Measuring Spillovers of Venture Capital

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VERY PRELIMINARY

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The contribution of venture capital-backed entrepreneurship to innovation and economic growth has been an important topic of economic research in the last thirty years. In this study we compare the impact of R&D activities on patent production when R&D is done by venture capital financed companies as opposed to R&D done by of established firms. We focus in particular on potential spillovers arising from venture-capital financed companies and from established firms on the patenting activities of other companies. Using panel data of U.S. firms we show that venture capital financed R&D generates significant spillovers on the patent production of both other venture capital financed firms and of established firms. In contrast, the patenting of venture capital financed firms seems to be little affected by R&D expenditures of established firms. We address potential concerns about causality with an proxy variable and an instrumental variable strategy using changes in federal and state tax incentives as instrumental variable for R&D and past fund raising as instrument for venture capital investment.

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1. Introduction

Governments around the world are eager to replicate the success story of venture capital in the United States. Companies such as Google, Apple, Microsoft or Oracle received financing from venture capital funds during their infancy. These companies are at the forefront of innovation, and are seen as key to robust economic growth. Not surprisingly, governments all over the world try to stimulate the venture capital industry through public policy: venture capital funds are tax free in France and the UK, the Canadian government directly acts as a venture capitalist through the Business Development Bank of Canada and the European Union provides financing for venture capital funds with the help of the European Investment Fund.

However, government intervention seems justified only if there are market failures that prevent venture capital funds from investing the efficient amount of capital. Such market failures could arise from externalities generated by venture capital financed firms on other firms.[1] In this paper we focus on innovation spillovers as one potential motivation for government intervention. In particular, we attempt to measure spillovers from venture capital financed firms on the research productivity of established companies and other venture capital financed companies. Furthermore, we compare these spillovers to innovation spillovers generated by established companies. A comparison of the relative size of these spillovers is important in order to be able to judge whether or not VC financed innovation activities deserve preferential treatment over innovation activities of established companies.

For this purpose we study two groups of firms, venture capital financed firms on the one hand and publicly listed "established" firms on the other hand. As a measure for the innovation outcome of each firm we use the number of patents and the number of patent citations where the latter is often interpreted as reflecting the quality of patents. To

[1]Other motivations for government intervention could arise from capital market imperfections.

capture the innovation input, we use the R&D stock of established companies ($R\&D$) and the venture capital stock received by VC-financed firms (VC), the idea being that (early round) venture capital investment is devoted to a large extent to innovation activities. To gauge the effect of $R\&D$ and VC on innovation we regress the number of patents and the number of cites of each firm on two spillover measures, $Spillover^{VC}$ and $Spillover^{Est}$, and on their own R&D activity.

To determine potential spillovers we first identify the companies from which spillovers might originate - the spillover pool - by calculating the distance in technology between each pair of companies. The underlying assumption is that it is more likely that spillovers come from companies that do research on similar things, i.e. that the spillover pool are companies in the close technological vicinity. To capture the distance in technology space between two firms, we use two different measures, the Jaffe-measure and the Mahalanobis-measure, as described in Bloom et al. [2012]. Next we calculate a measure of how much spillovers a company might receive from the spillover pool. To capture the spillovers a firms experiences from VC-financed firms, we multiply for each firm the technological distance to every VC-financed company with its respective venture capital and then we sum up over all VC-financed firms. Similarly, we calculate a spillover measure from established firms' R&D.

For our estimation, we use a negative binomial model since our dependent variables are count data variables. To account for firm heterogeneity, we control for pre-sample fixed effects. One potential concern about the estimation one might have is that the empirical specification might suffer from an endogeneity problem. Suppose a particular technology field experiences a positive technological shock. Then it might be easier to produce patents in this field and at the same time companies working in the same technology field might increase their research and development outlays. Similarly, venture capital funds might allocate their investment to technology fields hit by a positive shock. Therefore the two spillover terms might pick up the effect of technological progress and as a result could be spuriously high. To address this endogeneity problem we first use a proxy variable and then an control variable approach with two instrumental variables.

Technological progress might either come from the research done from basic research institutes such as universities or from R&D of other companies. The latter technological progress is not problematic because this is the exactly what we want to measure as spillovers. In contrast, technological opportunities originating from academic research might bias our estimates. Therefore we include measures for the patenting activity of universities in the technological field of the considered company as proxy for technological progress.

For the control function approach we instrument R&D expenditures of established companies with the level of R&D tax credit in a state as in Bloom et al. [2012] and venture capital investment with past fund-raising of buyout funds [Nanda and Rhodes-Kropf, 2012]. The idea is that the introduction of R&D tax credits in the different U.S. states has a direct influence on the level of research and development by lowering costs. At the same time, it is unlikely that government officials are able to react in time to a change in the technological frontier. Venture capital is instrumented with past fund-raising of private equity buyout funds. Buyout funds and venture capital funds belong both to the class of private equity. Institutional investors often allocate funds to private equity without distinguishing between the two subclasses. Therefore buyout fund-raising is correlated with venture capital fund-raising but supposedly uncorrelated with the arrival of technological opportunities of VC backed companies.

To arrive at our dataset, we combine data from the Compustat database with venture capital data from Thomson Reuters VentureXpert. Compustat contains balance sheet data for all U.S. publicly listed companies. VentureXpert is a prime source for venture capital investment and fund-raising data. We select all companies which patented at least once in the period form 2000 to 2010. Patent data are from the NBER U.S. Patent Citations Data File for which we create a name match per hand to the venture capital data. For the Compustat Data, the NBER provides a unique identifier to match the balance sheet data with patent counts and cites.

The contribution of our paper is twofold. First, we provide a direct measurement of innovation spillovers generated by venture capital financed firms that are technologically close. We find that increasing venture capital in the technological vicinity of a company increases the propensity of other companies to produce (highly cited) patents, both for VC financed as well as established companies. In contrast, our results suggest that R&D expenditures of established companies generate positive but relatively small spillovers on other companies. A back of the envelope calculation suggest that around 150 million dollar additional R&D spending leads to one more spillover-induced patent, while for the same effect only 3 million dollar of venture capital are necessary. However, R&D is privately much more effective than venture capital: An established company needs to invest only 5 million dollar to get an additional patent while a venture capital backed company needs to invest 2.5 times the amount.

A second contribution of our paper is to investigate potential channels through which these spillovers might be effective. TO BE COMPLETED.

Our analysis complements the paper by Bloom et al. [2012] who study spillovers generated by established companies. They find positive spillovers from R&D to cite-weighted patents, but also consider the effect of spillovers on Tobin's Q and productivity. It is therefore part of the large literature on the private and social returns of R&D which is summarized in Hall et al. [2009]. In general, this literature finds large and positive social returns of R&D, yet does not consider any effects from venture capital.

Our paper is also related to Kortum and Lerner [2000] which started the literature on the contribution of venture capital to innovation. They find that venture capital is much more potent than R&D in producing patents. From 1983 to 1992 venture capital accounted for 8% of industrial innovation, while the ratio of venture capital to R&D was only 3%. Our paper confirms that venture capital is more effective in generating patents. However, in addition to this finding, we disentangle direct and indirect effects of venture capital financing on patent production and show that VC is less effective in stimulating patent production than R&D, but generates significantly higher spillovers to other companies.

Literature survey: TO BE COMPLETED

The paper proceeds as follows: In section 2 we lay out the conceptual and empirical framework for measuring spillovers of R&D and venture capital. In section 3 we discuss data construction and in section 4 we present our empirical results and section 5 concludes.

2. Conceptual and Empirical Framework

2.1. Patent Production Function

Suppose that the patent production function of company i at time t has the following Cobb-Douglas form:

$$P_{i,t} = \left(Spillover_{i,t}^{VC}\right)^{\gamma^{VC}} \cdot \left(Spillover_{i,t}^{Est}\right)^{\gamma^{Est}} \cdot G_{i,t}^{\beta} \cdot N_{i,t} \cdot A_i \cdot \varepsilon_{i,t} \tag{1}$$

$G_{i,t}$ is the R&D stock ($R\&D$) if the company is already established in the market or the venture capital stock (VC) if the company is backed by a venture capital fund. $N_{i,t}$ is the general technological progress which makes it easier or harder to innovate, A_i is the firm-specific constant productivity, $\varepsilon_{i,t}$ is a company and time specific shock and $Spillover_{i,t}^{VC}$ and $Spillover_{i,t}^{Est}$ are the spillovers from venture capital financed companies and established companies respectively. This simple functional form is used in the innovation literature at least since Griliches [1979] and employed in numerous studies of the R&D-patenting nexus. In this model spillovers change the marginal productivity of R&D investment for a company depending on the the two parameters γ^{VC} and γ^{Est}. A priori we allow these two parameters to be different, reflecting the potentially different effectiveness of spillovers of venture capital-backed companies and established companies. The reason for this difference might be that venture capital-backed focus on more radical innovations than conventional R&D or define completely new applications of existing technologies.

Spillovers between companies might come from different sources: A successful novel product might serve as a proof of concept for an experimental technology signaling the commercial value of further development. Thus a company company might be able to avoid errors and dead ends inherent to research. More concretely it could learn specifics by reverse engineering the product of the competitor, thus lowering the costs of imitation. Another possibility is, that scientists or other employees switch between companies taking knowledge about successful procedures and processes with them. Or quite simply, company scientists read the results of other companies' research in journal articles or hear about them on conferences. In short, learning from other companies might result in positive spillovers. In contrast, if companies do research on similar things they might engage in patent races to secure the property rights of a certain invention. This might lead to negative spillovers. If the learning effect or the competitive effect is larger is an empirical question which we address in this study.

In all cases spillovers predominantly originate from companies which do similar things in a technological sense: Learning from products or employees of other companies might be easier within a technological area. For example it is likely that Google can learn more from Microsoft than from an aluminum producing company such as Alcoa. Similarly patent races only happens between companies which aim to invent exactly the same thing.

Therefore, there is for every company a set of companies from which it is more likely that spillover might originate. This set is called the spillover pool and is defined by technological proximity. The technology proximity and the resulting spillovers are calculated with the methods set out in Bloom et al. [2012].

2.2. Calculating Spillovers

We first calculate the share of patents company i has in each technology class, thus establishing the technological profile T_i for this company. Then calculate the technology proximity $Proximity_{i,j}$ between company i and company j by using the uncentered correlation between these two vectors following Jaffe [1986]:

$$Proximity_{i,j} = \frac{T_i T_j'}{(T_i T_i')^{0.5} \cdot (T_j T_j')^{0.5}}$$

As this index is a correlation coefficient it ranges from zero to 0. A value of one implies a perfect overlap between the share vector of the two companies and thus a very similar technological focus. If two companies have a technological proximity of zero, then they do not have a single patent in the same patent classes.

In later versions of this study we also plan to use the alternative Mahalanobis proximity measure which introduces the weighing matrix Ω in the Jaffe metric:

$$Proximity_{i,j}^{Mal} = \frac{T_i \Omega T_j'}{(T_i T_i')^{0.5} \cdot (T_j T_j')^{0.5}}.$$

This weighing matrix is calculated as the uncentered correlation of patent shares across patent classes. This means that two companies with the same overlap in patents would receive a higher score if the underlying technologies are similar compared to the case that the technologies are dissimilar.

After determining the proximity between each and every company, we can construct the spillover from established companies to company i by summing up the proximity weighted investment in R&D for all other companies:

$$Spillover_{i,t} = \sum_{j \neq i} Proximity_{i,j} \cdot R\&D_{j,t}$$

Analogously the the spillovers from venture capital financed companies are defined by

$$Spillover_{i,t}^{VC.} = \sum_{j \neq i} Proximity_{i,j} \cdot VC_{j,t}$$

2.3. Econometrics

In order to be able to use standard count data methods for estimation, we rewrite Equation (1) to

$$P_{i,t} = exp(\gamma^{VC} \cdot lnSpillover_{i,t}^{VC} + \gamma^{Est} \cdot lnSpillover_{i,t}^{Est} + \\ + \beta \cdot lnG_{i,t} + lnN_{i,t} + lnA_i + \delta X_{i,t} + u_{i,t}) \quad (2)$$

where $X_{i,t}$ is additionally a vector of control variables influencing patent production. The firm fixed effect lnA_i is estimated Blundell [2002] using pre-sample mean scaling, because of the non-linearity of the estimating equation. The idea is that the average patents in the ten years prior to the sample period is a consistent estimator for the time-invariant firm productivity.

Estimating Equation 2 is not straightforward, because we cannot observe technological progress, $N_{i,t}$, directly. Consequently technological progress might bias our estimates if it is correlated with either of the other explanatory variables. The source of such a correlation could be, that all or subset of companies observe technological progress (for example originating from university research) and in response adjust their R&D spending or venture capital investment, resulting in an increase of the spillover measures. Then we would attribute all of the resulting increase in patenting to spillovers while it is in reality driven by the change in technological opportunities. But there are also two cases where technological progress does not cause any harm: First, if no one can observe technological progress and it is transitory then our estimates are consistent as technological process is subsumed in the error term $u_{i,t}$. Second, if technological progress originates from the R&D of one of the companies in our sample then these are exactly the spillovers we want to measure.

In our setting we can think of three possible ways to address this left out variable bias: (1) using a proxy for technological opportunities or (2) instrumental variables influencing investment but not technological progress and (3) with functional form restrictions. We discuss the first two methods in turn and relegate the discussion of third method, which is much less commonly used in applied work, to the appendix.

To proxy technological progress we need a variable which is highly correlated (optimal would be a sufficient statistic) with technological progress and observable to us. Then, after controlling for the proxy, the bias in our estimates should vanish or at least be reduced. Our candidate for such a proxy variable is the share-weighted patent count of research institutes and universities in the technology classes in which a company is active. More active patenting of basic research institutions or competitors might indicate a shift in technological opportunities. A problem of this approach is that these institutions might patent more because of the R&D of US companies. Then these variables would be bad controls and bias our estimates.

The second possibility to deal with endogeneity is the use of instrumental variables. With this method we measure technological progress by excess investment in R&D or venture capital over and above the level expected from exogenous factors, the instruments. Following Bloom et al. [2012], we use supply side shocks introduced by the introduction of R&D tax-credits as instruments for R&D expenditures of established companies. These tax-credit lower the cost to do R&D and therefore should in equilibrium increase its optimal level. Furthermore, the existing literature surveyed in Bloom et al. [2012] suggests that there is a large degree of randomness in the introduction and the level of R&D tax-credits across states and therefore it is plausible that a change in the instrument is exogenous to technological progress.

As instrument for venture capital spending we use fund-raising of leveraged buyout funds one year before the investment following Nanda and Rhodes-Kropf [2012]. The supply of venture capital is greatly influenced by the asset allocation of institutional investors into "private equity", the broad category encompassing venture capital and buyout funds. By using buyout fund-raising we hope to capture that part of VC investments which are due to increases in available capital unrelated to technological opportunities presenting to investee companies. This instrument is therefore helpful if past fund-raising does not systematically predict technological opportunities two years later.

The application of instrumental variable techniques in this setting is not straightforward as the estimation equation is nonlinear. Therefore we have to resort to control function methods. For that reason we use a four step procedure: First, we regress the instrument on current R&D expenditures ($R\&D^{current}$) and current venture capital investments ($VC^{current}$) to calculate predicted values for these two quantities. Second, we multiply the predicted values with the distance matrix to arrive at predicted spillovers. In a third step we regress the actual spillovers on the predicted spillovers and calculate the residuals. Given that the predicted values are exogenous these residuals should capture all of the technological progress. In the final step we calculate the fifth order polynomial of these residuals and use them as controls in the estimation equation (2).

Thus technological progress is here the identified with the excess investment in venture capital and R&D over and above what would be expected from the prediction of the instrumental variables. We relegate the first stage regressions and the calculation of the control function to the appendix.

3. Data

We combine three standard data-sources to arrive at our final dataset: The NBER Patent-Citation Data File, Thomson Reuters VentureXpert and the U.S. CompuStat File. The NBER Patent Data contains all utility patents filed in the US with name of the applicant, year of application, the state of application, the number of cites a patent receives from 1976 to 2006 and a classification according to the US 3-digit current classification (CCL). This classification is determined by the patent examiner and sorts patents into one of 400 functional groups.[2] Therefore this classification give a fine grained view of the the wide variety of patents and correspondingly of the technological focus of the patent assignee. As we have only data on US companies we restrict our attention to patents filed in the US by US companies. The resulting dataset contains around 1.45 million Patents and is matched to the two firm data sources which we discuss next.

Our first firm level data source is the US CompuStat file. This data can be easily matched to the the NBER Patent-Citation Data File over a unique identifier provided by the NBER team [Hall et al., 2001]. The CompuStat File contains yearly accounting data for US publicly listed companies with company name, the fiscal year, the state of the firm head quarter, the four-digit SIC code, sales and research and development expenditures. From this file we keep all companies which report R&D expenditures for at least four successive years. To calculate the R&D stock from R&D expenditures we apply the perpetual inventory method with a 15% depreciation rate (following inter alia Hall et al.

[2]In theory there are 800 functional groups, yet we only observe a positive patent count in 400 of them.

2005), so the R&D stock in year t is given by $R\&D_t = (1-0.15) \cdot R\&D_{t-1} + R\&D_t^{current}$. Additionally, we delete all companies with an increase in sales of more than 100% or a sales decrease of more than 50% in two consecutive years because this reflect either M&A activity or an error in the data. The resulting database contains 2389 companies with 500'480 patents. Summary statistics are shown in Table 1.

Table 1: Summary statistics: Established Companies

	mean	sd	min	max	p10	p90
# patents	19.94	100.91	0.00	4339.00	0.00	36.00
# cites	190.39	1086.35	0.00	45512.00	0.00	282.00
ln(Spillover VC)	4.08	1.98	-10.89	8.52	1.70	6.61
ln(Spillover Est.)	9.64	1.04	3.03	12.00	8.28	10.82
ln(R&D)	3.14	2.24	-5.81	10.69	0.38	6.13
ln(pre-sample F.E.)	0.90	2.08	-2.30	5.60	-1.61	3.94
ln(pre-sample F.E.)	3.25	2.15	-1.61	8.47	0.69	6.22
Observations	20666					

The second firm level data source is Thomson Reuters VentureXpert which comprises investments data in US venture capital (VC) financed companies. Each dataset contains the name of the investee company, the investment date, an four-digit SIC code and the estimated amount invested. The latter is our main measure for total available funds of a company, assuming it does not get additional outside funding. In addition we know the investment stage of the company, so if it is a seed, a early stage, expansion or late stage investment. As we are only interested in the effect of R&D done by VC-backed companies, we delete all rounds except seed and early stage rounds, because it seems reasonable to assume that VC-backed companies are focused in later stages on marketing and not on product development. Additionally, we delete all companies which first investment is before 1980. Analogous to the calculation of the R&D stock we calculate the VC stock with perpetual inventory method, so the VC stock is given by $VC_t = (1-0.15) \cdot VC_{t-1} + VC_t^{current}$.

We match this investment data by company name to the patent data with the help of algorithms from the Apache Lucene library. In a second step we check the matches per hand. The resulting dataset contains 1620 companies with 65'367 patents. Summary statistics are shown in Table 2.

Table 2: Summary statistics: venture capital-Backed Companies

	mean	sd	min	max	p10	p90
# patents	1.53	4.18	0.00	186.00	0.00	4.00
# cites	19.42	77.38	0.00	3008.00	0.00	46.00
ln(Spillover VC)	5.33	1.83	-10.03	8.44	3.05	7.41
ln(Spillover Est.)	9.81	0.95	4.72	11.86	8.60	10.84
ln(VC)	1.79	1.46	-7.36	5.70	-0.13	3.48
ln(pre-sample F.E.)	0.78	0.86	0.00	4.72	0.00	2.08
ln(pre-sample F.E.)	3.37	1.46	0.00	6.79	1.39	5.15
Observations	9136					

4. Results

4.1. Main results

Table (3) summarizes the results for the effect of spillovers on the number of patents and the number of citation-weighted patents as dependent variables. In the first two columns the observational unit are the established companies while in column three and four, we analyze the patenting behavior of venture capital backed companies. All but one of the estimated coefficients are positive and significantly different from zero on conventional levels. This counts as prima facie evidence for technology driven spillovers, but — as discussed above — the coefficients might just take up the influence of technological progress. If this is the case our estimated coefficient overstate the true effect.

Our first step to address this endogeneity problem is to use the patenting activity of academic institutions around the world as a proxy variable for technological progress.

Table 3: Baseline Results

	Established Companies		*venture capital Companies*	
	# Patents	# Cites	# Patents	# Cites
ln(Spillover VC)	0.14***	0.20***	0.15***	0.15***
	(0.03)	(0.04)	(0.05)	(0.05)
ln(Spillover Est.)	0.31***	0.29***	0.50***	0.33***
	(0.06)	(0.07)	(0.09)	(0.10)
ln(R&D)	0.59***	0.53***		
	(0.02)	(0.02)		
ln(VC)			0.20***	0.22***
			(0.05)	(0.04)
Firm F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	20666	20666	9136	9136

Notes:

Technological progress might originate from academic research and as we are predominantely interested in patentable innovation it seems sensible to assume that at least some of the patents resulting from the novel technology are taken out by the inventive university. Therefore we use the number of patents in the current and the next year as well as the number these patents are cited as proxy variables. As technological progress might differ between technological fields in a given year, we only use the patents in the field a company is active, making our proxy firm-specific.

We report the results controlling for the proxy variables in Table 4. It is reassuring to note that the coefficient for most proxy variables are significantly different from zero. Compared to the estimates in Table 3, the resulting coefficients are - as expected - mostly smaller. This is in line with the idea, that technological progress biases the uncontrolled estimates away from zero. Still, with this proxy variable strategy we miss out all technological opportunities which require some further development before they become patentable, such as basic research.

Table 4: Proxys for the Technological Frontier

	Established Companies		*venture capital Companies*	
	# Patents	# Cites	# Patents	# Cites
ln(Spillover VC)	0.09**	0.10***	0.11**	0.14***
	(0.04)	(0.04)	(0.05)	(0.04)
ln(Spillover Est.)	0.24***	0.23***	0.41***	0.35***
	(0.06)	(0.07)	(0.09)	(0.10)
ln(R&D)	0.59***	0.54***		
	(0.02)	(0.02)		
ln(VC)			0.19***	0.22***
			(0.05)	(0.04)
ln(# Patents Univ)	-0.15***	-0.30***	-0.18**	-0.59***
	(0.06)	(0.08)	(0.07)	(0.11)
ln(# Cites Univ)	0.15***	0.30***	0.15***	0.33***
	(0.04)	(0.05)	(0.05)	(0.07)
ln(# Patents Univ_t+1)	0.08*	-0.13*	0.17**	-0.02
	(0.04)	(0.07)	(0.07)	(0.10)
ln(# Cites Univ_t+1)	0.05**	0.26***	0.04	0.28***
	(0.02)	(0.04)	(0.04)	(0.04)
Firm F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	20666	20666	9136	9136

Notes:

Our second approach to deal with the left-out variable problem is to use instrumental variable regression with changes tax credits as instruments for R&D spending and past fund-raising as instruments for venture capital investment. We use a control function approach instead of the usual two-step IV because the estimating equation (2) is non-linear . The first stage regressions and the regressions for calculating the control function are reported in Appendix A. The F-Values for joint significance of the instruments are mostly above 10 and therefore seem sufficient to consistently estimate the coefficients and standard errors.

The estimation results with control functions are reported in Table 5. For the sake of brevity we only report the first term of the fifth order polynomial of the control function.

Although the first term is not in all specification significantly different from zero, all five terms are jointly significant in all cases. Again, the estimated coefficients are smaller than the estimates in Table 3. Therefore both, the proxy variable and the instrumental variable approach seem to make some headway controlling for technological progress.

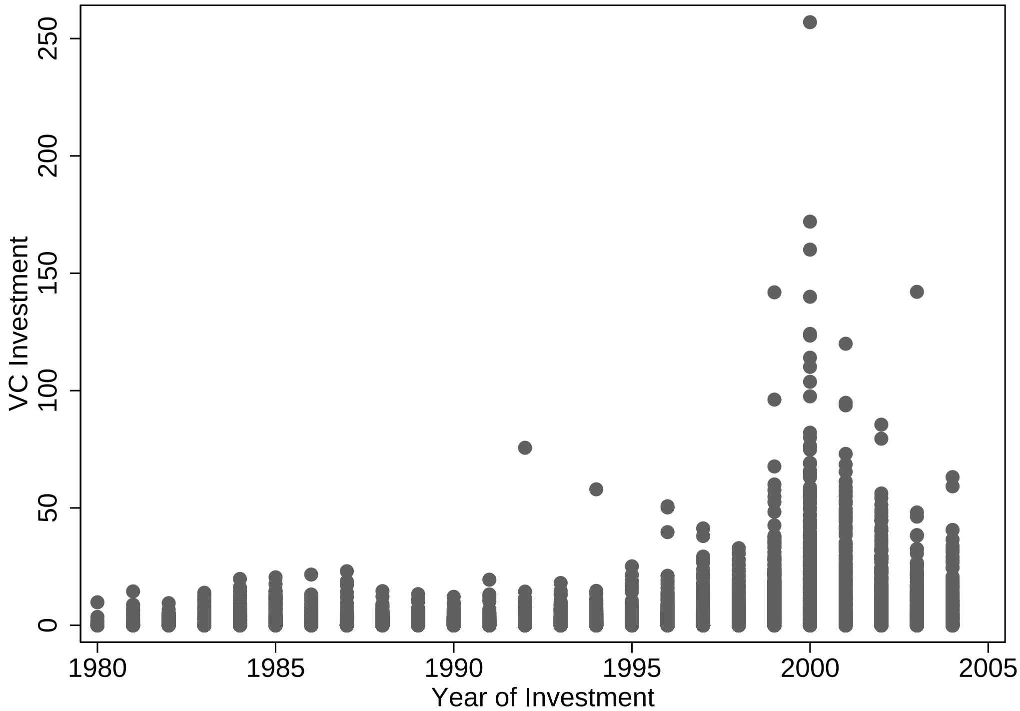
Table 5: Control Function Results

	Established Companies		*venture capital Companies*	
	# Patents	# Cites	# Patents	# Cites
log Spillover Venture	0.09**	0.17***	0.15**	0.31***
	(0.05)	(0.05)	(0.07)	(0.09)
log Spillover Est.	0.28***	0.22**	0.59***	0.29**
	(0.08)	(0.09)	(0.11)	(0.15)
log Cum. R&D	0.68***	0.61***		
	(0.03)	(0.03)		
Cum. Venture Capital			0.26***	0.32***
			(0.04)	(0.04)
Control Spill VC	0.12	-0.08		
	(0.08)	(0.10)		
Control Spill Est.	-0.45	-0.22		
	(0.35)	(0.46)		
Control R&D	-0.38***	-0.54***		
	(0.06)	(0.07)		
Control Spill VC			-0.09	-0.60***
			(0.14)	(0.18)
Control Spill Est.			-1.52***	-3.49***
			(0.46)	(0.67)
Control VC			-0.21***	-0.39***
			(0.06)	(0.08)
Firm F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	18069	17843	10131	10131

Notes:

As both methods work through adding control variables, we can also combine these two approaches. The resulting coefficients are reported in Table 6. Even columns report the coefficients for the full sample for the years 1980 to 2005 and uneven columns report the estimates for the years before 1999. In the full sample, the spillover terms are again

Figure 1: Seed and Early stage venture capital investment over time



smaller than in the baseline case and even smaller than the estimates resulting from either the proxy variable or the instrumental variable approach alone. All coefficients (but one) associated with spillovers from venture capital are close to zero and insignificant.

If we restrict the sample to the twenty years from 1980 to 1998, the coefficients turn significant again. Starting in 1998 a tremendous run up of prices of any stock related to computer technology led to a surge in venture capital investing (Figure 1). Apparently, companies which received investment during this period were significantly different compared to companies which received investment before. In unreported regressions we achieve similar results in the full sample after dropping the SIC codes related to the production of computers (3674) and software engineering (7372). In the following we interpret the size of coefficients and the quantitative impact of spillovers by using the results from the pre-bubble sample in Table 4.

Table 6: Control Function Results

	Established Companies				*venture capital Companies*			
	# Patents	#Patents	# Cites	# Cites	# Patents	# Patents	# Cites	# Cites
log Spillover Venture	0.02	0.11**	0.05	0.17***	0.10	0.23**	0.28***	0.42***
	(0.05)	(0.05)	(0.06)	(0.06)	(0.07)	(0.09)	(0.09)	(0.11)
log Spillover Est.	0.20**	0.19**	0.18**	0.25***	0.48***	0.45***	0.36***	0.35**
	(0.08)	(0.08)	(0.08)	(0.09)	(0.11)	(0.12)	(0.14)	(0.14)
log Cum. R&D	0.68***	0.66***	0.64***	0.53***				
	(0.03)	(0.03)	(0.03)	(0.03)				
Cum. Venture Capital					0.25***	0.21***	0.32***	0.27***
					(0.04)	(0.05)	(0.04)	(0.04)
ln(# Patents Univ)	-0.15**	0.03	-0.36***	-0.19**	-0.16**	-0.09	-0.52***	-0.35**
	(0.06)	(0.07)	(0.10)	(0.10)	(0.08)	(0.11)	(0.11)	(0.14)
ln(# Cites Univ)	0.15***	0.02	0.39***	0.24***	0.13***	0.05	0.29***	0.24**
	(0.04)	(0.05)	(0.07)	(0.08)	(0.05)	(0.07)	(0.07)	(0.10)
ln(# Patents Univ_t+1)	0.12***	-0.02	-0.14	-0.14	0.11	0.02	-0.13	-0.32**
	(0.04)	(0.06)	(0.09)	(0.09)	(0.07)	(0.11)	(0.09)	(0.15)
ln(# Cites Univ_t+1)	0.04*	0.06	0.24***	0.09	0.06	0.13*	0.31***	0.36***
	(0.02)	(0.05)	(0.06)	(0.07)	(0.04)	(0.08)	(0.04)	(0.11)
Sample	All	$<$2000	All	$<$1999	All	$<$1999	All	$<$1999
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18069	13943	18069	13701	10131	5413	10131	5413

Notes:

4.2. Back of the envelope: Size of Effect

Calculating the size of the spillover effects the results in Table 6 is complex because all coefficients are in percentage terms: Increasing the R&D capital stock of a established company by 10% increases the number of patents by 6.6 %. Obviously, 10% percent are quite different in dollar terms for a large and a small company and therefore the underlying firm heterogeneity might matter a lot for the quantitative implications. So we do two things: First, we calculate the size of the effects for a company which is exactly at the mean of the sample (Table 1 and Table 2). This is simple, transparent and the numbers can be easily verified. In a second step we calculate a complete counterfactual simulation.

Taking the estimates of Table 6 at face value, a 10% increase in the R&D stock results in 6.6% more patents taken out by this firm, while a 10% increase in the venture capital stock results in around 2.2% more patents for the venture capital backed company. In dollar terms, a 10% increase in R&D stock is around 2.31 million dollar and 6.6% correspond to 1.32 patents as shown in Table 7. Correspondingly an increase of 0.60 million dollar results in 0.4 patents for venture capital backed companies (Table 8). According to these estimates a patent from conventional R&D costs 1.76 million dollar while from VC it costs 1.50 million dollar.

Comparing the relative sizes of the spillovers is tricky, because spillovers are distance weighted R&D/VC stocks. Therefore the simplest counterfactual is to abstract from the technological proximity and just calculate what would happen if a company with technological proximity one would increase its spending.

If we consider an established company, a 10% percent increase in spillovers originating from another established company of proximity one (i.e. 1536 million dollar) results in 2% or 0.38 more patents, while a 10% increase originating from another VC company (6.7 million dollar) results in 1.1% (0.22 patents). Thus, spillovers from VC companies

Table 7: Established Companies: A 10% increase at the mean delivers...

	Mean	Coefficient	Δ Patent	Δ Investment	dollar per Patent
# patents	19.94				
log R&D	3.14	0.66	1.32	2.31	1.76
log Spillover Venture	4.08	0.11	0.22	5.91	26.97
log Spillover Est.	9.64	0.19	0.38	1536.73	4056.21

Table 8: venture capital: A 10% increase at the mean delivers...

	Mean	Coefficient	Δ Patent	Δ Investment	dollar per Patent
# patents	1.53				
log VC	1.79	0.21	0.42	0.60	1.43
log Spillover Venture	5.33	0.23	0.46	20.64	45.01
log Spillover Est.	9.81	0.45	0.90	1821.50	2023.98

are much more effective with 27 million dollar per patent compared to 4 Billion dollar per patent for spillovers from established companies. Similarly, for venture capital backed companies to create one additional patent, established companies must increase their R&D by 2 billion dollar while venture capital backed companies must increase their spending by just 45 million dollar. In sum, research from venture capital financed companies appears to be similarly effective as research from established companies while their spillovers are much more effective than corporate R&D.

A similar pattern emerges, if we calculate the effect with a complete counterfactual simulation. To do this, we compute for every company separately what would happen if we increase the R&D stock (VC stock) for all years by one million dollar. This is different to the 10% increase before, but to be able to properly interpret the resulting statistics it is convenient to hold the variation in investment fixed. Increasing the capital stock for one company potentially increases the spillover term for all other companies, so we re-compute the increase in spillovers for all companies and all type of spillovers. In a next step we multiply the increase in spillovers with the corresponding coefficients to calculate the percentage increase in patents induced by the spillovers. Then we evaluate the percentage increase at the average predicted number of patents for each company. Summing up all these contributions by company-year, results in the distribution summarized in Table 9 for established companies and in Table 10 for venture capital backed companies.[3]

Again, the effects of spillovers from classical R&D is smaller than for an increase in venture capital stock: In total, a one million dollar increase in R&D results in 0.007 patents for other companies (142 million dollar per patent), while the same increase in venture capital results in 0.35 patents (2.85 million dollar per patent). Rather surprisingly the much larger effect of venture capital is predominantely caused by its impact on patenting of established companies. Taking firm heterogeneity in account, the private gain from investing in R&D is stronger than for investing in venture capital: One million dollar more R&D results in 0.200 patents (5 million dollar per patent) while a patent from venture capital costs about 12.5 million dollar. Taken together, venture capital seems privately a bit less profitable in terms of patent production than classical R&D, yet the spillover originating from these companies are much larger.

4.3. Robustness: splitting the sample

In this section, we estimate specification of Table 6 in the sample before 1999 for the five largest industries. In Figure 2 we then plot the coefficient for the venture capital spillovers in the upper panel for established companies and in the lower panel for venture capital backed companies. The overall pattern in these two pictures is clear: spillovers from venture capital are strong for pharma, medical appliances and software, while they are non-existent or even negative for electronics and the computer industry. In all cases the estimates are rather imprecise, so establishing a difference within these groups is not

[3]We windsorize the predicted number of patents at the 99% percentile.

Table 9: Established Companies: dollar 1 million more (cum.) R&D results in

	mean	sd	min	max	p10	p90
Patents for VC companies	0.003	0.003	0.000	0.014	0.000	0.006
Patents for Est. companies	0.004	0.003	0.000	0.015	0.001	0.008
Total External Effect	0.007	0.005	0.000	0.026	0.002	0.014
Patents for own company	0.200	0.308	0.000	2.749	0.023	0.461
Total Effect	0.207	0.309	0.001	2.755	0.030	0.468
Observations	17910					

Table 10: venture capital: dollar 1 million more (cum.) venture capital results in

	mean	sd	min	max	p10	p90
Patents for VC companies	0.10	0.07	0.00	0.33	0.02	0.20
Patents for Est. companies	0.25	0.17	0.00	1.10	0.07	0.51
Total External Effect	0.35	0.22	0.01	1.23	0.12	0.68
Patents for own company	0.08	0.11	0.00	0.84	0.01	0.18
Total Effect	0.42	0.27	0.01	1.67	0.14	0.80
Observations	8975					

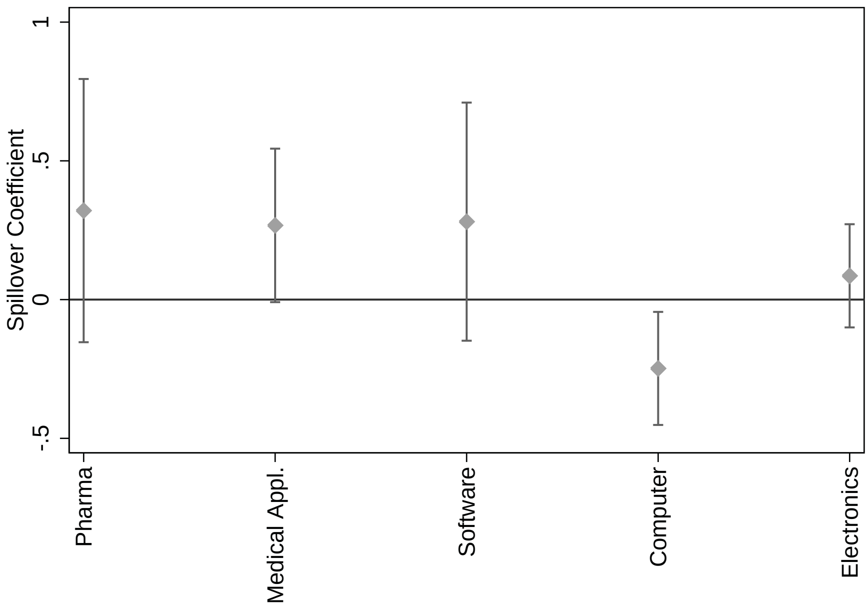
possible.

5. Conclusion

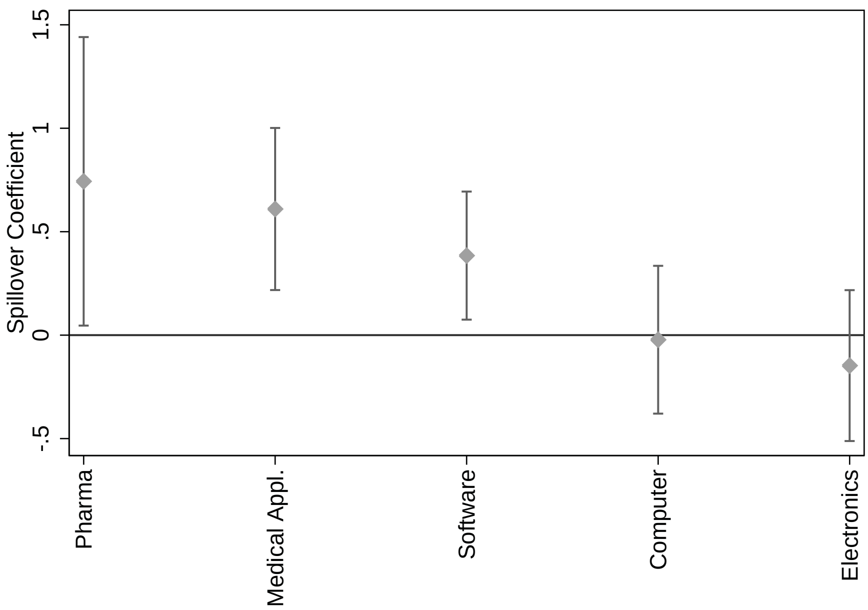
In this paper we measure the spillovers from venture capital and R&D and compare their relative quantitative importance for patent production. We find that spillovers from venture capital are much stronger than spillovers from R&D: Back of the envelope calculation suggests that around 142 million dollar in additional R&D spending of established companies results in an external effect of one patent. To get the same effect with venture capital an increase of only 3 million dollar is necessary. In contrast R&D is much more privately profitable: One patent created through traditional R&D costs around 5 million while a venture capital backed company needs 2.5 times the sum in venture capital.

This paper is still very much in its infancy and there are at least three areas which

Figure 2: Industry: Spillover from venture capital on



(a) patents of established companies



(b) patents of venture capital backed companies

require significant further work: First, it is not satisfactory that we do not understand what drives the spillovers. For example if spillover are caused by scientists changing companies, we should include the flow of scientists in our regression. Second, the large underlying heterogeneity in the firm population makes the quantitative magnitude of the results appear fragile. Here we should either control for more variable or restrict our subsample to one particular industry. Thirdly, the run-up in venture capital investment during the dot-com bubble significantly changed the economics of venture capital and the resulting spillovers. It would be interesting what drives this change and how one can account for it in the main regression.

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A. First Stage Regression

Table 11 shows first stage regressions of our instruments on R&D and venture capital investment. Table 12 reports the regression of the predicted spillovers, our instruments, on the actual spillovers. The residuals from these regressions are used as control functions. TO BE COMPLETED

Table 11: First Stage Regressions

	(1) VC	(2) VC	(3) VC	(4) Ln(R&D+1)	(5) Ln(R&D+1)	(6) Ln(R&D+1)
Lagged raised funds	0.08***	0.04***	0.05***			
	(0.01)	(0.01)	(0.01)			
Ln(R&D user cost_i,t)				-3.24***	-2.92**	-3.30***
				(0.27)	(1.32)	(0.72)
F-Value	32.9	16.99	12.82	148.81	4.87	21.08
Year Fixed Effect	No	Yes	Yes	No	Yes	Yes
Firm Fixed Effect	No	No	Yes	No	No	Yes
R-square						
Number of Observations	35502	35502	35502	19994	19994	19994

Table 12: Calculation of Control Function

	(1) Spill VC	(2) Spill Est	(3) Spill VC	(4) Spill Est	(5) R&D	(6) VC
pred. log Spillover Est.	-0.05	0.05***	0.02	0.00	0.20*	-0.09
	(0.11)	(0.02)	(0.05)	(0.01)	(0.11)	(0.12)
pred. log Spillover Est.	6.97***	3.39***	4.77***	2.38***	4.44***	12.80***
	(0.89)	(0.24)	(0.61)	(0.21)	(0.78)	(1.60)
pred. log VC			-0.00***	0.00	0.00	
			(0.00)	(0.00)	(0.00)	
pred. log R&D	-0.28	0.04				1.43***
	(0.20)	(0.07)				(0.34)
F-Value	22.51	97.2	26.12	44.24	11.48	36.63
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R-square						
Number of Observations	23861	23861	49471	49541	24084	21391

B. Details of Size of Effect Calculation

TO BE COMPLETED

C. Functional Form Identification

In the main part of the paper we already used two different identification methods: Proxy variables and instrumental variables. In this appendix we discuss a third method: Identification by functional form. In the following we assume that the patent production function is literally of the Cobb-Douglas form described in Equation 1. This form of identification was first explored by Kortum and Lerner [2000] to estimate the productivity of venture capital in US on the industry level.

The idea is, that by suitable standardizing the patent production function on the industry level, we can eliminate technological progress from the estimation equation. Kortum and Lerner [2000] standardizes the patent production function with R&D expenditure while we standardize the patent production function of venture capital financed companies with the patent production function of established companies.

TO BE COMPLETED