capital on firms' patent productivity has been mixed. We aim to assess this effect through simultaneous models that predict the likelihood that firms attract venture capital, the likelihood that they patent and the number of patents applied for and being granted. While prior research has estimated these equations independently, we allow for endogeneity of venture capital investment. When estimating simple models with independent equations, we confirm prior findings of a positive impact of venture capital on patenting, which can be interpreted as the beneficial effect of coaching or "smart money". If we account for endogeneity, however, this effect becomes insignificant or negative in most cases. Although venture capital investments appear to have a negligible impact on patenting in general, some evidence suggests that new patent applications fare worse than patents granted after an investment. 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 activity of firms is concerned the selection function of venture capital is stronger than its coaching function. Other relevant predictors of patenting are market size and product development time. Expected growth plays a minor role, whereas industry competition is irrelevant for patenting activities.

Keywords: Venture capital; Innovation; Propensity to patent

JEL classification: G24, G32, O31

1. Introduction

Does venture capital contribute to the patenting performance of firms? This question, although simple to ask, has a rich underlying structure, since reverse causation between firms' patenting behaviour and their ability to attract venture capital places significant econometric obstacles in the path to correct identification of causes and effects. The main themes that have to be addressed in order to answer this question are the signalling function of patents as indicators of firm quality, the selection of quality firms by venture capital (VC) funds and the role venture capitalists play in improving firm patenting performance.

Several studies find a positive relation between patenting activity and VC-financing (Kortum and Lerner, 2000; Baum and Silverman, 2004; Ueda and Hirukawa, 2008; Popov and Roosenboom, 2009; Bertoni, Croce and D'Adda, 2010). This is often interpreted as evidence that VC firms are able to coach their portfolio companies, thereby increasing patent output. There are, however, alternative explanations: venture capital firms might be exceptionally good at selecting promising portfolio companies. These companies produce an above-average number of patents after the investment simply because investors were able to forecast this output without actively contributing to it. Cross-sectional studies often find increased patenting activity in firms with VC involvement. In this case, causality can run from patenting to a higher probability of obtaining VC financing, because patents granted or pending can be strong signals of firm quality for investors, as the literature has begun to appreciate. And yet the reverse impact of venture capital on innovation has proved difficult to assess, because it is difficult to establish a control group of firms with identical characteristics apart from the venture capital "treatment".

We aim to tackle causality problems by explicitly accounting for endogeneity of VC investments. Incorporating into a simultaneous model the investor's decision to invest or, stated differently, the firm's ability to signal its quality to investors, should help distinguish signalling from selection and coaching effects. Baum and Silverman (2004) propose to disentangle these effects by investigating whether start-up characteristics that predict VC investments coincide with the influences of these same characteristics on firm performance. They argue that coaching might be at work if characteristics that affect VCs' investment decisions are different from those affecting firms' post-investment performance. We build on this idea by modelling both mechanisms simultaneously. We further contribute to the literature by modelling firms' patenting as two sequential decisions, in which firms first decide whether to patent and then determine the intensity of their patenting.

Studies trying to establish a control group of firms that do not obtain VC financing but are otherwise identical often rely on propensity score matching or comparable algorithms to identify similar firms (Engel and Keilbach, 2007; Peneder, 2010). Firms with VC investors are usually collected first, and only thereafter a sample of control firms is matched by various firm characteristics. Instead, we collect information on both types of firms at the same time by sampling from the population of US and UK small and medium-sized enterprises (SMEs). From a life-cycle perspective of a firm, this seems more plausible. A major difference to ex-post matching is that we first identify firms that actually seek finance. Within this sample, we can investigate the impact of venture capital on patenting performance.

Contrary to prior research, the effect of venture capital on the number of patents produced is insignificant or negative if we account for endogeneity. If we look at the decision to patent, the only exception seems to be one model for granted patents using the full sample including merger targets, for which the likelihood of having a latent patenting status increases after venture capital investments. We can only reproduce prior findings of a positive impact of venture capital on patenting activities in results for *separate* equations. Our results support the view that venture capital follows patent signals to invest in companies with commercially viable products instead of actively contributing to patent production. They confirm emergent anecdotal evidence (Stuck and Weingarten, 2005) that shows that even technologically experienced venture capitalists act like businesspeople, avoiding risks and focusing on entrepreneurs that have value propositions that can be realised within the fund's lifetime. Other relevant predictors for patent applications and grants are market size and product development time. Adding market size as a predictor might explain why industry competition does not seem to change patenting activities of firms.

The remainder of this paper is organised as follows. Section 2 reviews prior literature from a methodological point of view and yields insights into variables that might drive patenting and venture capital investments. We present our dataset and methodology in section 3 and discuss our results in section 4. Section 5 summarises and concludes.

2. Related literature

The literature related to our research question falls into two categories corresponding to our patenting and venture capital equations. In this section, we briefly review this literature on the determinants of venture capital investments and on the decision to use patents to protect the firm's intellectual property. Most authors study either the impact of VC on patenting behaviour or the signalling effect of patents for VC investments. A few take endogeneity into account, but with other outcome variables in mind, such as sales growth, or with an industry or country focus. In the following overview of the literature, we put an emphasis on relevant independent variables and modelling decisions like estimation of count data and endogenous binomial choice situations.

Patent productivity

Among the first studies to empirically study the relation between R&D and patenting behaviour are Scherer's (1965a, 1965b) contributions. He regresses the number of patents granted to Fortune 500 firms in 1959 on 1955 firm data and finds an elasticity of patent grants to the number of R&D employees scaled by sales with an indication of diminishing returns to R&D input intensity. While he explicitly considers the time lag between the inception of an invention and the patent approval by the US Patent Office, not all studies that followed have done so. Pakes and Griliches (1980) include current and lagged R&D expenditure and find a strong cross-sectional contemporaneous effect of R&D expenditures on patent applications, but a less strong one in a time-series context. Pakes (1981) shows this contemporaneous effect for patent grants.

Scherer (1965b) discusses the recurring theme of how to treat zero patent counts in log-linear specifications of R&D input (employees) and output (patents) and finds large differences in estimation results. Zeros usually appear in firm-level studies, whereas studies modelling production functions on a country or industry basis (for example, Kortum and Lerner, 2000) rarely encounter zero cell counts. Some authors choose to drop offending zeros from their sample, while others assume that observing zero patents really means one patent, or a fraction (Zhang, 2009).

Hausman, Hall and Griliches (1984) suggest using Poisson and negative binomial models and find a strong influence of contemporaneous R&D expenditures and patent applications. Negative binomial models that allow for random or “fixed” firm effects perform best. Comparing different specifications, they find that most of the variation in their panel data is found in the between firms (cross-sectional) dimension but there is also additional variability in the time dimension. Unobserved heterogeneity between firms is particularly important in our model setup, since it might be correlated with both patenting and VC investments.

Bound, Cummins, Griliches, Hall and Jaffe (1984) estimate a more traditional OLS model, in which the logarithm of R&D explains the number of patent grants in logs. They set the log of patents to zero whenever patents are zero and allow for a different intercept for these firms. Their results indicate a highly significant impact of R&D, while firm size measured by gross plant value is also positive and significant. Similar to Hausman, Hall and Griliches (1984), they try Poisson and negative binomial specifications but find large variation in estimated parameters, which they attribute to the large number of zero patents (half their sample). Sample separation into high R&D (>USD2m) and low R&D firms leads to more coherent estimates across specifications, but much smaller positive coefficients for R&D in small firms.

Scherer (1983) plots the relative frequency of patenting in groups of firm’s lines of business that are selected on the basis of R&D expenditures. His graph shows the typical sigmoid-type relation between R&D and the propensity to patent. We follow this line of thinking by modelling this most basic decision to patent. In his linear regressions of patent grants he finds that patenting rises roughly proportionately with R&D effort within individual industries. Company diversification appears to increase patenting activities, whereas industry concentration is associated with fewer patents. Brouwer and Kleinknecht (1999) estimate probit models for having at least one patent application and Poisson models for the number of applications. They find that firm size given by the (log) number of employees is the most significant predictor of applications, followed by R&D expenditures as a percentage of sales. R&D collaborations, sales of innovative products and firms operating in high-tech sectors are all associated with a higher propensity to patent.

While much research has focused on the patenting behaviour of firms, fewer studies have incorporated venture capital as an explanatory variable. The importance of venture capital and business angels in situations of asymmetric information between firm insiders and investors has long been recognised (Sahlman, 1990; Gompers, 1995; Hellman, 1998, Gompers and Lerner, 1999, 2001; Kaplan and Strömberg, 2003, 2004). These equity investors seem to be able to increase firm value beyond the provision of financial resources (see also Bergemann and Hege, 1998; Riyanto and Schwienbacher, 2006; Schwienbacher, 2008). The literature broadly agrees that for small innovative firms venture capitalists are much more skilled than large banks at screening firms and providing value-added to their portfolio companies (Gorman and Sahlman, 1989; MacMillan, Kulow and Khoylian, 1989; Bygrave and Timmons, 1992; Keuschnigg and Nielsen, 2004; Ueda, 2004).

One of the most prominent studies on the relation between VC financing and patenting is Kortum and Lerner's (2000) empirical account of venture capital and its contribution to the patent production function. With the benefit of aggregation by industry and thus avoiding zero patent counts, they find a positive and significant effect of VC financing on patent grants. However, both patenting and venture funding could be related to unobserved technological opportunities, thereby causing an upward bias in the coefficient on venture capital. In regressions that exploit a policy shift in venture fund legislation to construct an instrumental variable, they again find a positive impact on patenting. 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. Finally, Hirukawa and Ueda (2008) estimate autoregressive models for TFP growth and patent counts by industry. Although TFP growth appears to be positively related to future VC investment, they find little evidence that VC investments precede an increase in patenting. To 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 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.

Engel and Keilbach (2007) use propensity score matching and balanced score matching to compare German venture-funded firms to non-VC ones with respect to innovation output and growth. VC-funded firms apply for ten times as many patents as matched non-VC firms. However, this difference is only weakly significant. Caselli, Gatti and Perrini (2009) use a similar matching procedure to assess the difference in patenting and related growth variables in venture-backed IPOs of Italian firms. They find a higher average number of patents in venture-backed firms than in their matched counterparts. They argue, however, that VCs select firms based on patents rather than promote continued innovation after the investment.

Zhang (2009) estimates a log-linear tobit model of patents before and after an IPO with endogenous VC investment. Venture capital appears to be positively related to patents in the pre-IPO period, but not thereafter. Significant variables are the percentage of shares owned by the VC, R&D expenditures and dummy variables for bank-affiliated, corporate, independent or foreign venture capital funds. The assumption of firms always having at least one patent when taking logs may bias these results. Bertoni, Croce and D'Adda (2010) estimate random effects logit models for the likelihood of observing one or more patents and random effects negative binomial models for the number of patents, depending on lagged patent stock and lagged VC backing, in a panel of Italian technology firms. Patent applications depend on VC backing, size (employees), the founders' technical work experience, founders' university education and cash flow. In summary, research using firm-level information is mixed but indicates that the positive findings of prior studies could be driven by venture firms' selecting investee companies based on patents instead of fostering innovation after the investment.

Venture capital investment

The second equation of our model determines whether venture capitalists decide to invest in a firm or, when seen from the investee's perspective, the firm is able to attract venture capital to fund its growth. The literature on venture capital finance emerged during the venture capital revolution in the 1990's (Gompers and Lerner, 2001). As in the literature on patenting, early papers started to look at the determinants of VC finance without regard to patents. For example, although Hellmann and Puri (2000) do not study the impact of patents directly, they find that innovator firms are more likely to attract venture capital than imitator firms and obtain venture capital much earlier in their life.

Baum and Silverman (2004) are the first to estimate models for VC financing and patent applications and grants on the same dataset. 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 rounds, total investment and exit status. A start-up firm's prior patenting attracts larger amounts of VC funds in Cao and Hsu's (2011) study of venture-backed firms.

In Baum and Silverman's (2004) negative binomial models for patent applications, the most significant predictors are lagged applications, having a corporate parent, being a university spin-off, government assistance and, with negative coefficients, age, cash flow, diversification and industry concentration. The latter finding is in line with Scherer (1983) who finds a negative relation between concentration and patenting in some specifications, whereas he finds a positive coefficient for diversification. Patent grants and applications strongly predict future patent grants, in addition to sector-specific VC financings and, negatively, industry concentration.

Two other studies that relate patents to outcome variables associated with venture funding are those by 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 of Hsu and Ziedonis' (2008) study of VC-financed semiconductor start-ups suggest that patent applications increase both the likelihood of obtaining initial capital from a prominent VC and of going public.

Closely related to our model are studies that employ 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 predictors. Peneder (2010) aims to assess the impact of venture capital on firm growth by matching VC- and non-VC funded firms. While estimating propensity scores for his matching procedure in a probit model, he finds a positive impact of patents, employment and a firm's credit rating on the likelihood of VC financing, and a negative effect of age, cash flow and return on capital employed. 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. Furthermore, firms obtain capital from venture funds or business angels if they were founded by a team rather than a single person.

3. Data and methodology

This paper builds on a unique comparative survey of UK and US businesses jointly carried out by the Centre for Business Research of the University of Cambridge and the Industrial Performance Center of MIT in 2004-2005.[1] The basis for the sampling was the Dun & Bradsheet (D&B) database, which contains company-specific information drawn from various sources, including Company

[1] Cosh et al. (2006) contains a full description of the survey design, sampling and instrument.

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. We restrict our sample to firms that sought finance during the two years prior to being interviewed. Since the survey does not contain information on the financing behaviour of large firms, the sample contains firms with up to 1000 employees only. In total, this leaves us with a working sample of 940 firms, 513 in the US and 427 in the UK. A separate set of analyses contains 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 source of external finance. We incorporate this information as an endogenous binary variable in our models. 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 and 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.

[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 economically plausible predictors for the propensity to patent. R&D intensity is a variable of first choice. 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. We try to account for the arrival of technological opportunities by including an estimate of the firm's growth opportunities, as reported by the company. Other variables are more straightforward controls for age, country, whether a firm was founded as a university spin-off 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 and 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. Baum and Silverman (2004) also argue that lagged dependent variables help account for unobserved heterogeneity (Jacobson, 1990).

Estimation

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 and Jaffe, 1984; Hausman, Hall and Griliches, 1984).

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). At the same time, we have to deal with endogenous VC investments, which complicates models that are no longer analytically tractable. 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 comparing firms by propensity score matching (Engel and Keilbach, 2007).

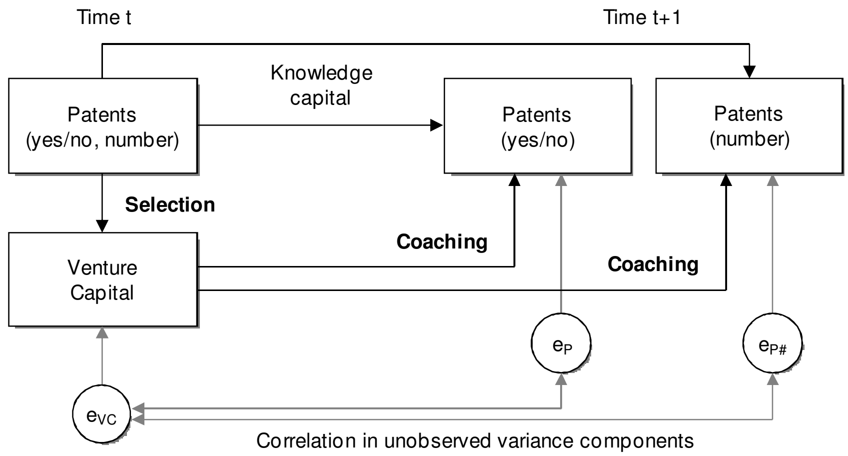

Figure 1. Model framework
Dependent variables are venture capital investment at time t and the number of patent applications or grants at time t+1. In the binary bivariate case, "Patents (yes/no)" measures whether we observe any number of patents for the firm at time t+1. In zero-inflated Poisson models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

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 adds 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 one.

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

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

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

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

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

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

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

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

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 and 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 includes 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[2] (see, for example, Gouriéroux and Monfort (1996) and Train (2009)).

Our data are constrained to a cross-section by survey design. However, we are able to match patent data from PatStat for the periods before and after the survey period. We therefore use the subscript t mainly to conceptually distinguish between these periods. As the original data were obtained through interviews over a period of almost a year, there is some variation in the time period the firms are referring to when answering questions regarding their patenting and other economic activities "over the last three years". Therefore, an observation designated by subscript t for one firm does not necessarily lie at exactly the same point in time as that for another firm.

[2] We use 200 random draws from a truncated normal distribution in all models estimated by maximum simulated likelihood. Further estimation details including likelihood function and MSL methodology are available from the authors upon request.

4. Empirical 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 becomes very weak and disappears in all but one model. The effect of endogenising 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 contemporaneous error correlation between the venture capital equation and the patenting equation. Finally, tables 6 and 7 include an additional equation for the number of patents in addition to an equation that determines firms' latent patenting status.

[Insert tables 3 and 4 about here]

Independent equations – Patenting

If patenting activity is estimated in univariate probit regressions, venture capital appears to strongly increase 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, Croce and D'Adda 2010, Kortum and 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, Hall and Griliches (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.

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, Cummins, Griliches, Hall and Jaffe's (1984) study, we find a positive effect on future applications, but none for grants. Other observed variables do not seem to explain variation in patenting that size would explain if these variables were excluded. Collinearity in our models is generally 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 models. Manufacturing is sometimes found to show 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 this likelihood.

There is an increased likelihood of receiving patent grants in US firms, which we do not find for applications. In contrast to findings presented by Bertoni, Croce and D'Adda (2010), the CEO's higher education does not increase the likelihood of being granted one or more patents. We find no effect of the CEO's education in any of our model specifications.

University spin-offs can be seen as a vehicle to exploit the commercial potential of inventions made within universities or public-private collaborations. We would therefore expect a positive impact on granted patents, if not on patent applications. Unlike in results presented by Baum and Silverman (2004), in none of our models the spin-off indicator produces a significant impact. This could be due to the small number of university spin-offs in our sample (=20). Another explanation can be found in the time pattern of patenting in spin-offs. If a spin-off company is formed to exploit a patent after it has been granted, the relation between spin-off and patents would be stronger for past patents than for future ones. Indeed, we find a correlation between past patent grants and university spin-offs in a separate analysis, but not for future patent applications or grants.

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 deter potential competitors from entering their market by erecting fences of accumulated patents (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. We test the hypothesis that competition is more relevant if the firm operates internationally, but do not find significance for such an interaction.

Expected firm growth as estimated by the firm does not appear to affect the likelihood to patent. This result can be interpreted as firms using patents not to prepare for future growth, but to defend themselves against competitors or potential market entrants. In the latter case, we would not expect to see a relation between patenting and growth opportunities.

Prior studies found conflicting evidence on the impact of profitability on patenting. Bertoni, Croce and d'Adda (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.

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, but being a university spin-off again does not lead to a greater likelihood of being a target for investments. Although comparable to other predictors in its effect size, we find a slightly significant spin-off indicator in only one specification.

Interestingly, venture capital funds appear to invest in large firms more often than in smaller ones. This finding can be explained in light of our sample of small and medium-sized companies.

Since our sample contains firms with 10 to 1000 employees, we can expect that most tiny 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 to the finding 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. Expected growth does not seem to play a role in VC investments, which is surprising, since venture capital is often seen as capital that helps young companies exploit their product's market potential. Firms with a long product development time are neither more nor less likely to obtain venture capital. Although collinearity is no big 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.

The set of equations 4 to 6 in table 3 addresses the concern that results might be driven by sample attrition due to firms being taken over. Although the entity would still be producing patents, 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 (not all of which are shown here to conserve space).

Simultaneous equations – Patenting and VC

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 about here]

Venture capital does not seem to increase patenting activity and even decreases the likelihood of filing patent applications after the investment. Studies on an industry level have found a positive association (Kortum and Lerner, 2000; Ueda and Hirukawa, 2008 for TFP growth), while results for samples of individual firms are mixed. Future patent grants are not negatively affected by venture capital, 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. The impact of this correlation can be seen in the coefficients for venture capital, 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 a case, 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 between models. Age is now insignificant in all models for patenting, while the importance of R&D increases. The positive effect on patent grants for US firms becomes weaker in a simultaneous model but is still weakly significant. Firm size, however, increases its effect size, but only on future patent applications. We do not have an explanation for this result, but we can rule out collinearity as a cause of spurious effects. The effect of employment on future patenting also exists in simple bivariate correlations between employment and patenting variables, whose sizes roughly mirror the coefficients in our multivariate models.

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 on this subsample. Whether or not a firm obtains finance can have a profound impact on its ability to start or sustain patenting activities. Results of separate regressions confirm our findings in table 5. Three small changes appear, however, in the patenting equations. First, firms founded as university spin-offs experience a higher likelihood of applying for patents than in our earlier results. Due to the small group of spin-offs in our sample, this result has to be taken with a grain of salt, but indicates the plausible mechanism that spin-offs that are able to attract sufficient funding can afford to realise their development plans. Second, the effect size of development time decreases slightly and loses its significance. Third, coefficients on product market competition all increase in magnitude, and the one predicting future applications is slightly significant now.

Putting everything together – 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 Poisson models, as the overdispersion parameter introduced in negative binomial models turned out to be unnecessary.

[Insert table 6 about here]

Ignoring the potential endogeneity of venture capital in the patenting decisions, we find opposing effects of venture capital on the decision to patent and the number of patents granted. Similar to binary models that ignore endogeneity, VC exerts a strong and positive influence on the likelihood of being granted at least one patent (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 VC pursue an extremely selective strategy that encourages firms to patent only the most promising of their developments.

A more plausible picture emerges if endogenously determined venture capital is added to the models (see table 7). The effect of VC on the number of granted patents becomes insignificant now, while VC investments increase the likelihood of (latent) patenting in our results for the full sample, as would be expected if venture capitalists perform a coaching function in their portfolio companies. Moreover, and surprisingly similar to the “exogenous” model setup, the number of patent applications appears to decrease after VC investments. This result holds for the sample excluding merger targets (model 4), while there are no effects of VC on either patenting variable in the full sample.

[Insert table 7 about here]

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 is weak, it has a positive negative impact on patent applications and a positive one on the success of these applications in some models. Venture capitalists seem to be attracted by firms that produce patents, but contribute only to the exploitation of existing technology. 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. Estimating three equations simultaneously 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. Long product development times are a significant predictor for patenting status, but not for the number of patents applied for or granted.

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 highly significant. External shocks leading to VC investment correlate with the likelihood to patent, but coefficients are hardly significant for patents granted. Estimated error correlations between VC investment and patent numbers are similarly large and significant. We 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. 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 made 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 distinguishing signalling from selection and coaching effects. As a second contribution to the literature, we model patenting as a two-step process, in which firms first decide whether to use patents at all and then determine the number of applications they file.

We find that the causal link from venture capital to patenting is weak, contrary to studies on aggregate patenting and venture capital investment (Kortum and Lerner, 2000). A positive effect can only be found consistently if potential endogeneity of VC financing is ignored. Instead, venture capital even appears to exert a negative influence on future patent applications in the sample of firms excluding merger targets. Venture capital funds seem to primarily select portfolio companies based on the signalling function of patents and thereby help them to commercialise their ideas. This signalling function of patents is most strongly associated with patent applications rather than granted ones. The number of patents appears not to play a major role in attracting venture capital, but it is the fact that a firm patents at all that makes them attractive targets for investments.

Our results for determinants of patenting mostly confirm 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 and significant one for the number of applications. Age effects on granted patents are all negligible. The founder's education does not increase the likelihood to patent. Results for university spin-offs are similarly insignificant. The proportion of scientific staff, however, 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.

Results for the VC investment equation are very similar in all 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, nor does expected growth.

By modelling the VC's decision to invest and the portfolio company's patenting activity simultaneously, we are able to answer the question 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 be more successful in being granted patents, but tend to reduce applications. If venture capitalists are performing a coaching function, their activities appear to affect the outcome of patent applications, but not firms' efforts to generate additional products.

Our models greatly reduce the possibilities in which 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 correlation between the VC equations and our two patenting equations are both highly significant, which supports our estimation strategy.

We find evidence for a two-step decision process in patenting: In the first step, firms decide whether or not to patent, and it is this decision which determines the likelihood of VC financing. Only after a firm has established an R&D programme, an estimation of the number of patents yields sensible results. Models aiming to explain firms' patent numbers should thus incorporate a mechanism that determines whether a firm patents at all before estimating the number of patent applications or grants.

References

Audretsch, D. B., Bönte, W. & Mahagaonkar, P. (2009), Financial Signaling by Innovative Nascent Entrepreneurs, Jena Economic Research Papers No. 2009-012, available at http://www.wiwi.uni-jena.de/Papers/jerp2009/wp_2009_012.pdf.

Baum, J. A. C. & Silverman, B. S. (2004), Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups, Journal of Business Venturing 19(3), 411–436.

Bergemann, D. & Hege, U. (1998), Venture capital financing, moral hazard, and learning, Journal of Banking & Finance 22(6-8), 703–735.

Bertoni, F., Croce, A. & D'Adda, D. (2010), Venture capital investments and patenting activity of high-tech start-ups: a micro-econometric firm-level analysis, Venture Capital 12(4), 307–326.

Bound, J., Cummins, C., Griliches, Z., Hall, B. H. & Jaffe, A. (1984), Who Does R&D and Who Patents?, in Zvi Griliches, ed., 'R&D, patents, and productivity', University of Chicago Press, 21–54.

Bygrave, W. & Timmons, J. (1992), Venture Capital at the Crossroads, Harvard Business School Press, Boston.

Cao, J. & Hsu, P.-H. (2010), Patent Signaling, Entrepreneurial Performance, and Venture Capital Financing, Working Paper, available at http://ssrn.com/abstract=1678809.

Caselli, S., Gatti, S. & Perrini, F. (2009), Are Venture Capitalists a Catalyst for Innovation?, European Financial Management 15(1), 92–111.

Colombo, M. G. & Grilli, L. (2010), On growth drivers of high-tech start-ups: Exploring the role of founders' human capital and venture capital, Journal of Business Venturing 25(6), 610–626.

Engel, D. & Keilbach, M. (2007), Firm-level implications of early stage venture capital investment – An empirical investigation, Journal of Empirical Finance 14(2), 150–167.

Gelman, A. & Hill, J. (2006), Data Analysis Using Regression and Multilevel/Hierarchical Models, Cambridge University Press.

Gompers, P. A. (1995), Optimal Investment, Monitoring, and the Staging of Venture Capital, The Journal of Finance 50(5), 1461–1489.

Gompers, P. A. & Lerner, J. (1999), An analysis of compensation in the U.S. venture capital partnership, Journal of Financial Economics 51, 3–44.

Gompers, P. A. & Lerner, J. (2001), 'The Venture Capital Revolution', Journal of Economic Perspectives 15(2), 145–168.

Gorman, M. & Sahlman, W. A. (1989), What do venture capitalists do?, Journal of Business Venturing 4(4), 231–248.

Gouriéroux, C. & Monfort, A. (1996), Simulation-Based Econometric Methods, Oxford University Press.

Hausman, J., Hall, B. H. & Griliches, Z. (1984), Econometric Models for Count Data with an Application to the Patents-R&D Relationship, Econometrica 52(4), 909–938.

Häussler, C., Harhoff, D. & Müller, E. (2009), To Be Financed or Not… – The Role of Patents for Venture Capital Financing, ZEW - Centre for European Economic Research Discussion Paper No. 09-003, available at http://ssrn.com/abstract=1393725.

Heckman, J. (1990), Varieties of Selection Bias, The American Economic Review 80(2), 313–318.

Hellmann, T. (1998), The Allocation of Control Rights in Venture Capital Contracts, The RAND Journal of Economics 29(1), 57–76.

Hellman, T. & Puri, M. (2000), The interaction between product market and financing strategy: the role of venture capital, Review of Financial Studies 13(4), 959–984.

Hsu, D. & Ziedonis, R. H. (2008), Patents as quality signals for entrepreneurial ventures, Academy of Management Best Paper Proceedings.

Jacobson, R. (1990), Unobservable Effects and Business Performance, Marketing Science 9(1), 74–85.

Kaplan, S. N. & Strömberg, P. (2003), Financial Contracting Theory Meets the Real World: An Empirical Analysis of Venture Capital Contracts, Review of Economic Studies 70(243), 281–315.

Kaplan, S. N. & Strömberg, P. (2004), Characteristics, Contracts, and Actions: Evidence from Venture Capitalist Analyses, The Journal of Finance 59(5), 2177–2210.

Keuschnigg, C. & Nielsen, S. B. (2004), Start-ups, venture capitalists, and the capital gains tax, Journal of Public Economics 88(5), 1011–1042.

Kortum, S. & Lerner, J. (2000), Assessing the Contribution of Venture Capital to Innovation, The RAND Journal of Economics 31(4), 674–692.

Lambert, D. (1992), Zero-Inflated Poisson Regression, with an Application to Defects in Manufacturing, Technometrics 34(1), 1–14.

Lerner, J., Sorensen, M. & Strömberg, P. (2011), Private Equity and Long-Run Investment: The Case of Innovation, The Journal of Finance 66(2), 445–477.

MacMillan, I. C., Kulow, D. M. & Khoylian, R. (1989), Venture capitalists' involvement in their investments: Extent and performance, Journal of Business Venturing 4(1), 27–47.

Mann, R. J. & Sager, T. W. (2007), Patents, venture capital, and software start-ups, Research Policy 36(2), 193–208.

Miranda, A. & Rabe-Hesketh, S. (2006), Maximum likelihood estimation of endogenous switching and sample selection models for binary, ordinal, and count variables, The Stata Journal 6(3), 285–308.

Pakes, A. (1981), Patents, R&D, and the stock market rate of return, NBER Working Paper. Available at http://www.nber.org/papers/w0786.

Pakes, A. & Griliches, Z. (1980), Patents and R&D at the firm level: A first report, Economics Letters 5(4), 377–381.

Peneder, M. (2010), The Impact of Venture Capital on Innovation Behaviour and Firm Growth, WIFO Working Paper 363/2010, available at http://www.wifo.ac.at/wwa/downloadController/displayDbDoc.htm?item=WP_2010_363$.PDF.

Popov, A. & Roosenboom, P. (2009), Does private equity investment spur innovation? Evidence from Europe, Working Paper, available at www.ecb.int/pub/pdf/scpwps/ecbwp1063.pdf.

Riyanto, Y. E. & Schwienbacher, A. (2006), The strategic use of corporate venture financing for securing demand, Journal of Banking & Finance 30(10), 2809–2833.

Sahlman, W. (1990), The structure and governance of venture-capital organisations, Journal of Financial Economics 27(2), 473–521.

Scherer, F. M. (1965a), Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions, The American Economic Review 55(5), 1097–1125.

Scherer, F. M. (1965b), Size of Firm, Oligopoly, and Research: A Comment, The Canadian Journal of Economics and Political Science / Revue canadienne d'Economique et de Science politique 31(2), 256–266.

Scherer, F. M. (1983), The propensity to patent, International Journal of Industrial Organization 1(1), 107–128.

Schwienbacher, A. (2008), Innovation and Venture Capital Exits, Economic Journal 118(533), 1888–1916.

Stuck, B. & Weingarten, M. (2005), How Venture Capital Thwarts Innovation, IEEE Spectrum April 2005, available at http://spectrum.ieee.org/computing/hardware/how-venture-capital-thwarts-innovation.

Taber, C. R. (2000), Semiparametric identification and heterogeneity in discrete choice dynamic programming models, Journal of Econometrics 96(2), 201–229.

Train, K. E. (2009), Discrete Choice Methods with Simulation, Cambridge University Press.

Ueda, M. (2004), Banks versus Venture Capital: Project Evaluation, Screening, and Expropriation, Journal of Finance 59(2), 601–621.

Ueda, M. & Hirukawa, M. (2008), Venture Capital and Industrial 'Innovation', Working paper, available at http://ssrn.com/abstract=1242693.

Zhang, J. X. (2009), Shareholding by venture capitalists and patent applications of Japanese firms in the pre- and post-IPO Periods, Institute of Innovation Research Working Paper, Hitotsubashi University, available at http://ideas.repec.org/p/hit/iirwps/09-02.html.

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.
University spin-off	0.021	0	0.144	0	1	The firm is a university spin-off. 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.
Expected growth	3.117	3	1.007	0	4	Growth expected for national employment over the next 10 years. Coded as ordinal 0=a lot smaller the 4=a lot larger, 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 – univariate

This table presents probit models for the likelihood of observing venture capital or business angel investments. 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)	-0.102(0.08)			-0.112(0.09)		
Patent applications >0	0.598(0.20)***			0.630(0.21)***		
Patent grants (Log)		-0.155(0.12)			-0.238(0.13)*	
Patent grants >0		0.363(0.23)			0.403(0.24)	
Age (Log)	-0.334(0.09)***	-0.348(0.09)***	-0.346(0.09)***	-0.290(0.10)***	-0.303(0.10)***	-0.300(0.10)***
Size (Log(Employees))	0.203(0.07)***	0.199(0.06)***	0.191(0.06)***	0.176(0.07)**	0.178(0.07)**	0.165(0.07)**
US firm	-0.328(0.14)**	-0.318(0.14)**	-0.319(0.14)**	-0.353(0.15)**	-0.338(0.15)**	-0.342(0.15)**
Manufacturing sector	-0.377(0.13)***	-0.347(0.13)***	-0.341(0.13)**	-0.360(0.14)**	-0.329(0.14)**	-0.325(0.14)**
R&D expend. (yes/no)	0.455(0.21)**	0.484(0.21)**	0.507(0.21)**	0.748(0.26)***	0.768(0.26)***	0.795(0.26)***
R&D staff (in %)	0.649(0.33)**	0.828(0.32)**	0.824(0.31)***	0.799(0.35)**	1.040(0.34)***	0.967(0.33)***
CEO has a degree	0.357(0.17)**	0.364(0.17)**	0.386(0.17)**	0.360(0.18)**	0.361(0.18)**	0.380(0.18)**
University spin-off	0.465(0.32)	0.493(0.33)	0.531(0.33)	0.320(0.34)	0.381(0.36)	0.401(0.36)
Market size	0.213(0.09)**	0.220(0.09)**	0.232(0.09)***	0.197(0.10)**	0.203(0.10)**	0.213(0.09)**
Expected growth	0.021(0.07)	0.010(0.07)	0.007(0.07)	0.058(0.08)	0.047(0.08)	0.042(0.08)
Product dev. time	0.054(0.07)	0.060(0.07)	0.065(0.07)	0.051(0.07)	0.060(0.07)	0.065(0.07)
Competitors (Log)	-0.051(0.07)	-0.066(0.07)	-0.067(0.07)	-0.015(0.08)	-0.034(0.08)	-0.033(0.08)
Intercept	-2.027(0.49)***	-1.937(0.48)***	-1.934(0.47)***	-2.524(0.56)***	-2.439(0.55)***	-2.417(0.54)***
Observations	940	940	940	888	888	888
Log-Likelihood	-236.2	-238.7	-240.2	-202.8	-204.4	-206.6
Chi-sq. test	106.5	110.1	98.3	93.3	96.2	86.6
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo- R²	0.238	0.230	0.225	0.246	0.240	0.231

Table 4. Patenting activity – univariate

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

	Including VC/BA			Excluding VC/BA		
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	0.219(0.20)	0.627(0.19)***	0.473(0.24)**			
Patent applications (Log)	0.501(0.12)***		0.662(0.14)***	0.508(0.12)***		0.652(0.14)***
Patent applications >0	0.991(0.22)***		1.595(0.23)***	1.001(0.22)***		1.614(0.22)***
Patent grants (Log)		0.579(0.15)***			0.545(0.15)***	
Patent grants >0		1.234(0.22)***			1.249(0.22)***	
Age (Log)	0.154(0.08)*	0.026(0.10)	0.114(0.11)	0.144(0.08)*	-0.008(0.09)	0.095(0.11)
Size (Log(Employees))	0.139(0.06)**	0.026(0.06)	0.002(0.08)	0.145(0.06)**	0.046(0.06)	0.016(0.07)
US firm	0.116(0.13)	0.338(0.14)**	0.373(0.17)**	0.101(0.13)	0.286(0.14)**	0.332(0.17)**
Manufacturing sector	0.040(0.14)	0.180(0.16)	0.137(0.18)	0.017(0.14)	0.088(0.16)	0.066(0.18)
R&D expend. (yes/no)	0.453(0.18)**	0.366(0.19)*	0.528(0.22)**	0.462(0.18)**	0.408(0.19)**	0.559(0.22)**
R&D staff (in %)	0.076(0.36)	0.574(0.43)	-0.372(0.44)	0.138(0.36)	0.756(0.41)*	-0.274(0.42)
CEO has a degree	0.104(0.14)	-0.242(0.15)	-0.273(0.17)	0.116(0.14)	-0.197(0.15)	-0.232(0.17)
University spin-off	0.105(0.37)	-0.272(0.41)	-0.602(0.39)	0.138(0.36)	-0.156(0.41)	-0.484(0.37)
Market size	0.233(0.09)***	0.317(0.10)***	0.262(0.11)**	0.241(0.09)***	0.340(0.09)***	0.279(0.11)***
Expected growth	0.055(0.07)	0.047(0.07)	0.101(0.09)	0.052(0.07)	0.046(0.07)	0.098(0.09)
Product dev. time	0.173(0.06)***	0.136(0.06)**	0.115(0.07)	0.174(0.06)***	0.136(0.06)**	0.121(0.07)
Competitors (Log)	-0.068(0.06)	-0.049(0.06)	-0.097(0.08)	-0.069(0.06)	-0.058(0.06)	-0.096(0.08)
Intercept	-3.626(0.49)***	-3.048(0.54)***	-3.504(0.70)***	-3.601(0.49)***	-2.955(0.54)***	-3.458(0.70)***
Observations	940	940	940	940	940	940
Log-Likelihood	-258.6	-227.2	-165.8	-259.3	-232.4	-168.0
Chi-sq. test	238.0	210.2	238.2	238.0	214.7	247.5
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo- R²	0.418	0.436	0.588	0.416	0.423	0.583

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. 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	-0.808(0.36)**	0.007(0.50)	-0.260(0.34)	-1.342(0.60)**	0.143(0.60)	-0.237(0.36)
Patent applications (Log)	0.431(0.11)***		0.619(0.13)***	0.518(0.20)***		0.563(0.14)***
Patent applications >0	1.075(0.20)***		1.640(0.22)***	0.992(0.20)***		1.648(0.22)***
Patent grants (Log)		0.544(0.15)***			0.557(0.17)***	
Patent grants >0		1.256(0.22)***			1.274(0.23)***	
Age (Log)	0.058(0.09)	-0.024(0.11)	0.053(0.11)	0.006(0.15)	0.029(0.11)	0.054(0.11)
Size (Log(Employees))	0.174(0.06)***	0.049(0.06)	0.032(0.07)	0.170(0.06)***	0.058(0.07)	0.033(0.07)
US firm	0.029(0.13)	0.292(0.16)*	0.310(0.17)*	-0.026(0.17)	0.299(0.16)*	0.300(0.17)*
Manufacturing sector	-0.069(0.14)	0.117(0.16)	0.059(0.17)	-0.095(0.20)	0.096(0.17)	0.056(0.17)
R&D expend. (yes/no)	0.504(0.17)***	0.400(0.19)**	0.558(0.21)***	0.614(0.19)***	0.406(0.21)**	0.543(0.21)***
R&D staff (in %)	0.274(0.34)	0.720(0.43)*	-0.206(0.43)	0.659(0.35)*	0.994(0.43)**	0.028(0.45)
CEO has a degree	0.175(0.14)	-0.196(0.16)	-0.215(0.16)	0.214(0.16)	-0.255(0.16)	-0.203(0.17)
University spin-off	0.267(0.34)	-0.148(0.41)	-0.441(0.38)	0.019(0.37)	0.099(0.40)	-0.375(0.40)
Market size	0.260(0.08)***	0.334(0.09)***	0.282(0.10)***	0.264(0.08)***	0.291(0.09)***	0.276(0.10)***
Expected growth	0.052(0.07)	0.045(0.07)	0.099(0.09)	0.084(0.07)	0.020(0.07)	0.090(0.09)
Product dev. time	0.169(0.06)***	0.139(0.06)**	0.118(0.07)*	0.161(0.06)***	0.143(0.06)**	0.110(0.07)
Competitors (Log)	-0.072(0.06)	-0.055(0.06)	-0.100(0.08)	-0.040(0.06)	-0.070(0.06)	-0.095(0.08)
Intercept	-3.342(0.52)***	-2.927(0.57)***	-3.346(0.71)***	-3.307(0.74)***	-2.945(0.58)***	-3.295(0.70)***
VC/BA investment						
Patent applications (Log)	-0.103(0.08)		-0.104(0.08)	-0.123(0.09)		-0.117(0.09)
Patent applications >0	0.644(0.20)***		0.632(0.20)***	0.721(0.21)***		0.675(0.21)***
Patent grants (Log)		-0.159(0.12)			-0.241(0.12)*	
Patent grants >0		0.402(0.24)*			0.439(0.25)*	
Age (Log)	-0.338(0.09)***	-0.348(0.09)***	-0.344(0.09)***	-0.281(0.11)***	-0.303(0.10)***	-0.303(0.10)***
Size (Log(Employees))	0.197(0.07)***	0.205(0.06)***	0.204(0.07)***	0.174(0.08)**	0.184(0.07)**	0.179(0.07)**
US firm	-0.345(0.14)**	-0.317(0.14)**	-0.328(0.14)**	-0.407(0.17)**	-0.336(0.15)**	-0.355(0.15)**
Manufacturing sector	-0.377(0.13)***	-0.364(0.13)***	-0.385(0.13)***	-0.367(0.14)**	-0.347(0.15)**	-0.372(0.15)**
R&D expend. (yes/no)	0.459(0.21)**	0.484(0.21)**	0.461(0.22)**	0.713(0.27)***	0.770(0.26)***	0.762(0.27)***
R&D staff (in %)	0.651(0.33)**	0.793(0.33)**	0.612(0.33)*	0.793(0.35)**	1.004(0.34)***	0.755(0.35)**
CEO has a degree	0.379(0.16)**	0.367(0.17)**	0.361(0.17)**	0.402(0.17)**	0.364(0.18)**	0.364(0.18)**
University spin-off	0.449(0.33)	0.471(0.34)	0.450(0.33)	0.314(0.34)	0.361(0.37)	0.306(0.35)
Market size	0.208(0.09)**	0.223(0.09)**	0.218(0.09)**	0.192(0.10)**	0.208(0.10)**	0.204(0.10)**
Expected growth	0.045(0.08)	0.010(0.07)	0.018(0.07)	0.103(0.10)	0.049(0.08)	0.056(0.08)
Product dev. time	0.049(0.07)	0.061(0.07)	0.054(0.07)	0.036(0.07)	0.061(0.07)	0.052(0.07)
Competitors (Log)	-0.054(0.07)	-0.062(0.07)	-0.047(0.07)	-0.035(0.09)	-0.029(0.08)	-0.011(0.08)
Intercept	-2.069(0.49)***	-1.969(0.49)***	-2.021(0.49)***	-2.612(0.56)***	-2.484(0.57)***	-2.530(0.56)***
Observations	940	940	940	888	888	888
Log-Likelihood	-493.3	-465.5	-401.2	-432.9	-413.5	-361.4
Chi-sq. test	350.6	310.2	348.3	337.8	274.3	316.7
P-value	0.000	0.000	0.000	0.000	0.000	0.000
$\rho(\nu_{it}, \varepsilon_{it})$	0.572	0.337	0.403	0.866	0.310	0.415
P-value for ρ (Wald test)	0.012	0.187	0.005	0.358	0.319	0.010
Pseudo- R^2	0.327	0.347	0.437	0.359	0.347	0.429

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	-0.361(0.25)	-0.292(0.23)	-0.586(0.21)***	-0.419(0.21)**	-0.255(0.22)	-0.365(0.15)**
Patent applications (Log)	0.802(0.10)***		0.969(0.08)***	0.824(0.09)***		1.012(0.08)***
Patent applications >0	-0.688(0.38)*		-1.028(0.44)**	-0.559(0.38)		-1.185(0.45)***
Patent grants (Log)		0.641(0.09)***			0.583(0.08)***	
Patent grants >0		0.483(0.26)*			0.670(0.25)***	
Age (Log)	-0.201(0.22)	-0.446(0.20)**	-0.162(0.13)	-0.222(0.24)	-0.600(0.18)***	-0.042(0.12)
Size (Log(Employees))	-0.120(0.13)	0.180(0.13)	-0.184(0.12)	-0.190(0.19)	0.316(0.11)***	-0.133(0.09)
US firm	0.466(0.35)	0.557(0.23)**	0.269(0.17)	0.481(0.34)	0.644(0.20)***	0.259(0.15)*
Manufacturing sector	-0.079(0.25)	-0.059(0.23)	0.268(0.18)	-0.038(0.26)	-0.058(0.19)	0.284(0.16)*
R&D expend. (yes/no)	0.325(0.33)	-0.288(0.51)	0.201(0.22)	0.341(0.30)	0.169(0.56)	0.302(0.29)
R&D staff (in %)	1.363(0.67)**	0.882(0.40)**	1.485(0.29)***	1.368(0.68)**	0.490(0.42)	1.511(0.27)***
CEO has a degree	-0.011(0.29)	-0.167(0.28)	0.379(0.29)	0.046(0.34)	-0.277(0.28)	-0.025(0.24)
University spin-off	-0.205(0.33)	-0.341(0.35)	-0.215(0.20)	-0.339(0.35)	-0.107(0.28)	-0.209(0.18)
Market size	0.213(0.26)	0.439(0.21)**	-0.083(0.14)	0.181(0.22)	0.540(0.18)***	-0.006(0.14)
Expected growth	-0.184(0.14)	-0.309(0.17)*	-0.549(0.16)***	-0.200(0.19)	-0.292(0.15)**	-0.266(0.11)**
Product dev. time	-0.268(0.11)**	-0.121(0.11)	-0.258(0.08)***	-0.337(0.16)**	0.046(0.09)	-0.184(0.07)***
Competitors (Log)	0.023(0.16)	-0.106(0.19)	-0.331(0.15)**	0.043(0.19)	-0.025(0.15)	-0.088(0.13)
Intercept	2.193(1.30)*	1.796(1.28)	3.962(1.30)***	2.579(1.62)	0.579(1.25)	2.002(1.07)*
Not patenting (zero inflation)						
VC/BA investment	-0.308(0.22)	-0.721(0.22)***	-0.896(0.28)***	-0.283(0.25)	-0.831(0.23)***	-0.890(0.29)***
Patent applications (Log)	-0.446(0.13)***		-0.553(0.19)***	-0.627(0.13)***		-0.379(0.20)*
Patent applications >0	-1.107(0.25)***		-2.201(0.36)***	-0.995(0.25)***		-2.464(0.47)***
Patent grants (Log)		-0.549(0.15)***			-0.558(0.17)***	
Patent grants >0		-1.212(0.23)***			-1.206(0.24)***	
Age (Log)	-0.178(0.09)**	-0.106(0.11)	-0.071(0.13)	-0.186(0.10)*	-0.196(0.12)*	-0.013(0.15)
Size (Log(Employees))	-0.160(0.07)**	-0.003(0.07)	-0.030(0.10)	-0.164(0.08)**	0.010(0.07)	-0.033(0.10)
US firm	-0.056(0.15)	-0.256(0.16)*	-0.357(0.20)*	-0.073(0.16)	-0.226(0.16)	-0.340(0.19)*
Manufacturing sector	-0.041(0.15)	-0.193(0.17)	0.015(0.20)	-0.086(0.16)	-0.169(0.18)	-0.017(0.21)
R&D expend. (yes/no)	-0.452(0.18)**	-0.408(0.21)*	-0.638(0.26)**	-0.482(0.20)**	-0.341(0.26)	-0.572(0.26)**
R&D staff (in %)	0.058(0.37)	-0.458(0.45)	1.279(0.57)**	-0.225(0.41)	-0.801(0.45)*	1.153(0.63)*
CEO has a degree	-0.113(0.15)	0.219(0.17)	0.375(0.23)*	-0.095(0.16)	0.253(0.18)	0.258(0.21)
University spin-off	-0.197(0.38)	0.231(0.44)	0.573(0.53)	0.049(0.46)	-0.029(0.41)	0.120(0.56)
Market size	-0.210(0.09)**	-0.255(0.10)**	-0.310(0.13)**	-0.223(0.09)**	-0.176(0.10)*	-0.285(0.12)**
Expected growth	-0.078(0.08)	-0.095(0.08)	-0.215(0.13)	-0.105(0.09)	-0.064(0.08)	-0.120(0.12)
Product dev. time	-0.211(0.07)***	-0.166(0.07)**	-0.232(0.11)**	-0.230(0.08)***	-0.138(0.07)*	-0.205(0.10)**
Competitors (Log)	0.064(0.06)	0.024(0.07)	-0.030(0.08)	0.050(0.07)	0.064(0.07)	0.057(0.08)
Intercept	3.797(0.52)***	3.208(0.59)***	4.114(0.95)***	4.053(0.62)***	2.951(0.58)***	3.457(0.87)***
Observations	940	940	940	888	888	888
Wald test	1714.2	781.2	941.6	1564.3	2957.3	3907.4
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Log likelihood	-1546.0	-991.7	-760.9	-1407.2	-750.3	-562.3

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	0.121(0.12)	0.219(0.20)	0.066(0.23)	-0.742(0.22)***	0.071(0.20)	-0.331(0.18)*
Patent applications (Log)	0.954(0.04)***		1.009(0.08)***	0.945(0.06)***		1.008(0.06)***
Patent applications >0	-0.777(0.18)***		-0.584(0.29)**	-0.052(0.24)		-0.637(0.30)**
Patent grants (Log)		0.701(0.05)***			0.762(0.08)***	
Patent grants >0		0.511(0.21)**			0.561(0.24)**	
Age (Log)	-0.021(0.07)	-0.307(0.13)**	0.030(0.09)	-0.223(0.11)**	-0.506(0.14)***	-0.023(0.10)
Size (Log(Employees))	0.020(0.05)	0.133(0.11)	-0.109(0.07)	0.040(0.08)	0.150(0.11)	-0.179(0.07)**
US firm	0.427(0.12)***	0.017(0.18)	0.313(0.15)**	0.495(0.15)***	0.152(0.17)	0.317(0.14)**
Manufacturing sector	0.583(0.08)***	0.057(0.13)	0.365(0.23)	0.547(0.09)***	0.382(0.17)**	0.453(0.15)***
R&D expend. (yes/no)	-0.278(0.37)	-0.442(0.60)	0.233(0.30)	-0.048(0.44)	-0.312(0.62)	0.527(0.33)
R&D staff (in %)	1.741(0.11)***	0.886(0.32)***	0.858(0.25)***	1.680(0.16)***	0.890(0.20)***	1.006(0.22)***
CEO has a degree	-0.436(0.32)	0.047(0.31)	0.010(0.20)	-0.691(0.29)**	-0.113(0.28)	-0.049(0.19)
University spin-off	0.128(0.12)	0.070(0.28)	-0.147(0.31)	0.198(0.24)	-0.001(0.19)	-0.190(0.18)
Market size	0.037(0.10)	0.281(0.18)	-0.150(0.08)*	0.004(0.16)	0.249(0.11)**	-0.179(0.11)*
Expected growth	0.023(0.04)	-0.227(0.09)**	-0.208(0.07)***	-0.107(0.07)	-0.367(0.12)***	-0.177(0.09)**
Product dev. time	-0.055(0.05)	0.059(0.07)	-0.061(0.05)	-0.068(0.05)	0.105(0.06)*	-0.078(0.06)
Competitors (Log)	0.030(0.08)	0.186(0.12)	-0.069(0.09)	0.029(0.12)	0.181(0.14)	0.030(0.11)
Intercept	-0.207(0.66)	0.503(0.81)	0.908(0.59)	0.461(0.91)	1.210(0.88)	0.973(0.74)
Not patenting (zero inflation)						
VC/BA investment	0.057(0.47)	-1.003(0.94)	-1.501(0.74)**	1.005(0.99)	-0.274(0.78)	-0.177(0.47)
Patent applications (Log)	-0.128(0.28)		-0.410(0.26)	-0.658(0.30)**		-0.308(0.27)
Patent applications >0	-2.340(0.78)***		-2.577(0.60)***	-2.074(1.05)**		-2.831(0.75)***
Patent grants (Log)		-0.531(0.17)***			-0.503(0.23)**	
Patent grants >0		-1.217(0.26)***			-1.418(0.36)***	
Age (Log)	-0.148(0.13)	-0.123(0.13)	-0.033(0.15)	-0.202(0.21)	-0.178(0.14)	0.057(0.18)
Size (Log(Employees))	-0.179(0.09)*	0.002(0.08)	-0.007(0.11)	-0.221(0.15)	-0.042(0.09)	-0.076(0.11)
US firm	0.087(0.19)	-0.399(0.19)**	-0.352(0.22)	0.204(0.31)	-0.335(0.19)*	-0.262(0.24)
Manufacturing sector	0.173(0.21)	-0.204(0.19)	0.009(0.25)	0.279(0.30)	0.022(0.22)	0.123(0.23)
R&D expend. (yes/no)	-0.687(0.24)***	-0.483(0.23)**	-0.672(0.30)**	-0.967(0.48)**	-0.563(0.29)*	-0.657(0.31)**
R&D staff (in %)	0.714(0.53)	-0.358(0.54)	1.573(0.72)**	-0.187(0.70)	-1.005(0.62)	1.041(0.69)
CEO has a degree	-0.351(0.22)	0.302(0.22)	0.334(0.23)	-0.571(0.39)	0.277(0.21)	0.204(0.24)
University spin-off	-0.440(0.52)	0.362(0.50)	0.473(0.74)	0.061(0.91)	-0.094(0.62)	0.053(0.66)
Market size	-0.285(0.13)**	-0.272(0.12)**	-0.357(0.13)***	-0.417(0.17)**	-0.274(0.13)**	-0.389(0.14)***
Expected growth	-0.035(0.10)	-0.094(0.08)	-0.157(0.12)	-0.140(0.14)	-0.099(0.09)	-0.121(0.13)
Product dev. time	-0.260(0.09)***	-0.134(0.08)*	-0.194(0.11)*	-0.328(0.14)**	-0.129(0.10)	-0.197(0.12)*
Competitors (Log)	0.067(0.09)	0.087(0.07)	0.051(0.09)	0.060(0.14)	0.111(0.09)	0.103(0.10)
Intercept	3.691(0.77)***	3.130(0.67)***	3.679(0.89)***	5.136(1.32)***	3.348(0.77)***	3.423(0.91)***
VC/BA investment						
Patent applications (Log)	-0.089(0.08)		-0.090(0.09)	-0.115(0.09)		-0.108(0.09)
Patent applications >0	0.592(0.21)***		0.582(0.21)***	0.660(0.21)***		0.635(0.21)***
Patent grants (Log)		-0.168(0.13)			-0.242(0.12)**	
Patent grants >0		0.371(0.25)			0.437(0.24)*	
Age (Log)	-0.338(0.09)***	-0.343(0.09)***	-0.315(0.10)***	-0.302(0.10)***	-0.306(0.10)***	-0.304(0.10)***
Size (Log(Employees))	0.206(0.07)***	0.196(0.06)***	0.205(0.07)***	0.184(0.07)**	0.184(0.07)***	0.177(0.07)**
US firm	-0.327(0.14)**	-0.310(0.14)**	-0.319(0.14)**	-0.374(0.15)**	-0.336(0.15)**	-0.357(0.15)**
Manufacturing sector	-0.381(0.13)***	-0.343(0.13)**	-0.375(0.13)***	-0.356(0.14)**	-0.346(0.15)**	-0.366(0.14)**
R&D expend. (yes/no)	0.455(0.21)**	0.478(0.21)**	0.439(0.21)**	0.733(0.26)***	0.770(0.26)***	0.758(0.26)***
R&D staff (in %)	0.656(0.32)**	0.864(0.33)***	0.664(0.34)**	0.808(0.35)**	1.016(0.34)***	0.795(0.35)**
CEO has a degree	0.352(0.17)**	0.348(0.17)**	0.352(0.17)**	0.358(0.18)**	0.355(0.18)**	0.355(0.18)**
University spin-off	0.458(0.34)	0.508(0.34)	0.490(0.32)	0.308(0.33)	0.353(0.37)	0.291(0.35)
Market size	0.218(0.09)**	0.226(0.09)**	0.218(0.09)**	0.182(0.10)*	0.211(0.10)**	0.194(0.10)*
Expected growth	0.025(0.07)	0.014(0.07)	0.032(0.07)	0.065(0.08)	0.051(0.08)	0.048(0.08)
Product dev. time	0.045(0.07)	0.058(0.07)	0.048(0.07)	0.045(0.07)	0.062(0.07)	0.054(0.07)
Competitors (Log)	-0.056(0.07)	-0.068(0.07)	-0.055(0.07)	-0.015(0.08)	-0.030(0.08)	-0.011(0.08)
Intercept	-2.027(0.49)***	-1.946(0.48)***	-2.107(0.50)***	-2.489(0.55)***	-2.487(0.56)***	-2.461(0.55)***
Var(ω_{it})	1.517(0.19)***	0.515(0.08)***	0.435(0.07)***	1.405(0.18)***	0.594(0.11)***	0.395(0.09)***
$\rho(\nu_{it}, \varepsilon_{it})$	-0.296(0.17)**	0.137(0.42)	0.264(0.26)	-0.676(0.22)***	-0.358(0.33)	-0.364(0.15)***
$\rho(\nu_{it}, \omega_{it})$	-0.195(0.03)***	-0.291(0.12)***	-0.306(0.12)***	0.227(0.06)***	-0.167(0.08)**	0.167(0.16)
Observations	940	940	940	888	888	888
Wald test	11084	9115	12232	11664	8187	12486
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Log likelihood	-980.7	-864.6	-775.8	-864.9	-751.3	-678.2