Measuring the Spillovers of Venture Capital

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Abstract

We provide the first measurement of knowledge spillovers from venture capital-financed companies onto the patenting activities of other companies. These spillovers are nine times larger than those generated by the corporate R&D of established companies. The effects are heterogenous, depending on who generates the spillover and who is the likely recipient. In general, complex product industries tend to be more conducive to spillovers than discrete product industries. Spillovers are stronger for investments in a small set of start-ups that are characterized by an inventor team with prior patenting experience and that have a patented technology before receiving their first round of investment. This points to a complementarity between the supply of venture capital on the one hand and access to experience and technology on the other hand. The methodological contribution of our paper is the development of a novel definition of the spillover pool that combines elements of the citation-based and technological proximity-based approaches.

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1 Introduction

There is a broad consensus in economics that corporate R&D spending generates positive knowledge spillovers.[1] In a recent study, Bloom, Schankerman, and Van Reenen (2013) find that the social return of R&D is around three times the private return of R&D. They also find that the research of large companies (as measured by employees) generates more spillovers than the research of small companies, presumably because smaller firms tend to operate in technological niches. A certain type of small companies, however, - venture capital-backed start-ups - are considered by policy makers and researchers alike to be particularly innovative and important for economic growth.[2] Yet there exists no empirical evidence on the knowledge spillovers generated by venture capital-backed start-ups.

In this paper, we show that VC-financed firms generate positive knowledge spillovers onto the patent production of other firms. Our estimations suggest that per dollar of investment, the knowledge spillovers from venture capital are at least nine times larger than the spillovers from corporate R&D. The estimated total social return of venture capital is around three times as large as the social return of corporate R&D. These magnitudes of the social return based on firm-level data are consistent with those found in the study by Kortum and Lerner (2000) based on industry-level data.

Our analysis allows us to paint a nuanced picture of venture capital-induced spillovers. The effects are heterogenous, depending on what type of start-up increases its VC investment and who is affected by the potential spillover. We find that spillovers are stronger in industries that use a “complex” product technology as compared to a “discrete” product technology. Complex products, such as computers, need the input of numerous separately patentable elements, while discrete products, such as drugs, require only few of such inputs. Lower spillovers in discrete technology industries may be

[1] Hall, Mairesse, and Mohnen (2009)

[2] Based on the notion that venture capital stimulates innovation and growth, numerous governments give subsidies and tax breaks to the venture capital industry. Venture capital funds are exempt from taxation in France and in the UK, the Canadian Government acts directly 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.

due to the fact that patent protection is a more effective appropriation mechanism in discrete technology industries than in complex technology industries (Cohen, Nelson, and Walsh, 2000), thus limiting the potential for spillovers.

Moreover, the impact of venture capital on innovation seems to depend crucially on the type of start-up receiving the investment. Spillovers are stronger for investments in a small set of start-ups that are characterized by an inventor team with prior patenting experience and start-ups with a patented technology before receiving their first round of investment. This suggests that start-ups that commercialize existing technology have large knowledge spillovers.

The data for our study come from two sources, Compustat and VentureXpert. Compustat contains balance sheet data for all US publicly listed companies, including R&D expenditures. As start-ups are small private companies, no data on their R&D expenditures are available. Hence, a commonly used surrogate is the venture capital invested in a particular start-up in a given year (Kortum and Lerner, 2000).[3] We take this information from VentureXpert, which is a prime source for venture capital investment and fund-raising data.

We follow the literature in measuring innovation by the quantity and quality of patents. The patent data are from the NBER US Patent Citations Data File and from the data files of Lai, Amour, Yu, Sun, Torvik, and Fleming (2011). We match the patent data to Compustat using the unique identifier provided by the NBER (Hall, Jaffe, and Trajtenberg, 2001). For the venture capital data, we match the patent data with the help of algorithms from the Apache Lucene Library and check the results by hand.

Measuring spillovers is challenging because knowledge flows are unobserved and non-rivalrous, i.e. they can affect many different companies. The lack of observability implies that we have to infer spillovers indirectly from the observed co-movement of venture capital investment in start-ups and the patenting behavior of other companies, following inter alia Jaffe (1986) or Bloom, Schankerman, and Van Reenen (2013).

[3] While this measure may overestimate the actual amount of R&D carried out by the start-up company, it means that the spillover effects are likely to be underestimated.

One problem with such an indirect approach is that we might mistake such a co-movement as evidence of spillovers between companies when it is in fact driven by general technological progress that affects both venture capital or R&D investment and patenting in other companies. To address this endogeneity problem, we instrument the R&D expenditures of established companies with the level of R&D tax credit in a state, as in Bloom, Schankerman, and Van Reenen (2013), and venture capital investment with past fund-raising of private equity buyout funds (Nanda and Rhodes-Kropf, 2012).

As we cannot observe spillovers directly but have to infer them indirectly from the data, we would like to estimate for each company pair at least one parameter governing the co-movements between each and every company. Unfortunately, this is technically infeasible because it would result in an excessive number of parameters to be estimated (Azoulay, Graff-Zivin, Li, and Sampat, 2014). To address this problem, the approach taken in the literature is to restrict the set of companies that can potentially influence each other. This set of companies from which a company might learn is called the "spillover pool" of a company.

We use three different definitions of the spillover pool to make sure that our results are robust. For the first definition, we include all the companies whose patents are cited by a particular company in its spillover pool (Azoulay, Graff-Zivin, Li, and Sampat, 2014). This is the most direct way to assess whether or not the research of one company is influenced by the research of another company. The drawbacks are that it captures only the knowledge flows that are acknowledged by a formal citation and that citations might be endogenous to company characteristics.

The second definition includes all the companies in the spillover pool that patent in the same technology classes as the company under consideration (Jaffe, 1986).[4] The underlying assumption is that knowledge flows mainly within technological fields. However, this assumption is at odds with the observation that successful innovations

[4]Bloom, Schankerman, and Van Reenen (2013) extend this concept by also including companies that work in "similar" technologies and call this new measure the Mahalanobis proximity. According to this measure, two technologies are characterized as similar if companies often hold patents of the two corresponding patent classes together in their patent portfolio. Patents about robotics and artificial intelligence, for example, are complementary and therefore collocated in companies.

often recombine ideas across technological boundaries (Uzzi, Mukherjee, Stringer, and Jones, 2013; Weitzman, 1998). Hence, while this measure known as the Jaffe measure allows the capturing of knowledge flows without relying on direct evidence of citations, it may be overly restrictive in its focus on knowledge flows within technological fields.

To address these drawbacks, we develop the third definition of the spillover pool, which combines elements of the first two concepts. For this purpose, we calculate a weighting matrix based on the citation propensities between different technology classes. We then use this weighting matrix to augment the technological proximity measure of Jaffe (1986). This procedure enlarges the spillover pool by including companies that are active not in the same technology but in related technologies, as documented by backward citations. At the same time, we avoid the problem of considering only knowledge flows acknowledged by individual citations. As our measure of a spillover pool is constructed using average citation propensities, not individual citations, we avoid the endogeneity issues of the first measure. Another advantage of this citation augmented measure over the Jaffe measure is that it allows the spillover flows between companies to be asymmetric (as backward citations between two technology classes can be asymmetric), while the Jaffe proximity measure is symmetric by construction. Thus, our new measure captures a more general and arguably more realistic specification of knowledge flows between firms.

Using these three proximity metrics we estimate and compare the spillovers that arise from venture capital investments in start-ups and from R&D expenditures in established companies. Our estimates show that VC-financed start-ups generate significantly positive spillovers onto other firms' quantity and quality of patents. Our results are stable when using different spillover pools, different estimation methods, different subsamples or different outcome variables.

In sum, the contribution of our paper is threefold. First, we contribute to the literature on knowledge spillovers by providing the first measurement of innovation spillovers generated by venture capital-financed firms.[5] The availability of venture capital is well

[5] For recent summaries of the literature on venture capital see Da Rin, Hellmann, and Puri (2011), Dessí and Yin (2012) and Lerner and Hall (2010).

recognized as being crucial for translating scientific research into innovation as part of the national innovative system (Furman, Porter, and Stern, 2002), yet the empirical literature on how venture capital-backed start-ups contribute to innovation in an economy is limited.[6]

Our second contribution is to establish which industries are most likely to experience and which inventors are most most likely to generate spillovers. We confirm that complex technology industries tend to be more conducive to spillovers than discrete technology industries. Furthermore, we document that these knowledge spillovers are stronger for start-ups with an experienced inventor team and start-ups that have a patented technology prior to receiving their first round of investment.

Third, the methodological contribution of our paper is the development of a new measure for the spillover pool, combining elements of citation-based and technological proximity-based approaches. Our measure avoids the endogeneity issues of individual citation-based measures. Furthermore, it allows the spillover flows between companies to be asymmetric, whereas the Jaffe proximity measure by construction is symmetric.

The paper proceeds as follows. In section 2, we explain the empirical strategy for measuring the spillovers of R&D and venture capital. In section 3, we describe the data and the variables used and provide summary statistics. In section 4, we present our empirical results and section 5 concludes.

2 Data and Description of Variables

For our data set, we combine patent data with firm level data of venture capital-financed companies and established companies in the US from 1979 to 1999.

[6]A recent paper by González-Uribe (2014) investigates how venture capital affects knowledge diffusion by comparing patent citations before and after companies secure venture capital financing. She argues that venture capital certifies the commercial value of an invention, thus facilitating spillovers between companies. A major difference to our approach is that González-Uribe (2014) bases her counterfactual calculations on a mechanical assumption how citations of VC patents translate into the generation of new patents in other companies while we directly observe the patent production of other companies.

2.1 Patenting activity

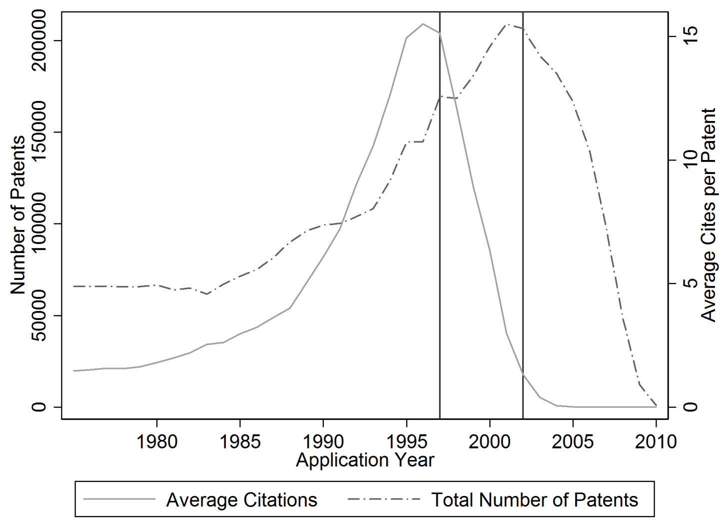
The patent data are from the NBER Patent-Citation Data File and contain all the utility patents filed in the US with the name of the applicant, year of application, location, patents that this patent cites and a classification according to the 3-digit US patent class. These patent data end in 2005. To identify additional patent citations in our database, we complement it with the Harvard patent dataset of Lai, Amour, Yu, Sun, Torvik, and Fleming (2011), which ends in 2010. The resulting dataset contains around 3.86 million patents.

To capture the quality of a patent, we use the number of citations that a patent receives from other patents ("forward cites", Hall, Jaffe, and Trajtenberg (2005). For comparability reasons, we consider only forward citations in patents that were applied for within three years after the patent to be cited was granted. One potential concern is that the citing behavior might change from year to year and from technology to technology. To account for these changes, we scale this measure by the average value in a particular year and in a particular technology class, following Bernstein (2012).

For our outcome variables, we consider only patents that were applied for up to 1999. The reason for this early cut-off date is that we are interested not only in the number of patents, but also in their quality, which is based on forward citations. This cut-off date is determined as follows. To capture all forward cites, we need to make sure that all the patents in which a patent can be cited are included in our database. In the years 1979 to 1999, it took on average 2.08 years for a patent to be granted. The 5% quantile was 1 year, while the 95% quantile was 4 years. Thus, if we want to make sure that we are missing fewer than 5% of all the patents granted that could cite a particular patent, we should consider only patents that were applied for up to 2006 (counting back from 2010). Furthermore, as stated above, we want to give patents three years to accumulate citations. This implies that our investigation of forward citations should be restricted to patents that were granted up to 2003.

Note, however, that we are interested in the number of patents by application date, as this arguably represents the time of the actual innovative activity. Thus, to be

Figure 1: Number of patents and citations per patent in the raw data



Note: This figure shows the number of patents in a particular application year and the number of citations to these patents for all patents available in our database. In the analysis we use only the subsample of patents assigned to established and venture capital-financed start-up companies from 1979 to 1999.

confident that we capture at least 95% of all the patents to be cited, we restrict our database to patents that were applied for up to 1999. If anything, stopping so late is too optimistic because in our raw data the pattern of a declining number in the citation rates starts around 1997 and the declining number of patents begins in 2002 (Figure 1). Note that the downward trend in the number of patents is a feature of end-year effects in our data and is not reflected in the published statistics of the USPTO.[7]

In robustness checks, we use the "generality" of a patent, its "originality" and indicators of whether it is among the top 5% ("I(Best 5% of citations)") or in the top 50% of the citation distribution within a technology class and year ("I(Best 50% of citations)"). To calculate the generality measure, we determine for each patent one minus the Herfindahl index across technology classes for the patents by which the patent is cited (Trajtenberg, Henderson, and Jaffe, 1997). With this measure we capture the dispersion across technology classes of patents using the patent. Similarly "originality" is calculated as one minus the Herfindahl index across technology classes for the

[7]US Patent Statistics Chart Calendar Years 1963 - 2013:
http://www.uspto.gov/web/offices/ac/ido/oeip/taf/us_stat.htm

patents that are cited by the patent. This measure captures the extent of dispersion of the information of which the patent draws.

2.2 R&D and venture capital investment

Our firm-level data source for established companies is the US Compustat file.[8] It contains yearly accounting data for publicly listed US companies with the company name, fiscal year, state of the firm headquarters, the four-digit SIC code, sales and R&D expenditures. We follow Bloom, Schankerman, and Van Reenen (2013) in the data selection procedure by restricting our data set to companies for which we have more than four years of R&D information and that do not exhibit very large jumps in sales, employment or capital.[9] Using the unique identifier provided by the NBER, these data are matched to the NBER Patent Citation Data File (Hall, Jaffe, and Trajtenberg, 2001). Lastly, we restrict the data to companies that applied for at least one patent in 1979 to 1999 and we drop all small industries with less than 10 companies over the whole observation period. The resulting database contains 1230 companies with 93'416 patents.

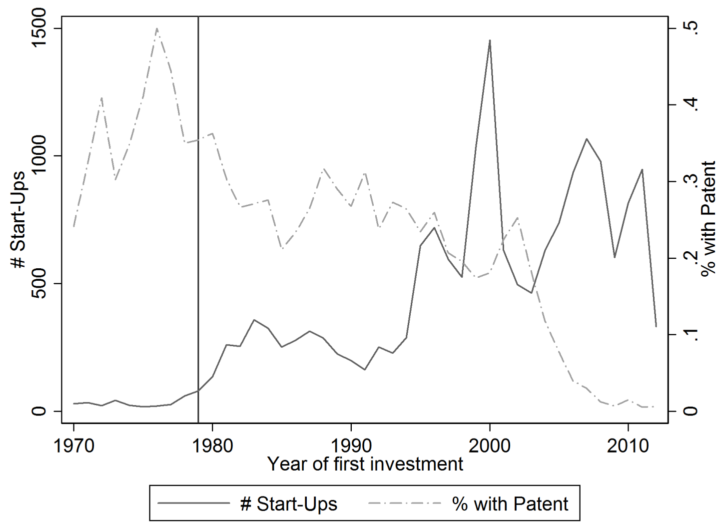
Start-ups are small private companies and therefore no data on R&D expenditures is available. Hence, a commonly used surrogate is the venture capital invested in a particular start-up in a given year (Kortum and Lerner, 2000). The rationale is that start-ups have no or little access to other sources of funding. Thus, using VC funds as a measure for R&D expenditures of start-ups almost certainly overestimates the true R&D expenses as part of the VC funds are used for other purposes like marketing. The venture capital investment data for the US come from Thomson Reuters VenturеXpert.[10] Each record contains the name of the investee company, the investment date,

[8]Data from Compustat was accessed at the Institute for Innovation Research (INNO-tec) at the University of Munich.

[9]In particular, we drop firms which never do R&D, are less than 5 years in the data, whose sales fall by more than 66% or increase by more than 200% year over year, have less than 0.1 million Dollar in assets per employee or more than 1 billion Dollar in assets, which have less than 2 million or more than 2 billion dollar in sales per employees. Furthermore if the company history in the data has years missing the company is deleted.

[10]Data from VentureExpert was accessed at the Institute for Innovation Research (INNO-tec) at the University of Munich.

Figure 2: Number of start-ups by year of first investment and share of start-ups with patent



Note: This figure shows the number of start-ups (# start-ups) in our sample by the year of the first investment. The grey line is the percentage of start-ups in the given first investment year for which we can identify at least one patent.

a four-digit SIC code and the total investment.

We match these investment data by the company name, state and time period to the patent data with the help of algorithms from the Apache Lucene library and check the results by hand. We restrict the data to companies that have at least one patent in the years between 1979 and 1999 and that have complete histories, that is their first investment round is a "seed" or "early stage" round, following Nanda and Rhodes-Kropf (2012). We do not start before 1979 because the number of start-ups in our database is relatively small (79 in the US in 1979,60 for 1978, 27 in 1977) and we find even fewer with at least one patent (28 in the US in 1979, 21 in 1978, 12 in 1977 - Figure 2) .

We use the data in the Harvard Citation File to determine for all start-ups the inventors of their first patent. For each of these inventors we determine whether or not she invented before and if so, at a university, at a start-up or at an established company in our dataset. Thus we can measure the prior patenting experience of the start-up inventor team.

In a last step, we drop all the patents that were applied for in the first year of investment because it seems unlikely that these patents were indeed financed by venture capital. Our VC data often does not record the failure or success of a start-up correctly. To mitigate this problem we drop observations for a company that are either later than two years after the last investment in this company or observations that are later than 10 years after the first investment. To be able to identify the industry fixed effect we drop industries with less than 10 companies in total. The resulting data set on VC-financed firms contains 1130 companies with 9,485 patents. The summary statistics for the dataset are shown in Table 1.

Table 1: Summary statistics

Established companies						
	mean	sd	min	max	p10	p90
Patent count	9.33	29.43	0	1033	0	22
Cite weighted patents	232.49	1240.38	0	42802	0	383
Scaled cite weighted patents	15.28	49.77	0	1327	0	38
Average complexity of companies' patents	0.53	0.40	0	1	0	1
Average citation-augmented proximity (x 100)	2.20	1.17	0	8	1	4
Average R&D (mio. dollars)	44.22	108.78	0	2271	1	112
Average Sales (billion dollars)	1.03	2.51	0	39	0	3
Years in data	7.12	4.69	1	21	2	14
Number of companies	1230					

Venture capital-backed start-ups						
	mean	sd	min	max	p10	p90
Patent count	1.68	3.39	0	62	0	4
Cite weighted patents	124.11	534.89	0	16394	0	249
Scaled cite weighted patents	4.30	11.06	0	176	0	11
# inventors	2.96	2.13	1	15	1	6
Inventors have prior patenting experience	0.62	0.49	0	1	0	1
Share with corporate patent	0.33	0.47	0	1	0	1
Share with academic patent	0.23	0.42	0	1	0	1
I(patent at first investment)	0.15	0.36	0	1	0	1
I(patent at first investment & prior experience)	0.09	0.28	0	1	0	0
Average complexity of companies' patents	0.69	0.42	0	1	0	1
Average citation-augmented proximity (x 100)	2.24	1.03	0	5	1	4
VC Investment (mio. dollars)	2.57	5.70	0	96	0	9
Years in data	4.82	2.81	1	11	2	10
Number of companies	1130					

2.3 Descriptive evidence on the innovation performance of VC-financed start-ups and established firms

Start-ups produce more patents per dollar than established companies (Table 2). This is in line with the findings of González-Uribe (2014) and Kortum and Lerner (2000). Furthermore, patents of start-ups are much more innovative than the patents of established companies both per patent and per invested dollar (Table 2). They receive more citations from other patents, are more original and are more general.[11] The higher quality of start-up patents is not driven by a particular time period or by outliers: the average number of ciations per patent are higher for the start-ups than for the established companies in all years (Figure 3).

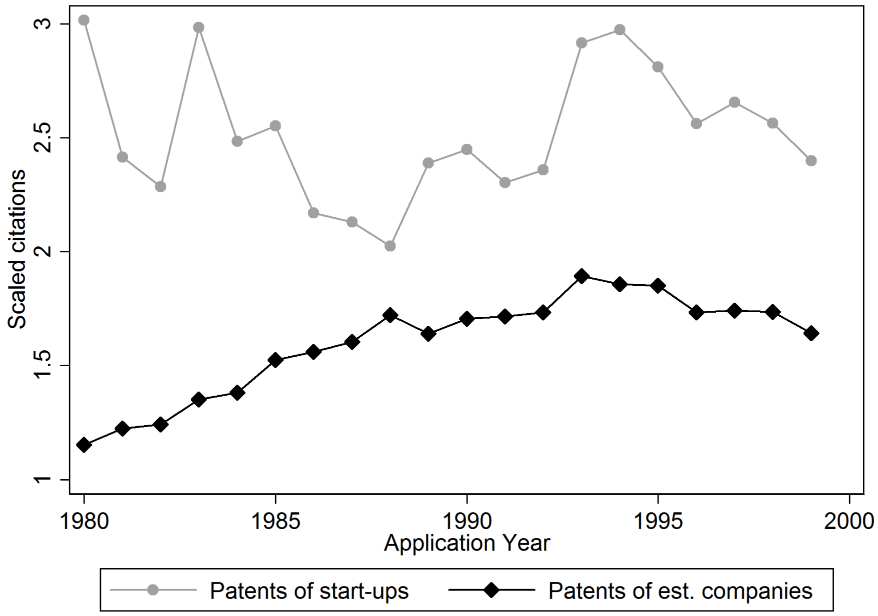
Table 2: Summary statistics of patents by company type

	Per patent				**Per dollar**			
	Established	Venture	Diff	P-Value	Established	Venture	Diff	P-Value
Forward Cites	22.37	55.84	33.47	0.00	7.17	89.41	82.24	0.00
Scaled Forward Cites	1.30	1.81	0.52	0.00	0.49	3.35	2.86	0.00
Generality	0.17	0.24	0.07	0.00	0.06	0.42	0.36	0.00
Scaled Generality	0.15	0.21	0.06	0.00	0.05	0.36	0.31	0.00
Originality	0.21	0.26	0.04	0.00	0.08	0.45	0.38	0.00
Scaled Originality	0.18	0.21	0.03	0.00	0.07	0.38	0.32	0.00
I(Best 50% of Citations)	0.57	0.63	0.06	0.00	0.22	1.21	0.99	0.00
I(Best 5% of Citations)	0.10	0.15	0.06	0.00	0.04	0.28	0.24	0.00
# Patents					0.29	1.43	1.14	0.00

Note: This table shows the summary statistics separately for start-ups and for established companies. The different statistics in the first four columns are standardized by the number of patents and in columns 5 to 8 they are standardized by the total amount of venture capital or R&D investment. The unit of analysis is the company. The p-value refers to a t-test of difference of means of the two groups, assuming unequal variance.

[11] Measured by the average citation-augmented proximity, they are also at least as central in technology space as established companies. This is in contrast with the finding of Bloom, Schankerman, and Van Reenen (2013) who report that small companies usually work in technological niches.

Figure 3: Number of scaled citations per patent over time



Note: This figure shows the average number of forward citations per patent scaled by the number of forward citations in the technology class and application year of the considered patent ("scaled forward citations") for the subsample of established companies (dark lines) and for the subsample of start-ups (grey lines) by the application year of the patent.

These descriptive statistics document that technologies created by start-ups are cited more often by other companies and in a more diverse set of technologies than the patented inventions of established companies. They cannot, however, provide causal evidence on the spillovers originating from these patents or how citations are related to patent production in other companies.

3 Empirical Strategy

The rationale for knowledge spillovers is that a firm may learn from other firms. Potential channels might be that scientists from different companies meet and exchange ideas, a firm hires scientists previously employed by another firm, or a firm learns via scientific publication or by reverse engineering a product of another firm. These activities are typically non-observable. The challenge is therefore to find a way of measuring these unobservable knowledge spillovers.

3.1 The problem of quantifying knowledge spillovers

To quantify the impact of knowledge spillovers on patent production, one would ideally proceed in two steps: first, estimate the knowledge creation in a company as a function of its investment in R&D or venture capital; and second, estimate the impact of this knowledge on the patent production of other companies. Consider for example a general knowledge production function $f(\cdot)$ and a general patent production function $g(\cdot)$. Then the knowledge spillovers originating from start-up i onto the patent production of company j can be deduced by estimating the following system:

$$Knowledge_i = f(VC_i, \ldots, \alpha) \tag{1}$$

$$Patent_j = g(Knowledge_i, \ldots, \beta) \tag{2}$$

Unfortunately, the knowledge created in a firm cannot be observed, nor can we observe the knowledge flows between companies. Thus, we can estimate only the reduced form impact of investment on patent production instead:

$$Patent_j = h(VC_i, \ldots, \gamma) \tag{3}$$

where the functional form $h(.)$ is unknown.

To make our estimates comparable with the literature we use the same reduced form function $h(.)$ as Bloom, Schankerman, and Van Reenen (2013):

$$ln(Patents_j) = \gamma \cdot ln(\sum_{j \neq i} \omega_{ji} \cdot VC_i) + \cdots + \varepsilon_i \tag{4}$$

where ω_{ji} indicates whether and if so how intensively the knowledge of start-up i was used in the production of the patent of company j. We call the set of all ωs the knowledge flow graph Ω.

As we cannot observe the knowledge flows between companies, we do not know which knowledge flow of which start-up influences the production of a particular patent.

Consequently we do not know the true values of the ω_{ji}s. A priori, all ω_{ji}s could be non-zero, since knowledge is non-rivalrous and hence the investment in every start-up might influence every innovation in the economy. For a reasonably sized dataset of 500 companies receiving and 500 start-ups generating spillovers this would require the estimation of 250'000 ω parameters, which is not possible. This curse of dimensionality precludes us from estimating all the ω_{ji}s from the data (Azoulay, Graff-Zivin, Li, and Sampat, 2014).

Instead, we follow the literature and address this problem by constructing the knowledge flow graph from auxiliary data. For example Bloom, Schankerman, and Van Reenen (2013) and Jaffe (1986) use patent data to calculate the technological proximity between companies assuming that companies closer in technology space are more prone to learn from each other. Azoulay, Graff-Zivin, Li, and Sampat (2014) use citations as a direct indicator for knowledge flows, measuring which patents cite and hence apparently benefit from knowledge created in academic articles sponsored by the National Institutes of Health.

The choice of method is not innocuous. In this framework, the expected external effect of an increase in venture capital, Γ, is given by

$$\Gamma = E\left[\frac{\partial Patents_j}{\partial VC_i}\right] = \gamma \cdot E\left[\omega_{ji} \cdot \frac{Patents_j}{\sum_{j \neq i} \omega_{ji} \cdot VC_i}\right] \tag{5}$$

and therefore a function of ω. As we do not know the true knowledge flow matrix (and therefore have to assume a value for ω_{ji}), the parameter Γ should be quantitatively and qualitatively robust to different plausible specifications of ω_{ji}. If this is not the case we should be worried that our results could be mainly driven by our modeling choices and that they are not a stable feature of the data. In the following, we describe three different ways to construct the knowledge flow graph and discuss their respective advantages and disadvantages.

3.2 Constructing the knowledge flow graph

To construct the knowledge flow graph we need to determine which auxiliary data to use, that is, which observables might serve as a good measure for knowledge flows. For method 1, we use patent citations following Azoulay, Graff-Zivin, Li, and Sampat (2014).[12] For method 2, introduced by Jaffe (1986) and recently employed by Bloom, Schankerman, and Van Reenen (2013), we use information on the technological proximity between firms. Method 3 combines information on the technological proximity and information on citation propensities.

Method 1: Using citations directly The most direct evidence for a knowledge flow between, say, a start-up and an established company can be seen if the established company's patents cite the patents of the start-up as prior art. The idea is that a patent citing another patent directly builds on the knowledge incorporated into this prior patent (Azoulay, Graff-Zivin, Li, and Sampat, 2014; Jaffe and Trajtenberg, 2002). To use citations to construct the knowledge flow graph, for each patent we use all the patents cited (excluding self-citations). Then, we aggregate these citations at the company level and standardize the number of citations by the total number of patents of the cited company. The resulting knowledge flow measure is

$$\omega_{ji}^{Citation} = \frac{\#Citations_{ji}}{\#Patents_i} \tag{6}$$

where $\#Citations_{ji}$ denotes how many times the patents of firm j cite patents of firm i. For example, if an established company j cites one out of ten patents of a start-up i, then the aggregated bilateral link is 10%, that is, we assume that company j uses one tenth of the knowledge of company i.

Citations are the most direct and intuitive way to construct the knowledge flow

[12] Azoulay, Graff-Zivin, Li, and Sampat (2014) use patent to journal article citations while we use patent to patent citations to link investment with outcomes.

A drawback of using patent citations is that many of them are added by the examiner (Alcacer and Gittelman, 2006). Therefore they are difficult to interpret. However, the survey results of Jaffe, Trajtenberg, and Fogarty (2000) show that around 50% of all backward citations correspond to some form of interaction between the inventors. Thus citations seem to be a valid but noisy measure of knowledge flows.

matrix, yet, the measure also has two drawbacks: First, it might suffer from measurement error because it does not capture knowledge flows that are not acknowledged by citations and because citations are also added by the patent examiner. Second, the measure suffers from a potential endogeneity issue because the knowledge flow may be correlated with the quality of the researcher. A more knowledgeable researcher may both produce more and better patents and at the same time be aware of a broader range of related research that he can cite.

Method 2: Using the Jaffe proximity measure The second method is based on the closeness of companies in "technology space." The idea is that a company learns more from another company if it is active in the same technology fields than if it is not. This concept was first proposed by Jaffe (1986). It defines the proximity in technology space as the uncentered correlation between the patent share vectors

$$\omega_{ji}^{Jaffe} = s_j' s_i \tag{7}$$

where s_i is the share of the patent stock $S_{i,t}$ of company i over various technology classes, standardized by their firm patent share dot product $s_i = \frac{S_{i,t}}{(S_{i.t} S_{i,t}')^{\frac{1}{2}}}$. The patent stock is the accumulated number of patents in the technology class up to $t-1$. Companies that have exactly the same patent share vector have a proximity of 1 while companies that are active in completely different technologies have a proximity of 0.

The advantage of using information about technology classes rather than actual patent citations is that current patenting behavior has no influence on the construction of the knowledge flow matrix.[13] However, a drawback of the Jaffe measure is that it assumes companies to learn only from companies active in the same technology classes. This assumption does not seem innocuous given that the literature suggests that high-quality innovations often come from the recombination of ideas from different

[13]Furthermore our outcome variable is scaled within patent class and year, therefore there is no bias if better researchers select into patent classes with more knowledge flows. In all specification we employ company fixed effects controlling for the possibility that a company generally employs better researchers influencing the technological position, e.g. by patenting in more diverse technological classes.

technological fields (Uzzi, Mukherjee, Stringer, and Jones, 2013; Weitzman, 1998).

Method 3: Using the Jaffe proximity measure augmented with citation propensities To integrate cross-technology knowledge flows into the Jaffe proximity measure, we introduce the matrix of citation flows between technology classes, W^{Cites}, as a weighting matrix.[14] The resulting citation-augmented proximity measure between company i and company j is given by

$$\omega_{ji}^{Cit.aug.} = s'_{i,t} W^{Cites} s_{j,t} \tag{8}$$

where s_i, s_j is the standardized patent share vector of companies i and j.

To construct the citation matrix W^{Cites} we calculate for each technology class A the share of citations it receives from every other technology class:

$$w_{B,A} = \frac{\#Citations_{B,A}}{\sum_M \#Citations_{M,A}} \tag{9}$$

where $\#Citations_{B,A}$ is the number of citations in technology class B to patents in technology class A. Then, we arrange these shares in a matrix, W^{Cites}.

The matrix W^{Cites} is plotted in Figure 4a.[15] As assumed by the Jaffe metric, there is indeed a strong tendency of patents in a particular technology class to cite patents from their own technology subcategory, but around 39% of all backward citations are drawn from other technology classes (Figure 4b).[16] An example of this general pattern is the subcategory "Computer Hardware and Software" which cites its own technology class with a probability of 61 % and other technology subcategories such as "Communications" or "Information Storage" with a probability of 25% (Figure 4c).

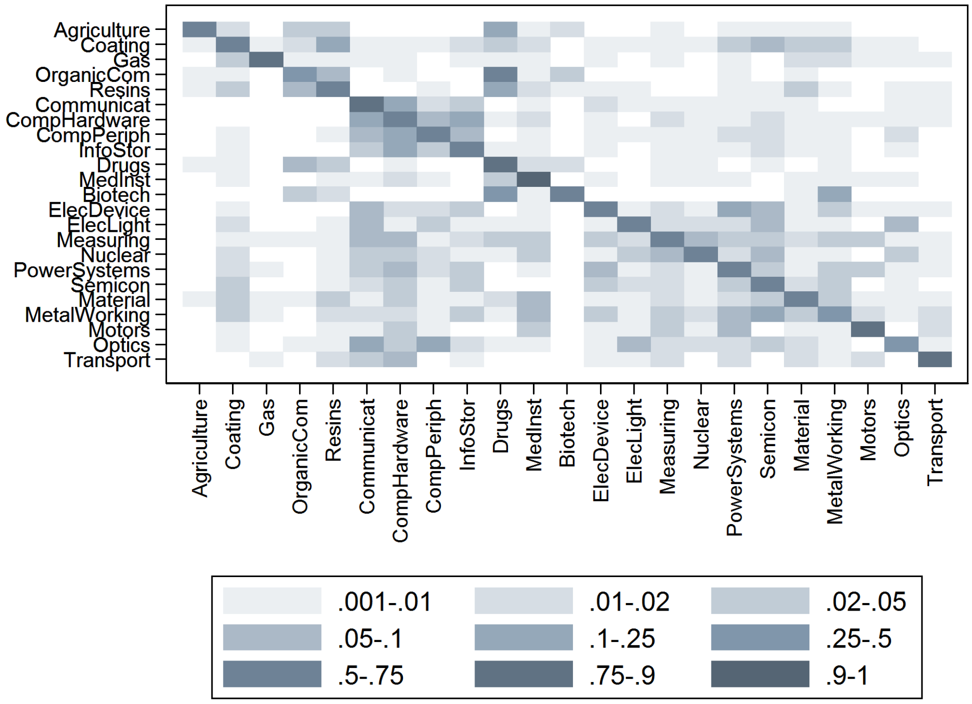
[14] Bloom, Schankerman, and Van Reenen (2013) modify the Jaffe proximity with a weighting matrix based on collocation of patent classes.

[15] In contrast to our empirical measure, for visualization we only plot the cross citations between broad technology subcategories. It is possible to use all 800 technological categories, but the graphical representation in this very fine grained level is not instructive. Every technology subcategory comprises several technology classes and the mapping is given in the appendix of Hall, Jaffe, and Trajtenberg (2001).

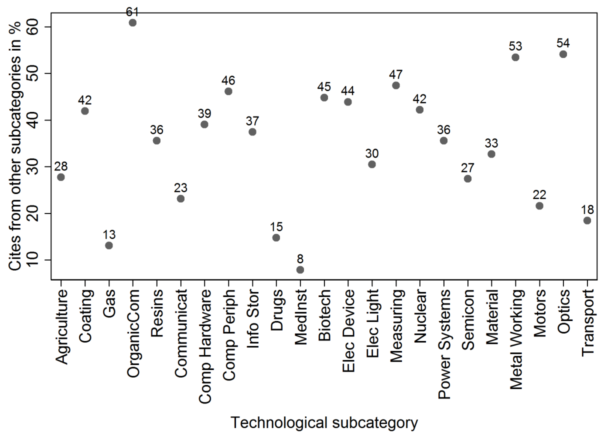
[16] One can see "clusters" of patent citations between similar technologies, as for example in computer hardware and software, comprising communication, computer periphery, and information storage. Another such cluster is drugs with organic compounds, resins, medical instruments and coating.

Figure 4: Citation patterns of technology classes

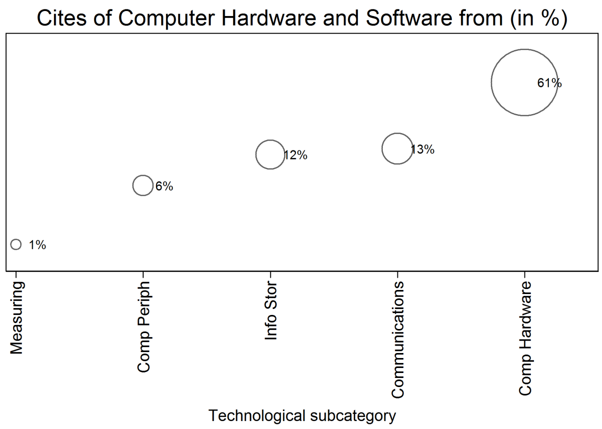
(a) Cross citation matrix



(b) Share of cites from other technological subcategories

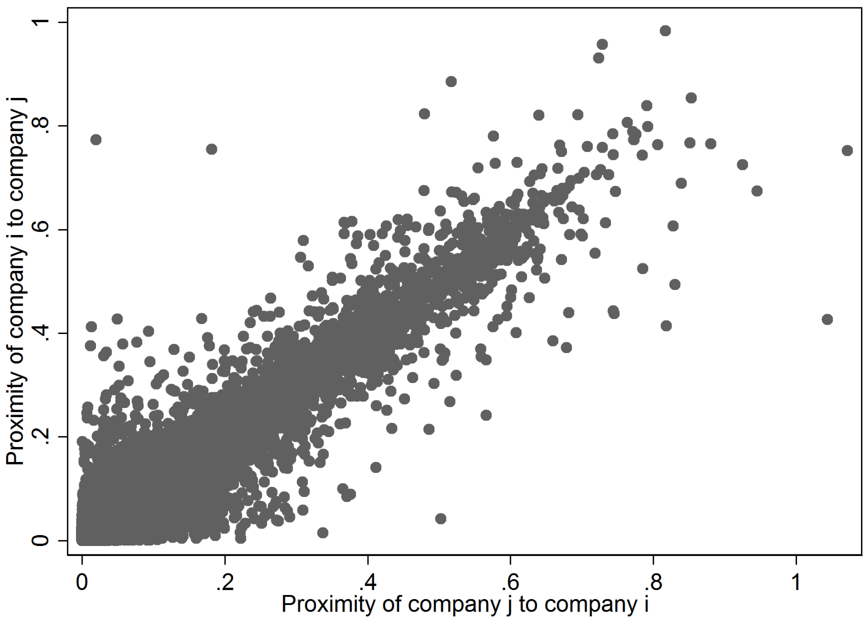


(c) Citations of Computer Hardware and Software



Note: Subfigure a) shows the share of cross citations between patents in broad technology subcategories. We use these broad subcategories defined by Hall et al (2005) instead of the finer technology classification of the USPTO (n-classes) to simplify visualization. The subcategory of the citing patent is on the vertical axis while the subcategory of the cited patent is on the horizontal axis. The rows therefore sum to 100%. Subfigure b) shows the share of patents that a patent in a particular subcategory cites from other subcategories. Subfigure c) shows the share of patents that patents in the subcategory "Computer Hardware and Software" cite from other technology subcategories.

Figure 5: Citation-augmented proximity between companies



Note: This figure shows the pairwise citations-augmented proximity between companies for a 0.5% sample of company pairs. The horizontal axis measures the proximity between a company j and another company i. The vertical axis is the proximity between the same companies but from i to j. In contrast to the Jaffe measure the citation-augmented proximity measure is not symmetric within company-pairs. For companies whose proximity is different from zero, the average proximity is 0.023. The average difference between the proximity from i to j (and vice versa) is 0.008 or 33%.

Thus, the advantage of this citation-augmented proximity measure is two-fold. (i) It allows capturing of knowledge flows that occur between companies that are not necessarily close in technology space, but that have a (backward citation) proven record of learning from each other. (ii) It allows the spillover flows between companies to be asymmetric, as backward citations between two companies can be asymmetric while by construction the Jaffe measure is symmetric. In Figure 5 we plot the proximity between companies pairwise for a 0.5% sample of our data, the proximity from company 1 to company 2 on the vertical and the proximity from company 2 to company 1 on the horizontal axis. The proximities are positively correlated, but not perfectly so.

3.3 The estimation equation

In the estimation of (4) we consider the spillovers of venture capital separately for the sample of established companies and for the sample of VC-backed start-ups. As control variables we include first the spillover term of venture capital

$$Spillover_{j,t}^{VC} = \sum_{j \neq i} \omega_{j,i} \cdot VC_{i,t-1}. \tag{10}$$

In addition, we include a spillover term for R&D investment

$$Spillover_{j,t}^{R\&D} = \sum_{j \neq i} \omega_{j,i} \cdot R\&D_{i,t-1}. \tag{11}$$

Furthermore, we use the direct effect of venture capital or R&D investment, depending on which sample of firms we investigate. As companies might differ in their unobserved research productivity, we use pre-sample mean scaling to account for firm-fixed effects. In robustness checks we also use de-meaning to control for firm fixed effects. In addition we include a complete set of year and industry dummies. The resulting estimation equation for a venture capital-financed company j at time t is:

$$\begin{aligned} ln(Patents_{j,t} + 1) = \beta_0 &+ \beta_1 \cdot ln\left[Spillover_{j,t-1}^{VC} + 1\right] \\ &+ \beta_2 \cdot ln\left[Spillover_{j,t-1}^{R\&D} + 1\right] \\ &+ \beta_3 \cdot ln[VC_{j,t-1} + 1] + Controls + \varepsilon_{j,t} \end{aligned} \tag{12}$$

where $VC_{j,t-1}$ is the stock of venture capital investment of company j at time $t-1$. In the case of an established company, $VC_{j,t-1}$ is replaced by $R\&D_{j,t-1}$, i.e.the stock of R&D investment of company j at time $t-1$. In robustness checks we repeat the main part of our analysis with a negative binomial model with control functions.

3.4 Identification

A potential endogeneity issue arises if the venture capital investments or R&D expenditures react to technological progress, which at the same time facilitates patent production.[17] Therefore we instrument the two spillover terms with instruments whose

[17]For example, Gompers, Kovner, Lerner, and Scharfstein (2008) showed that VC investors react to signals of the public market and this reaction is stronger for experienced investors.

construction we describe in turn.[18]

We use fundraising of leveraged buyout funds lagged by eight quarters as an instrument for venture capital investment, following Gompers and Lerner (2000) and Nanda and Rhodes-Kropf (2012). Venture capital funds receive most of their funds from institutional investors such as pension funds or university endowments. Institutional investors usually do not allocate capital to venture capital per-se but to the broader class of "private equity," a category encompassing venture capital and leveraged buyout funds. This mechanically results in an increase in investment in VC and in buyout funds and in a strong correlation between the two (Figure 6a). Thus, we can use buy-out fundraising as an instrument to isolate exogenous supply-side shocks in VC investment.

These supply-side shocks are exogenous to technological progress in the start-up market for three reasons. First, an institutional investor with private knowledge about future venture capital returns would invest in venture capital only instead of in private equity as a whole. Second, a shock to the demand for buy-out funds is most likely to be uncorrelated with the market for start-ups because leveraged buy-out funds are in the business of buying and improving mature companies. In contrast, start-ups receiving venture capital are concerned with creating innovative new products in industries with rapid technology progress and large growth potential. Thus, it is unlikely that demand shocks to these two types of funds are correlated. Third, it usually takes six to eight quarters between the commitment of the institutional investor and the first investment. This time lag makes the prediction of future technological progress by the institutional investor difficult.

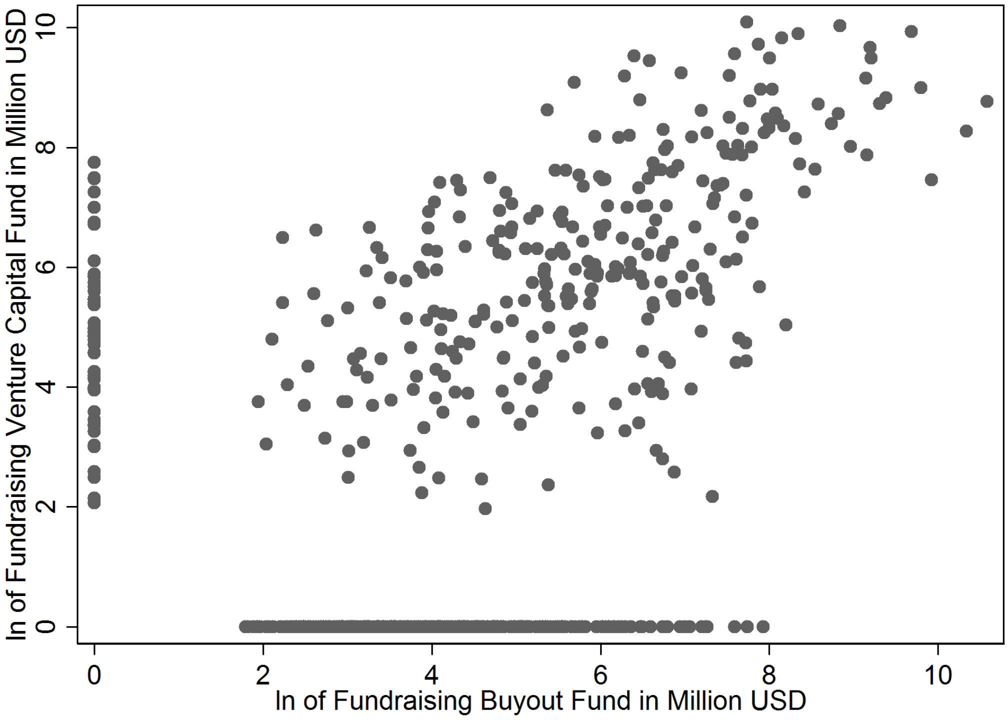
To convert fundraising data into a start-up-specific instrument, we follow two more steps. First we weight the fundraising in a state with a matrix of fund flows between states. Funds are often not invested where they are raised. The offices of venture capital funds and financed start-ups are usually co-located because VC managers intensely supervise their investee companies.[19] Fundraising often takes place where the

[18] We follow Bloom, Schankerman, and Van Reenen (2013) in only instrumenting the spillover terms.

[19] For example, Chen, Gompers, Kovner, and Lerner (2010) document that venture capital funds

Figure 6: Venture capital instrument

(a) Correlation between VC and Buyout Fundraising



(b) Fund-flows between US states

State of Start-up \ State of Fund	CA	FL	IL	MA	NJ	NY	OH	PA	TX	Rest
CA	273882	20532	1545	19736	12048	51694	471	1160	12394	70352
FL	4070	566	5	273	.	1128	.	416	518	2737
IL	3183	319	171	290	44	528	20	8	286	1130
MA	32691	3436	482	8141	2492	11690	260	118	1731	13542
NJ	5210	667	105	1632	1392	3560	.	0	334	4217
NY	3634	384	5	404	921	788	45	7	169	1831
OH	662	111	.	109	23	221	211	6	76	310
PA	5197	896	27	1149	213	1428	.	388	1102	3923
TX	10762	1273	60	1402	36	2975	.	718	3403	4986
Rest	69790	7816	1454	10709	3289	18691	137	749	5322	35481

Note: Subfigure a) shows the correlation between the natural logarithm of buyout fundraising and the natural logarithm of venture capital fundraising in million USD in a state-year sample. Subfigure b) shows the distribution of venture capital fundraising (measured by the state of the investment fund) in million USD and the state of venture capital investment between selected states for our sample period.

institutional investor is located. Therefore, to predict how much funding is available in each state, we weight the buyout-fundraising with the historical fund-flows in venture capital. Figure 6b depicts the absolute fund flows in the sample period for a selected number of states. In the second step, we follow Bloom, Schankerman, and Van Reenen (2013) and weight the available funds in a state according to the locations of the venture capital investee companies.[20]

Consequently, the instrument $Z_{i,t}^{VC}$ for the venture capital investment in start-up i at time t is calculated in the following way:

$$Z_{i,t}^{VC} = P'_{i,\sigma} X'_{\sigma,\sigma'} Fundraising_{\sigma',t-2} \tag{13}$$

where $P_{i,\sigma}$ is the patent share vector across states, $X_{\sigma,\sigma'}$ is the historical share of fund flows from state σ' to state σ and $Fundraising_{\sigma',t}$ is the fundraising of buyout-funds. The instrument is therefore the pool of funding available at a particular location.

To isolate exogenous variation in R&D expenditures, we use local supply-side shocks caused by the staggered introduction of R&D tax credits across states in the US. These tax credits lower the cost of conducting R&D and therefore in equilibrium should increase its optimal level. The literature surveyed by Bloom, Schankerman, and Van Reenen (2013) suggests that there is a 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. The R&D tax credits are again weighted with patent shares across different states of a company.

We use these fundraising and the tax policy instruments to predict the venture capital and R&D investment. Then, following Bloom, Schankerman, and Van Reenen (2013), we use these predicted values weighted by the different proximity measures as instruments for the two spillover variables in the second stage equations. Table 3 shows

and investment companies are highly concentrated in the US.

[20]From the patent data we can observe in which locations a start-up is active and therefore in which states it might search for funding. We then multiply the share of patents a company applied for in a particular state with the funds available in these states to arrive at a company specific instrument. The idea is that the location of patent application is related to the location of economic activity. The transformation is parallel to the instrumental variable strategy of Bloom, Schankerman, and Van Reenen (2013) and to the instrument for R&D spending below.

Table 3: Regression of VC and R&D expenditure on instruments

	ln(VC Investment+1)				ln(R&D+1)
VC Fundraising	3.56***				
	(1.24)				
Buy-out		2.04			
		(1.48)			
Buy-out / Cross-state			4.91***		
			(0.98)		
Buy-out / Cross-state / Firm specific				5.52***	
				(1.26)	
R&D Costs					-4.80***
					(1.51)
F-Value	8.31	1.90	24.99	19.19	10.13
R2	0.14	0.14	0.14	0.14	0.80
N	1753	1343	1880	1881	10010

Note: This table shows the results of estimating the first stage regression. The first four columns exhibit the first stage for venture capital investment and the last column is the first stage for R&D investment. On the first line, the instrument is venture capital fundraising in a state and year. On the second line, we use the fundraising of buyout funds. On the following two lines we weight buyout fundraising with the distribution of fund flows across states and with the distribution of states where a company produces its patents. On the last line, we use the costs for R&D as an instrument. All the standard errors are clustered on the four-digit industry level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. To increase the readability of the table we multiply each estimate by 100.

the regressions of venture capital and R&D expenditure on the two instruments. In the first column we use the fundraising of venture capital funds as an explanatory variable. The coefficient is large and significant. In the subsequent columns, we use buy-out fundraising, buy-out fundraising weighted by cross-state flows and buy-out fundraising additionally weighted by the location of the company. The last column shows the first stage for R&D investment. The F-values are above 10 in the last two columns, suggesting that the instruments used in the analysis are suitable for the estimation.[21]

[21] As instruments, we use the cumulative predicted R&D and VC stocks. Therefore, the F-values are not directly comparable with the critical values tabulated for example by Stock and Yogo (2005).

4 Results

4.1 Spillovers of venture capital

In this section we provide causal evidence that the spillovers of start-ups are larger than the spillovers of corporate R&D. We estimate the patent production function in equation (12) with three different knowledge flow measures. The results for established companies are reported in Table 4 and those for VC-financed start-ups are presented in Table 5. The first three columns of each table report OLS results, using citations directly, using the Jaffe proximity measure and using the Jaffe proximity measure augmented with citation propensities. In columns four to six we report the results of the instrumental variable regression for the three different specifications.

For the subsample of established companies, we find the expected positive effect of R&D expenditures, as well as the expected positive spillover effects from other established companies. In addition, we find for all three knowledge flow measures that the spillovers from venture capital investment have a measurable influence on patent production. The results are similar for both OLS and IV specifications. All the estimated elasticities are significantly different from zero at the 10% level or higher. Compared with the OLS specification in the study of Bloom, Schankerman, and Van Reenen (2013), our estimated elasticity of 0.15 for the spillover of established companies with the Jaffe metric is smaller than their elasticity of 0.49, while our R&D elasticity of 0.41 is larger than their estimate of 0.22. Other estimates for the R&D elasticity in the literature range from 0.2 to 0.9 (Hall, Jaffe, and Trajtenberg, 2001; Hausman, Hall, and Griliches, 1984).[22]

For the subsample of VC-financed start-ups, we again find the expected positive effect of venture capital investment on the patent outcomes of start-up firms. Further-

[22]The main difference between the Bloom, Schankerman, and Van Reenen (2013) study and our study is that we do not control for product market spillovers and we use linear regressions instead of a negative binomial model. Furthermore Bloom, Schankerman, and Van Reenen (2013) do not control for the spillovers of start-ups. In Table 14 in the Appendix we re-estimate our model with a negative binomial model and control functions. For this specification we estimate the elasticity for the spillovers of established companies to be 0.5, which is alsmost the same as in Bloom, Schankerman, and Van Reenen (2013). We still find a larger direct effect of R&D spending.

more, we confirm the expected positive spillover effects of established companies. The spillover effects of venture capital investment on other start-ups are not significantly different from zero for either proximity measure.

There could be several reasons why the spillover effects are not so large for VC-financed firms. First, it could simply be that they are not as precisely measured as they are for established firms. Second, smaller VC-financed firms may not have the absorptive capacity to take advantage of knowledge flows from other VC-financed firms. Another reason why VC-financed firms may have a lower inclination to absorb (potentially) patent-protected knowledge from other companies may be that small firms in general do not have patent portfolios that can serve as threat in a patent dispute or that can be useful to strike cross-licensing agreements. Hence they are less able to resolve patent disputes without resorting to the courts (Lanjouw and Schankerman, 2001).

As elasticities are hard to interpret quantitatively, we use equation (14) to calculate the average effect of a counterfactual increase in VC (R&D) by 1 million dollars, Γ, on the number of scaled forward-citation weighted patents. The results are presented in Table 6.

$$\Gamma = E\left[\frac{\partial Patents_i}{\partial VC_j}\right] = \beta_2 \cdot E\left[\omega_{ij} \cdot \frac{Patents_i}{\sum_{j \neq i} \omega_{ij} \cdot VC_j}\right]. \tag{14}$$

The average direct effect of venture capital investment on the own patent (Table 6, column 1) is larger than the average direct impact of R&D investment. The results imply that increasing the venture capital investment by 1 million dollars yields directly in between 0.12 and 0.15 patents with the average number of citations. This translates to costs per patent between 6.5 and 8.1 million dollars in venture capital funding. The comparable number for established companies is around 12 million dollars.

The estimates for the external effect vary more widely: 1 million dollars more venture capital yields in between 0.02 and 0.19 patents of average quality. Therefore it requires between 5 and 60 million dollars in venture capital to generate a patent in another company while it requires between 47 and 588 million dollars investment

Table 4: Results for scaled forward citation-weighted patents - Subsample: Established companies

	Scaled Forward Citation-Weighted Patents					
	OLS			IV		
	Direct citations	Jaffe proximity	Citation augmented	Direct citation	Jaffe proximity	Citation augmented
Ln(Spillover Est.)	7.4***	15.4***	31.9***	8.2***	18.6***	37.8***
	(0.9)	(3.2)	(6.5)	(1.0)	(3.4)	(6.6)
Ln(Spillover VC.)	15.3***	6.0***	7.9**	7.4*	5.7***	7.3**
	(4.7)	(1.7)	(3.5)	(4.4)	(1.9)	(3.6)
ln(R&D Stock)	40.7***	41.4***	39.5***	40.5***	41.0***	38.8***
	(2.6)	(2.4)	(2.3)	(2.6)	(2.4)	(2.3)
Pre-sample FE	3.2***	3.3***	3.2***	3.2***	3.2***	3.2***
	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)
F-Value	.	.	.	195.69	154.83	156.01
R2	0.46	0.45	0.46	0.46	0.45	0.45
N	10010	10010	10010	10010	10010	10010

Note: This table shows the results of estimating equation (12) for the subsample of established companies and for the three definitons of the spillover pool (Direct citations, Jaffe proximity and citation- augmented). The first three columns show the OLS results, while the second three columns show the instrumental variable results. All the standard errors are clustered on the four-digit industry level. ***, **, and * indicate statistical signicance at the 1%, 5% and 10% level, respectively. To increase the readability of the table we multiply each estimate by 100.

in R&D. If we take these results at face value, the spillovers of venture capital are in between 9 to 18 times larger than the spillover of corporate R&D.

In our main estimation we only consider start-ups that have at one point in their lifecycle applied for a patent because otherwise we cannot calculate the Jaffe technological proximity measure. To make sure that this sample selection does not drive our results we do the following robustness check: we multiply venture capital investment by a correction factor such that the total investment matches the investment in our sample. Then we repeat the estimation of the patent production function in equation (12) (the regression table is Table 15 in the appendix) and recalculate the marginal effects. On the basis of these marginal effects, we recalculate equation (14) to calculate the average effect of a counterfactual increase in VC (R&D) by 1 million dollars. The results are reported in the last section of Table 6. They are similar to the results for

Table 5: Results for scaled forward cite-weighted patents - Subsample: Start-ups

	Scaled Forward Cite-Weighted Patents					
	OLS			IV		
	Direct citations	Jaffe proximity	Citation augmented	Direct Citation	Jaffe proximity	Citation augmented
Ln(Spillover Est.)	0.9*	19.1***	58.4***	1.1*	23.7***	70.3***
	(0.5)	(3.0)	(7.6)	(0.6)	(3.4)	(8.5)
Ln(Spillover VC.)	-1.4	1.3	2.6	-3.7	-0.2	-0.1
	(2.7)	(1.9)	(3.5)	(2.9)	(2.1)	(4.3)
ln(VC Stock)	17.7***	15.5***	14.3***	17.7***	15.5***	14.2***
	(2.9)	(3.0)	(2.8)	(2.9)	(3.0)	(2.9)
Pre-sample FE	3.6***	3.8***	3.7***	3.7***	3.8***	3.7***
	(0.6)	(0.7)	(0.7)	(0.6)	(0.7)	(0.8)
F-Value	.	.	.	32.09	48.96	78.29
R2	0.03	0.05	0.08	0.03	0.05	0.08
N	5650	5650	5650	5650	5650	5650

Note: This table shows the results of estimating equation (12) for the subsample of venture capital financed start-ups and for the three definitons of the spillover pool (Direct citations, Jaffe proximity and citation-augmented). The first three columns show the OLS results while the second three columns show the instrumental variable results. All the standard errors are clustered on the four-digit industry level. ***, **, and * indicate statistical signicance at the 1%, 5% and 10% level, respectively. To increase the readability of the table we multiply each estimate by 100.

all other proximity measures.

There are no estimates in the literature for the external effect of venture capital with which to compare these results. However, these estimates appear to be of a sensible magnitude since they imply that the total return of venture capital is between 1.91 and 3.28 larger than the total return of R&D. This is about the same size as that found by Kortum and Lerner (2000) and Popov and Roosenboom (2012) who report that venture capital results in around 3 times more equally weighted patents than corporate R&D.

These numbers should be interpreted with caution as we are estimating average marginal effects as shown in equation (14). Average effects can mask a considerable heterogeneity in the strength of the spillovers across start-ups and established companies. This is why in the next sections, we investigate more closely which subsamples of start-ups generate relatively more knowledge spillovers and which subsamples of companies benefit most from spillovers.

Table 6: Counterfactual increase in forward citation-weighted patents when spending 1 million dollars more on...

Direct citations	Own company	Other companies	Total	Multiplier
R&D	8.52	0.17	8.68	
Venture Capital	15.27	1.65	16.92	1.91
Jaffe proximity	Own company	Other companies	Total	Multiplier
R&D	8.62	1.00	9.63	
Venture Capital	13.38	18.20	31.58	3.28
Citation-augmented	Own company	Other companies	Total	Multiplier
R&D	8.16	2.12	10.28	
Venture Capital	12.25	19.11	31.36	3.05
Citation-augmented - adjusted	Own company	Other companies	Total	Multiplier
R&D	8.16	2.12	10.28	
Venture Capital	12.51	12.01	24.52	2.38

Note: This table shows the expected increase in scaled forward citation-weighted patents if we were to increase the investment in R&D or venture capital of one company by 1 million USD at random. For the calculation of this counterfactual we use the estimated coefficients in Table 4 and 5 and the equation (15) in the text. In the first column, we display the effect of the increase on the patents of the company that increases its spending. In the second column we show the spillover effect, i.e. the increase in patents of other companies. In column three, we add these two effects to obtain the total increase. In the last column, we divide the total effect of an increase in R&D with the total effect of an increase in venture capital. To increase the readability of the table, we multiply each estimate by 100.

4.2 Spillovers in complex and discrete product industries

In the patent literature it is well recognized that patents are a more effective mechanism to appropriate returns of R&D in "discrete" as compared to "complex" product industries. An industry is complex if the products need the input of numerous separately patentable elements, while it is discrete if products require only few of such inputs (Cohen, Nelson, and Walsh, 2000). Effective appropriation of returns in an industry implies that a company can exclude another company from the using a patented invention. As a consequence spillovers should be weakly smaller in discrete than in complex product industries.[23]

We test this hypothesis by measuring separately the spillovers originating from

[23] Cohen, Nelson, and Walsh (2000) find that in discrete product industries firms seem to use their patents effectively to block cumulative innovation by their rivals. In complex technology industries, such as telecommunication or semiconductors, firms instead are more likely to use patents as a bargaing chip for negotiations with their rivals.

start-ups from both types of industries and by measuring the spillovers experienced by companies in both types of industries. We follow Galasso and Schankerman (2015) in characterizing the technology categories Computer and Communication (NBER Category 2), Electrical and Electronics (NBER Category 4), Medical Instruments (NBER subcategory 32), and Biotechnology (NBER subcategory 33) as complex. We classify a company as producing complex products if 50% or more of its patents are in complex technology categories.[24]

The results for established companies are displayed in Table 7, columns (1) to (4). For expositional convenience we report only the results for the IV estimations, and only for the citation-augmented proximity measure. Column (1) reproduces the estimation of Table 4, Column (6). In column (2) we separately include a venture capital spillover term for venture capital investment in start-ups that have more than 50% of its patents in complex technologies ("complex") and for venture capital investment in start-ups which have less ("discrete"). We find that established firms experience larger spillovers from VC-firms in complex industries.

We then repeat our baseline regression for the subsamples of companies in complex and in discrete product industries. As expected, we find that established companies in complex technology industries benefit more from spillovers than established companies in discrete product industries (columns 3 and 4). Furthermore, we find that they experience higher spillovers from VC-financed start-ups in complex product industries than from those in discrete product industries.

In columns (5) to (8) we present the results for VC-financed start-ups. Like established companies, start-ups experience higher spillovers from other VC-financed start-ups in complex product industries than from those in discrete product industries (column 6). We do not find a significant spillover effect experienced by start-ups in complex or discrete product industries although the mean estimate is larger in complex product industries.

To summarize, the results support that in general, complex product industries are

[24]Thus, we classify 702 established company and 809 start-ups as active in complex product industries, whereas 528 established companies and 321 start-ups are active in discrete product industries.

Table 7: Spillovers split by the complexity of the product industry

	Scaled Forward Citation-Weighted Patents - IV							
	Established companies				Start-ups			
Subsample	Full sample	Full sample	Discrete products	Complex products	Full sample	Full sample	Discrete products	Complex products
Ln(Spillover Est.)	37.8***	35.1***	28.8**	45.1***	70.3***	71.9***	92.5***	63.9***
	(6.6)	(6.2)	(11.3)	(7.1)	(8.5)	(8.0)	(12.2)	(10.0)
Ln(Spillover VC.)	7.3**		5.5	11.9***	-0.1		-1.6	4.9
	(3.6)		(6.3)	(3.4)	(4.3)		(8.5)	(6.0)
discrete		-0.7				-4.4		
		(3.4)				(3.6)		
complex		13.1***				6.0**		
		(3.7)				(2.9)		
ln(R&D Stock)	38.8***	38.3***	37.2***	39.8***				
	(2.3)	(2.3)	(3.6)	(2.7)				
ln(VC Stock)					14.2***	13.8***	8.5***	16.7***
					(2.9)	(3.0)	(3.0)	(4.1)
Pre-sample FE	3.2***	3.2***	3.0***	4.1***	3.7***	3.6***	8.2***	2.8***
	(0.5)	(0.5)	(0.6)	(1.1)	(0.8)	(0.8)	(0.8)	(0.6)
F-Value	156.01	130.20	89.80	121.11	78.29	60.90	37.07	44.96
R2	0.45	0.46	0.46	0.46	0.08	0.08	0.10	0.08
N	10010	10010	4637	5373	5650	5650	1657	3993

Note: This table shows the results of estimating equation (12) with instrumental variables for the subsample of established companies and for the venture capital-backed start-ups for the citation-augmented proximity measure. We divide the industries by their technological complexity. A company is classified as active in a complex product industry if more than 50% of its patent are in Computer and Communication (NBER Category 2), Electrical and Electronics (NBER Category 4), Medical Instruments (NBER subcategory 32), and Biotechnology (NBER subcategory 33). Otherwise it is classified as being in a discrete product industry. All the standard errors are clustered on the four-digit industry level. ***, **, and * indicate statistical signicance at the 1%, 5% and 10% level, respectively. To increase the readability of the table we multiply each estimate by 100.

more conducive to spillovers than discrete product industries. Established companies in complex technology industries experience larger spillovers from VC-firms than established companies in discrete product industries and the spillovers generated by VC-firms in complex product industries are larger than those generated by VC-firms in discrete product industries.

4.3 Spillovers depending on characteristics of the start-up

Next we investigate whether or not the strength of knowledge spillovers varies systematically with ex-ante characteristics of the start-ups. Prior research suggests that the founder team may play an important role for the success of a venture (Kaplan, Sensoy, and Stroemberg, 2009; Gompers, Kovner, Lerner, and Scharfstein, 2010).

Founders may differ in a number of characteristics. One characteristic studied in the literature is experience from previous employments. The literature on entrepreneurial spawning for example emphasizes that a prior affiliation with a start-up may help entrepreneurs learn how entrepreneurship works (the "Fairchild view" of entrepreneurial spawning). In addition, individuals with lower risk aversion might be more likely to be a serial entrepreneurs, consistent with the sorting processes hypothesized e.g. by Jovanovic (1979).

Entrepreneurs with prior experience in a large corporation may instead have access to a technology the established company is reluctant to commercialize (the "Xerox view" - e.g. Gompers, Lerner, and Scharfstein (2005); Klepper and Sleeper (2005)). Similarly, entrepreneurs with a prior affiliation to a university may be able to commercialize technology developed at universities (e.g. Di Gregorio and Shane, 2003; Nerkar and Shane, 2003). Experience may thus improve the entrepreneurial skills of the founders (skills hypothesis) or it may give them access to technologies to be commercialized at the new start-up firm (commercialization hypothesis).

As we are interested in innovation we focus on the inventors, not the founders of the start-ups, bearing in mind that these are often the same persons. For this purpose, we use the information on the inventors of the first recorded patent of the start-up. We do not have a complete curriculum vitae of each inventor so we cannot directly observe experience from previous employments. Thus, we follow the literature by using prior patenting as an indicator for a movement between employers (Marx, Strumsky, and Fleming, 2009). We check whether the inventor of this first patent already patented prior to joining the start-up, and if she did so at an established company or a start-up or at a university. In Table 8 we cross tabulate the number of start-ups with the different experience profiles.

Table 8: Number of start-ups by experience profile

	Corporate experience in				
	none	start-ups	established	both	Total
No academic experience	541	80	299	46	858
Academic experience	163	35	69	16	255
Total	708	116	368	62	1130

Note: This table shows the number of start-ups with at least one inventor with prior patenting experience. E.g. column 2 presents all start-ups with at least one inventor with prior patenting experience in another start-up, but no academic experience (line 1) or with at least one inventor who patented before for a university ("academic experience" - line 2). The sum in column 5 is calcuated by adding columns 1 to 3 and substracting column 4 as start-ups with prior experience in both are double counted in columns 2 and 3.

To investigate the role of experience, we split the spillover generating start-ups in two groups, companies with experienced inventors and companies without experienced inventors, and re-calculate the venture capital spillover measure. The results for these splits are reported in Tables 9 and 10. For expositional convenience we only report the results for the IV estimations, and only for the citation-augmented proximity measure. In columns (1) to (3), we split spillover generating start-ups in inventors with prior experience (either as a corporate or as an academic inventor) and inexperienced inventors. In columns (4) to (6), the split is between inventors with experience as a start-up inventor and no such experience. In columns (7) to (9), the split is between inventors with experience in an established company and no such experience. In columns (10) to (12) experience means experience as an academic inventor.

Start-ups with experienced inventors generate significantly more spillovers onto established firms in complex product industrie (Table 9). For established firms the

Table 9: Split by inventor team- Subsample: Established companies

	Scaled Forward Citation-Weighted Patents - IV											
Split by	Prior experience			Start-up inventor			Established inventor			Academic inventor		
	Full sample	Discrete technologies	Complex technologies	Full sample	Discrete technologies	Complex technologies	Full sample	Discrete technologies	Complex technologies	Full sample	Discrete technologies	Complex technologies
ln(Spillover Est.)	37.3***	28.2**	46.2***	37.8***	29.2***	47.9***	37.5***	28.0**	47.4***	35.9***	24.7**	43.6***
	(6.7)	(11.2)	(7.6)	(6.5)	(11.2)	(7.4)	(6.6)	(11.6)	(7.8)	(6.5)	(11.3)	(7.1)
ln(Spillover VC)												
wo experience	3.9	7.8	-1.2	6.3	3.9	6.6	2.6	6.9	-3.5	8.4*	19.8*	1.9
	(5.4)	(10.9)	(6.6)	(4.3)	(6.4)	(6.2)	(5.1)	(10.4)	(5.2)	(4.6)	(10.9)	(5.3)
w experience	4.3	-0.9	13.4**	1.5	1.8	4.7	5.7	-0.8	15.4**	1.8	-8.6	14.4***
	(6.4)	(9.8)	(6.7)	(4.6)	(6.5)	(6.8)	(6.3)	(10.2)	(6.3)	(4.9)	(9.0)	(4.9)
ln(R&D stock)	38.7***	37.1***	39.4***	38.8***	37.2***	39.2***	38.7***	37.2***	39.2***	38.6***	36.7***	39.5***
	(2.3)	(3.6)	(2.7)	(2.3)	(3.7)	(2.6)	(2.3)	(3.6)	(2.6)	(2.3)	(3.6)	(2.7)
Pre-sample FE	3.2***	2.9***	4.1***	3.2***	3.0***	4.1***	3.2***	3.0***	4.1***	3.2***	3.0***	4.1***
	(0.5)	(0.6)	(1.1)	(0.5)	(0.6)	(1.1)	(0.5)	(0.6)	(1.1)	(0.5)	(0.6)	(1.1)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Value	134.64	75.04	125.44	132.06	75.30	108.23	139.04	78.81	113.36	131.02	76.40	114.21
R2	0.45	0.46	0.45	0.45	0.46	0.45	0.45	0.46	0.45	0.46	0.46	0.45
N	10010	4637	5152	10010	4637	5152	10010	4637	5152	10010	4637	5152

Note: This table shows the instrumental variable results of estimating equation (12) for the subsample of established companies and the citation-augmented proximity measure. In the first three columns we split the spillover generating start-ups according to the prior patenting experience of the inventors on the first patent. In the following three columns we consider for the sample split only the patenting experience in a start-up. In columns (7) to (9) we split by experience in an established company. In the last three columns we split by the patenting experience at a university. An inventor is considered to have experience if her name is mentioned on a patent before she joins the start-up. A company is classified as active in a complex product industry if more than 50% of its patent are in Computer and Communication (NBER Category 2), Electrical and Electronics (NBER Category 4), Medical Instruments (NBER subcategory 32), and Biotechnology (NBER subcategory 33). Otherwise it is classified as being in a discrete product industry. All standard errors are clustered on the four digit industry-year level. ***, ** and * indicate statistical signicance at the 1%, 5%, and 10% level, respectively. To increase the readability of the table we multiply each estimate by 100.

Table 10: Split by inventor team- Subsample: VC backed start-ups

	Scaled Forward Citation-Weighted Patents - IV											
Split by	Prior experience			Start-up inventor			Established inventor			Academic inventor		
	Full sample	Discrete technologies	Complex technologies	Full sample	Discrete technologies	Complex technologies	Full sample	Discrete technologies	Complex technologies	Full sample	Discrete technologies	Complex technologies
ln(Spillover Est.)	69.5***	91.5***	64.3***	71.7***	92.7***	67.3***	69.2***	92.2***	65.2***	70.9***	84.5***	66.1***
	(8.9)	(13.1)	(10.9)	(8.0)	(12.4)	(9.4)	(8.5)	(13.8)	(9.9)	(9.0)	(10.9)	(11.0)
ln(Spillover VC)												
wo experience	-5.3	3.7	-3.1	-6.2*	1.8	-3.7	-6.4	-2.4	-1.5	4.3	15.7	2.0
	(4.3)	(11.3)	(5.9)	(3.7)	(8.4)	(5.8)	(4.0)	(11.9)	(5.8)	(3.8)	(14.2)	(5.4)
w experience	5.0	-4.5	8.1	6.9**	-6.6	8.6*	7.6*	1.6	6.8	-4.1	-10.4	2.8
	(4.6)	(8.5)	(6.1)	(3.3)	(9.5)	(4.4)	(4.2)	(11.3)	(4.6)	(3.7)	(10.3)	(4.9)
ln(VC stock)	14.3***	8.5***	16.7***	14.2***	8.9***	16.6***	14.3***	8.4***	16.6***	14.0***	8.2***	16.7***
	(3.0)	(3.0)	(4.2)	(2.9)	(3.1)	(4.1)	(2.9)	(3.0)	(4.1)	(2.8)	(3.0)	(4.2)
Pre-sample FE	3.7***	8.2***	2.7***	3.7***	8.1***	2.7***	3.7***	8.2***	2.6***	3.6***	8.2***	2.6***
	(0.7)	(0.8)	(0.8)	(0.7)	(0.8)	(0.8)	(0.8)	(0.8)	(0.8)	(0.7)	(0.8)	(0.8)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Value	66.04	33.48	38.94	64.91	30.99	43.11	62.59	32.86	37.06	80.55	43.32	38.93
R2	0.08	0.09	0.08	0.08	0.10	0.09	0.08	0.10	0.08	0.08	0.10	0.08
N	5650	1657	3850	5650	1657	3850	5650	1657	3850	5650	1657	3850

Note: This table shows the instrumental variable results of estimating equation (12) for the subsample of venture capital backed start-ups and the citation-augmented proximity measure. In the first three columns we split the spillover generating start-ups according to the prior patenting experience of the inventors on the first patent. In the following three columns we consider for the sample split only the patenting experience in a start-up. In columns (7) to (9) we split by experience in an established company. In the last three columns we split by the patenting experience at a university. An inventor is considered to have experience if her name is mentioned on a patent before she joins the start-up. A company is classified as active in a complex product industry if more than 50% of its patent are in Computer and Communication (NBER Category 2), Electrical and Electronics (NBER Category 4), Medical Instruments (NBER subcategory 32), and Biotechnology (NBER subcategory 33). Otherwise it is classified as being in a discrete product industry. All standard errors are clustered on the four digit industry-year level. ***, ** and * indicate statistical signicance at the 1%, 5%, and 10% level, respectively. To increase the readability of the table we multiply each estimate by 100.

spillover effect seems to be mostly driven by inventors with a background in established companies and in academia, whereas for VC-financed firms the effect is strongest for inventors with a corporate background, in start-ups or in established companies. These observations are consistent with both the skills and the commercialization hyptheses.

To dig deeper into this question of whether any of the two hypotheses has particular merit we use the information whether or not the start-up has a patent application before the year of its first investment. The reasoning is as follows: If the skills hypothesis holds, i.e. experience matters because it improves the inventor's skills we would expect experience to matter independent of prior patenting. If instead the commercialization hypothesis is relevant, i.e. experience matters because it provides access to a technology which the inventor then commercializes in the new start-up company, then experience should not matter over and above a patent application prior to obtaining funding.

To investigate these different hypotheses we split the spillover generating start-ups in two groups: start-ups that had at least one patent before they received the first investment round and start-ups that had not. Table 11 gives descriptive statistics on the numbers of start-ups with and without prior patents.

The results are presented in Table 12. Again, we report only the results for the IV estimations, and only for the citation-augmented proximity measure. According to Table 12, start-ups that already have a patent at the time of the first investment generate significantly more spillovers than start-ups without such a patent, both onto

Table 11: Number of start-ups by prior patent

	Experience in				
	None	Start-up	Established	Academic	Total
No prior patent	432	72	253	225	942
At least one prior patent	109	9	46	30	188
Total	541	81	299	255	1130

Note: This table shows the number of start-ups that have at least one patent before the first investment split by the experience of the inventors. E.g. 18 start-ups have both an inventor who patented before joining the start-up and a patent before the first investment (column 2, line 2). The sum in column 5 gives the total number of start-ups with or without prior patent, taking into account double counting in the previous columns.

established and onto VC-financed firms. Furthermore, if we split the sample of start-ups in four categories with regard to patent holding and experience, we find that in complex product industries spillovers are significantly stronger for start-ups that have an experienced inventor team and that have a patented technology prior to receiving their first round of investment. This supports the commercialization hypothesis, as it seems that prior experience is valuable mostly by giving access to existing technologies that are commercialized in the new start-up. In discrete product industries the results are inconclusive.

To summarize, we find that in complex product industries spillovers are stronger for start-ups with an experienced inventor teams and start-ups that have a patent at the time of the first investment. Overall, this suggests that the commercialization hypothesis has particular merit. An increase in venture capital has the biggest impact if it goes to a firm that already has a patent. This points to a complementarity between the supply of venture capital on the one hand and the supply of technology and experience on the other hand. For policy makers this implies that promoting just one of these factors may be less effective than expected if the other factors are not available as well.

4.4 Robustness

As a robustness check we investigate whether the mechanism described above is stable with respect to other observable characteristics, such as the sample period or the geographic location. Suppose, for example, that the measured average effect were driven by companies in the San Francisco area between 1980 and 1985. Then we should be cautious in drawing conclusions for today's policies in Massachusetts.

The robustness checks are visualized in Figure 7. For expositional simplicity we report only the results for the citation-augmented proximity measure and we plot only the coefficient of the venture capital spillover measure for established companies. All the other figures are available from the authors on request.

The sample period does not seem to matter, the spillover effect is - except for a dip

Table 12: Split by prior patent

	Scaled Forward Citation-Weighted Patents - IV											
	Established companies						Start-ups					
Subsample		Discrete	Complex		Discrete	Complex		Discrete	Complex		Discrete	Complex
ln(Spillover Est.)	37.6***	30.9***	41.6***	36.8***	23.5**	42.1***	66.6***	73.4***	61.9***	66.8***	70.5***	62.1***
	(6.3)	(11.5)	(6.8)	(6.4)	(11.4)	(7.3)	(7.7)	(13.6)	(9.3)	(7.7)	(12.1)	(9.7)
ln(Spillover VC)												
wo patent	-2.1	-3.9	0.6				-7.4	-12.3	-0.5			
	(3.9)	(6.0)	(5.6)				(4.8)	(8.4)	(6.3)			
w patent	16.5***	18.5**	19.5***				13.1***	20.7*	9.8**			
	(6.2)	(8.8)	(7.3)				(4.4)	(11.7)	(4.2)			
w patent wo experience				9.1**	20.5***	3.7				2.7	15.5**	-1.4
				(4.5)	(7.4)	(5.5)				(4.1)	(6.7)	(5.2)
w patent with experience				11.7*	14.9**	16.5**				10.9**	7.1	8.7
				(6.0)	(7.6)	(8.0)				(5.5)	(13.8)	(6.2)
wo patent wo experience				8.6	21.5**	-1.1				-1.8	-1.0	-1.8
				(6.2)	(10.9)	(7.4)				(2.8)	(9.6)	(3.2)
wo patent with experience				-9.9*	-22.3**	2.2				-5.1	-7.7	2.8
				(6.0)	(9.3)	(5.8)				(6.1)	(9.6)	(8.0)
ln(R&D stock)	39.5***	39.3***	38.8***	39.2***	39.0***	38.8***						
	(2.3)	(3.6)	(2.6)	(2.3)	(3.5)	(2.7)						
ln(VC stock)							14.9***	12.2***	17.0***	14.7***	12.1***	17.0***
							(2.8)	(3.0)	(4.1)	(2.8)	(3.0)	(4.2)
Pre-sample FE	3.3***	3.2***	3.7***	3.3***	3.2***	3.7***	2.3***	3.6**	1.9***	2.3***	3.6**	2.0***
	(0.5)	(0.6)	(1.0)	(0.5)	(0.6)	(1.0)	(0.5)	(1.5)	(0.5)	(0.5)	(1.4)	(0.5)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Value	154.19	86.59	130.72	121.79	69.61	95.81	72.83	43.58	41.62	56.93	43.51	27.97
R2	0.46	0.46	0.43	0.46	0.47	0.43	0.08	0.07	0.09	0.08	0.07	0.09
N	10010	4877	5133	10010	4877	5133	5650	1729	3921	5650	1729	3921

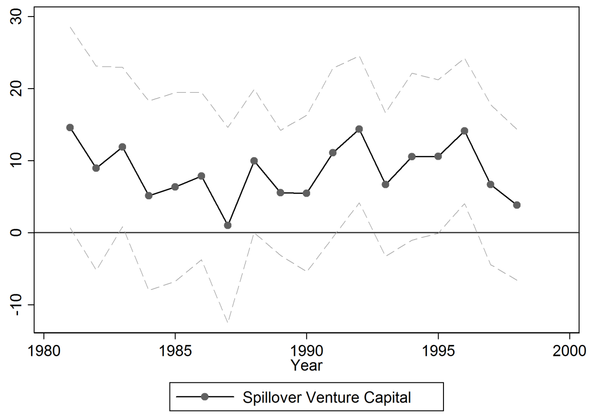
Note: This table shows the instrumental variable results of estimating equation (12) for the subsample of established companies (column 1-6) and for venture capital backed start-ups (column 7-12). For concisness we only show the results for the citation-augmented proximity measure. In the first three columns we split the spillover generating start-ups into one sample that had a patent before the first investment and one that did not. In the following three columns we additionally split these subsamples according to the prior patenting experience of the start-ups team. A company is classified as active in a complex product industry if more than 50% of its patent are in Computer and Communication (NBER Category 2), Electrical and Electronics (NBER Category 4), Medical Instruments (NBER subcategory 32), and Biotechnology (NBER subcategory 33). Otherwise it is classified as being in a discrete product industry. All standard errors are clustered on the four digit industry-year level. ***, ** and * indicate statistical signicance at the 1%, 5%, and 10% level, respectively. To increase the readability of the table we multiply each estimate by 100.

in the mid 1980s - stable over time. Yet taking each period separately the coefficient is mostly not significant on the 5% level (Figure 7a). The spillover effect is stable if we use different patent related outcome measures (Figure 7b).

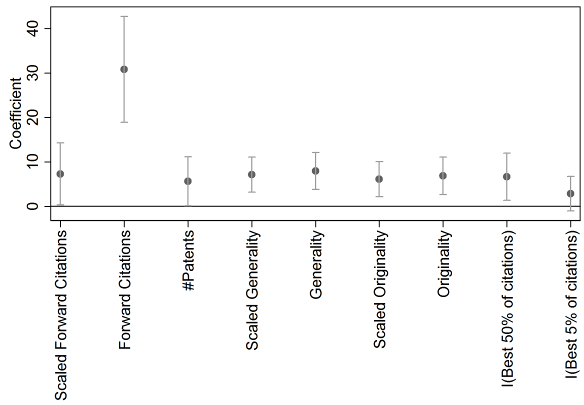
For the the geographic classification we report both, spillovers originating from start-ups residing in a particular state and spillovers received by companies in that state (Figure 7c). For the sample split we only consider the subsamples of California and Massachusetts because for all other states we have less than 50 venture capital financed start-ups in our data.

Figure 7: Robustness Checks

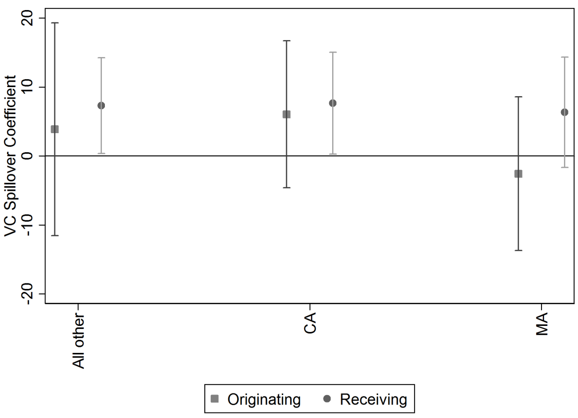
(a) Time-Pattern



(b) Alternative Outcomes



(c) Spillovers of VC by State of Start-Up



Note: This figure shows various robustness checks for the main regression for the subsample of established companies. In all the subfigures we plot the coefficient of the venture capital spillover measure for the established companies. In subfigure a) we calculate the coefficient of the spillover measure for each year in the sample separately. In subfigure b) we use various patent based outcome measures. In subfigure c) we split the sample by state of the start-up ("originating") and by state of the established company ("receiving"). The 95% confidence intervals displayed in each picture are derived from s.e. errors clustered on the four digit SIC code level.

We find that start-ups in California seem to have more spillover potential, but the coefficients are very imprecisely estimated The effect on established companies is relatively homogenous in California and Massachusetts, i.e. established companies all over the US benefit from venture capital spillovers (Figure 7c).

In the Appendix we repeat the main part of our analysis using two other estimation methods, a version of firm fixed effects based on de-meaning and a negative binomial model with control functions. We find that the results are largely robust to these different specifications, though the estimates are less precise.

5 Conclusion

Knowledge spillovers and their contribution to innovation and growth are the primary justification for government R&D support policies. In this paper, we show that VC-financed firms generate significant and positive spillovers on other firms' patent quality. Counterfactual calculations suggest that the external effect of venture capital is around nine times larger than the external effect of R&D spending.

As the channel of the spillovers cannot be observed directly, we employed three different ways to construct the spillover pool, including a novel construction that combines elements of both a citation-based and a technological proximity based approach. All three approaches lead to similar results, even though the magnitudes may differ. This confirms that our findings are robust to different specifications.

Our analysis allows us to paint a nuanced picture of venture capital-induced spillovers. The effects are heterogenous, depending on what type of start-up increases its VC investment and who is affected by the potential spillover. In general, complex technology industries tend to be more conducive to spillovers than discrete technology industries: established companies in complex technology industries experience larger spillovers than established companies in discrete technology industries and the spillovers generated by VC-firms in complex industries are larger than those generated by VC-firms in discrete industries.

Overall, our results are consistent with the commercialization hypothesis. Experience and access to technology seem to matter: Spillovers are significantly stronger for investments in a small set of start-ups that are characterized by an inventor team with prior patenting experience and start-ups that have a patented technology before receiving their first round of investment. This complementarity between supply of venture capital on the one hand and supply of technology and experience on the other hand should be kept in mind when drawing policy conclusions on how to boost spillovers.

One measurement problem we encounter in our analysis is that we cannot observe whether or not firms renumerate the spillover they experience through licensing fees. Thus, parts of the spillovers may be in fact internalized through licensing agreements. This is an issue the spillover literature in general has not been able to tackle yet, due to lack of data on licensing, and that has to be left for future research.

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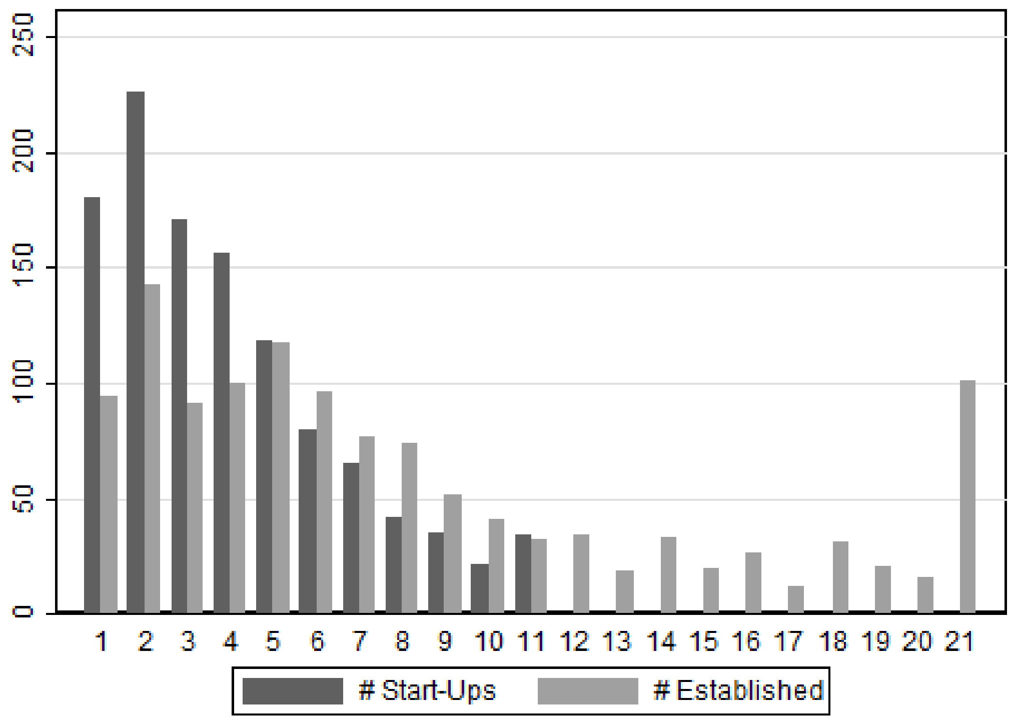
A Appendix: Estimation Methods.

In the main specification we use pre-sample mean scaling to adjust for fixed effects and we use linear instrumental variable estimation. Both choices deserve discussion.

Pre-sample mean scaling uses pre-sample periods to calculate the fixed effects. For the subsample of start-ups this is the appropriate choice since a lot of start-ups are observed only for a few periods as shown in (Figure 8). For the subsample of established companies instead we have a sufficiently long time series in the data to use de-meaning for fixed effects. We present the fixed effect results based on de-meaning for both subsamples in Table 13. The main difference to our results in the main section is that the results for the established companies are less significant. This might be due to sample selection as we lose around a thousand observations. For the start-ups the same pattern of spillovers (more spillovers for experienced teams, more spillovers with a patent prior to investment) emerges as in the case of pre-sample mean scaling.

Figure 8: Number of Companies by Years in Data



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The obvious alternative to linear instrumental variables regression is to use control functions and negative binomial models. We show the results for this specification in Table 14. The results are qualitatively similar to the linear instrumental variable model.

Finally, Table15 presents the estimation of the patent production function with

Table 13: Main results with de-meaning as fixed effects

	Scaled Forward Cite-Weighted Patents IV											
	Established companies						Start-ups					
Subsample	Full	Discrete	Complex	Full	Full	Full	Full	Discrete	Complex	Full	Full	Full
ln(spillover est.)	26.6***	26.2**	35.6***	28.6***	25.1***	27.0***	81.2***	60.3**	94.1***	80.1***	78.6***	78.6***
	(7.9)	(11.2)	(10.8)	(7.8)	(7.7)	(7.5)	(12.7)	(23.6)	(15.8)	(12.7)	(12.5)	(12.6)
ln(spillover VC)	7.1	1.3	13.1**				16.2**	32.0**	8.1			
	(4.4)	(7.0)	(6.0)				(6.4)	(12.5)	(8.3)			
wo experience				-5.8						-3.5		
				(5.2)						(7.0)		
with experience				11.8**						20.8***		
				(5.2)						(6.5)		
wo patent					4.2						9.9	
					(4.4)						(6.4)	
w patent					6.4						11.6**	
					(5.0)						(5.8)	
w patent wo experience						-2.2						1.1
						(4.3)						(4.8)
w patent with experience						10.6**						13.3**
						(4.4)						(5.3)
wo patent wo experience						-1.9						-7.8
						(5.2)						(6.2)
wo patent with experience						4.2						16.9***
						(5.2)						(6.4)
ln(R&D stock)	46.4***	46.1***	47.8***	46.2***	46.3***	45.9***						
	(4.2)	(6.8)	(5.3)	(4.2)	(4.2)	(4.2)						
ln(VC stock)							16.3***	7.0	20.7***	16.3***	16.5***	16.4***
							(4.2)	(6.4)	(5.3)	(4.2)	(4.1)	(4.1)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Value	66.45	25.02	47.82	50.22	49.95	33.86	50.01	17.56	32.43	38.56	38.05	27.24
R2	0.07	0.06	0.09	0.07	0.07	0.07	0.04	0.03	0.05	0.04	0.04	0.04
N	9916	4865	5051	9916	9916	9916	5603	1726	3877	5603	5603	5603

Note: This table shows the results of estimating Equation (12) with firm fixed-effects based on de-meaning, instrumental variables and the citation augmented proximity measure. The first six columns show the results for established companies and the following six columns for the sample of start-ups. All standard errors are clustered on the four digit industry level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. To increase the readability of the table we multiply each estimate by 100.

Table 14: Main results: Negative binominal model and control functions

	Scaled Forward Citation-Weighted Patents - Control Functions											
	Established companies						Start-ups					
Subsample	Full	Discrete	Complex	Full	Full	Full	Full	Discrete	Complex	Full	Full	Full
Ln(Spillover Est.)	0.5***	0.5**	0.7***	0.5***	0.5***	0.6***	1.4***	1.3***	1.5***	1.2***	1.3***	1.2***
	(0.12)	(0.21)	(0.14)	(0.13)	(0.12)	(0.14)	(0.14)	(0.23)	(0.20)	(0.11)	(0.14)	(0.10)
Ln(Spillover VC.)	0.2**	0.1	0.2**				-0.1	0.0	-0.1			
	(0.08)	(0.14)	(0.09)				(0.09)	(0.15)	(0.15)			
wo experience				-0.2						-0.3***		
				(0.16)						(0.10)		
with experience				0.2						0.3***		
				(0.18)						(0.10)		
wo Patent					0.1						-0.3**	
					(0.07)						(0.11)	
w patent					0.2*						0.3***	
					(0.10)						(0.09)	
w patent wo experience						-0.1						0.1
						(0.11)						(0.08)
w patent with experience						0.4***						0.3***
						(0.12)						(0.11)
wo patent wo experience						-0.0						-0.3***
						(0.14)						(0.08)
wo patent with experience						-0.2						-0.0
						(0.14)						(0.11)
ln(R&D Stock)	0.6***	0.6***	0.6***	0.6***	0.6***	0.6***						
	(0.03)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)						
ln(VC Stock)							0.3***	0.1**	0.3***	0.3***	0.3***	0.3***
							(0.06)	(0.07)	(0.08)	(0.06)	(0.06)	(0.06)
N	10010	4858	5152	10010	10010	10010	5650	1800	3850	5650	5650	5650

Note: This table shows the results of estimating Equation (12) with a negative binomial model, control functions and the citation augmented proximity measure. The first six columns show the results for established companies and the following six columns for the sample of start-ups. For the description of the sample splits please refer to the text. All standard errors are clustered on the firm level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. To increase the readability of the table we multiply each estimate by 100.

Table 15: Results for adjusted VC spending

	Scaled Forward Citation-Weighted Patents			
	Established companies		Start-ups	
	OLS	IV	OLS	IV
Ln(Spillover Est.)	31.4***	37.4***	59.3***	71.3***
Ln(Spillover VC.)	8.3***	7.9**	1.6	-1.9
ln(R&D Stock)	39.4***	38.6***		
ln(VC Stock)			14.4***	14.5***
Pre-sample FE	3.2***	3.2***	3.7***	3.7***
F-Value	.	159.31	.	77.71
R2	0.46	0.46	0.08	0.08
N	10010	10010	5650	5650

Note: This table shows the results of estimating Equation (12) with the citation-augmented proximity measure. Venture capital spending is multiplied for a correction factor such that the total investment matches the investment in our sample in every year and industry. The first and third third column show the OLS results, while the second and fourth column show the instrumental variable results. All the standard errors are clustered on the four-digit industry level. ***, **, and * indicate statistical signicance at the 1%, 5% and 10% level, respectively. To increase the readability of the table we multiply each estimate by 100.

adjusted venture capital investment such that the total investment matches the investment in our sample, as discussed in Section 4.1.