Dicsussion Papers on Entrepreneurship, Growth and Public Policy

MAX-PLANCK-GESELLSCHAFT

#2205

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by

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Number of Pages: 23

The *Papers on Entrepreneurship, Growth and Public Policy* are edited by the Group Entrepreneurship, Growth and Public Policy, MPI Jena.
For editorial correspondence,
please contact: egppapers@mpiew-jena.mpg.de

ISSN 1613-8333

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Firm Level Implications of Early Stage Venture Capital Investment.*
– An Empirical Investigation –

Dirk Engel† Max Keilbach‡

Abstract

The paper analyses the impact of venture capital finance on growth and innovation activities of young German firms. Among other variables, our panel of firm data includes data on venture capital funding and patent applications. With statistical matching procedures we draw an adequate control group of non-venture funded but otherwise comparable firms. The analysis confirms other findings that venture funded firms in Germany have higher number of patent applications than those in the control group. However, they do so already before the venture capitalists engagement. After this engagement, the number of patent applications does not differ significantly from that of the control group, however the venture funded firms display significantly larger growth rates. We conclude that the higher innovation output of venture funded firms is mainly driven by the selection process made by the venture capitalist.

Keywords: Firm Demography, Firm Start-Ups, Firm Growth, Venture Capital, Patented Inventions, Microeconometric Evaluation Methods

JEL-Classification: L 21, D21, D92, C14, C33

1 Introduction

Between 1995 and 2000 the German venture capital market evolved extraordinarily in that the volume of newly closed deals has increased by a factor of nearly 8.[1] One major factor in this regard was certainly the implementation of the "Neuer Markt", the German equivalent to the United States' NASDAQ, and the exit opportunities related to it. A second major factor was the diffusion and adoption of information and communication technologies and a corresponding wave of firm start-ups. These start-ups were expected to exhibit large growth rates but required large initial investments

*We gratefully acknowledge financial support by the German Science Foundation (DFG) within research focus "Interdisziplinäre Gründungsforschung" under contract number STA 169/10-1.

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[1] Between 2001 and 2004, the number and volume of newly closed deals has decreased considerably.

that classic banks were usually not able or willing to finance. Finally, a third factor in Germany was the influence of the "Technologiebeteiligungsgesellschaft (tbg)", a public organization that co-invests with private lead investors to double the financial volume of the deal. Moreover, it acts like an insurance by partly covering the risk that the deal fails.

The commitment of the German government to ease the access of young technology oriented firms to venture funds is based on the assumption that these firms are more innovative and will be able to open or capture new market niches more easily. Thus, these firms are supposed to grow faster, therefore generating employment and fostering structural adjustments to the German economy. If these firms are provided with venture capital along with corresponding services (such as management support) – so the implicit assumption – they will be able to perform even better.

In this paper, we investigate these assumptions empirically. Is it true that venture funded firms perform better in terms of employment growth rates and innovative output? To do so, we set up a new dataset on young German firms. For each of these firms we identify a number of variables on the firm level, the industry level and the regional level. Moreover, we identify whether the firm has been venture capital funded or not. By merging this dataset with data from the German Patent Office, we are able to describe the innovative behavior of these firms using the number of patent applications as a proxy variable for innovative output. Then, venture capital funded firms are compared with others in terms of growth rate and innovative output using a statistical matching approach. This approach corrects for statistical biases that would occur when firms of different characteristics are compared on the basis of standard econometric methods.

The paper gives evidence on several levels: Firms with a higher number of patents have a higher probability of getting venture capital. Once a venture capitalist is involved, firms show greater employment growth rates but no significant differences in innovative output. We conclude from these findings that after the involvement of a venture capitalist, firms switch from innovation to commercialization of their products and therefore are able to realize superior growth rates.

The following section gives an overview on the literature on the implications of venture capital funding on firm growth and innovation, section 3 presents the dataset, section 4 presents the evaluation procedure, results are dicussed in sections 5 and 6.

2 The Impact of Venture Capital Funding on Growth and Innovative Behavior of Firms

Venture capital is a financing form suitable for projects or ventures that have great financial needs and great risks involved, but at the same time a high potential for growth hence for potentially large profits. A deal between a venture capitalist and a portfolio firm implies that the former provides not only venture funding but also management advice to close the gap in managing non-technical shortcomings (Amit *et al.*, 1998, Berger and Udell, 1998, Gompers and Lerner, 1999, Hellmann and Puri, 2002).

Very often, the selection of portfolio firms is made under the assumption that *innovative firms* have a greater growth potential and therefore offer larger potential profits. In this section we give a survey on the literature on venture capital and its relation to firm performance and innovation.

2.1 Venture Capital and Firm Growth

A number of studies examine empirically the relationship between venture funding and firm performance (see Schefczyk (2000) for a detailed overview). Sapienza (1992) found that the provided services are positively related to the performance of venture funded firms. Jain and Kini (1995) show that publicly listed venture funded firms in the U.S. have a higher cash flow and sales growth compared to non-venture funded ones. Bottazzi and da Rin (2002), analyzing the growth performance of 270 venture funded firms listed at European Stock Exchanges, cannot support these findings. While both studies use an adequate number of variables to select a control group, the selection of the venture funded firms itself does not seem to be appropriate: since only successfully funded firms go public, the growth impact of venture capital is overstated by this selection.

Lerner (1999) evaluates the long run success of firms participating in the Small Business Innovation Research (SBIR) program, a major public assistance initiative in the United States for high-technology firms. Those firms receiving assistance from SBIR achieved significantly higher employment and sales growth rates than similar Non-SBIR assisted firms between 1983 and 1995. These differences are even more pronounced in ZIP codes with high venture capital activity. The findings of Manigart and Hyfte (1999) for 187 Belgian venture funded firms are quite different. Belgian venture funded firms do not achieve a significant higher employment growth compared to non-venture funded firms of the same industries, of similar size, and similar age. However, they observe higher growth rates in total assets and cash flow. Buergel *et al.* (2000) do not observe any significant effect of venture capital finance on firms' sales and employment growth. Their multivariate analysis of the determinants of firm growth is based on a survey of 500 German and British high-tech start-ups. Coopers & Lybrand and EVCA (1996) found that venture funded firms grew more than seven times faster than the European top 500 firms. This is impressive, however it remains unclear what drives this difference since the choice of the control group seems not to be made appropriately in that study. In setting up the approach to be used in this paper (in section 4), we will discuss this further and suggest a more appropriate method.

2.2 Venture Capital and Firms' Innovative Bevahior

Despite the increasing importance of venture capital investment, the relation between this type of investment and the innovative behavior of firms has rarely been analyzed. For Germany, we have been unable to find any analysis. Kortum and Lerner (2000) examine the influence of venture capital on patented innovation in the US. Their analysis is based on data on manufacturing industries between 1965 and 1992 using observations on counts of issued patents and venture funding. Using a number of different structural forms of a patent production function, they estimate the productivity of venture capital financed innovation projects to be significantly higher as compared to projects financed by private R&D funds, although these estimates differ widely according to the specification of the regression equation.[2]

Kortum and Lerner also address the concern that this result might be due to a different patenting behavior of firms in search of venture funding due to strategic reasons. Obviously, a firm increases its chances to close a deal if it can prove that its innovative performance is high. A corresponding strategy would be to apply for a maximum of patents before trying to find a venture partner. Secondly, firms that seek for venture investment have an incentive to patent in order to protect the embodied knowledge against leakage to the venture capital firm. Otherwise the venture capital firm might communicate that knowledge to another portfolio firm in order to exploit it that way. Hence, in that case, the patent plays its role as protection mechanism. Both reasons would lead to a significant positive bias in the number of patent applications, and probably in the number of subsequently issued patents. However, Kortum and Lerner (2000) can not find evidence for such a behavior. On the other hand, Hellmann and Puri (2000) find on the basis of a dataset of 149 Silicon Valley firms that innovating firms are indeed more likely to obtain venture funding than imitator firms.

Based on a sample of 530 firms located in Middlesex county in Massachusetts, Kortum and Lerner (2000) could show that venture funded firms do not only receive a larger number of patent awards but also higher scores concerning different variables that can be expected to be correlated with the value of the patent.[3] They take these findings as evidence in favor of the hypothesis that venture funded firms are more

[2]Depending on the form of the regression equation, they estimate that the productivity of venture funded firms is between 1.5 and 40 times larger compared to non-venture funded ones, most of the estimation results lying between 1.5 and 3.

[3]See e.g. Lanjouw, Pakes and Putnam (1998), Lanjouw and Schankerman (1999), Harhoff, Scherer and Vopel (2003) for a discussion of this issue.

innovative, producing a larger and higher valued stock of patents.

The approach chosen in this paper differs to the one chosen by Kortum and Lerner. Since we use firm level data instead of industry data, we are able to identify a number of firm specific variables that can be expected to influence firms' growth and innovative performance. Specifically, we are able to identify two effects. First, for venture funded firms, we can identify the exact moment of the venture engagement and thus the ex ante and ex post performance of these firms. Second, we are able to identify "twin" firms, i.e. firms that are similar with respect to age, size, industry affiliation and other variables while only one firm of each twin receives venture funding. By building these matched pairs, and analyzing their behavior statistically, we implicitly correct for industry affiliation and timing effects that might bias the results by Kortum and Lerner. Indeed, based on our data we find that while on the aggregate level, venture funded firms do indeed grow faster and show stronger innovative behavior, a microeconometric, i.e. firm level analyses leads to different results. We conclude that an aggregate analysis might not be appropriate and previous studies on this level might be biased.

The following section describes the data, section 4 gives a short overview on the matching process and section 5 discusses the results.

3 The Data

Our analysis is based on a microlevel database on German firms that is developed and maintained by the ZEW in Mannheim, Germany. The raw data of this firm-specific information has been provided by *Creditreform*, the largest German credit rating agency (see Almus, Engel and Prantl (2000) for more details on this data). The data is updated and extended twice a year which allows the ZEW to build up a panel structure. These updates cover information on previously surveyed firms and information about newly created firms.

This dataset comprises virtually all firms registered in the German trade register. However, firms are entered in the database only with a time lag. Thus, only 60 percent of the firms created in 2000 are recorded by January 2002; after a 4 year time lag, virtually full coverage is attained. Therefore, we limit our analysis on new firms with foundation date between 1995 and 1998. Plausibility checks with data from the German Venture Capital Association (BVK, 2000b) indicated that our database covers virtually all firm start-ups from that time period that received venture capital, i.e. we have full coverage for this period.

This database covers a number of firms specific variables, such as number of firms' employees, foundation date, main economic activity (i.e. industry affiliation expressed by NACE classification), legal state, details on natural and legal owners, owners liability status and finally firms' addresses. A number of variables concerning the spatial environment of firms can be derived from the latter. This includes e.g. information on the population density of the region of the firm or distances to different types of scientific research centers. The database does not explicitly cover information on whether the firm is venture funded, on the firms' growth rate or on the number of patents applied for by each firm. These variables are computed or merged to our dataset from other sources.

The identification of *venture funded firms* is based on a computer-assisted string search (including information on names and office of venture capital companies) in the variables covering ownership information. All venture capital companies that are private equity investors and full members of European Venture Capital Association (EVCA) or German Venture Capital Association e.V. (BVK) are considered. We identify these on the basis of the corresponding registers (BVK, 2000a, 2000b; EVCA, 2000). Associate members are not taken into consideration because their business activities focus exclusively on management support. Additionally, members of U.S. National Venture Capital Association are considered with activities in 1999 at the U.S. venture capital market (VentureOne, 1999) and a search for key words like "venture capital", "Private Equity" was carried out to identify firms with obvious venture capital activities. We did not include ventures with a silent partner (such as e.g. business angels) since they are not recorded in the trade register (Jacobs and Scheffler, 1998). However, exclusively silent partnerships do not play an important role in early stage financing of profit accounting venture capitalists (see Engel (2004) for further explanations).

In this study we use two measures of firm performance, one is firm growth and another is firms' innovative behavior.

We measure *firm growth* as the *rate of average annual employment growth* g_i for each firm i, hence

$$g_i = \frac{\ln E_{i,t_l} - \ln E_{i,t_k}}{t_l - t_k}, \tag{1}$$

where t_k, t_l denote points in time ($t_l > t_k$) and $E_{i,t}$ denotes the number of employees of firm i at time t. Note that t_k and t_l might be different for firms of different cohorts.

Of course, employment growth is not part of the objective function of venture capital investors. Their interest is rather in the growth of the firm value, which determines the rentability of the venture investment at time of exit. However, a measure for value of the firm is not available for the firms in our dataset. Other measures that are closely related to firm value such as sales or returns[4] are also not available. Measuring

[4]Highly innovative start-ups rarely generate profits in the early stage of their life-cycle. Indeed, in

firm performance by employment growth has three advantages. First, it allows us to relate our findings to other studies (cited in section 2.1) that also used employment growth as performance measure. Second, although employment growth might not be in the objective function of venture capitalists, it is certainly in that of public venture capitalists. Indeed the SBIR program (Lerner, 1999) or the activity of the German tbg are motivated by the expectation of such impacts on employment. Third, using another database on small and medium sized german firms, we found sales and number of employees to be nearly linearly correlated,[5] therefore growth of both variables can be expected to be also highly correlated. We therefore consider the development of the employment level as the best appropriate measure of the potential of the business idea.

Innovative behavior is measured using count data on patent applications at the German Patent Office (DPA). To apply for a patent at the DPA implies lower fees as compared to applications at the European Patent Office (EPO). This implies that smaller firms that are not able (or not willing) to bear the higher fees will apply at the DPA alone. On the other hand, applications at the EPO that cover the German territory will appear in the DPA dataset (PATDPA) as well. Hence, we can expect the German database to be more complete.

The assignment of patent applications to firms is realized using a computer-assisted merging procedure similar to the one used for identification of venture funded firms. Both data bases, the firm data and the patent application data, cover information on the firms' names and their location. The merging algorithm synchronizes both databases using the information in these strings.

The use of patent applications as an output measure of innovative behavior has often been criticized. Patents are primarily legal titles that protect the output of an innovation process from being copied. Hence firms can be expected to apply for a patent if they believe that this is a meaningful way of protecting their intellectual property. However firms might use other strategies to protect their innovations, such as secrecy or speed of innovation. Thus, due to at least three reasons, not all innovative output can be expected to be patented. First, not all innovations are patentable such as e.g. innovations in the service sector. Second, even if an innovation is patentable, a firm might choose to not apply for a patent since the duration of the procedure is too long relative to the duration of the innovation cycle and third, a firm might not apply since it discloses at least some of the knowledge that is imbedded in the innovation (see Griliches (1990) for an extended discussion of this topic.)

our observation period, the value of a firm when going public was often large even though the firm had generated considerable financial losses. Hence returns is not an appropriate measure for value here.

[5]The correlation coefficient is at 0.94 and statistically significant. This database is the Mannheim Innovation Panel (MIP) that is based on questionnaires. It is therefore very detailed but small.

Nevertheless, using patent applications is still the dominant approach to measuring innovative output (e.g. Kortum and Lerner, 2000) since it is the most detailed and best documented data on innovative output available. Other datasets, such as the Community Innovation Survey of the European Union, give more general measures of innovative output. However the number of observations is very small and in connection with our research question not viable. We therefore follow Kortum and Lerner (2000) and refer to patent applications as measure of firms' innovation output. We control for the strategic aspect of patenting by controlling for industry affiliation in our analysis, assuming that the strategies of protecting innovative output are similar within industries.

We limit our analysis to industries where we observed at least one venture funded firm. Also, we only consider firms with Limited Partnership (GmbH or GmbH & Co. KG) or Public Limited Companies (AG) as legal forms. The registration of the startup date of a firm with other legal forms can be very biased (i.e. delayed). Note however that all firms in our database that received venture capital had limited legal forms, i.e. we do not reduce our sample of venture funded firms due to this restriction. Moreover, we included only firms that have at least two entries with respect to their firm size such that a growth rate can be computed according to equation (1) and we limit our analysis to industries that have at least one patent application. On the basis of these requirements, our sample covers 21,375 non-venture funded and 142 venture funded firms (i.e. 0.66% of the firms in the sample).

Table 1 enumerates the variables in the dataset. We use an ad-hoc mixture of 2 digit and 3 digit industry classifications such that industries with higher shares of venture funding (mainly in the service sector) are implemented on a more detailed level. The corresponding NACE codes are given in brackets. Columns 2 (VF: venture funded) and 3 (NVF: non-venture funded) of this Table show the mean value of each variable for each of both sets of firms as well as the results of a statistical test for identity (with significance levels denoted by stars). The values express shares unless denoted otherwise (i.e. where shares are not meaningful).

Table 1: Difference between Venture Funded and non-venture Funded Firms in our dataset

	Shares (unless denoted otherwise)	
Firm characteristics at foundation	**VF**	**NVF**
Firm-specific characteristics		
Startup size (number of employees)	6.979	5.165**
Limited partnership (GmbH & Co KG)	0.148	0.092*
Public limited company (AG)	0.099	0.016***
Involvement of other (non VC) firms	0.472	0.279***

Continued on next page

Table 1: (continued)

	Shares (unless denoted otherwise)	
Firm characteristics at foundation	**VF**	**NVF**
Team foundation	0.620	0.451***
Founding team of mixed gender	0.106	0.123
Founders are of female gender	0.014	0.103***
Gender Unknown	0.120	0.083
Education of Founders		
Doctoral degree	0.289	0.078***
Postgraduate degree	0.528	0.385***
Higher education on the job	0.014	0.074***
Medium education on the job	0.254	0.389***
Low education	0.021	0.028
Education level unknown	0.296	0.244
Patenting Behavior		
No patents before foundation date	0.894	0.979***
One patent before foundation date	0.035	0.009*
2...4 patent before foundation date	0.028	0.008
5...19 patent before foundation date	0.042	0.004*
20...49 patent before foundation date	0.000	0.000
Industry Affiliation (with Nace code)		
Manuf. of food products etc. (15)	0.007	0.021*
Manuf. of wearing apparel etc. (18)	0.007	0.005
Manuf. of wood and its products etc. (20)	0.014	0.015
Publishing, printing etc. (22)	0.021	0.045*
Manuf. of chemicals and chemical products (24)	0.028	0.014
Manuf. of rubber and plastic products (25)	0.007	0.020*
Manuf. of other non-metallic mineral products (26)	0.021	0.023
Manuf. of fabricated metal products etc. (28)	0.021	0.071***
Manuf. of machinery and equipment n.e.c. (29)	0.021	0.060***
Manuf. of office machinery and computers (30)	0.021	0.011
Manuf. of electrical machinery and apparatus n.e.c. (31)	0.042	0.015
Manuf. of radio, television and communication equipment (32)	0.021	0.010
Manuf. of medical, precision and optical instruments etc. (33)	0.035	0.039
Manuf. of motor vehicles, trailers and semi-trailers (34)	0.014	0.012
Manuf. of furniture; manufacturing n.e.c. (36)	0.007	0.022**
Recycling (37)	0.021	0.014
Postal and telecommunication services (64)	0.007	0.005
Computer and related activities (72)	0.197	0.129**
Research and development (73)	0.148	0.024***
Other business activities (740)	0.007	0.006
Business related services (741)	0.148	0.144
Architectural and engineering activities (742)	0.049	0.135***
Technical testing and analysis (743)	0.000	0.000
Advertising (744)	0.042	0.047
Industrial cleaning (747)	0.007	0.016

Continued on next page

Table 1: (continued)

	Shares (unless denoted otherwise)	
Firm characteristics at foundation	**VF**	**NVF**
Misc. business activities n.e.c. (748)	0.085	0.098
Foundation Date		
1995	0.070	0.152***
1996	0.134	0.237***
1997	0.373	0.304*
1998	0.423	0.307***
Regional Characteristics		
Firm is located in Eastern Germany	0.204	0.207
Located in Bavaria	0.197	0.151
Firm is located in Brandenburg	0.028	0.036
Population Density in 1996 (corresponding counties)	6.940	6.389***
Distance to nearest science or technology part	2.704	2.760
Scientific personnel in Universities within 50 km dist.	7.609	7.657
Distance to next Fraunhofer-Institute	2.725	3.126***
Distance to next Helmholtz-Institute	3.053	3.492***
R&D employees in resp. industry	7.350	6.523***
Other		
Average annual employment growth	0.326	0.174***
Entry has been edited within last year	0.923	0.877**
Nr. of observations	142	21,375

****/**/* Difference of mean is significant from zero at 1/5/10 per cent level of significance.*
VF: venture funded firms, begin of involvement is latest twelve months after foundation date, NVF: non-venture funded firms.
Data sources: ZEW Foundation Panels, German Patent Agency, Federal Office for Regional Planning.

This Table shows that in average, venture funded firms have a larger startup size, they have a larger management team[6], their founders are better educated, they have a larger number of patents at foundation date[7], they are less frequent in traditional sectors (such as mechanical engineering) but more frequent in R&D intensive and computer related industries.

Finally, they are mainly founded after 1996 (the takeoff year of the German venture capital market), and they are created in more densely populated areas, but with larger distance to applied research centers. Also, we see at the bottom of Table 1 that firms differ significantly in their average annual employment growth rate.

[6] We derive this from the fact that they more fequently are founded as Public Limited Company and have more than one founder.

[7] While roughly 10% of venture funded firms have at least one patent at foundation date, only 2% of non-venture funded firms do so. For these start-ups, the innovation that underlies the patent might be considered as the motive to start up a new firm. Think e.g. of a patent that is owned by a university researcher who starts up a new firm on this basis.

Table 2 compares average growth rates of venture funded and non-venture funded firms grouped into different industry aggregates. These figures suggest that venture funded firms grow faster on average, however this difference is driven by the technology intensive service (which includes software developers) subgroup. Section 5 will show whether these results hold after correcting for potential selection biases.

Table 2: Comparison of annual growth rates of venture funded and non venture funded firms

	Means		p-value*
	VF	*NVF*	
All Firms	0.367	0.193	0.003
(Number of firms)	(216)	(37,122)	
Manufacturing Industry	0.286	0.180	0.183
(Number of firms)	(65)	(14,118)	
Technology Intensive Services	0.451	0.203	0.005
(Number of firms)	(88)	(10,934)	
Other Business Related Services	0.334	0.198	0.224
(Number of firms)	(63)	(12,070)	

VF: Venture-Funded; NVF: Non-Venture-Funded
**p-values express probabilities of means to be identical, based on a two sided t-test.*

Table 3: Comparison of the average number of patent applications by venture funded and non venture funded firms

	Means		p-value*
	VF	*NVF*	
All Firms	1.084	0.134	0.000
(Number of firms)	(274)	(50,754)	
Manufacturing Industry	2.524	0.265	0.000
(Number of firms)	(82)	(17,957)	
Technology Intensive Services	0.620	0.090	0.000
(Number of firms)	(108)	(14,919)	
Other Business Related Services	0.274	0.052	0.122
(Number of firms)	(84)	(17,878)	

VF: Venture-Funded; NVF: Non-Venture-Funded
**p-values express probabilities of means to be identical, based on a two sided t-test.*

Table 3 compares average number of patent application by firms in the sample at the industry level using the same industry aggregates as above. The computation of these numbers has been done on the industry level, therefore Table 3 is similar to Table 6 in Kortum and Lerner (2000, p.690). The results of the t-tests on identical means suggest that venture funded firms show a significantly larger number of patent-applications compared to their non-venture funded counterparts. While the numbers in our table differ in magnitude from those given by Kortum and Lerner (2000, Table 6), the ratio of patent applications from venture funded firms to non venture funded firms is roughly the same. This difference is due to the fact that we consider only young firms. As for firm growth, these results will be reconsidered in section 5.

4 Description of the Evaluation Procedure

4.1 Background: Evaluation and The Selection Problem

To assess the contribution of venture capital funding to firms' growth and innovative behavior, we aim to quantify the difference between the state of the firms after funding and the hypothetical state of their innovative behavior if they had not been funded by a venture capitalist. Of course, this latter state – called *counterfactual* – is not observable, and therefore has to be estimated (e.g. Heckman *et al.*, 1999). Let "(1)" denote venture funding (or *treatment*) and "(0)" denote non-venture funding (or *non-treatment*). Then denote $\mathbf{Y}^{(1)}$ the outcome of the target variable of treated firms (in our case growth and innovative behavior of venture funded firms) and $\mathbf{Y}^{(0)}$ the outcome of this variable for non-treated firms. Then the evaluation task is expressed formally as measuring the *average treatment effect*

$$\theta^{(1)} \quad = \quad \mathrm{E}[\bar{\mathbf{Y}}^{(1)} - \bar{\mathbf{Y}}^{(0)} | VC = 1] \quad = \quad \mathrm{E}[\bar{\mathbf{Y}}^{(1)} | VC = 1] - \underbrace{\mathrm{E}[\bar{\mathbf{Y}}^{(0)} | VC = 1]}_{c},$$

where c denotes the counterfactual and $VC = 1$ indicates venture funding. If we were able to assume that venture capital funded firms did not differ significantly non-funded firms in their characteristics, it would be straightforward to estimate this counterfactual using observations on the latter. However, two factors will make it impossible to maintain this assumption, i.e. lead to a systematic difference in treated and non-treated firms and therefore to a statistical bias when comparing both (Lechner, 1998 discusses this problem in detail). First, venture capitalists are investing only into those firms that have survived an extensive pre-investment screening process. That is, venture funded firms have been selected on the basis of superior performance. Second, firms who believe that their performance will not be sufficient for being considered for venture funding will not apply for venture funding, i.e. they will even not participate in the screening process. This phenomenon leads to a statistical bias through *self-selection.*

Table 1 has made these differences between venture funded and non-venture funded firms explicit. However, due to the implicit bias in the selection of firms into one of both groups, these differences cannot yet be taken as evidence in favor of a positive contribution of venture funding to firm growth or to firms' innovative behavior. This selection bias can be corrected for by explicitly modelling the selection process. Different approaches have been suggested to doing so (e.g. Heckman *et al.* (1999) or Keilbach (2005) for a survey). In this paper we choose a statistical matching procedure, which is described in the following section.

4.2 Description of the Matching Procedure

Microeconomic evaluation studies would be straightforward if the "treated participants" (i.e. the venture funded firms) are chosen at random and the number of firms is sufficiently large to assure that we can find identical ("twin") firms, one of which is treated while the other is not. This approach of a *randomized experiment* is used in other disciplines such as pharmaceutics. However, due to the systematic selection of firms into venture funding, we cannot expect such a random assignment.

Assume, however, that we can identify a set of k variables $\mathbf{X}$ that are correlated with the selection process. The *conditional independence assumption* (CIA), put forward by Rubin (1977) states that different firms i with nevertheless identical realizations of $\mathbf{X}_i$ (denoted $\mathbf{x}_i$) differ in their target variable Y_i significantly only, through the implications of their treatment. Put formally, in the case of venture capital financing, the CIA states

$$\mathrm{E}[\mathbf{Y}^{(0)}|VC = 1, \mathbf{X} = \mathbf{x}] \quad = \quad \mathrm{E}[\mathbf{Y}^{(0)}|VC = 0, \mathbf{X} = \mathbf{x}],$$

If this assumption is met, the average treatment effect $\theta^{(1)}$ can be estimated as

$$\widehat{\theta}^{(1)} \quad = \quad \mathrm{E}[\bar{\mathbf{Y}}^{(1)}|VC = 1, \mathbf{X} = \mathbf{x}] - \mathrm{E}[\bar{\mathbf{Y}}^{(0)}|VC = 0, \mathbf{X} = \mathbf{x}].$$

Given however the large number of variables, their metric nature and the implied high dimensionality of the matching procedure, it is virtually impossible to find two firms with identical realisation of $\mathbf{X}$,[8] i.e. to find exact matches ("twin pairs") of venture funded an non-venture funded firms.

Rosenbaum and Rubin (1983) show that if there exists a function $b : \mathbb{R}^k \mapsto \mathbb{R}^1$, the use of $b(\mathbf{X})$ is equivalent, i.e. the average treatment effect $\theta^{(1)}$ can be estimated with

$$\widehat{\theta}^{(1)} = \mathrm{E}[\bar{\mathbf{Y}}^{(1)}|VC = 1, b(\mathbf{X}) = b(\mathbf{x})] - \mathrm{E}[\bar{\mathbf{Y}}^{(0)}|VC = 0, b(\mathbf{X}) = b(\mathbf{x})].$$

Once this function is identified, the matching task simplifies considerably since the dimensionality of the task reduces to 1 and the matching partner can be found through simple computation of differences in $b(\mathbf{x})$ between treated i and non-treated counterpart j. There exist mainly two main approaches to realize this computation. One is *caliper matching* (Cochran and Rubin, 1973), defining j to match i if the difference of their realization of $b(\mathbf{x})$ is within a predefined range δ, hence if $[b(\mathbf{x})_i - b(\mathbf{x})_j] < \delta$. On the other hand, *nearest neighbor matching*[9] defines j to match i such that $\min_{i,j}[b(\mathbf{x})_i - b(\mathbf{x})_j]$. While the first approach accepts all counterparts within a certain distance between $b(\mathbf{x})_i$ and $b(\mathbf{x})_j$ (usually a fraction of the

[8] The first column of Table 1 enumerates the variables in the database.

[9] See Heckman and Ichimura (1998) or Heckman *et al.* (1999, p. 1953) for a discussion of this method. Cochran and Rubin (1973) compare caliper matching and nearest neighbor matching.

standard deviation of the estimate of that distance), the second approach chooses the counterpart with minimal distance. The second approach is therefore more efficient as long as the distributions of the propensity scores of treated and non-treated groups overlap.

An intuitive and often used realization of $b(\cdot)$ is the *propensity score* that expresses the firms' conditional probability (i.e. their "propensity") to be subject to venture funding (conditional on $\mathbf{X}$). This probability can be estimated with a standard probit model of the form

$$\mathrm{E}(VC_i|\mathbf{x}_i) = \Pr(VC_i = 1|\mathbf{x}_i) = \Phi(\mathbf{x}_i'\boldsymbol{\beta}) \qquad \forall\, i = (1, 2, \ldots, N).$$

where $\Phi(\cdot)$ represents the cumulated density function of the standard normal distribution. Based on these estimation results, it is possible to compute each firm's propensity score ps via

$$\widehat{ps}_i = \mathbf{x}_{i'}'\widehat{\boldsymbol{\beta}} \tag{2}$$

which is a scalar for each firm.[10] With an estimated propensity score for each firm at hand, the matching procedure simplifies to finding for each venture funded firm i a non-venture funded counterpart j using one of the distance definitions given above. This approach is referred to as *propensity score matching* (e.g. Rosenbaum and Rubin, 1983).

The main advantage of propensity score matching – simplicity – may be outweighed by the fact that this procedure might identify matching pairs that are close in their propensity score but actually differ in a number of characteristics or variables that should be strictly identical given the topic of investigation (such as e.g. industry affiliation). Of course it is possible to require matching partners to have identical realizations of these variables. This more generalized approach preselects on these variables and then chooses the matching partner under this restriction using a multidimensional distance measure. This method is known in the literature as *balancing score matching*.[11] The cost of this increased accuracy is a reduction in the number of potential matching partners, i.e. this method is suitable for large datasets with small share of treated individuals or firms.

Once the matching partners are identified (i.e. we have determined $\widehat{Y}^{(c)}$), we can estimate the average treatment effect (i.e. the average contribution of venture capital funding to firms' innovative behavior) consistently as (Lechner, 1998)

$$\hat{\theta}^{(1)} = \frac{1}{N^{(1)}} \left(\sum_{i=1}^{N^{(1)}} Y_i^{(1)} - \sum_{j=1}^{N^{(1)}} \widehat{Y}_j^{(c)} \right). \tag{3}$$

[10] Average values of estimated propensity scores are given in Table 5.

[11] See e.g. Heckman *et al.* (1999), Lechner (1998) or Keilbach (2005) for more detailed and formalized presentations of this approach.

The variance of $\hat{\theta}^{(1)}$ can be estimated with

$$\mathrm{Var}\left(\hat{\theta}^{(1)}\right) = \frac{1}{N^{(1)}}\left([S^{(1)}]^2 + [S^{(c)}]^2\right), \tag{4}$$

$S^{(j)}$ being the standard deviation of subsample j.

4.3 Implementation and Result of the Matching Procedure

Firm level variables that can be expected to influence the venture capitalists' selection to invest or not (i.e. variables that should enter $\mathbf{X}$) are mainly the firm's industry affiliation and previous excellence in innovation. We approximate self-selection through contacts and networks by using locational variables, i.e. population density and distance to scientific facilities. Thus, the matching approach assumes implicitly that both groups do not differ with respect to unobservable variables such as commitment of firm founders or scope of the business idea.

Based on this set of variables we run a probit estimation of the propensity score using our sample of 142 German venture funded firms and 21,375 control firms. The results are shown in Table 4. These estimation results can be interpreted economically. Thus, Table 4 provides evidence that firms size has a positive influence on the probability of being venture funded or not. However, firms with limited legal forms are funded with significantly higher probabity. Also firms whose managers have high education degrees and firms with a larger number of patents at foundation date are venture funded with higher probability. This confirms the findings of Hellmann and Puri (2000). The estimation results for industry variables point at the expected direction, i.e. firms in R&D oriented industries are more likely to be venture funded. Again, this probably reflects the dynamic development of the German venture capital market during our observation period, especially for early stage investments. It is remarkable that the probability of being venture funded decreases significantly with increasing regional density of scientific personnel. We leave this for further research.

Table 4: Determinants of Venture Capitalist's Involvement, Probit Estimation

Dependent Variable: Involvement of venture capital company within one year after foundation date

Characteristics at foundation date	*Coeff.*	*p-value**
Firm-specific characteristics		
Startup size (number of employees)	0.0080	0.023
Limited partnership (GmbH & Co. KG)	0.0810	0.522
Public limited company (AG)	0.5964	0.000
Involvement of other (non VC) firms	0.1996	0.024
Team foundation	0.1977	0.006

Continued on next page

Table 4: (continued)

Dependent Variable: Involvement of venture capital company within one year after foundation date

Characteristics at foundation date	Coeff.	p-value*
Founding team of mixed gender	−0.1690	0.128
Founders are of female gender	−0.5302	0.023
Gender unknown	−0.0159	0.896
Education of Founders		
Doctoral degree	0.4158	0.000
Postgraduate degree	0.1448	0.096
Higher education on the job	−0.3187	0.170
Low level of education	0.0656	0.772
Low education	0.2799	0.004
Patenting Behavior		
One patent before foundation date	0.4426	0.036
2...4 patent before foundation date	0.3657	0.114
5...19 patent before foundation date	0.9311	0.000
Industry Affiliation (with NACE code)		
Manuf. of food products etc. (15)	−0.1601	0.638
Manuf. of wearing apparel etc. (18)	0.4644	0.242
Manuf. of wood and its products etc. (20)	0.2462	0.384
Publishing, printing etc. (22)	−0.1725	0.447
Manuf. of chemicals and chemical products (24)	0.2364	0.317
Manuf. of rubber and plastic products (25)	−0.2004	0.575
Manuf. of other non-metallic mineral products (26)	0.0451	0.849
Manuf. of fabricated metal products etc. (28)	−0.1575	0.478
Manuf. of machinery and equipment n.e.c. (29)	−0.3049	0.197
Manuf. of office machinery and computers (30)	0.2841	0.289
Manuf. of electrical machinery and apparatus n.e.c. (31)	0.5718	0.005
Manuf. of radio, television and communication equipment (32)	0.3221	0.230
Manuf. of medical, precision and optical instruments etc. (33)	−0.0055	0.976
Manuf. of motor vehicles, trailers and semi-trailers (34)	0.0653	0.810
Manuf. of furniture; manufacturing n.e.c. (36)	−0.1284	0.711
Recycling (37)	0.3057	0.219
Post and telecommunications (64)	0.0092	0.984
Computer and related activities (72)	0.2020	0.123
Research and development (73)	0.5732	0.000
Other business activities (740)	0.1671	0.682
Business related services (741)	0.0312	0.818
Architectural and engineering activitiesx (742)	−0.2780	0.093
Advertising (744)	0.0917	0.617
Foundation date		
1996	0.0232	0.865
1997	0.3319	0.008
1998	0.3445	0.006
Regional Characteristics		

Continued on next page

Table 4: (continued)

Dependent Variable: Involvement of venture capital company within one year after foundation date

Characteristics at foundation date	Coeff.	p-value*
Firm is located in Eastern Germany	−0.0652	0.515
Located in Bavaria	0.0920	0.337
Firm is located in Brandenburg	0.1114	0.610
Population density in 1996 (corresponding counties)	0.0869	0.056
Distance to nearest science or technology park	−0.0124	0.711
Scientific personnel in universities within 50 km dist.	−0.0609	0.009
Distance to next Fraunhofer-Institute	−0.0043	0.904
Distance to next Helmholtz-Institute	−0.0295	0.332
R&D-employees in resp. industry	0.0359	0.218
Constant	−3.5279	0.000
Number of observations (of which venture funded)	21,571	(142)
Wald-test (*p-value*)	332.9	0.000
Pseudo R^2	0.1548	

**p-value: Probability of coefficient estimate not to differ significantly from zero.*
Data sources: ZEW Foundation Panels, Germany Patent Agency, Federal Office for Regional Planning.

With the results of this estimation we can compute the propensity score for each firm as is specified in equation (2). On this basis, we employ different matching procedures. First, we use a standard propensity score with nearest neighbor *propensity score matching*. However, as previously discussed, the protection of innovation is done with different strategies within different industries. To control for this effect, in a second procedure, we require matching partners to have identical industry affiliation[12], identical year of firm creation and similar number of patents at the time of the venture capital investment. Given that our control group is roughly 200 times larger than the group of treated firms, these requirements can be met without loss of data. We refer to the second procedure as *balancing score matching*. Both procedures are done without replacement, i.e. non-venture funded firms can be selected only once.[13]

To obtain a measure of the quality of each match we computed the mean and the standard deviation of the distribution of the respective propensity scores as well as the difference of the means. Table 5 compares score estimates for both matching approaches. While for the propensity score matching, the difference is roughly 0.005 times the standard deviation of the untreated propensity score, it amounts to 0.08 in case of the balancing score. This increase is due to the stronger restrictions in the second procedure. Nevertheless, both results can be considered to be close matches.[14]

[12] Our industry classification is implicitly given in Tables 1 and 4.

[13] The results for matching procedure *with* replacement are nearly identical. They are available from

Table 5: Comparison of score estimates under propensity score and balancing score matching

	Propensity Score Matching	Balancing Score Matching
Score under No Treatment	-2.0809	-2.0809
(Standard Deviation)	(0.5345)	(0.5345)
Score under Treatment	-2.0833	-2.1258
(Standard Deviation)	(0.5270)	(0.4857)
Difference of Scores	0.0024	0.0448

5 Results

Table 6 reports the results of the two matching procedures, denoting the estimated average treatment effects for three measures: firm growth, probability of applying for at least one patent and the number of patents applied for. Since balancing score matching imposes stronger restrictions and therefore leads to better matches, we refer to this procedure in the interpretation of the estimation results. Hence, in our discussion, we refer to the last column of Table 6. We nevertheless show the results of the other matching method in the middle column for illustrative purposes. Let us consider the result for firm growth first.

5.1 Estimated Treatment Effects for Firm Growth

The upper part of Table 6 compares venture funded firms (i.e. treated) and non-venture funded matched firms on the basis of their average employment growth rates. Venture funded firms in our sample grow roughly twice as large as their non-venture funded counterparts, the difference being significant at α=5%. In the business related services, venture funded firms grow even approximately three times as much as the corresponding non-venture funded firms, (significant at α=5%). The growth rate of venture funded firms in the manufacturing industry is about twice of that one of non-venture funded firms, significant at α=10%. Interestingly, the growth rate of technology intensive services does not differ significantly between venture funded and non-venture funded firms. Overall, venture funded firms grow significantly faster and, apparently, the difference is mainly driven by business related services. However, the difference in the growth rate is much lower in magnitude than in other studies such as e.g. Coopers & Lybrand and EVCA (1996).[15]

the authors upon request.

[14]Cochran and Rubin (1973, p.421) consider a value of $0.2\sqrt{(\sigma_1^2 + \sigma_2^2)/2}$ as one that "removes practically all the bias". Our estimates are below that value, i.e. we meet this criterion.

[15]The significance in the difference of the growth rates are confirmed by an alternative test based on median values of the growth rates. In this test, we observe a significant higher number of venture funded

Table 6: Results of different matching procedures

	VF	NVF[1)]	NVF[2)]
Employment growth rate			
All firms (142)	0.326	0.166	0.157
(*p-value)*		(0.001)	(0.001)
Manufacturing Industry (44)	0.299	0.203	0.113
(*p-value)*		(0.242)	(0.052)
Technology Intensive Services (50)	0.317	0.172	0.230
(*p-value)*		(0.033)	(0.190)
Other Business Related Services (48)	0.361	0.109	0.123
(*p-value)*		(0.019)	(0.013)
Number of patents			
All firms (142)	0.732	0.204	0.070
(*p-value)*		(0.187)	(0.090)
Manufacturing Industry (44)	1.545	0.563	0.114
(*p-value)*		(0.417)	(0.227)
Technology Intensive Services (50)	0.520	0.036	0.800
(*p-value)*		(0.168)	(0.213)
Other Business Related Services (48)	0.208	0.000	0.021
(*p-value)*		(0.274)	(0.327)
Probability of patent application			
All firms (142)	0.092	0.049	0.049
(*p-value)*		(0.165)	(0.165)
Manufacturing Industry (44)	0.182	0.104	0.068
(*p-value)*		(0.296)	(0.110)
Technology Intensive Services (50)	0.060	0.036	0.060
(*p-value)*		(0.566)	(1.000)
Other Business Related Services (48)	0.042	0.000	0.021
(*p-value)*		(0.160)	(0.562)

VF: Venture Funded Firms; NVF: Non-Venture Funded Firms
[1)] *Propensity Score Matching;* [2)] *Balancing Score Matching;*
p-values denote probabilities that respective estimates for NVF are identical to corresponding values for VF

Comparing these results to those in Table 2 that presents the difference between treated an non treated firms before application of the matching procedure, we find that estimated values as well as significance levels differ considerably. It is noteworthy that while the technology intensive service sector was the driving one in the difference in Table 2, the matching procedure leads to an inversion of that result. Obviously, in the data underlying Table 2, there were non-venture funded fast growing firms in the technology intensive service sector. This result clearly illustrates the impact of the correction of the sample selection bias as effectuated by the matching procedure.

5.2 Estimated Treatment Effects for Innovative Behavior of Firms

5.2.1 On the Number of Patent Applications

The middle part of Table 6 compares both types of firms on the basis of the average number of patent applications. In average, the venture funded firms in our sample apply for ten times as many patents as their non-venture funded matched firms. The difference is statistically significant at $\alpha = 0.1$. Considering the industry subaggregates, venture funded firms apply for 5 to 15 times the number of patents as compared to their non-venture funded counterparts. However, the difference is not statistically significant. This shows that the variance of the number of patent applications is very high in the matching sample. Therefore, we have to conclude from these tests that venture funding does not make a statistically significant difference with respect to firms innovative behavior. Let us emphasize again, that we only consider the number of patent applications. and do not take into account the scope or other value correlated measures of the patent let alone non patentable inventions.[16]

Nevertheless, since this finding is in contradiction with previous studies (such as Kortum and Lerner, 2000, who used the same variable – number of patent applications – to measure innovation), we ran another test to investigate if this result is sensitive with respect to the specification.

5.2.2 On the Probability of Applying for at least one Patent

To compare venture funded and matched non-venture funded firms on the basis of a different test, we analyzed if the firms applied for *at least one patent*. This leads to a Binomial distributed variable indicating "1" if the firm applied for a patent and "0" otherwise. The lower part of Table 6, displays the share of firms that applied for at

firms with growth rates above the median compared to the group of non-venture funded firms (test statistic: Pearson $\chi^2_{(1)}$ corrected = 6.21 and p-value=0.013).

[16]As for firm growth rates, we double-check this test with an alternative test based on the median numbers of patent applications. As for growth rates, the results do not change i.e. we do not detect significant differences (Pearson $\chi^2_{(1)}$ corrected = 1.34 and p-value=0.246).

least one patent. A value of 0.092 means that 9.2 per cent of all firms applied for at least one patent.

For the group of “All Firms”, roughly twice the number of firms applied for at least one patent. However the difference is not significant. This holds also for the industry sub-aggregates, the differences are insignificant in all cases. It is noteworthy, however, that in the “Technology Intensive Services”, the number of firms that applied at least for one patent is higher for *non*-venture funded firms than for venture funded matched firms. Apparently in this industry, a larger share of firms applied for a smaller number of patents (both differences being insignificant).

6 Summary and Conclusion

In this paper, we investigate the implication of venture capital funding on firms’ growth performance and innovative behavior at the firm level. This is done using a sample of 21,541 German firms of which 0.66 per-cent are venture funded. On the basis of this sample, we determine the growth rate of firm sizes and innovative behavior of venture funded and non-venture funded firms. Using a probit estimation, we find evidence that firms with higher innovative output (measured by the number of patent applications, corrected for size) and with a higher educated management have a larger probability of getting venture capital.

Then we identify matched pairs with non-venture funded firms, where we require startup size, age, number of patents and industry classification as well as an estimated measure of the firms’ probability to receive venture funding to be identical or of minimal distance. On this basis, we are able to compare venture funded and non-venture funded firms with respect to growth and innovative behavior while minimizing the statistical bias due to systematic selection of firms for venture funding.

Based on this approach we find evidence that venture funded firms display significantly higher growth rates compared to their non-venture funded counterparts, hence venture capital firms do make a significant contribution in this respect. For patenting behavior, the finding is different. Overall, venture funded firms do show a significantly larger number of patent applications (corrected for firm size) compared to their non-venture funded counterparts; however they do so already *before* the engagement of the venture capitalist. After the engagement of a venture capitalist, the number of patent applications by venture funded firms is still larger, however the difference is not significant for the industry sub-aggregates, it is only weakly significant overall. Similarly, the probability to apply for at least one patent is larger, but the difference between venture funded an non-venture funded firms is insignificant. Hence, there is only very weak evidence for the patenting behavior of venture funded firms to differ from the one of non-venture funded ones.

These results give rise to the following hypothesis on the sequence of innovation, venture funding and firm growth: Venture capital firms screen potential portfolio firms to select out those with the best growth perspectives. The innovative potential (as signaled by patent applications and by the founders' education levels) plays an important role in that respect. This screening process is very selective though successful since venture capital funded firms in our sample display indeed a growth rate that is twice as large as the one of the control group. This stronger growth rate could be a result of a commercialization of previous innovations since innovation output of venture funded firms in the sample does not differ from that of the control group. A plausible explanation for this finding could be that venture capital investors assist their portfolio firms mainly in this commercialization, rather than in further innovation, to maximize the value of their portfolio firms, hence their return. This commercialization is done by financial means but also by means of management assistance. In that respect, one contribution of venture capital investors is not only a financial one but could be their network of business partners and thus a larger number of possible commercialization channels.

Overall, these findings underline the importance of commercialization and marketing of innovation, hence of funding these activities. non-venture funded firms might improve their growth perspectives by putting more emphasis on these aspects of the business.

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