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Money for Novelty: The Role of Venture Capital Investments for Innovation in Young Technology-based Firms

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Non-technical summary

Financing is a crucial but scarce factor especially in technology-oriented industries where the risk of failure is high and information asymmetries are substantial, e.g. because the marketplace for the new and innovative products is unclear. Particularly young technology-based firms are often perceived to lack capital. Hence, debt investors may generally be reluctant to invest in this type of firm so that entrepreneurs often need to rely on equity financing, e.g. on venture capital (VC).

This paper tries to shed light into the link between venture capital financing and firms' innovation activities. We reflect innovation activities by using two different variables: Patent counts and an index on firm's innovativeness of the technology applied. The data set was generated by a computer-assisted telephone survey for which over 1,000 young firms in technology-oriented service and manufacturing sectors were called. The firms have been founded between 1996 and 2005. The data contains information on the characteristics of the founder team, the firm and innovation indicators.

Analyzing the role of VC for financing innovative young firms has to deal with potential endogeneity of VC financing. In order to account for endogeneity we use full-information maximum likelihood (FIML) methods which simultaneously handle the objective function and an endogeneity-correcting equation. We confirm that VC financing positively contributes to young firms' innovation activities in high-tech industries.

Das Wichtigste in Kürze

Finanzierung ist ein wichtiger aber knapper Faktor vor allem in Hochtechnologiesektoren, in denen das Risiko und die Informationsasymmetrie besonders ausgeprägt sind, z.B. aufgrund des schwer einzuschätzenden Marktpotenzials der Produkte. Insbesondere junge Unternehmen zeichnen sich durch nicht gedeckten Kapitalbedarf aus. Oft ist Fremdkapital für diese Unternehmen nicht zu erhalten, so dass sie oft auf Eigenkapitalfinanzierung zurückgreifen müssen, z.B. auf Venture-Capital(VC)-Investitionen.

Dieses Papier versucht Evidenz für den Zusammenhang zwischen VC-Finanzierung und Innovationsaktivitäten von Unternehmen zu finden. Innovationstätigkeit wird hierbei durch zwei Indikatoren abgebildet: Einerseits über das Vorliegen von Patentanmeldungen und andererseits über einen Innovativitäts-Index. Der Datensatz beruht auf computergestützten Telefoninterviews unter mehr als 1.000 jungen Unternehmen in technologieorientierten Sektoren im Verarbeitenden und Dienstleistungsgewerbe, die zwischen 1996 und 2005 gegründet wurden. Der Datensatz liefert Informationen zu Eingenschaften des Gründungsteams, des Unternehmens und zu Innovationsindikatoren.

Um kausale Effekte zu erhalten, muss für die mögliche Endogenität von VC-Finanzierung korrigiert werden. Hierbei stützen wir uns auf Full-information-maximum-likelihood(FIML)-Methoden: In simultanen Schätzverfahren werden die interessierende Gleichung und eine endogenitätskorrigierende Gleichung geschätzt. Die Ergebnisse bestätigen, dass VC-Finanzierung einen positiven Einfluss auf Innovationsaktivitäten von jungen Hightech-Unternehmen hat.

Money for novelty: The role of venture capital investments for innovation in young technology-based firms

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Diana Heger*‡

Abstract

This paper examines the role of venture capital on a firm's innovation activities by using a data set of German technology-based firms founded between 1996 and 2005. Innovation is proxied by patent counts and an index of innovativeness which reflects the degree to which a young firm has developed new technologies based on its own or external resources. The results show that VC financing has a positive impact on both patenting and innovativeness, even if we account for endogeneity of VC financing.

Keywords: Innovation, venture capital, young technology-based firms, discrete choice methods, count data models, endogeneity

JEL-Classification: O31, G24, C31, C35, L20

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1 Introduction

Financing is a crucial input factor to corporate innovation activities (hottenrott???). However, innovation is characterized by a high level of uncertainty. For example, Stevens and Burley (1997) estimate that on average 3,000 raw ideas are tried and tested to get one major commercially successful innovation. Consequently, innovations often show a considerable variance in terms of time involved and money spent, and hence present a process which is difficult to predict. Furthermore, substantial information asymmetries exist for external capital providers so that internal financing is often viewed to be the most adequate source of funding innovation activities (see Hall(2002, 2005), Harhoff (1998), Himmelberg, Petersen (1994)). However, young technology-oriented firms mostly lack enough internal funds and need to rely on external financing. Venture capital (VC) is supposed to play a major role in the financing of young innovative firms and is often perceived to spur innovation. Anecdotal evidence particularly exists for the U.S., since many of today's big players in innovative markets, like computer or biotechnology, have been VC-financed in their early stages (see e.g. Apple, Microsoft and Genentech). At the beginning, they were characterized by high risk and a potential to generate high returns. Within the first years after their emergence, they were able to grow substantially in terms of employment and gained a leading position in the generation of new knowledge and markets.

This paper empirically investigates the impact of VC investment on firms' innovation activities. Seminal studies investigating the link between firms' innovation activities and VC financing provide evidence on the industry level for the U.S. (see Kortum, Lerner, 1998, 2000). They report a positive impact of VC financing on innovation activities. This paper provides evidence for young German firms in technology-oriented industries. First we look at patenting behavior as an approximation for innovation activities. However, the literature discusses whether patents are good proxies for innovation activities (see e.g. Griliches et al. (1987)). In order to expand the notion innovation activities beyond patenting activities we use an alternative variable which measures innovativeness in terms of the degree of novelty of the technologies applied by firms and its developer.

Empirical analyses of VC investments in firms usually suffer from endogeneity problems which may arise because of the selectivity of the VC investment process. Most studies in this field do not account for this issue. But ignoring it only reveals correlations but no causalal relations. Hence, a major contribution of this paper is to provide causal evidence for the link between VC investment and innovation activities. Therefore, we use techniques which enable us to solve the endogeneity problem. We use full-information maximum likelihood (FIML) methods to account for this issue. These methodologies are constructed such that they simultaneously estimate an objective function, e.g. for innovation activities, and an endogeneity-correcting function. The methods are explained in Section **??**.

The paper is organized as follows. Section 2 reviews the literature on VC's impact on innovation. In Section 3.1 the hypotheses tested in this paper are derived. Section 3.2 presents the data set and depicts some descriptive statistics. Section 4 shows the empirical models and results. Endogeneity issues are discussed in Section **??**, and Section

5 concludes the paper.

2 Literature Review

As a consequence of the intangibility of the innovation process' outcome, the limited collateral value of technology investments, the higher default risk and the limited internal funds (Carpenter, Petersen (2002), Carpentier, Suret (2005), Berger, Udell (1998), Fritsch et al. (2006)) young technology-oriented firms have difficulties in accessing debt financing. Hence, they often need to finance their innovation activities using external equity sources. VC investors are one group of equity providers. Beyond capital, VC companies are assumed to provide management support which is supposed to be particularly crucial for young technology-oriented firms because founders of this type of firms are assumed not to be good managers because of their primarily technical backgrounds (Cressy, Hall (2005), Moore (1994)).

Many of the studies investigating the link between venture capital financing and innovation analyze effects on the industry level. Kortum and Lerner (1998, 2000) test whether venture capital spurs innovation activity. They estimate a patent production function at the industry level similar to Griliches (1979) and find a positive and significant effect of venture financing on the number of patent grants. However, Kortum and Lerner (2000) suspect that venture capital may spur patenting while having no impact on innovation and analyze this effect by comparing indicators of patent quality between VC- and non-VC-backed firms. They account for technological and economic importance of the patents by using patent citations (see Trajtenberg, 1990) and the frequency and extent of patent litigation (see Lanjouw and Schankerman, 1997). For both measures of patent quality, they find that VC-backed firms hold higher quality patents than non-VC-backed firms, and conclude that VC financing has an impact on innovation. Tykvovà (2000) confirms a positive influence of venture capital on patent application at the industry level for Germany using a similar approach than Kortum and Lerner.

However, Ueda and Hirukawa (2003) state that the opposite causality may also exist and argue that opportunities for firms to innovate and/or grow fast will lead to an augmented demand for venture capital and hence lead to growth of the venture capital market. Using the growth of total factor productivity as a measure for innovation they find that the complementarity of innovation and venture capital investments does not only stem from the positive impact of VC investments on innovation but also from the positive impact of innovation on VC investment.

As Lerner (2002) states the impact of venture capital on innovation is not uniform and depends on the cyclicality of the VC market. Extending the studies by Kortum and Lerner to the growth period of the VC industry during the late 1990s Ueda and Hirukawa (2006) confirm the results of Kortum and Lerner However, they could not verify their previous results as they find no significant effect on TFP growth.

The effects of VC financing on innovation activities using firm-level data reveals in many studies a positive and significant effect. Bretoni et al. (2006) find a highly positive effect of VC financing on firm's patenting activities for new technology-based firms in

Italy. Hellmann and Puri (2000) state that the time to market is shorter if venture capital is present in the firm, particularly if the firm follows an innovator strategy for startups in Silicon Valley.

Da Rin and Penas' (2007) results suggest that VC financing has an impact on innovation strategies, since the entry of a VC investor is associated with higher absorptive capacity reflected by an increase in the firm's make decision.

Timmons and Bygrave (1986) investigate the role of venture capital in financing innovation for economic growth. They study 464 venture-capital firms and find that less than 5 % of them account for nearly 25 % of all investments in highly innovative technological ventures. Their most important result is that it is not the provided capital that fosters technological innovation but the nonmonetary, high value-added contributions.

Baum and Silverman (2004) find no significant effect in Canadian biotechnology for VC spurring innovation activities of start-ups. On the contrary, they find that the amount of pre-IPO financing is positively affected by patents in the year before financing. Hence, their results suggest that patenting is a signal of innovative capabilities and prospective return to investors.

Other papers at the firm level find the reverse causality. Haeussler et al. (2009) find that patent applications reduce the time to the first VC investment and interpret their find as evidence that patents are able to certificate quality to VC investors. Hence, VC investors respond to patenting activity. Engel and Keilbach (2007) state that the number of patent applications is higher for VC-funded firms than for non-VC-financed firms prior to the investment. This effect, however, vanishes looking at the differences after the investment (see also Caselli et al. (2008)). Hence, VC investors seem to rather focus on the commercialization than on cutting edge innovation.

These results in the literature with the unexplained direction of causality show that endogeneity is a problem when studying the relation between firms' innovation activities and the fact that they receive VC financing.

3 Research Strategy

3.1 Hypotheses

This paper investigates the impact of VC financing on firms' innovation activities looking at young German firms in technology oriented sectors. There may be two reasons why VC funds may spur firm's innovation activities: First, VC investors provide funds, and thus help firms to bridge their funding gap. Since innovation projects are costly and time demanding the provision of funds help young technology-oriented firms to dedicate more money and time in their innovation projects which may positively contribute to the success of those projects. Second, VC investors also provide management support, and their advice is supposed to be useful because they generally are equipped with industry and technology experience. Hence, VC investors may be able to push firms in specific, more promising fields of research.

Patent counts is our first indicator for innovation activities. The following equation roughly illustrates the assumed relation between VC investment and firms' patenting

$$P_i = f(VC_i, controls),$$

where P_i reflects the counts of patent grants and VC_i indicates whether the firms has received VC funds. The corresponding hypothesis is:

Hypothesis 1: *Venture Capital spurs firm's patenting behavior.*

Griliches, Pakes and Hall (1987) discuss some problems that arise when relying on patent counts as an indicator for innovative activities: Patents differ in size and/or value, not all R&D activities are patentable or patented, and the fraction patented varies across industry, firm and time. Furthermore, as patents also disclose the newly generated knowledge firms may retain from patenting (Anton, Yao (2004), Heger, Zaby (2013)).

Additionally, Kortum and Lerner (2000) point out that venture capital may spur patenting while having no impact on innovation. Hence, we try to capture another aspect of innovation activities by using a new variable. Like patents this variable still looks at the result of an innovation process but tries to capture the spectrum of firms' innovation activities. This innovativeness indicator is a categorical variable which displays the degree of newness as well as the extent to which a young firm has developed new technologies based on own resources (for definition see Table 1).

We argue that VC funding provides firms with more time to and with new triggers for their innovation activities. Hence, we suppose that VC-financed firms should be enabled to develop new methods and technologies as they bridge their funding gap and receive (technical) guidance by VC investors. A simple illustration of the conjectured link is represented by the following equation:

$$I_i = f(VC_i, controls)$$

,

where I_i is the categorical variable innovativeness, VC_i is again VC investment. A positive impact of VC_i is particularly expected for the category of self-developed new technologies. The corresponding hypothesis is the following:

Hypothesis 2: *Firms are more likely to develop the methods and technologies they use to build their products themselves if they are VC-backed.*

3.2 Data set and variable description

The data we use for investigating the impact of VC funding on firms' innovation activities is the ZEW Technology Start-ups Survey 2006 which is a telephone survey of German technology-oriented firms founded between 1996 and 2005. The survey sample was drawn from the ZEW Enterprise Panel provided regualarly by Creditreform, Germany's largest credit rating agency. The sample was stratified by foundation periods and sectors. The survey targets technology sectors following the classifications of Grupp et al. (2000) for manufacturing and Engel and Steil (1999) and Nerlinger (1998) for service sectors. Foundation periods have been clustered into two groups: founded between 1996 and 2000 and between 2001 and 2005, which represent the boom and the post-boom period in high-tech industries in Germany. Interviews were carried out in February and March 2006. The persons interviewed were either owners or executives. Altogether, 6,315 firms have been contacted within the pre-defined survey period of three weeks. 1,085 interviews could be completed, thus the response rate was 17 %.

We merge patent information from the PATSTAT data up to the year 2006 in order to capture the innovative output of the firms. We consider European and German priorities. Information on stakeholders, location and credit rating is taken from the ZEW Enterprise Panel. The distance to the nearest university or public research institution was calculated based on ZIP code areas to account for possible spillovers. Table 2 depicts the descriptive statistics of the variables included in the regressions below.

Two different dependent variables are used to test the hypotheses: the number of patents applied after firm foundation and innovativeness (see Table 1). The average firm has applied for 0.41 patents (*patents*). The fractions of the different categories of innovativeness (*innovativeness*) are displayed in Table 1. The index refers to the top-selling product of a firm. It is possible that innovative firms with more than one product may indicate that their top-selling one is not innovative. However, as young, small firms usually produce a small number of products this issue should not be severe.

Table 1: Characteristics of the variable *innovativeness*

cat.	**The product is characterized by...**	**Fraction**
3	...new methods and technologies developed by the firm itself	46.7%
2	...new methods and technologies developed by a third party	25.0 %
1	...a new combination of tried and tested methods and technologies	16.3 %
0	...a known combination of tried and tested methods and technologies	12.0 %

The key explanatory variable of interest is *venture capital*, a dummy variable, indicating whether the firm has received venture capital financing. The descriptives statistics of this and the following variables can be found in Table 2

< *Insert Table 2 about here.* >

We control for different types of potential impact factors with respect to corporate innovation activities. We group these factors according to the firm's product strategy regarding the innovation, the characteristics of the founding team and general firm characteristics.

Regarding the firm's product strategy which is supposed to influence the corporate innovation activities, we first use a dummy variable *continuous R&D*. If a firm continuously performs R&D surely impacts on the characteristics of the innovation as displayed in the innovativeness variable as well as on firm's patenting. R&D performing firms are more vulnerable to knowledge expropriation and may have a higher probability to generate a completely new product. Furthermore, we account for *intermediate* products because in this case the customers tend to be a clearly cut, mostly small group. Hence, the market potential for this product may be clearer compared to final products. At the same time customers are more important, hence, may exert more (buyer) power. With respect to the newly generated knowledge, these innovation may suffer a higher exposure to expropriation and higher risk of granting a dependent innovation/use. Moreover, Blundell et al. (1995) proposing a dynamic feedback model with fixed effects approximated by information of pre-sample periods state that unobservable permanent heterogeneity is an important feature of empirical models of innovation. As our data set is cross-sectional we try to control for heterogeneity in patenting experience by including the dummy *patent_before*. This variable indicates whether the firm uses patents which have been filed before the foundation of the firm. For example, a founder could have discovered a new drug during his PhD and then try to commercialize his discovery by founding a startup.[1]

The characteristics of the founder team are crucial for young firms, e.g. they may determine the absorptive capacity of the firm, in particular, during the first years. First, we control for the number of the founding team members (*team*). We conjecture that a higher number of team members increases the availability of necessary abilities and skills, particularly regarding management and marketing. This reasoning is corroborated by the theoretical work of Lazear (2004) who finds that entrepreneurs or entrepreneurial teams are more generalists with regard to abilities than specialists (jacks-of-all-trades). Hence, starting a business requires a balanced skill portfolio. In this respect, building up entrepreneurial teams may be necessary to cope with the relevant portfolio of abilities. In line with this argument, we further include several indicator reflecting the abilities and skills available in the team. We include indicators regarding prior knowledge and experience of the founder team which are assumed to influence the identification, assimilation and exploitation of external knowledge, e.g. generated by research facilities (Cohen, Levinthal (1989)). The dummy *m_graduate* reflecting that at least one founder holds a PhD or university degree. Besides the educational level achieved the field in which the education was completed is important. So we account for technical degrees (*m_technical*). Additionally, an indicator showing whether at least one member of the initial management team has previous industry experience either as an employee or as

[1] This variable we only include in the patent estimation. For the investigation of innovativeness, we are not able to use this indicator because all firms with patent experience indicate that they developed the methods and technologies by themselves. This finding is quite intuitive, since patents are defined by the newness of the invention.

an entrepreneur (*m_indexp*) is included. This variable also reflects that some abilities are available in the team which can only be achieved by working in an enterprise or founding a firm and which cannot be learned otherwise.

A third group of controls are firm characteristics. First, we account for ownership structure, i.e. separation of ownership and control, which may influence a firm's risk exposure. *m_majority* displays unit value if the management at time of firm establishment held majority stake. According to the principle agency theory, managers who do not own the firm may act in a way that serves themselves and not the firm, e.g. they could be reluctant to invest in risky projects like innovation projects because they may be fired in case of failure. Moreover, innovation often depends on spillover effects in which firm may benefit from specific research facilities. In order to account for such effects, the distance to the nearest university or public research facility (*log(distance)*) is included in the regressions. Furthermore, we include two indicators concerning the credit rating index reflecting a *good* and a *medium rating*. The rating is supposed to display firms' risk exposure and the access to debt markets[2]. Other firm characteristics that are typically linked to innovation activities include firm size, which is included as the logarithm of the number of employees at founding date (*initial size*). Furthermore, foundation year dummies are included to reflect the cyclical differences at the time when the business was started. All firms have been founded during a period in which the German technology-oriented sectors have experienced an extraordinary boom period 1997 to 2000 and a downturn period afterwards. Finally, industry dummies (*high-tech, medium-to-high-tech, ICT, software*) are also included.

As stated before, we want to identify the causal effect of VC financing on innovation activities. As VC financing is suspected to be endogenous we need to find exclusion restrictions for identification. These instruments need to be related with VC financing while having no effect on innovation activities. The variables we propose as instruments reflect regional specificities as those may influence the provision and accessibility of financing but at the same time should not influence a firm's innovation activities. Hence, we include two indicators regarding a characterization of the county. We conjecture that VC investors tend to invest in startups located in more densely populated areas. So we include two indicators showing whether it is a *metropolis* or a *rural* area. In line with Zucker et al. (1998), we further account for the availability and experience of VC investors in the county in that we include a variable displaying the share of early stage startups having received VC financing which are located in the same county and are associated with the same 3-digit NACE industry.

[2] The rating indicators are based on the rating index provided by Creditreform. The index ranges from 1 to 5, whereas 1 is the best and 5 the worst rating. Since the rating index is not a metric variable, we include two indicator variables. Czarnitzki and Kraft (2007) state that Creditreform clusters the rating index in classes. We refer to *good rating* if the rating index ranges between 1.9 and 2.5 and *medium rating* between 2.5 and 3.5.

4 Empirical results

To investigate the impact of VC financing on patenting we use count data models (Greene, 2003, Winkelmann, 1994). However, over 75% of the firms report that they do not make use of own patents, i.e. the patent variable exhibits excess zeros. Two models may be applicable with excess zeros: the hurdle and the zero-inflated model. In the patent case, the zero-inflated model is preferred because the zero patents may stem from two different sources: First, the firm is not innovative, and thus will never file a patent and second, the firm is innovative, but has not filed a patent yet, because either the outcome of the innovation process is not patentable or the firm has decided to keep the knowledge secret.[3] The intuition of the zero-inflated models is to simultaneously estimate a count data and a binary model reflecting whether the zero outcome observed stems from or is not part of a Poisson (Negbin) process (see Cameron and Trivedi, 1998, pp.125-128).

Table 4 depicts the results for a zero-inflated Poisson model with robust standard errors and a zero-inflated Negative Binomial model. The Vuong tests confirm that the zero-inflated versions of count data indeed fit the data better than the non-zero-inflated ones. We chose a logit type model to represent the zero outcomes. The coefficients and the unconditional average marginal effects can be found in Tables 3 and 4.

< *Insert Table 3 about here.* >

< *Insert Table 4 about here.* >

The results show that venture capital funding has a positive impact on patenting, i.e. the VC-backing can be associated with an increasing number of patents. This result confirms Hypothesis 1 that VC financing spurs firms' patenting activities even if accounting for excess zeros.

Since the literature provides arguments and empirical evidence for endogeneity problems in the context of VC financing and firms' innovation activities, we now try to take the endogeneity of VC financing into account. Particularly in the context of patenting, Kortum and Lerner (2000) state that patents may serve as certification for firm's quality to potential VC investors, i.e. patents may help to attract VC with the consequence that firms wishing to get VC are more prone to patent their inventions. Thus, endogeneity arises because it is not clear whether the firm is innovative because it is able to bridge the funding gap by receiving venture capital or whether VC companies select

[3]In the context of the underlying data set one might argue that all high-tech firms are potential innovators so that all firms are potentially innovative and able to patent so that a hurdle model would be appropriate. But the definition of high-tech firms is based on the industry-level and considers the industry R&D intensity, i.e. it is probable that the data set includes firms which will never be innovative and hence will not file any patents.

firms which have a high probability to be innovative. In line with the selection argument is the fact that a rigorous due diligence process takes place preceding VC investments, which strongly influences the VC decision regarding investment opportunities. This argumentation resembles very much a selection problem, i.e. receiving VC financing is not random. Furthermore, endogeneity may arise because of the existence of variables that are correlated with innovative activities – both patenting and innovativeness – and VC financing. Such factors can be observable, like the educational background of the founding managers, or unobservable, like the quality of an innovative idea, a prototype or a new product.

Terza (1998) proposes a FIML framework for the estimation of count data model with a binary endogenous regressor. Suppose that the probability density function of the count dependent variable is $f(y|x, d, \epsilon)$, i.e. it depends on the covariates x, the binary (endogenous) variable d and the random (heterogeneity) component ϵ. The switching variable d can be represented by the index function $I(z\alpha + \nu > 0)$.

The resulting likelihood function is:

$$\mathcal{L} = \prod_{i=1}^{n} \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} f(y_i|x_i, z_i, d_i, \epsilon) \Big[d_i \Phi_i^*(\epsilon) + (1-d)(1-\Phi_i^*(\epsilon)) \Big] exp(-\xi^2) d\xi.$$

For Poisson model:

$$f(y_i|x_i, z_i, d_i, \sqrt{2}\sigma\xi) = \frac{exp(x_i\beta + \epsilon)^y exp\big[-exp(x_i\beta + \epsilon)\big]}{y!},$$

For Negbin model:

$$f(y_i|x_i, z_i, d_i, \sqrt{2}\sigma\xi) = \frac{\Gamma(y_i + (1/\alpha))}{\Gamma(1/\alpha)\Gamma(y_i + 1)} \big(\alpha exp(x_i\beta + \epsilon)\big)^{y_i} \big(1 - \alpha exp(x_i\beta + \epsilon)\big)^{(y_i + 1/\alpha)},$$

with $\epsilon = \sqrt{2}\sigma\xi$.

Since this likelihood cannot be evaluated in closed form it has to be approximated by using the Gauss-Hermite quadrature (see Butler and Moffitt (1982), Miranda (2004)).

The results of the FIML estimation of the endogenous switching Poisson and Negative Binomial models are presented in Table 5. The F-test of joint significance of the instruments is highly significant which is a hint that the instruments are strong. With respect to VC financing we find that if we control for its endogeneity the positive and significant effect on firms' patenting behavior is confirmed. Thus, we can confirm our hypothesis regarding the link of VC financing and patenting activities. Whether this effect also hints at an increasing impact on firms' innovation activities cannot be assessed (see Kortum, Lerner (2000))

< Insert Table 5 about here. >

Regarding the control variables we find that firms performing continuously R&D have a higher probability to file more patent applications. We also confirm that previous patenting experience also has a positive impact. This may be an indication that technology-oriented firms are highly heterogeneous regarding their patenting behavior. As firms producing intermediate products reveal a positive effect on patent application we suspect that those firms may be subject to a higher expropriation risk.

Concerning possible spillover effects and absorptive capacities we find positive effects of team members who hold a university or PhD degree and who have a technical education. Furthermore, the distance to research facilities is negative showing that proximity plays a positive role for spillover translating in a higher patenting activity. However, team size and industry experience seem to have a detrimental effect on patenting activities.

As expected larger firms display a higher propensity to patent and medium rating has a negative impact. Both effects may indicate that firms with sufficient financial resources are more prone to patent as ratings may be used by banks as a source of information on the firm.

To test our second hypothesis, we run regression with the innovativeness indicator. Since innovativeness is measured as a categorical variable with four exclusive categories, we estimate a multinomial logit model. As before the endogeneity of VC financing has to be taken into account. In order to correct for the endogeneity bias in the multinomial regressions, we estimate a FIML model which enables us to correct for this bias. We use an approach proposed by Terza (2002). In this framework, the underlying latent model is a conventional multinomial model (see McFadden (1973)) for the categorical variable y where the binary (endogenous) variable d is expressed as the index function $d = I(z\alpha + \nu > 0)$, i.e. ν captures the combined effects of the unobservable confounders which may be correlated to y and d. z is a vector of instrumental variables including all exogenous variables of the multinomial logit and the identifying variables. The conditional expected values, representing the multinomial logit and simultaneously correcting for the endogeneity of d, are

$$\begin{aligned} E(y_0|d,x,\nu) &= \frac{1}{1+\sum_{r=1}^{3} exp(d\gamma_r + x\beta_r + \nu\theta_r)} \\ E(y_m|d,x,\nu) &= \frac{exp(d\gamma_m + x\beta_m + \nu\theta_m)}{1+\sum_{r=1}^{3} exp(d\gamma_r + x\beta_r + \nu\theta_r)}, \end{aligned}$$

for m=1,2,3. The corresponding likelihood function that is maximized using FIML is

$$\mathcal{L}(\alpha,\gamma_m,\beta_m,\theta_m) = \prod_{i=1}^{n} d_i \int_{-z_i\alpha}^{\infty} P_{im}^{y_{im}} \phi(\nu) d\nu + (1-d_i) \int_{-\infty}^{-z_i\alpha} P_{im}^{y_{im}} \phi(\nu) d\nu,$$

with $i = 1, ..., n$ and where $P_m = E(y_m|d, x, \nu)$. This estimator has no closed-form so that numerical integration procedures apply here. Terza uses in his program code[4] the Gauss-Legendre quadrature for closed integrals for which 12 is supposed to be the "quasi-infinity" limit of the integrals. We program this FIML estimator by approximating the one-sidedly bounded integral with the Gauss-Legendre quadrature. This quadrature formula numerically integrates integrals which are bounded two-sidedly. Therefore, we adopt the procedure used by Terza and adopt a number reflecting the "quasi-infinity".

The results of the endogeneity-corrected multinomial logit are displayed in Table 6. Venture capital has a significantly positive effect on firm's innovativeness, particularly on the probability of using new self-developed methods and technologies and on using innovative combinations with respect to using known combinations of tried and tested methods and technologies, so that in this respect hypothesis 2 is confirmed. This result suggests that if the VC invests the firm is more probably innovative either by self-developing technologies or by using innovative combinations which are presumably combined by the firm itself.

< Insert Table 6 about here. >

We find positive effects of continuous R&D activities on all degrees of innovation. The positive effect of continuous R&D on the use of externally developed technologies may, for example, reflect that researching firms may incorporate new externally developed process innovations[5]. Furthermore, a positive impact is found for firms with a management team characterized by the presence of at least one technical degree, thus the importance of technical background for innovative activities is confirmed. A technical degree also seems to be needed to assess the usefulness of technological innovations, because we also find a positive effect on the probability of using new technologies developed by others with respect to being non-innovative. University degrees as such seem to be not important which is surprising as self-development of technologies supposedly linked to the fact that an academic background may enable the entrepreneurs to get in touch with cutting-edge technologies and to be able to refine them and develop a totally new product or process. Firms which are initially classified to have a medium risk display a lower probability of developing new technologies themselves with respect to being non-innovative. Interestingly, there is no significant effect of good rating compared to bad rating. This may hint at the fact that medium ratings may lower the chance for business mandates or contacts. e.g. banks may refer to external ratings to confirm the chance and risk profile of their investment opportunities. Interestingly our results show that if firms are more distant to research facilities their probability of using innovative combinations of known methods and technologies increases.

[4] We are very grateful to Prof. Terza for providing the Gauss program code which was particularly helpful for determining the numerical integration procedure, e.g. the adoption of quasi infinity, and for transferring the log likelihood in a STATA code.

[5] The question in the survey was intended to also capture process innovation as it also asks for methods.

5 Concluding remarks

This paper investigates the impact of venture capital financing on innovation activities of young firms in technology-oriented sectors. Anecdotal evidence suggests that a link between innovation activities and VC funding exists. However, the causal direction is unclear. The literature discusses and provides evidence for both effects. Hence, endogeneity issues have to be taken into account.

We use two different measures to reflect innovation activities. The first is the number of patent applications which is traditional means to reflect innovation output. We only take into account the patent applications after firm foundation. Furthermore, we use a variable on the innovativeness. This categorical variable displays the degree of novelty of the technologies applied by firms and its developer. It shows whether a firm developed new methods itself or mandates an external party to develop those new methods. Furthermore, it reveals whether tried and tested methods have been combined in a new manner.

Moreover, in this paper we explicitly account for the endogeneity issue of VC financing. For both models we use full-information maximum likelihood (FIML) methods (see Terza (1998, 2002)). We find a positive effect of VC investment on the number of patent applications and the use of self-developed methods and technologies. Concluding our results show that VC financing spurs innovation in terms of patent applications as well as the innovation's newness.

Both of our innovation indicators only provide a rough approximation of innovation activities. Different measures of innovation inputs like R&D activities would be interesting to look at. This is left to future research.

Tables

Table 2: Descriptive statistics for the link between VC financing and innovative activities (both models)

Variable	Mean	Std.Dev.	Min	Max
Dependent variable				
patents_after	0.498	2.349	0	33
Explanatory variables				
venture capital	0.077	0.266	0	1
continuous R&D	0.336	0.473	0	1
patent_before	0.042	0.201	0	1
intermediate	0.408	0.492	0	1
log(team members)	0.565	0.544	0	1.792
m_graduate	0.645	0.479	0	1
m_technical	0.597	0.491	0	1
m_indexp	0.761	0.427	0	1
m_majority	0.276	0.447	0	1
log(initial size)	1.090	0.833	-0.693	3.807
good rating	0.292	0.455	0	1
medium rating	0.574	0.495	0	1
log(distance)	1.667	1.903	-2.303	4.552
East Germany	0.157	0.364	0	1
Instruments				
earlystage	0.017	0.050	0.000	0.667
metropolis	0.118	0.322	0	1
rural	0.170	0.376	0	1
Number of observations		833		

Table 3: Coefficients of zero-inflated count models

Model	**ZIP**		**ZINB**	
Model	**Poisson**	**Inflation**	**Negbin**	**Inflation**
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
venture capital	0.351**	-1.460***	1.182***	3.201
	(0.149)	(0.427)	(0.395)	(31.313)
cont. R&D	-0.022	-2.025***	1.024***	-100.768
	(0.162)	(0.313)	(0.278)	(68.488)
patent_before	0.229		2.327***	
	(0.163)		(0.429)	
intermediate	-0.074	-0.362	-0.385	-165.312
	(0.150)	(0.286)	(0.276)	(111.944)
log(team)	-0.188	0.210	0.481	83.721
	(0.149)	(0.306)	(0.322)	(66.615)
m_graduate	0.742***	0.034	1.394***	105.046
	(0.221)	(0.367)	(0.349)	(72.262)
m_technical	-0.431**	-0.356	-0.843***	-128.707
	(0.169)	(0.312)	(0.307)	(87.725)
m_indexp	-0.403***	0.307	-0.424	-63.425
	(0.141)	(0.299)	(0.324)	(46.516)
m_majority	0.150	-0.191	0.836**	111.379
	(0.152)	(0.323)	(0.333)	(83.999)
log(initial size)	0.261***	-0.159	0.195	-15.679
	(0.076)	(0.173)	(0.167)	(16.931)
good rating	-0.172	0.006	0.853*	129.934
	(0.215)	(0.457)	(0.456)	(96.447)
medium rating	0.211	0.220	0.270	55.842
	(0.183)	(0.407)	(0.368)	(58.732)
log(distance)	-0.080**	-0.042	0.077	10.307
	(0.032)	(0.074)	(0.075)	(8.723)
east	-0.101		0.171	
	(0.146)		(0.354)	
constant	1.644***	3.655***	-1.495**	-13.216
	(0.357)	(0.721)	(0.745)	(44.754)
α			3.136***	
		(0.539)		
industry dummies	included		included	
foundation years	included		included	
log Likelihood	-486.25		-423.10	
LR test of $\alpha = 0$			199.26***	
Vuong test	3.64***		6.34***	
χ^2 *(all)* [a]	192.50***		127.72***	
χ^2 *(industries)* [b]	5.45		8.27*	
χ^2 *(foundation years)* [b]	61.40***		55.78	
Number of observations	833		833	

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the coefficients and standard errors of a zero-inflated Poisson and Negative Binomial models.
[a] χ^2(all) displays an χ^2-test of the joint significance of all variables.
[b] χ^2(industries) and χ^2(foundation years) display χ^2-tests on the joint significance of industry and foundation year dummies. Four industry dummies for high-tech 1, high-tech 2, hardware and software are included.

Table 4: Unconditional marginal effects of zero-inflated count data models regarding patenting activities

Model	**ZIP**	**ZINB**
	Marg.Eff. (Std.Err.)	**Marg.Eff. (Std.Err.)**
venture capital	0.609***	1.186*
	(0.143)	(0.690)
cont. R&D	0.600***	1.090**
	(0.105)	(0.556)
patent_before	0.110	2.340*
	(0.076)	(1.261)
intermediate	0.074	-0.289
	(0.097)	(0.421)
log(team)	-0.154	0.434
	(0.106)	(0.432)
m_graduate	0.346**	1.339*
	(0.136)	(0.735)
m_technical	-0.100	-0.771
	(0.108)	(0.525)
m_indexp	-0.286**	-0.389
	(0.114)	(0.358)
m_majority	0.130	0.774
	(0.111)	(0.537)
log(initial size)	0.173***	0.205
	(0.063)	(0.174)
good rating	-0.084	0.781
	(0.151)	(0.716)
medium rating	0.035	0.238
	(0.133)	(0.412)
log(distance)	-0.026	0.071
	(0.025)	(0.089)
east	-0.048	0.172
	(0.070)	(0.378)
industry dummies	included	included
foundation years	included	included

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts the unconditional average marginal effects of a zero-inflated Poisson with robust standard errors and Negative Binomial models. Marginal effects of dummy variables are interpreted as discrete change from 0 to 1. Standard errors are obtained by using the delta method.

Table 5: Results for FIML count data model accounting for endogeneity of VC financing

Model	**Poisson**		**Negative Binomial**	
	Patent equation	**Switching equation**	**Patent equation**	**Switching equation**
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
venture capital	0.290 (0.191)		3.430*** (0.234)	
cont. R&D	1.628*** (0.189)	0.328** (0.158)	1.759*** (0.197)	0.341** (0.156)
patent_before	3.285*** (0.239)	0.744** (0.290)	3.328*** (0.241)	0.923*** (0.282)
intermediate	0.488*** (0.138)	0.311** (0.153)	0.502*** (0.133)	0.328** (0.152)
log(team)	-0.566*** (0.161)	0.305* (0.157)	-0.597*** (0.156)	0.327** (0.154)
m_graduate	1.071*** (0.220)	0.513** (0.216)	1.097*** (0.189)	0.514** (0.215)
m_technical	0.175 (0.176)	0.058 (0.158)	0.619*** (0.182)	0.029 (0.156)
m_indexp	-0.577*** (0.169)	0.126 (0.192)	-0.556*** (0.161)	0.134 (0.187)
m_majority	0.314** (0.152)	-0.287 (0.201)	0.085 (0.151)	-0.270 (0.195)
log(initial size)	0.234*** (0.081)	0.084 (0.097)	0.515*** (0.077)	0.075 (0.096)
good rating	-0.934*** (0.230)	0.248 (0.261)	-0.301 (0.216)	0.193 (0.253)
medium rating	-0.634*** (0.221)	0.172 (0.234)	-0.518** (0.208)	0.135 (0.226)
log(distance)	-0.137*** (0.040)	-0.063 (0.040)	-0.087** (0.040)	-0.052 (0.038)
east	-0.037 (0.166)	0.148 (0.189)	-0.133 (0.167)	0.146 (0.186)
earlystage		2.380** (1.104)		2.316** (1.056)
metropolis		0.492** (0.199)		0.461** (0.196)
rural		0.010 (0.228)		0.002 (0.222)
constant	-3.748*** (0.437)	-3.140*** (0.475)	-4.941*** (0.517)	-3.215*** (0.470)
industry dummies	included		included	
foundation years	included		included	
$\hat{\sigma}$	0.873*** (0.055)		0.974*** (0.054)	
$\hat{\rho}$	0.204 (0.131)		-0.547*** (0.123)	
$\hat{\alpha}$			-17.861 (550.068)	
Log likelihood	-587.90		-577.07	
χ^2 *(all)* [a]	589.93***		590.89***	
χ^2 *(instruments)* [b]	11.56***		11.25**	
Number of observations	833		833	

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts coefficients of an endogenous switching count model which corrects for the endogeneity of the binary variable VC financing in the count models by estimating simultaneously a Poisson (Negbin) model and a probit type VC equation by using a full-information maximum likelihood approach according to Terza (1998).

[a] χ^2(all) displays a test of the joint significance of all variables.

[b] χ^2(instruments) displays a test of the joint significance of instrumental variables in the VC equation.

Table 6: Results for FIML multinomial logit accounting for endogeneity of VC financing

	Multinomial logit for innovativeness			Switching eq.
Category	**self**	**others**	**innovative**	
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
venture capital	4.073**	2.440	9.048***	
	(1.705)	(1.649)	(1.787)	
cont. R&D	1.603***	1.305**	3.893***	0.291**
	(0.594)	(0.552)	(0.706)	(0.138)
intermediate	0.264	0.417	0.585	0.442***
	(0.403)	(0.362)	(0.485)	(0.129)
log(team)	0.114	-0.132	0.642	0.405***
	(0.412)	(0.368)	(0.506)	(0.126)
m_graduate	0.135	-0.398	0.537	1.033***
	(0.471)	(0.399)	(0.616)	(0.188)
m_technical	1.005**	0.741**	1.068**	0.084
	(0.420)	(0.373)	(0.504)	(0.146)
m_indexp	0.544	-0.111	0.396	0.097
	(0.459)	(0.388)	(0.558)	(0.147)
m_majority	0.328	-0.375	0.726	-0.352**
	(0.476)	(0.410)	(0.584)	(0.151)
log(initial size)	-0.255	-0.119	-0.187	-0.036
	(0.248)	(0.221)	(0.301)	(0.082)
good rating	-0.620	0.043	-0.935	0.358*
	(0.692)	(0.621)	(0.838)	(0.212)
medium rating	-1.435**	-0.492	-1.729**	0.153
	(0.681)	(0.625)	(0.801)	(0.177)
log(distance)	0.101	0.087	0.291**	-0.062
	(0.114)	(0.105)	(0.138)	(0.039)
east	0.760	0.724	0.336	0.112
	(0.568)	(0.516)	(0.689)	(0.160)
patent_before				0.596***
				(0.189)
earlystage				1.068
				(0.917)
metropolis				0.511***
				(0.161)
rural				0.037
				(0.152)
constant	0.790	1.145	-1.185	-3.561***
	(1.199)	(1.122)	(1.500)	(0.379)
industry dummies		included		included
foundation years		included		included
$\hat{\nu}$	-2.644***	-2.090**	-4.716***	
	(0.943)	(0.929)	(0.941)	
Log likelihood		-1242.18		
χ^2*(instruments)* [a]		12.22***		
Number of observations		833		

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts coefficients of an endogenous switching multinomial logit model as proposed in Terza (2002) which corrects for the endogeneity of the binary variable VC financing in the multinomial logit by estimating simultaneously a multinomial logit model and a probit type VC equation by full-information maximum likelihood.
[a] χ^2(instruments) displays a test of the joint significance of instrumental variables in the VC equation. Clearly, the instruments are jointly significant.