Innovation in High-tech Entrepreneurship: Does It Depend on the Provision of Smart Money?

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Abstract

This paper examines the role of venture capital on firm's innovation activities by using a data set on young German high-tech firms founded between 1996 and 2005. Innovation is proxied first by patent counts and second by categorical variable called innovativeness which reflects whether the methods and technologies are developed by the firm, by a third party or whether it is an innovative combination of tried and tested technologies. The results show that VC financing has a positive impact on both patenting and innovativeness even if accounting for excess zeros and endogeneity of VC financing.

Keywords: High-tech entrepreneurship, venture capital, innovation

JEL-Classification: G24, C35, L20

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1 Introduction

Venture capital (VC) is often perceived to spur innovation. Anecdotic evidence exists, particularly for the US, where today's big players in innovative markets, like computer or biotechnology markets, have been VC-financed in their early stages, i.e. Apple, Microsoft, Genentech. These firms were characterized at the beginning by high risk and a potential to generate high returns.

The starting point of this paper is a model proposed by Kortum and Lerner (1998, 2000). They test the hypothesis that the provision of smart money influences firm's innovation activities. They base their investigation on a knowledge production function where patenting depends on the provision of venture capital disbursement and R&D expenditures. They find a positive impact of VC investments on innovation in the US at the industry-level.

This paper looks at the firm-level and tries to clarify whether the provision of venture capital has a positive effect on firm's innovation activities. Innovation activities are proxied first by the number of patents. In the literature, the use of patents as indicator for innovation is discussed since patents only display innovation output to a certain extent because not all output is patentable or patented. A second proxy of innovation activities is a categorial variable named innovativeness, i.e. if the product or service embodies methods and technologies that are totally new developed by the firm itself or by a third party or if the product or service comprises an innovative or a known combination of tried and tested methods and technologies. A problem with respect to VC financing is the fact that VC financing may be endogenous. The causality may be viceversa, i.e. innovative activities by a firm attract VC funding. Therefore, I account for this endogeneity in both models.

The paper is organized as follows. Section 2 reviews the literature focusing on the role of Venture capital for young technology-oriented firms and its presumed impact on innovation and the hypotheses tested in this paper are derived. Section 3 depicts some descriptive statistics. Section 4 shows the empirical models and results and Section 5 concludes the paper.

2 Literature Review

This section briefly reviews the literature on innovation and entrepreneurship, financing of innovation, and finally, the link between VC financing and innovation. When talking about innovation and entrepreneurship a point to start is Schumpeter (1934, 1939, 1947). Schumpeter's views are the basis for two streams of research: The first outlines the importance of new ventures by individual entrepreneurs and the role of corporate entrepreneurship in the renewal of large firms. Relying on Schumpeter (1934) the first strand emphasizes the role of the entrepreneur in carrying out innovation and technological change. The second stream of research is based on Schumpeter (1949) where he states that the entrepreneur need not be a physical person but is seen in terms of the function in a company. Consequently, large firms might be the drivers of innovation because they have the resources and capital to invest in R&D activities (Hagedoorn, 1996).

There is some evidence for the individual entrepreneur. The OECD (1996) states that innovative projects have the greatest chance of success if they are undertaken in small technology-based firms. Scherer (1992) shows that in the 1980s small firms carried out relatively more innovation than large firms. Acs and Audretsch (1991) find that small firms achieve more innovation per million dollars of R&D spending than large companies. Furthermore, the arrival of significant innovation is supposed to be positively associated with new firm entries (see e.g. Gilbert and Newbery, 1982, Reinganum,1983).

Baumol (2002) claims that the difference between innovation in large firms and entrepreneurial firms is that breakthrough innovation are provided by the entrepreneur whereas the innovation process carried out by large, established firms is more routinized and often enhances the breakthroughs by making them more useful. Hence, innovation by entrepreneurial and large firms are complementary and entrepreneurs play a critical role for the economy's growth. A similar point of view is taken by Acs and Grifford (1996)**?**. They postulate that as firms grow, new product innovations become less important than the maintenance of profitability by building up new product lines. Contrary to Baumol's view is the position of Cohen and Klepper (1992). They acknowledges that large firms have fewer innovation comparing the relative R&D expenditures, but the average innovation in large firms is of higher quality. They state that large firms and basic research institutions constitute the scientific and technological base for major innovation whereas technological opportunities are exploited and commercialized by small innovative firms.

Furthermore, in high-tech sectors, large firms may be inefficient because, particularly in those sectors, firms should be able to react quickly to changing environment and technologies. There are several reasons for that: First, running a business in high-tech sectors is often characterized by learning by doing processes which large firms normally do not or cannot implement. Second, the market size may be too small. In this respect small enterprizes may have an advantage because they may focus on product specialization and may be able to deal with specificities of market segments (Rothwell, 1989).

2.1 Financing of innovation activities

Financing is a crucial input factor of the innovation process. However, this process is characterized by a high level of uncertainty. It begins with an idea which is researched and developed and includes a process of trial and error. Stevens and Burley (1997) estimate that on average 3000 raw ideas are tried and tested to get one major commercially successful innovation. Consequently, innovation often show a considerable variance in terms of time involved and money spent, and hence, is a process which is difficult to predict.

Financing of innovation and R&D activities can be viewed as an investment in the future of the firm since they are supposed to strengthen the firm's competitive position and performance and contribute to future profits (Hall (2002)). Arrow (1962) postulates that innovation activities usually are not adequately financed, i.e. firms do not invest enough funds in innovative activities. The reasons are mainly linked to the characteristics of the innovation process' output, knowledge which exhibits some characteristics of public goods. As a result, the returns to innovative activities cannot be fully appropriated by the innovator because of the nonrival character of knowledge. The consequence is that the innovation process suffers from an underinvestment.

Looking at innovation activities as investment there are some specificities that are not common to other investments, like physical investments. First, a major part of R&D investments are wages and salaries for highly educated R&D employees, like scientists and engineers. The newly generated knowledge is often tacit, firm- and product-specific and is largely incorporated in the R&D employees. Thus, those are highly valuable for the firm (Hall (2002, 2005)). Consequently, the innovation process cannot easily be altered which causes R&D spending patterns to be similar to investments with high adjustment costs (Hall et al. (1986), Lach and Schankerman (1988), Hall (1992)). Adjustment costs in this case may arise because firing R&D employees results in a loss of knowledge which cannot easily be transmitted to or regenerated by newly hired R&D employees (Harhoff (1998), Himmelberg,Petersen, (1994)). A second difference is output uncertainty which is particularly high at the beginning of an innovation process and concerns the unpredictability of the result and the time span of the process (see Hall (2002, 2005), Arrow (1962)).

A common starting point for the discussion about corporate finance and investment is the so-called Modigliani-Miller theorem (Modigliani, Miller, 1958). For investment decisions, the firm's capital structure, and hence, the source of finance, is irrelevant, the price is the same for all investments. This stylized result is based on restrictive assumptions, like perfect capital markets and the absence of taxes. Since capital markets are not perfect, investment decisions may depend on specific factors like the availability of internal finance, access to debt or equity finance or the functioning of particular credit markets (Fazzari et al., 1988).

There are some reasons why the costs of external and internal capital may fall apart for investments and particularly for innovation investments. Agency problems arise in this context because of the separation of ownership and control and the resulting moral hazard problems. Furthermore, the relationship between the inventor and the outside financier is characterized by asymmetric information since the inventor has better information about the quality of the innovation. This results in a higher lemon premium for external financing of R&D investments (Leland and Pyle, 1977). Applying the pecking order model of Myers (1984) and Myers and Majluf (1984) this statement leads to a preference for internal funding of innovation activities.

In line with this theoretical result are the findings of the literature investigating whether R&D investments are financially constrained. Leland and Pyle (1997) and Bhattacharya and Ritter (1983) show that, due to moral hazard problems in the relation between entrepreneur and investor, R&D investments are constrained by cash flow. This underlines the view that internal finance is often seen as the best funding source of R&D activity. Even if it was costless to reduce the information asymmetries, firms would be reluctant because of strategic considerations (Himmelberg, Petersen (1994)). Himmelberg and Petersen (1994) find a substantial effect of internal finance on R&D investment. Harhoff (1998) confirms an effect of cash flow on R&D activities in Germany whereas Bond et al. (1999) comparing British and German firms find only a significant effect for British firms which do not perform R&D. Mulkay et al. (2001)**?** find impacts of cash flow on R&D and ordinary investments for the US and France. Bourgheas et al. (2001)**?** find that R&D investment are financially constrained in Ireland.

Focusing on high-tech entrepreneurship the problems in financing R&D and innovation activities are similar. But contrary to established innovative firms, young high-tech firms are not able to rely more or less exclusively on internal funds. The empirical findings are mainly derived for large firms. There is evidence that the financial sources of the R&D process depends on firm size. Large firms prefer internal R&D expenditures, whereas small and medium-sized firms rely more on external financial sources. Hence, small and medium-sized firms are more likely to encounter financial constraints compared to large firms which is particularly true for high-tech industries (Audretsch, Vivarelli (1996), Acs, Audretsch (1990). In high-tech entrepreneurial firms, high initial investments often need to be made which cannot wholly be financed by the entrepreneur and his “private” sources, like family and friends. Since financing is usually not available for those firms because of the lack of collateral, the high risk and the relatively low return for debt providers, young high-tech firms rely on external equity financing.

2.2 The relation between VC financing and firm's innovation activities

Many of the studies investigating the link between venture capital financing and innovation analyze the 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 for the period 1983-1992 derived from the knowledge production function introduced in Griliches (1979) and find a positive and significant effect of venture financing on firms' patenting behavior. A limitation of their results is that the reduced-form regression may overstate the VC impact since VC funding as well as patenting may be affected by the unobserved arrival of technological opportunities. Kortum and Lerner address causality concerns by using an instrumental variable approach, and further, by exploiting the fact that in the history of the US venture capital industry there has been a substantial increase in the size of funds raised by VC companies due to a policy shift in the late 1970s. The so-called "prudent man" rule of the Employee Retirement Income Security Act clarified by the Department of Labor allows pension funds to invest in venture capital. In a second approach, they use R&D expenditures as control for the arrival of technological opportunities anticipated by the firms which they identify to be one of the major drivers of the causality problem. Furthermore, Kortum and Lerner (2000) suspect that venture capital may spur patenting while having no impact on innovation. They investigate whether VC-funding only augments the propensity to patent without stimulating innovation. Kortum and Lerner analyze this effect by comparing indicators of patent quality between VC- and non-VC-backed firms. They use patent citations (see Trajtenberg, 1990) per patent to measure the average importance of the firms' patent awards. Furthermore, they use the frequency and extent of patent litigation to investigate the importance of the patents (see Lanjouw and Schankerman, 1997). For all measures of patent quality they find that VC-backed firms hold higher quality patents than non-VC-backed firms, i.e. 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 as Kortum and Lerner.

Ueda and Hirukawa (2003) criticize the interpretation of the Kortum and Lerner (1998, 2000) papers. They state that it is one-sided because the opposite causality may also exist. They 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. Ueda and Hirukawa remark that venture capital is a complementary asset for young and innovative firms, particularly, in times when significant innovations arrive. Reasons may be that with substantial innovations business opportunities arise which may trigger firm startups. Ueda and Hirukawa address the causality issue by using the growth of total factor productivity as a measure for innovation and test for Granger type causality. 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.

Ueda and Hirukawa (2006) extent the studies by Kortum and Lerner to the "bubble" period which includes the growth period of the VC industry during the late 1990s and ask whether the productivity of VC investments has been diminished during the boom. As Lerner (2002) states that the impact of venture capital on innovation is not uniform and depends on the cyclicality of the VC market. E.g. during boom periods the effectiveness of VC may be less due to an overfunding within particular sectors whereas in long bust periods promising firms may remain unfunded. The period Ueda and Hirukawa (2006) cover consists of the years 1968 to 2001. They confirm the results of Kortum and Lerner and state that VC investments continue to be a highly effective driver of patent activities. Furthermore, they reinvestigate the findings of their 2003 paper with the new data set and find, instead, that VC investments have no significant effect on TFP growth but that they positively affect labor productivity growth which they associate with technology substitution using more energy and material and less labor in VC-intensive industries. Ueda and Hirukawa give several explanations for their puzzling results of the positive impact of VC funding on the propensity to patent and the insignificant impact on TFP growth: First, venture capitalists prefer start-up firms as investees and those are supposed to have a higher patent propensity than established firms in order to appropriate the returns to innovation. Second, a change in the patent policy may have affected patenting and VC investment. Third, VC facilitates firm entry and may help increase the competitive pressure which, in turn, may increase the patent propensity of established firms, i.e. established firms may patent for strategic reasons since the threat of entry is strong due to the support by venture capitalists.

Some studies investigate the relation of VC funding and innovation at the firm level. Da Rin and Penas (2007) link venture financing and firm's absorptive capacities by influencing the innovation decision. They use the Dutch CIS survey and focus on combinations of R&D 'make' and 'buy' which correspond to the build-up of absorptive capacity. Their results suggest that VC financing has an impact on innovation strategies since the entry of a VC investor is associated with an increase in the combination of both strategies and in ‘make’ but not in ‘buy’ R&D activities.

Engel and Keilbach (2002) investigate the impact of VC financing on firm’s growth rates in terms of employment and on innovative output. They use a nearest neighbor matching technique and find in the first stage that VC involvement depends on pre-foundation patenting behavior. Regarding the patenting activities of VC-backed firms, they show that the VC-backed firms have only a weakly significant positive effect with respect to patent counts than non-VC firms.

Bretoni et al. (2006) find a highly positive effect of VC financing on firm’s patenting activities for Italian new technology-based firms using a hand-collected panel data set of high-tech manufacturing for the years 1993 to 2003. They show that after receiving VC financing the propensity to patent increases whereas they find not such a high patenting propensity before the VC investment. 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.

Hellmann and Puri (2000) link the firm’s product market strategy with the provision of venture capital analyzing a data set of Silicon Valley high-tech startups. They particularly focus on innovator and imitator strategies. They find that innovators are more likely to be financed by venture capital and obtain the funding earlier in the life cycle than imitators. Moreover, they find that the time to market is shorter if venture capital is present in the firm, particularly if the firm follows an innovator strategy.

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. Those highly valuable nonmonetary contributions consist of helping to find key management-team members, providing credibility with suppliers and customers and helping to shape the business strategy are of particular importance.

Schwienbacher (2004) presents a model which links innovation to the stage of VC exit and claims that prospective exit causes agency problems because the exit decision produces uncertainty to the entrepreneur about the future control of the firm. According to Schwienbacher, the entrepreneur may favor IPO as exit route – an IPO may enable him to participate to the firm’ strategy shaping as a manager or a shareholder – and thus chooses the strategy that favors the IPO. This in turn may have an impact on the extent of innovation since in the model the strategy includes also R&D activity. Whether this leads to more or less innovation depends on the market game.

2.3 Hypotheses

The first hypothesis is based on the results of Kortum and Lerner (1998, 2000) confirm this evidence for the US. They investigate whether VC funding spurs innovation and estimate a patent production function at the industry level with VC funding and R&D expenditures as input factors. They find a positive effect of VC financing on firm's patenting behavior. This chapter tests whether this link also holds for the firm-level. At the industry-level the significant effect may also reflect the behavior of firms which do not receive VC financing. For example, incumbent firms patent their innovation output to prevent firm entry, so-called preemptive patenting (see e.g. Gilbert, Newbery (1982)), which may have been made possible due to the existence and the investment behavior of the VC industry. The question in this chapter is whether the provision of VC enables the individual firm to be (more) innovative.

Hypothesis 1: Venture Capital spurs innovation proxied by firm's patenting behavior.

Griliches, Pakes and Hall (1987) describe some problems that arise when relying on patents as indicator for innovative activities. First, the size or value varies over different patents and second, the output of R&D activities is only represented in fraction by patents since not all R&D activities are patentable or patented. Furthermore, the fraction patented may also vary over industry, firm and time. When a firm has successfully innovated, it can decide to either use secrecy or patenting to protect their finding and appropriate the returns of it innovative activities. Patenting protects the results against imitation by (possible) competitors in that it assures the firm a monopolistic position in the corresponding market.

Moreover, Kortum and Lerner (2000) point out that venture capital may spur patenting while having no impact on innovation. First, patents may serve as a signal of 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 invention. Second, patents are used as protection mechanism against expropriation of the entrepreneur's ideas by the VCs. Kortum and Lerner account for patent quality by using several quality measures. Hence, it would be worthwhile to control for the quality of the patents. A caveat of quality measures is that they are right-censored since future citations and litigations cannot be detected. In the case of very young firms – like in this data set – the right-censoring deteriorates these measures because the patent filing does not date back for a long time.

But the data set provides a categorical indicator of firm's innovativeness, i.e. whether the innovative activity that results in a totally new technology is done mainly by the firm itself or by a third party or whether the innovative activity results in a new combination of tried and tested technologies (for a more detailed variable description, see Table 4.1 on page 15 and Appendix D). With this variable I am able to display the effects of VC financing on the result of innovative activity. Since VC companies are often perceived to concentrate on industries which are characterized by a high innovative potential resulting in totally new products and/or technologies, I conjecture that VC-backed firms are characterized by high innovativeness.

Hypothesis 2: Firms more probably develop the methods and technologies, they use to produce their products, themselves if they are VC-backed.

The first two hypotheses only concentrate on changes to firm's behavior. But more important should be the contribution of the VC investor to firms' innovation activities. This contribution mainly consists of management support and active involvement as the results by Timmons and Bygrave (1986) – presented in Section 2.2 – show. A variable that should display the VC companies' contribution to innovation is the interaction of VC and R&D employees.

Hypothesis 3: The active involvement of the VC investor contributes positively to firm's innovation activities.

As regards the model of Kortum and Lerner (1998, 2000), patenting also depends on R&D activities measured as R&D expenditures. This conjecture is quite intuitive since R&D is normally interpreted as input factor for the innovation process. The data set used here does not contain any information on expenditures but information on the number of R&D employees which is highly correlated to R&D expenditures since R&D expenditures largely consist of wages for qualified personnel (see Hall, 2002, 2005, and Griliches, 1990). Therefore, I conjecture that the number of R&D employees influence positively on innovation and patenting.

Hypothesis 4: R&D activities, proxied by the number of R&D employees, have a positive impact on patenting and firm's innovativeness.

3 Data Set

3.1 The set-up of the data set

The data set is based on a computer-assisted telephone survey of high-tech firms founded between 1996 and 2005. The survey has been effectuated by the Centre for European Economic Research (ZEW) in February and March 2006. The data set is based on the

ZEW Foundation Panel, which is provided by Creditreform, Germany's largest credit rating agency. Creditreform is decentrally organized and collects information on firms in order to provide credit ratings. The gathered information contains inter alia firm name, address, NACE code and founding date (for more details see Almus et al. (2000)).

The underlying population sample from which the sample of firms called has been drawn has been defined by foundation dates between 1996 and 2005 and by specific technology and knowledge intensive sectors. The high-tech manufacturing sectors are classified according to Grupp et al. (2000). Their classification of technology-based industries is based on the industry R&D intensity. To be considered a high-tech industry, an industry needs to have an R&D intensity of at least 3.5 %. This list is completed by technology-based service sectors, e.g. R&D facilities and software industries (based on a classification by Nerlinger, (1998)**?**; Engel and Steil (1999)). The list of the considered manufacturing and service sectors is given in Table 8 in the Appendix. Furthermore, firms are dropped for which the ZIP Code is missing since the ZIP Code is mandatory for possible re-investigations of the address and telephone number. Firms for which Creditreform has information whether they have been closed are also not included in the population sample as well.

The population sample of firms founded between 1996 and 2005 comprises 73,332 firms. The sample underlying the survey is a stratified sample of 8,000 randomly drawn firms. Stratification is based on the foundation date and on industries. Foundation dates have been clustered into two groups: founded between 1996 and 2000 and between 2001 and 2005, which represents the boom and the post-boom period of high-tech industries in Germany. Industries are classified into five groups. High-tech manufacturing is divided into three groups. First, high-tech manufacturing including all manufacturing sectors on four-digit NACE level with a R&D intensity above 8 percent, so called "Spitzentechnik"(named hereinafter high-tech 1). Second, high-tech manufacturing including all manufacturing industries with a R&D intensity between 3.5 and 8 percent, so called "Hochwertige Technik" (named hereinafter high-tech 2). From these two clusters, the hardware sector has been taken apart. The technology-oriented service sectors have been divided into software industry and other technology-oriented services (see Table 10 in the Appendix for the distribution of industries and foundation cohorts in the stratified sample and the respective probabilities of draw). 1,065 firms have been interviewed. Table 1 depicts the distribution of the interviewed firms to the stratification criteria. For those firms we have information about obstacles and factors for success, innovativeness, strategies, foundation process etc. Furthermore, I merged patent information of the European Patent Office and the German Patent and Trademark Office up to the year 2003 to the data set in order to capture the

Table 1: Distribution of industries and cohorts in the sample

	high-tech 1	high-tech 2	hardware	software	tech. serv.	total
1996 to 2000	84	116	91	114	116	521
2001 to 2005	93	123	96	114	118	544
total	177	239	187	228	234	1,065

innovative output of the firms. This merge is done using a computer-assisted string search in the applicant variable. I have only searched the applicant because the information on who has the right to use the property right is important for the analysis. Since the firms in the data set are relatively young and some of them have indicated that the patents they use have been granted before firm foundation I have searched the firm names as well as the names of the members of the management team in the applicant variable, i.e. the managers may have filed a patent which their firm is allowed to use.
Moreover, information on the distances of the firm to universities and research institutes has also been appended. This has been done to account for possible knowledge-spillover effects. Finally, information provided by Creditreform is merged as well to the data set so that information on rating, stakeholders and legal form are included as well.

3.2 Descriptive Statistics

Table 3 depicts the descriptive statistics of the variables included in the regressions below. Two different dependent variables are used: the number of patents applied after firm foundation and innovativity (see Section 4.1, Table 4.1 and Appendix D for a detailed description of the variable). The average firm has applied for 0.68 patents after firm foundation (*pat-after*). The fractions of the different categories of innovativenes (*innovativeness*) are displayed in the following table

Table 2: Characteristics of the variable *innovativeness*

description	fraction
known combination of tried and tested	12.2%
innovative combination of tried and tested	17.4%
new methods by third party	26%
new methods by firm	44.4%

For the test of the hypotheses the variables (*venture capital*) and *log(R&D employees)*) are included. In the data set on high-tech entrepreneurship 6% of the firms are VC-backed.

and 1.5% R&D employees. Since the data set contains only small firms (the maximum number of employees is 400 and the average 12 employees) almost half of them have no R&D employees. In order not to lose to many observations I replaced the zero by unit values and include in the regressions a dummy variable indicating whether this observation has been replaced (*d_fue*). Furthermore, to capture the impact of management support by the VC an interaction term of VC-backing and R&D employees is included as well (*log(vc * R&D)*).

Besides the variables that help to test the hypotheses, I also include control variables which may account for or are supposed to have an impact on innovation activities. They are described below.

Factors concerning the management team

The variables regarding the management team (*m_*) reflect the situation of the founding management team but since all firms are relatively young this should be approximately the current situation. The educational background and experience of the founding management team are represented by the dummies *m_phd* and *m_university* which reflect that at least one manager holds a a PhD (almost 15% of the firms) or university degree (half of the firms). Furthermore, over 85% of the firms have a management team with at least one technical degree (*m_technical*). Other crucial characteristics of the management team are their professional curricula. Almost 80% of the management team have at least one member who has been employed by a company (*m_company*) and almost 44% have at least one member who has got entrepreneurial experience (*m_serial*).

Firm characteristics

For the regression concerning the firm's innovativeness I also include an indicator whether the firm uses own patents which have been filed before foundation (*patents_before*). For example, one of the managers could have filed a patent and in order to commercialize this idea he founds a company. About 5% of the firms use patents which have been filed before their foundation.

Furthermore, foundation year dummies are included(*founded 1999 to founded 2004*) to reflect the different starting conditions of the firms. During the observation period the high-tech sectors have experienced an extraordinary boom period from 1997 until the beginning of 2000 and a downturn period for the later observation years. Finally, industry dummies (*high-tech 1, high-tech 2, hardware, software*) are also included.

Innovation often depends on spillover effects by specific research facilities. In order to account for such effects the distance to universities (*log(dist_uni)*) and public research facilities (*log(dist_inst)*) are included in the regressions.

Factors reflecting product/service characteristics

Product or service (hereinafter only called product) characteristic included in the regressions are whether the product is an intermediate product (*intermediate*) and whether it combines characteristics of a product and service (*package*). An intermediate product which more than 40% of the firms produce may increase the propensity to patent since this product may be more likely subject to expropriation by the customers. About 40% of the firms produce a package product. The effect of this variable is ambivalent concerning the inclination to patent. On the one hand, package products may increase the number of patents since it is – by definition – constructed by the usage of several methods and technologies. On the other hand, package products may be difficult to patent and the likelihood that this combination of product and service is imitated quickly may be low.

More strategic components of the innovation decision are variables measuring whether there is a risk that the technology may get obsolete in a short time (*risk_obsolete*) or the risk of governmental regulations (*risk_govern*). About 12% of the firms fear that their company runs the risk of technology obsolescence and almost 32% fear future governmental regulations and legislation to impede firm's evolution.

Table 3: Descriptive statistics

Variable	mean	std. dev.	min	max
patents_after	0.682	3.631	0	62
innovativeness	2.027	1.052	0	3
venture capital	0.062	0.241	0	1
log(R&D employees)	0.147	0.644	0	2.708
*log(vc * R&D)*	0.061	0.321	0	2.708
m_phd	0.147	0.355	0	1
m_university	0.525	0.500	0	1
m_technical	0.853	0.355	0	1
m_company	0.794	0.405	0	1
m_serial	0.436	0.496	0	1
risk_obsolete	0.123	0.329	0	1
risk_govern	0.320	0.467	0	1
intermediate	0.410	0.496	0	1
package	0.390	0.488	0	1
patents_before	0.053	0.225	0	1
log(dist_uni)	2.464	1.354	-2.303	4.587
log(dist_inst)	2.127	1.755	-2.303	5.180
founded 1999	0.165	0.372	0	1
founded 2000	0.209	0.407	0	1
founded 2001	0.133	0.340	0	1
founded 2002	0.122	0.327	0	1
founded 2003	0.119	0.324	0	1
founded 2004	0.111	0.314	0	1
high-tech 1	0.160	0.367	0	1
high-tech 2	0.206	0.405	0	1

hardware	0.173	0.378	0	1
software	0.237	0.426	0	1
No. of obs.		713		

4 Empirical Models and Results

4.1 Empirical Model

This paper's empirical model is inspired by Kortum and Lerner (1998, 2000). They estimate a patent (P) production function with R&D expenditures (R) and VC disbursement (V) as input variables. Their analysis is based on industry-level data. Kortum and Lerner estimate the following patent production function by using a nonlinear least squares approach:

$$P_{it} = (R_{it}^{\rho} + bV_{it}^{\rho})^{\frac{\alpha}{\rho}} \tag{1}$$

In this context Kortum and Lerner (2000) use R&D expenditures to control for the arrival of technological opportunities that are anticipated by the firms.

In the data I do not have information about the amount of venture disbursement. The only information, I can rely on, is whether a firm has been financed by VC. The use of patents as proxy for innovation is quite popular. If innovation is defined as the additions to knowledge Griliches (1990) and linked to R&D activities knowledge increments are a transformation of R&D (Pakes, Griliches (1980))

$$\dot{K} = R + u \tag{2}$$

As new knowledge is not observable, patents are used as an indicator of at least a fraction of newly generated knowledge.

$$P = a\dot{K} + v = aR + au + v \tag{3}$$

In the context of this paper this patent production functions of Griliches (1990) of equation (3) and Kortum and Lerner (1998, 2000) of equation (1) are translated into an equation which outlines the role of venture capital financing in the production of patents.

$$P = aR + VC + l$$

where patenting is explained by R&D employees (R), an indicator of venture capital financing (VC) and a stochastic term l.

Besides the doubts that patents are valuable indicators of knowledge increments, hence innovative activities, Kortum and Lerner (2000) add two reasons why in the context of venture capital patenting may be spurred while VC having no impact on innovation. First, patents may serve as a signal of firm's quality to potential VC investors, i.e. patents may help to attract VC. Second, patents are used as protection against expropriation of the entrepreneur's ideas by the VCs. In order to account for these effects I use the categorical indicator of firm's innovativeness[1] as dependent variable which.

Table 4: Characteristics of the variable *innovativeness*

value	The product is characterized by...
0	... a known combination of tried and tested methods and technologies
1	... a new combination of tried and tested methods and technologies
2	... new methods and technologies developed by a third party
3	... new methods and technologies developed by the firm itself

It was designed such that it includes product as well as process innovation. With this variable I am able to display the effects on the "degree" of innovative activity.

$$I = cR + VC + e.$$

4.2 Patents as Innovation Indicator

4.2.1 Empirical Methodology

Hausman et al. (1984) propose for the estimation of the influence of R&D activities on patenting count data models since the dependent variable is represented by integer values and a large number of zeros. This kind of model is appropriate in this context because the patent data contains many zeros and has a discrete nature whereas many observations have only small values (Greene, 2003, Winkelmann, 1994**?**).

In this paper, the patent variable consists of many zero counts: Over 75% of the firms report that they do not make use of own patents, i.e. the patent variable exhibits excess zeros. A common method is to account for the generation of the zeros. Two models may be applicable with excess zeros: the hurdle and the zero-inflated model.

[1]The Appendix D contains a translation of the question asked in the interviews.

The hurdle model which changes the probability of the zero outcome and scales the remaining probabilities. The hurdle models determine with the aid of a binary probability model, e.g. a probit or logit model, whether a zero or a nonzero outcome occurs. The positive outcomes of the count variable are modeled using a "truncated" Poisson model (Mullahy, 1986, Greene, 2003, pp. 749-752).
An extension of the hurdle model is a zero-inflated model (see Lambert, 1992) in which two different regimes are supposed to generate zero outcomes. In one regime, the outcome is always zero (*regime1*) and in the other regime the zeros stem from a usual Poisson process which includes zeros as well (*regime2*) so that

$$Prob(y_i = 0|x_i) = Prob(regime1) + Prob(y_i = 0|x_i, regime2)Prob(regime2).$$

In the patent case the zero-inflated model is preferred because the zero patents may come from two different sources: First, the firm is not innovative, and thus, will never file a patent (*regime1*), and second, the firm is innovative but has not filed a patent because either the outcome of the innovation process is not (yet) patentable or the firm has decided to keep the knowledge secret (*regime2*).
The intuition of the zero-inflated models is to estimate a binary probability model for which the indicator is one if the zero outcome stems from the usual Poisson process (regime2) and zero if it is always zero (regime1). The zero-inflated models can be described as follows (Cameron and Trivedi, 1998, pp.125-128):

$$\begin{aligned} Pr(y_i = 0) &= \varphi_i + (1-\varphi_i)e^{-\mu_i} \\ Pr(y_i = r) &= (1-\varphi_i)\frac{e^{-\mu_i}\mu_i^r}{r!}, \ r = 1, 2, ... \end{aligned}$$

It is assumed that the proportion of zeros, φ_i, takes logistic function, so that

$$\begin{aligned} y_i &= 0 \ with \ probability \ \varphi_i \\ y_i &\sim Po(\mu_i) \ with \ probability \ (1-\varphi_i) \\ with \ \varphi_i &= \frac{exp(z_i'\gamma)}{1+exp(z_i'\gamma)} \end{aligned}$$

.

The zero-inflated Poisson model is overdispersed. This overdispersion results from the nature of the zero-generating process. But the overdispersion may also stem from heterogeneity which cannot be captured by the Poisson model. So a test for "non-Poissonness" of the distribution is needed which is a LR test on $\alpha = 0$. Furthermore, Vuong (1989) proposes a likelihood-ratio test for non-nested models. Let $f_j(y_i|x_i)$ be the predicted probability that the count is y_i under the assumption that the distribution is $f_j(y_i|x_i)$ for the models $j = 1, 2$ and $m_i = log(\frac{f_1(y_i|x_i)}{f_2(y_i|x_i)})$ then the test statistic for model 1 versus model2 is

$$v = \frac{\sqrt{n}[\frac{1}{n}\sum_{i=1}^{n} m_i]}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i - m)^2}}$$

The limiting distribution of the test statistic is standard normal. This test is used to show if the zero-inflated version of the count model is to be preferred, i.e. it tests if there is a significant difference between the zero-inflated model and its non-zero-inflated counterpart. The results of the Vuong test in Table 5 indicate that the zero-inflated models fit the data better then the non-zero-inflated versions. The estimation of the Poisson and the Negative binomial models can be found in Appendix E.

4.2.2 Empirical Results

First looking at the bottom of Table 5 the Vuong tests for the ZIP and the ZINB confirms that the zero-inflated versions of count data fits – as expected – better to the data than the non-zero-inflated one. Furthermore, the χ^2-test that the variance parameter α equals zero can clearly be rejected. As a consequence, the model that fits best to the data is the zero-inflated negative binomial count data model.

Table 5 displays the incidence rate ratios (IRRs) and the coefficients of the count model (column 1 and 2 for the zero-inflated Poisson and column 4 and 5 for the zero-inflated Negative Binomial model). For the equation reflecting the probability of belonging to the Poisson or Negbin distribution, only the coefficients are displayed. The model used for this equation is a logit model. Since count data model belong to nonlinear regression models the coefficients cannot be interpreted. For interpretation, the incidence rate ratios are interpreted. The incidence rate ratios corresponds to the fraction

$$\frac{E(y|x, z + \delta)}{E(y|x, z)} = exp(\beta_z \delta)$$

. The standard errors of the incidence rate ratios are transformed using the delta rule to get an estimate of the standard errors of the IRRs, i.e. IRR times the standard error of the coefficient. The reported significance levels reflect the test that the respective IRRs=1 and correspond to the significance levels of the original model since the IRRs are just a univariate transformation of the coefficients.

According to Table 5, venture capital funding has a positive impact on patenting. The effect of VC-backing increases the expected number of patents by over 4 times with

respect to non-VC-backed firms. This effect confirms Hypothesis 2.3 and confirms that VC financing spur firm's innovation activity, and therefore, may contribute to the economy's competitiveness and growth. Furthermore, an increase of log(R&D employees) by one unit increases the expected number of patents by a factor of 0.8 which confirms Hypothesis 2.3. The results suggest that the management support of VC (*log(vc * R&D)*) companies has no significant on the expected number of patents, so that Hypothesis 2.3.
Regarding the control variables the results indicate that a management team technical degree has a negative significant effect on the expected number of patents. This may reflect that management

Table 5: Result of count data models

Model	ZIP			ZINB		
	$Po(y_i = j)$		$Pr(y_i > 0)$	$Po(y_i = j)$		$Pr(y_i > 0)$
Variable	IRR (Std.Err.)	Coeff. (Std.Err.)	Coeff. (Std.Err.)	IRR (Std.Err.)	Coeff. (Std.Err.)	Coeff. (Std.Err.)
venture capital	3.212**	1.167**	-1.372**	5.032*	1.616*	-0.741
	(1.875)	(0.584)	(0.638)	(4.672)	(0.929)	(3.661)
log(R&D employees)	1.664**	0.509***	-0.461*	1.823*	0.600*	-0.925
	(0.328)	(0.197)	(0.257)	(0.658)	(0.361)	(1.538)
d_R&D	1.031	0.031	0.813**	0.352	-1.045	-0.173
	(0.557)	(0.540)	(0.411)	(0.310)	(0.881)	(2.440)
*log(vc * R&D)*	0.424**	-0.859**	0.032	0.537	-0.622	-0.577
	(0.172)	(0.407)	(0.644)	(0.368)	(0.685)	(2.630)
m_phd	1.012	0.012	-1.210***	1.995	0.691	-1.922
	(0.490)	(0.484)	(0.456)	(2.173)	(1.089)	(2.601)
m_university	1.248	0.222	-0.548	1.268	0.237	-1.472
	(0.492)	(0.394)	(0.360)	(0.427)	(0.337)	(0.910)
m_technical	0.387**	-0.950**	-0.685	0.229***	-1.472***	-2.758
	(0.160)	(0.413)	(0.486)	(0.113)	(0.491)	(1.939)
m_company	0.531**	-0.633**	-0.304	0.580	-0.545	-0.925
	(0.168)	(0.317)	(0.335)	(0.316)	(0.545)	(1.274)
m_serial	0.731	-0.313	0.176	0.406**	-0.901**	-0.921
	(0.250)	(0.342)	(0.331)	(0.171)	(0.422)	(1.702)
intermediate	1.364	0.311	0.171	1.697	0.529	1.146
	(0.426)	(0.312)	(0.308)	(1.237)	(0.729)	(2.510)
package	1.607	0.474	0.063	3.978	1.381	2.142
	(0.611)	(0.380)	(0.307)	(4.812)	(1.210)	(1.917)
risk_obsolete	0.848	-0.165	0.121	0.581	-0.543	-1.149
	(0.314)	(0.370)	(0.460)	(0.337)	(0.581)	(2.917)
risk_govern	0.457*	-0.783*	-0.384	0.254**	-1.371**	-3.196
	(0.198)	(0.434)	(0.364)	(0.163)	(0.644)	(3.064)
log(dist_uni)	1.110	0.104	0.014	0.957	-0.044	-0.358
	(0.121)	(0.109)	(0.127)	(0.150)	(0.156)	(0.525)
log(dis_inst)	0.868**	-0.142**	0.006	1.041	0.041	0.046
	(0.056)	(0.064)	(0.089)	(0.180)	(0.173)	(0.464)
founded 1999	0.313**	-1.161**	0.615	0.127	-2.061	-1.508
	(0.160)	(0.512)	(0.468)	(0.178)	(1.396)	(3.637)
founded 2000	0.400***	-0.916***	0.294	0.295	-1.220	-0.685
	(0.133)	(0.332)	(0.427)	(0.299)	(1.011)	(2.244)
founded 2001	0.460	-0.776*	0.366	0.628	-0.466	1.305

	(0.217)	(0.472)	(0.439)	(0.454)	(0.723)	(2.493)
founded 2002	1.600	0.470	1.814***	1.097	0.093	3.323
	(0.677)	(0.423)	(0.574)	(1.306)	(1.190)	(3.128)
founded 2003	0.479	-0.736	0.595	0.256	-1.364	0.250
	(0.295)	(0.616)	(0.551)	(0.264)	(1.032)	(2.729)
founded 2004	0.082***	-2.506***	-0.630	0.055***	-2.909***	-16.929***
	(0.044)	(0.536)	(0.780)	(0.053)	(0.968)	(2.592)
high-tech 1	1.732	0.549	-0.076	1.981	0.683	0.423
	(0.808)	(0.466)	(0.465)	(1.830)	(0.924)	(1.580)
high-tech2	1.010	0.010	-0.973**	0.569	-0.564	-2.997**
	(0.459)	(0.455)	(0.427)	(0.451)	(0.793)	(1.435)
hardware	0.752	-0.284	-0.778*	0.246*	-1.403*	-4.780
	(0.340)	(0.452)	(0.454)	(0.201)	(0.820)	(3.830)
software	0.777	-0.252	1.217**	0.117	-2.146	0.147
	(0.588)	(0.756)	(0.519)	(0.196)	(1.675)	(3.718)
constant		2.782**	2.748***	3.158**	6.625**	1.056***
		(1.144)	(0.822)	(1.463)	(2.692)	(0.331)
α					2.874	
					0.951	
N		713			713	
ll		-506.35			-424.25	
chi2		312.92			189.65	
Vuong test		4.82***			5.01***	
LR-test $\alpha = 0$					164.20***	
McFadden's R-squared		0.357			0.176	
AIC		1116.71			954.50	
BIC		1354.32			1196.68	

One, two and three asterisks indicate significance at the 10%, 5% and 1% level respectively.

4.3 Estimation for Innovativeness

4.3.1 Empirical Methodology

Since the variable, of how innovative the product or service of a firm is, is measured by a categorical variable, I estimate a multinomial logit model. The standard starting point for discrete choice models is the latent regression

$$y^* = x'\beta + \epsilon \quad \text{and } y^* \text{ is unobserved}$$

I only observe the discrete variable y consisting of four categories (here: innovativeness as described in Appendix 4). Greene (2003) states that this methodology enables to represent a set of probabilities for $J+1$ choices which depend on individual firm characteristics x_i. Normalizing $\beta_0 = 0$ the following probabilities are obtained

$$Prob(Y_i = j|x_i) = \frac{e^{\beta_j' x_i}}{1 + \sum_{k=1}^{J} e^{\beta_k' x_i}} \text{ for j=1,2,3, } \beta_0 = 0$$

The results of the multinomial logit are interpreted as odd ratios due to the normalization.

An important property of the multinomial logit is the so-called independence from irrelevant alternatives (IIA) assumption, i.e. the independence of the odd ratios of the other alternatives. This condition derives from the assumption that the disturbances are independent and homoscedastic. Hausman and McFadden (1984) state that if the IIA holds the exclusion of one choice equation from the estimation will not change the estimates. If the remaining odd ratios are not independent from these alternatives, the estimates will be inconsistent. The Hausman specification test

$$HT = (\hat{\beta}_s - \hat{\beta}_f)'[\hat{V}_s - \hat{V}_f]^{-1}(\hat{\beta}_s - \hat{\beta}_f) \sim \chi^2$$

where s indicates estimates based on the restricted subset and f based on the full set of choices . If the Hausman specification test rejects the IIA an alternative and computationally more demanding estimation procedure has to be chosen, e.g. the multinomial probit. The results of the Hausman test in this analysis yields that the difference in coefficients between the full and the restricted set of choices is not systematic, e.g. the IIA holds. The results of the multinomial logit estimation are presented in Table 6.

4.3.2 Empirical Results

Table 6 depicts the results of the multinomial logit estimation where the effects of R&D and financial sources on the level of innovativeness are tested. As hypothesized (see hypotheses 2.3 and 2.3), the effect of VC funding is significantly positive for the probability to develop the methods and technologies by oneself the impact of R&D activities reflected by a higher number of R&D employees, is significantly positive for the probability to develop new methods and technologies by the firm itself with respect to innovative combinations of tried and tested methods and technologies. This means a higher R&D activity is as expected a major input for innovation.

Furthermore, whether at least one member of the management team holds a university degree or PhD degree influences positively the probability of high innovativeness. The "topic" of the degree has no effect on being innovative but, measured as holding a technical degree, impacts negatively on the probability of being non innovative compared with using innovative combination of tried and tested methods and technologies.

Table 6: Result of multinomial logit

Model	inno=3	inno=2	inno=0
Variable	Coeff.	Coeff.	Coeff.
	(Std.Err.)	(Std.Err.)	(Std.Err.)
venture capital	2.115***	1.344	1.113
	(0.785)	(0.862)	(0.958)

log(R&D employees)	1.270***	0.609*	0.133
	(0.287)	(0.349)	(0.500)
d_R&D	-0.919***	0.074	0.614
	(0.259)	(0.305)	(0.379)
m_phd	0.674*	0.370	0.369
	(0.388)	(0.448)	(0.539)
m_university	0.725***	0.264	0.475
	(0.239)	(0.264)	(0.305)
m_technical	0.187	0.336	-0.762**
	(0.308)	(0.356)	(0.336)
m_company	0.350	0.268	0.096
	(0.262)	(0.298)	(0.333)
m_serial	0.121	0.129	-0.045
	(0.219)	(0.247)	(0.288)
intermediate	-0.046	-0.326	-0.208
	(0.219)	(0.251)	(0.289)
package	0.002	0.078	-0.507*
	(0.220)	(0.248)	(0.306)
risk-obsolete	0.162	-0.002	-0.590
	(0.318)	(0.363)	(0.491)
risk-legislation	-0.154	-0.036	-0.269
	(0.228)	(0.254)	(0.296)
log(dist-uni)	-0.043	0.115	-0.059
	(0.106)	(0.126)	(0.134)
log(dist-res)	-0.003	-0.085	-0.007
	(0.082)	(0.090)	(0.104)
constant	-0.424	-0.842	0.223
	(0.610)	(0.694)	(0.764)
foundation year dummies		included	
industry dummies		included	
Log-likelihood		-772.664	
No. of obs.		713	
Pseudo-R^2		0.148	

One, two and three asterisks indicate significance at the 10%, 5% and 1% level respectively.

4.4 Endogeneity of venture financing

The previous section suggests that the impact of VC on patenting and innovativeness is positively significant. However, some concerns about the binary variable *venture capital* exists which have already been indicated in the literature review in Section 2.2, particularly, in the context of patenting, Kortum and Lerner (2000) state that patents may serve as a signal of 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 invention. Thus, endogeneity arises in the context of patenting and innovativeness 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 firms which have a high probability to be innovative.

In order to get rid of the endogeneity, I somewhat estimate a VC equation in both models. For identification reasons, the VC equation is specified using additional regressors, hence instruments, i.e. variables that influence the probability of VC financing but not the patenting or innovative behavior. To account for endogeneity, I specify the decision of venture capitalists to invest in a firm, or in other words the probability that the firm receives VC funds and identify additional variables which help me identify the coefficient. I include four variables in the VC equation which should all reflect the firm risk and may help the VC investor to evaluate this risk. First, I control for the number of the founding team members (*team*), the higher the number of team members the more probable the necessary abilities and skills are reflected in the management team and the lower the risk. Furthermore, patents before foundation (*pat-before*) may be a signal of quality and prove that the project of the firm has a good potential to get commercialize and to generate profits. Another indicator of risk is the dummy variable whether a firm has been founded as a capital company (*cap-com*). The limited liability of the company may seduce the managers to take higher risks. Finally, a good measure of risk is the first rating score given by Creditreform (*rating*) which indicates the external assessment of the firm reflecting its market potential and financial exposure. Finally, to account for the independence of the executives, a variable is included which indicates if the manager team holds the majority stake at foundation (*majority*).

In order to account for the endogeneity problem one may try to estimate both equations sequentially. A natural point to start is to use an IV approach, e.g. a two-stage estimation in which the first stage estimates the probability for the binary indicator. In the second stage, the fitted values are included and the downward bias of the standard errors is corrected, e.g. by bootstrapping them. Alternatively, a sort of Heckman correction may be plugged in the second stage. However, a two-stage estimation only applies to linear models. With non-linear estimation procedures – including count and discrete choice models – a two-stage estimation yields inconsistent estimates. Therefore, full information maximum likelihood (FIML) approaches are used in which the two equations are estimated simultaneously.

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 variable d

and the random (heterogeneity) component ϵ. The switching variable d can be represented by the index function $I(z\alpha + \nu > 0)$
ϵ and ν are assumed to be jointly normal distributed with mean vector zero and covariance matrix

$$\Sigma = \begin{pmatrix} \sigma & \sigma\rho \\ \sigma\rho & 1 \end{pmatrix}$$

By setting $\xi = \frac{\epsilon}{\sqrt{2}\sigma}$ the joint conditional probability density function of y and d is approximated by using the Hermite quadrature (see Butler and Moffitt, 1982) and is given by

$$f(y_i, d_i|x_i, z_i) = \frac{1}{\sqrt{\pi}} \int_{-\infty}^{z} f(y_i|x_i, z_i, d_i, \sqrt{2}\sigma\xi)[d_i\Phi_i^*(\sqrt{2}\sigma\xi)+(1-d)(1-\Phi_i^*(\sqrt{2}\sigma\xi))]exp(-\xi_2)d\xi$$

with

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

Thus, the likelihood function to be estimated with the FIML framework is $\mathcal{L} = \prod_{i=1}^{n} f(y_i, d_i|x_i, z_i)$. The results of the FIML estimation of the endogenous switching Poisson model are presented in Table 7. Venture capital is still positive significant regarding patenting behavior.

Table 7: Result of endogenous switching Poisson model

Variable	Patent equation Coeff. (Std.Err.)	Switching eq. Coeff. (Std.Err.)
venture capital	0.4030**	
	(0.1598)	
log(R&D employees)	1.8333***	0.2752
	(0.3263)	(0.3206)
man-university	0.7366***	0.2243
	(0.2095)	(0.2622)
man-technical	-0.2665	-0.2465
	(0.3119)	(0.2417)
man-tech-ba	0.0821	-0.4527
	(0.3698)	(0.2900)
man-company	-0.3075*	0.1883
	(0.1809)	(0.2321)
man-serial	-1.2021***	-0.0645
	(0.1547)	(0.2255)
risk-obsolete	0.2549	-0.0514
	(0.1793)	(0.2597)
risk-government	-0.1582	-0.2862

	(0.1882)	(0.1901)
log(dist-uni)	0.0213**	-0.0088
	(0.0091)	(0.0079)
log(dist-res)	-0.0222***	0.0005
	(0.0065)	(0.0054)
team		0.2762
		(0.2207)
pat-before		0.1759
		(0.2759)
man-major		-0.1148
		(0.2113)
cap-com		-0.0514
		(0.3423)
rating		-0.4564**
		(0.2964)
dummies foundation year	included	
industry dummies	included	
constant	-4.8537***	0.7898
	(0.3610)	(0.9037)
sigma	1.8560***	
	(0.0755)	
rho	0.3612***	
	(0.0968)	
Log-likelihood	729.9834	
No. of obs.	713	

One, two and three asterisks indicate significance at the 10%, 5% and 1% level respectively.

5 Conclusion

This paper investigates the impact of venture capital financing on innovation. The starting point for the analysis are the papers by Kortum and Lerner (1998, 2000). This paper first looks at the relationship of VC financing on patenting as well as at the impact of R&D employees. In a second analysis the impact factors on firm's innovativeness are focused whereas VC and R&D activities are supposed to play a major role.

The hypotheses tested in this paper state that VC financing as well as R&D employees influence positively both patenting and innovativeness of a firm. For the investigation regarding patenting behavior a count data model is estimated and concerning the innovativeness issue a multinomial logit model is applied. The estimations concerning the patenting activities show the conjectured signs which are all significant. Patenting also depends positively on the proximity to research facilities which may reflect knowledge spillovers but at the same time the innovative results have to be protected against being acquired by the research institute. The impact of VC financing on innovativeness is significant for the probability of developing the new methods and technologies by the firm itself. Finally, we also account for the endogeneity issue of VC. The results are robust and display a positive significant effect for patenting.

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A High-tech industries

Table 8: List of high-tech industries used in the telephone survey

Manufacturing sectors	
NACE Code	**Industry**
2233	Reproduction of computer media
2330	Processing of nuclear fuel
2411	Manufacture of industrial gases
2412	Manufacture of dyes and pigments
2413/2414	Manufacture of other inorganic and organic basic chemicals
2417	Manufacture of synthetic rubber in primary forms
2420	Manufacture of pesticides and other agro-chemical products
2430	Manufacture of paints, varnishes and similar coatings, printing ink and mastics
2441	Manufacture of basic pharmaceutical products
2442	Manufacture of pharmaceutical preparations
2461	Manufacture of explosives
2462	Manufacture of glues and gelatines
2463	Manufacture of essential oils
2464	Manufacture of photographic chemical material
2466	Manufacture of other chemical products
2911	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
2912	Manufacture of pumps and compressors
2913	Manufacture of taps and valves
2914	Manufacture of other general purpose machinery
2931	Manufacture of agricultural tractors
2932	Manufacture of other agricultural and forestry machinery
2940	Manufacture of machine tools
2952	Manufacture of machinery for mining, quarrying and construction
2953	Manufacture of machinery for food, beverage and tobacco processing
2954	Manufacture of machinery for textile, apparel and leather production
2955	Manufacture of machinery for paper and paperboard production
2956	Manufacture of other special purpose machinery
2960	Manufacture of weapons and ammunition
3001	Manufacture of office machinery
3002	Manufacture of computers and other information processing equipment
3110	Manufacture of electric motors, generators and transformers
3140	Manufacture of accumulators, primary cells and primary batteries
3150	Manufacture of lighting equipment and electric lamps
3162	Manufacture of other electrical equipment
3210	Manufacture of electronic valves and tubes and other electronic components
3220	Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy

NACE Code	Industry
3230	Manufacture of television and radio receivers, sound or video recording or reproducing apparatus and associated goods
3310	Manufacture of medical and surgical equipment and orthopaedic appliances
3320	Manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes, except industrial process control equipment
3330	Manufacture of industrial process control equipment
3340	Manufacture of optical instruments and photographic equipment
3410	Manufacture of motor vehicles
3430	Manufacture of parts and accessories for motor vehicles and their engines
3520	Manufacture of railway and tramway locomotives and rolling stock
3530	Manufacture of aircraft and spacecraft
Technology-oriented service sectors	
642	Telecommunications
72	Computer and related activities
731	Research and experimental development on natural sciences and engineering
742	Architectural and engineering activities and related technical consultancy
743	Technical testing and analysis

Table 9: Distribution of stratification criteria in the basic population

	high-tech 1	high-tech 2	hardware	software	tech. serv	total
1996 to 2000	839	2,743	2,489	10,971	20.554	37,596 (51%)
2001 to 2005	763	3,088	2,250	10,767	18,868	35,736 (49%)
total	1,602 (2%)	5,831 (8%)	4,739 (6%)	21,738 (30%)	39,422 (54%)	8,000 (11%)

B Conception of the ZEW Hightech Founders Survey 2006

The survey consists of telephone interviews of about 1,000 young firms in technology- and knowledge-intensive sectors which have been founded between 1996 and 2005. The survey is based on a sample of the ZEW Foundation Panels (ZEW-FP) provided by Creditreform a decentrally organized credit-rating agency.

The basic population underlying the telephone interviews isolated out of the ZEW-FP needed to fulfil several conditions besides the specific sector assignment and the founding date. First, the ZIP Code needed to be entered in the ZEW-FP since besides the name of the firm it is mandatory to identify a firm if any reinvestigation would be necessary. Only one percent of the basic population lacked the ZIP Code. Furthermore, all firms are excluded for which Creditreform entered a closing comment.

The distribution of the basic population according to sectors and cohorts is given in Table 9. From this basic population the population sample for the telephone interviews has been drawn in a stratified random manner. The stratification is done according to the foundation date which have been divided into two periods, the pre- and post-boom-phase of high-tech industries. The second stratification criteria is based on the industries.

Since the distribution of the stratification criteria is very skewed (see Table 9), the probability of one firm to be drawn and to be interviewed is quite different in the cells of the stratification criteria (see Table 10). Therefore, the survey design is in line with the so-called choice-based sampling.

Table 10: Distribution of industries and cohorts in the stratified sample and respective probabilities of draw

	high-tech 1	high-tech 2	hardware	software	tech. serv	total
1996 to 2000	680	920	680	840	880	4,000
	(81%)	(34%)	(27%)	(8%)	(4%)	(11%)
2001 to 2005	680	920	680	840	880	4,000
	(89%)	(30%)	(30%)	(8%)	(5%)	(11%)
total	1,360	1,840	1,360	1,680	1,760	8,000
	(85%)	(32%)	(29%)	(8%)	(4%)	(11%)

C Distribution of the population sample

D Question for innovativeness

In the following we want to know more about the characteristics of your product/your service. I read some statements. Please tell me whether these statements apply to your product/your service.

1	Is your product/service characterized by the input of new methods and technologies, which have been developed by your firm?
2	Is your product/service characterized by the input of new methods and technologies, which have been developed by other firms?
3	Is your product/service characterized as an innovative combination of tried and tested methods and technologies?
4	Is your product/service characterized as an established combination of tried and tested methods and technologies?

E Poisson and Negative Binomial Models

In this section the results of the non-zero inflated models are displayed. The Poisson distribution has only one parameter which determines conditional mean and variance, i.e. $E(Y_i) = var(Y_i) = \lambda_i$. This characteristic is called equi-dispersed. The Poisson regression model assumes that $E(Y_i|x_i) = exp(x_i\beta) = \lambda_i$. The advantages of a Poisson regression model are that it captures the discrete and non-negative nature of the variables. Furthermore, the outcome zero is attributed a non-negligible probability and inference is allowed to be drawn on the probability of event occurrence, thus, it accounts for the heteroskedastic and skewed distribution of non-negative data.
The log-likelihood function to be estimated takes the following form

$$ln(L(\beta; y, x)) = \sum_{i=1}^{n}(-\lambda_i + y_i x_i^{'}\beta - ln y_i!) = \sum_{i=1}^{n}(-exp(x_i\beta) + y_i x_i^{'}\beta - ln y_i!)$$

.

The results are presented in Table 11.
A crucial assumption of the Poisson regression, which is often violated in applied work, is the equality of mean and variance. Often the problem of overdispersion arises. The negative binomial regression model allows for overdispersion. To test for overdispersion and which Negbin model should apply I conduct the following auxiliary regressions (see Cameron and Trivedi, 1986, 1994**?**, 1998).

$$(y_i - \hat{\lambda}_i^{\,2}) = \alpha\hat{\lambda}_i + u_i \; for \; Negbin1$$

$$(y_i - \hat{\lambda}_i^{\,2}) = \alpha\hat{\lambda}_i^{\,2} + u_i \; for \; Negbin2$$

where $\hat{\lambda}_i$ are the predictions for $x_i\hat{\beta}$ and test whether α is positive significant, i.e. overdispersion is confirmed.
Since we have tested overdispersion against the Negbin 2 form we now estimate a count data model of this kind. The negative binomial model can be interpreted and derived as a mixture of Poisson and Gamma models (Cameron and Trivedi, 1998). The random count y_i is still Poisson distributed as in equation **??**, where

$$\begin{aligned}
\lambda_i &= exp(\beta_0 + x_i^{'}\beta_1 + \epsilon_i) \\
&= e^{(\beta_0 + x_i^{'}\beta 1)} e^{\epsilon_i} \\
&= \mu_i v_i \text{ where } v_i \text{ has gamma density}
\end{aligned}$$

It follows that

$$Pr(y_i|\mu,\alpha) = \frac{\Gamma(\alpha^{-1}+y)}{\Gamma(\alpha^{-1}\Gamma(y+1))}(\frac{\alpha^{-1}}{\alpha^{-1}+\mu})^{\alpha^{-1}}(\frac{\mu}{\mu+\alpha^{-1}})^{y}$$

where $\mu = exp(x_i\beta)$
The conditional moments are

$$\begin{aligned} E(y|\mu,\alpha) &= \mu \\ var(y|\mu,\alpha) &= \mu(1+\alpha\mu) \end{aligned}$$

If $\alpha > 0$ the variance is larger than the mean so that this model accounts for overdispersion. The results are presented in Table 11 in the Appendix.
Table 11 displays the results of the Poisson and Negbin regressions. A first look at the bottom of the table indicates that the Likelihood-ratio test that the variance parameter α equals zero is rejected. That means that the appropriate model to interpret is the Negbin model. The table display the incidence rate ratios and indicates that VC-financing and the number of R&D employees have a positive impact on the expected number of patents.

Table 11: Result of count data models

Model	Poisson	NegBin 1	Negbin 2
Variable	IRR	IRR	IRR
	(Std.Err.)	(Std.Err.)	(Std.Err.)
venture capital	9.071***	5.413***	5.933***
	(5.956)	(2.665)	(3.336)
log(R&D employees)	3.170***	1.790***	2.338***
	(0.851)	(0.393)	(0.498)
d_R&D	0.593	0.477**	0.419**
	(0.277)	(0.148)	(0.141)
log(vc * R&D)	0.245**	0.467**	0.822
	(0.140)	(0.174)	(0.408)
m_phd	2.314**	2.337**	2.982***
	(0.417)	(0.818)	(1.241)
m_university	1.908	1.786*	1.946*
	(0.395)	(0.559)	(0.662)
m_technical	0.614	1.323	0.740
	(0.400)	(0.514)	(0.332)
m_company	0.553*	0.801	0.855
	(0.193)	(0.209)	(0.261)

m_serial	0.719	0.791	0.762
	(0.192)	(0.176)	(0.213)
intermediate	1.094	1.065	1.211
	(0.294)	(0.251)	(0.322)
package	1.116	1.110	1.826**
	(0.326)	(0.259)	(0.521)
risk_obsolete	1.047	1.019	0.585
	(0.386)	(0.375)	(0.201)
risk_govern	0.424**	0.861	0.614
	(0.161)	(0.217)	(0.191)
log(dist_uni)	1.206**	1.032	1.079
	(0.115)	(0.084)	(0.130)
log(dist_inst)	0.824***	0.940	0.998
	(0.061)	(0.063)	(0.089)
foundation years		included	
industry dummies		included	
N	713	713	713
ll	-875.07	-452.04	-461.55
chi2	1171.51***	126.10***	107.08***
LR-test ($\alpha = 0$)		846.07***	827.05***
Goodness-of-fit test	1464.15***		
Pearson's Gof test	6259.01***		
McFadden R-squared	0.401	0.122	0.104
aic	1802.14	958.07	977.09
bic	1920.95	1081.45	1100.47

One, two and three asterisks indicate significance at the 10%, 5% and 1% level respectively.