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. On average, these spillovers are nine times larger than those generated by the R&D investment of established companies. Spillover effects are larger in complex product industries than in discrete product industries. Start-ups with experienced inventors holding a patent at the time of receiving the first round of investment produce the largest spillovers, indicating that venture capital fosters the commercialization of technologies. Methodologically, we contribute by developing a novel definition of the spillover pool, combining citation-based and technological proximity-based approaches.

JEL Classification: G24, O3, O31, O32

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1 Introduction

There is a broad consensus in the literature that corporate R&D spending generates positive knowledge spillovers.[1] For example, Bloom et al. (2013) find that the social return of R&D is two to three times the size of the private return of R&D. They also report that large companies (measured by employees) generate more spillovers than small businesses, presumably because smaller firms tend to operate in technological niches. But there is one particular type of small businesses - venture capital-backed start-ups - that policy makers and researchers consider as particularly innovative and important for economic growth. Consistent with this narrative, Kortum and Lerner (2000) find that one dollar of venture capital invested at the industry level is associated with three times more patents than one dollar of corporate R&D.

What we do not know is how many of the venture capital-induced patents are filed by the start-ups themselves and how many are filed by other companies that benefit from knowledge spillovers. Understanding the impact of knowledge spillovers from venture capital-backed start-ups is important because it informs whether and if so by how much a government should support venture capital investment, as it often does in case of corporate R&D (Lerner, 2012).

This paper provides the first measurement of knowledge spillovers generated by VC-financed firms onto the patent production of other firms. Our estimations suggest that these knowledge spillovers are significant. Two-thirds of the total increase in quality-weighted patents resulting from venture capital investment is due to more patenting by other companies. Furthermore, we show that the estimated venture capital-induced spillovers are at least nine times larger than the spillovers from corporate R&D.

Our analysis allows us to paint a nuanced picture of venture capital-induced spillovers. 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 product industries may be due to the fact that in these industries patent protection is a more effective appropriation mechanism than in complex product industries (Cohen et al., 2000), thus limiting the potential for spillovers.

The spillovers generated by venture capital vary also by the type of start-up receiving the investment. Start-ups with an experienced inventor team holding a patent at the time of receiving their first round of investment generate the largest spillovers. This suggests that spillovers are highest when start-ups employ venture capital for the commercialization of

[1] Refer to Hall et al. (2010) for a survey.

their technologies.

For our analysis, we use two data sources, Compustat and VentureXpert. Compustat contains balance sheet data for all U.S. publicly listed companies, including R&D expenditures. As start-ups are small private companies, no data on their R&D expenditures are available. A commonly used surrogate is the venture capital invested in a particular start-up in a given year (Kortum and Lerner, 2000).[2] 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 U.S. Patent Citations Data File and from the data files of Li et al. (2014). We match the patent data to Compustat using the unique identifier provided by the NBER (Hall et al., 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 nonrivalrous, i.e. they can affect many different companies. 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 et al. (2013). One problem with such an indirect approach is that we might mistake a co-movement of venture capital and patenting in other companies that is driven by general technological progress as evidence of spillovers between 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 et al. (2013), and venture capital investment with past fund-raising of private equity buy-out funds (Nanda and Rhodes-Kropf, 2013).

As we have to infer spillovers indirectly from the data, we would ideally like to estimate for each ordered company pair at least one parameter governing the co-movements of investment and innovation. Unfortunately, this is technically infeasible because it would result in an excessive number of parameters to be estimated (Azoulay et al., 2015). The approach taken in the literature to address this problem 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 specify the spillover pool of a particular company as the set of all the companies whose patents are cited by this company (Azoulay et al., 2015). This is the most direct way to assess whether or not the research of one company is influenced by

[2] 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.

the research of another company. The drawbacks of this definition 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, known as the Jaffe technological proximity measure, includes all the companies in the spillover pool that patent in the same technology classes as the company under consideration (Jaffe, 1986).[3] The underlying assumption is that knowledge flows mainly within technological fields. However, this assumption is at odds with the observation that successful innovations often recombine ideas across technological boundaries (Uzzi et al., 2013; Weitzman, 1998). Hence, while this measure allows to capture 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 a third definition of the spillover pool that combines elements of the first two concepts. Specifically, we calculate a weighting matrix based on the citation propensities between different technology classes. We then use this weighting matrix to augment the Jaffe measure. 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 measure is symmetric by construction. Thus, our new measure captures a more general and arguably more realistic representation of knowledge flows between firms.[4]

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 results are stable when using different spillover pools, different estimation methods, different subsamples or different outcome variables.

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

[3]Bloom et al. (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.

[4]Zacchia (2015) proposes a weighting matrix based on actual inventor movements. While this has the advantage of tracking actual knowledge flows, it has the drawback that these movements are likely to be endogenous to firm characteristics.

venture capital-financed firms.[5] The availability of venture capital is recognized as a crucial part of the national innovative system as it helps translate scientific research into innovation (Furman et al., 2002). Yet, the empirical evidence on how venture capital-backed start-ups contribute to innovation in an economy is limited.[6] Our analysis allows us to quantify the knowledge spillovers of VC-financed firms onto both established and other VC-backed firms.

Our second contribution is to establish which industries are most likely to experience and which inventors are most likely to generate spillovers. Our findings relate to the patent literature, which has found patents to be a more effective mechanism to appropriate returns for R&D in discrete as compared to complex product industries (Cohen et al., 2000). Consistent with this mechanism, we document that complex product industries tend to be more conducive to spillovers than discrete product industries. Our analysis also speaks to the debate on the importance of the founder team and its prior experience for the success of a venture. While the "skills hypothesis" emphasizes that a prior affiliation with a start-up may help entrepreneurs learn how entrepreneurship works, the "commercialization hypothesis" stresses that prior experience in established firms or affiliations with universities help get access to technologies (Gompers et al., 2005). Although a priori it is not clear whether knowledge spillovers follow the same patterns as private returns, we find that spillovers are indeed stronger for start-ups with an experienced inventor team, but only if they have a patented technology at the time they receive their first round of investment. This speaks in favor of the commercialization hypothesis.

The third contribution of our paper is methodological. We develop 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. In terms of desirable properties as specified by Bloom et al. (2013), our measure does at least as well as other technological proximity measures. But it has the additional advantage of taking the directionality of knowledge flows into account. Moreover, we find that our citation-augmented proximity measure is better in predicting actual citations than other technological proximity measures. Thus, we expect our measure to provide a more precise estimate of the spillovers generated than previous measures.

The paper proceeds as follows. In section 2, we describe the data and the variables

[5] For recent summaries of the literature on venture capital see Rin et al. (2013), Dessí and Yin (2012) and Lerner and Hall (2010).

[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.

used, and we provide summary statistics. In section 3, we explain the empirical strategy for measuring the spillovers of R&D and venture capital. In section 4, we present our empirical results. Section 5 concludes.

2 Data and Description of Variables

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

2.1 Patenting activity

The patent data are from the NBER Patent-Citation Data File. They contain all the utility patents filed in the U.S. with the name of the applicant, year of application, location, patents that this patent cites, and a classification according to the 3-digit U.S. patent class. These patent data end in 2005. To identify additional patent citations in our database, we complement it with the Harvard patent data set of Li et al. (2014), which ends in 2010. The resulting data set contains 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 et al., 2005). 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 (2015) ("scaled forward citations"). To construct our main outcome variable we aggregate all scaled forward citations for all patents filed by a company in a year ("scaled forward citation-weighted patents").

For our outcome variables, we consider only patents that were filed by 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, measured by forward citations, and those take time to accumulate. 90% of the patents filed in 1999 were granted by 2003 and started to receive citations.[7] If we want to give each patent three years to accumulate citations we need to include citing patents filed in the years 2003 to 2006. We expect that patents filed in these years were published by 2010 and thus are part of our data.[8] If anything, a cut-off date as late as 1999 is too optimistic because in our raw data the pattern of a declining number of citations per patent

[7]For the filing year of 1999, the average and the median publication year is 2001. The 90% quantile is 2003 and the 99% quantile is 2007.

[8]For the filing years 1979 to 1999, the average publication lag was two years. The 5% percentile was 1 year, while the 95% percentile was 4 years.

starts around 1997, and the pattern of a declining number of patents begins in 2002 (Figure 1a).[9]

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 (Henderson et al., 1998). With this measure, we capture the dispersion across technology classes of patents citing the patent. Similarly, "originality" is calculated as one minus the Herfindahl index across technology classes for the patents that are cited by the patent. This measure captures the extent of dispersion of the information on which the patent draws.

2.2 R&D and venture capital investment

Our firm-level data source for established companies is the U.S. Compustat file.[10] It contains yearly accounting data for publicly listed U.S. companies with the company name, fiscal year, the state of the firm headquarters, the four-digit SIC code, sales and R&D expenditures. We follow Bloom et al. (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.[11] Using the unique identifier provided by the NBER, these data are matched to the NBER Patent Citation Data File (Hall et al., 2001). Lastly, we restrict the data to companies that filed at least one patent in 1979 to 1999. The resulting database contains 1221 companies with 93,325 patents.

Start-ups are small private companies. Therefore, no data on R&D expenditures are publicly available. 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. 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 U.S.

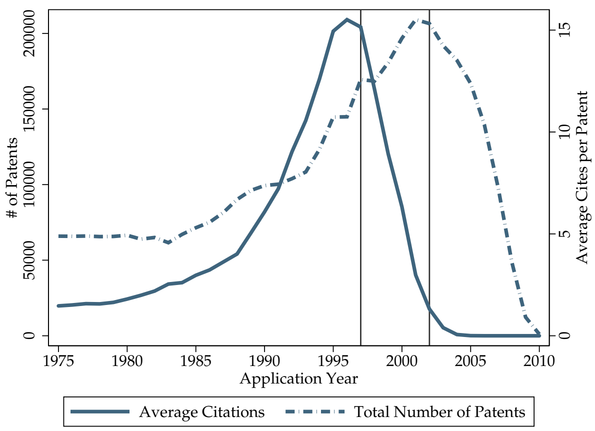
[9]The downward trend in the number of patents is a feature of end-of-sample effects in our data and is not reflected in the published statistics of the USPTO. Please refer to the US Patent Statistics for the years 1963 to 2013 available on
http://www.uspto.gov/web/offices/ac/ido/oeip/taf/us_stat.htm

[10]Data from Compustat and VentureXpert were accessed at the Institute for Innovation Research (INNO-tec) at the University of Munich.

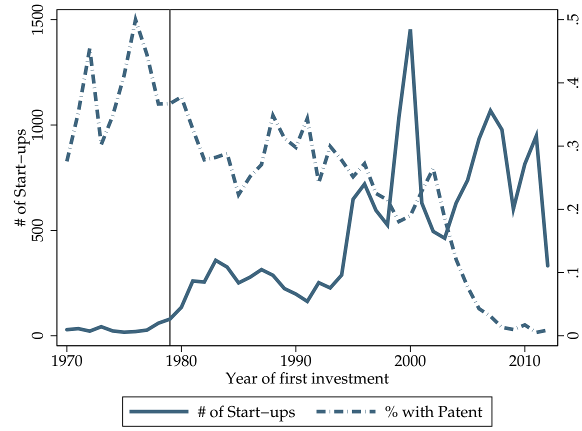
[11]In particular, we drop firms that never do R&D, are less than 5 years in the data, whose sales fall by more than 66% or increase by more than 200% year over year, have less than 0.1 million dollars in assets per employee or more than 1 billion dollars in assets, that have less than 2 million or more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

Figure 1: Descriptive Statistics

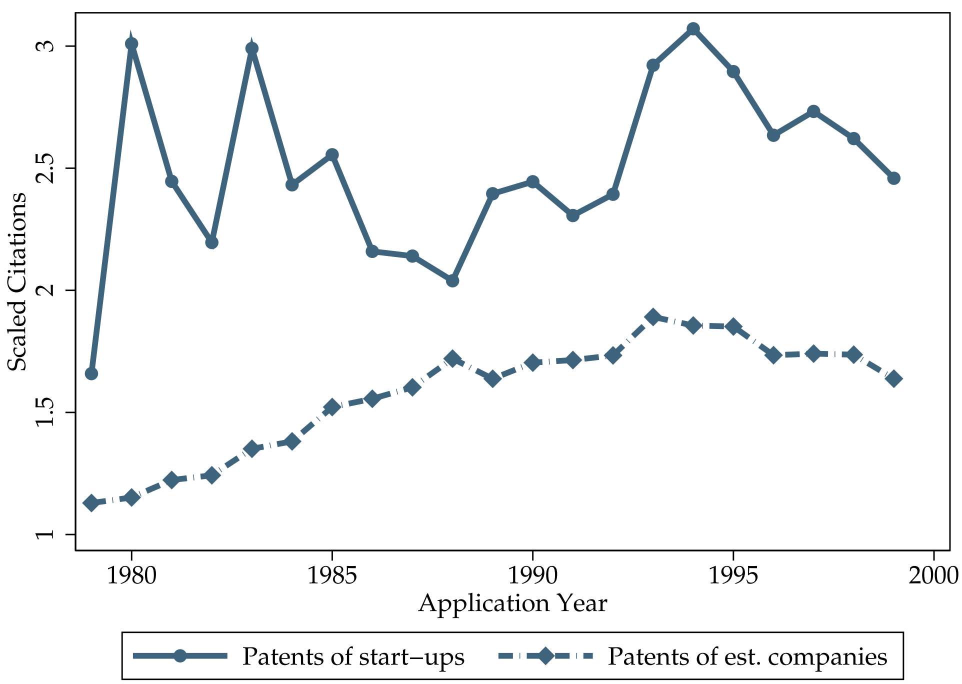
(a) # of Patents and Citations per Patent



(b) # of Start-ups and Share with Patent



(c) Average Scaled Citations per Patent over Time



Note: Subfigure a) 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. Subfigure b) shows the number of start-ups (# start-ups) in our sample by the year of the first investment. The gray line is the percentage of start-ups in the given first investment year for which we can identify at least one patent. Subfigure c) 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 line) and for the subsample of start-ups (gray line) by the application year of the patent.

come from Thomson Reuters VentureXpert. Each record contains the name of the investee company, the investment date, a four-digit SIC code, and the total investment.

We match these investment data to the patent data by the company name, state and time period 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 (2013). We do not start before 1979 because for earlier years the number of start-ups in our database is relatively small (79 in the U.S. in 1979, 60 for 1978, 27 in 1977 - Figure 1b), and we find even fewer start-ups with at least one patent (29 in the U.S. in 1979, 22 in 1978, 12 in 1977 - Figure 1b).

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, whether she invented at a university, at a start-up or at an established company in our data set. This provides us with a measure of the prior patenting experience of the start-up inventor team.

In the last step, we drop for our outcome variable all patents that were filed in the first year of investment because it seems unlikely that these patents were indeed financed by venture capital. In addition, to mitigate problems arising from potentially incorrect records of the failure or success of a start-up, we drop company observations 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. The resulting data set on VC-financed firms contains 1206 companies with 10,341 patents. The summary statistics for the data set are shown in Table 1. The mean patent count is 9.38 for established companies and 1.72 for VC-financed firms. Established companies have on average 15.35 scaled citation-weighted patents, whereas VC-financed firms have 4.51 (Table 1.).

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

Table 1: Summary Statistics

Panel A: Established Companies	mean	sd	min	max	p10	p90
Patent count	9.38	29.51	0	1033	0	22
Citation-weighted patents	233.61	1244.16	0	42802	0	385
Scaled citation-weighted patents	15.35	49.91	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	1.18	0	8	1	4
Average R&D (million dollars)	44.44	109.09	0	2271	1	113
Average sales (billion dollars)	1.04	2.51	0	39	0	3
Years in data	7.17	4.71	1	21	2	15
Number of companies	1221					

Panel B: Venture Capital-backed Start-ups	mean	sd	min	max	p10	p90
Patent count	1.72	3.57	0	62	0	4
Citation-weighted patents	130.95	548.16	0	16394	0	261
Scaled citation-weighted patents	4.51	11.86	0	176	0	12
# inventors	2.97	2.15	1	15	1	6
Inventors have prior patenting experience	0.62	0.49	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)	2.26	1.05	0	6	1	4
VC investment (million dollars)	2.57	5.69	0	96	0	9
Years in data	4.81	2.82	1	11	2	10
Number of companies	1206					

Note: In Panel A, we show summary statistics for the subsample of established companies. Panel B shows summary statistics for the subsample of venture capital-financed start-ups. The reported summary statistics are the yearly mean ("mean"), the standard deviation (sd), the minimum, the maximum and the 10% and 90% quantile. The "patent count" is the number of patents a company files in a year. "Citation-weighted patents" is the sum of citations received by the patents of a company filed in a particular year. To calculate the "scaled citation-weighted patents" we scale the number of citations of each patent with the average number of citations a patent in this year and technology class receives on average. Then we aggregate these scaled citations by company and filing year. To calculate the "average complexity of companies' patents" we assign a one to each patent in the NBER subcategory Computer and Communication (NBER Category 2), Electrical and Electronics (NBER Category 4), Medical Instruments (NBER subcategory 32), and Biotechnology (NBER subcategory 33) and a zero otherwise. Than we take the averages by company and filing year. The "average citation-augmented proximity" is the average proximity of each company to all other companies measured by the citation-augmented proximity defined in the text. The "average R&D" and "average sales" are the average investment in research and development and the average turnover for established companies, as reported by Compustat. "Years in the data" is the number of years a company is in the data. For the subsample of start-ups, we look up for all inventors on the first patent of a start-up whether they patented before to determine whether a start-up has inventors with "prior patenting experience". "VC investment" is the average investment across funding rounds. I(.) is an indicator function.

patents, they are more original and more general.[12] The higher quality of start-up patents is not driven by a particular time period or by outliers: the average number of citations per patent is higher for the start-ups than for the established companies in all years (Figure 1c).

Table 2: Summary Statistics of Patents by Company Type

	Per patent				**Per dollar**			
	Estab-lished	Ven-ture	Diff	P-Value	Estab-lished	Ven-ture	Diff	P-Value
Forward citations	22.31	56.21	33.90	0.00	7.18	91.69	84.51	0.00
Scaled citations	1.29	1.82	0.53	0.00	0.49	3.45	2.96	0.00
Generality	0.17	0.24	0.07	0.00	0.06	0.43	0.37	0.00
Scaled generality	0.15	0.21	0.06	0.00	0.05	0.37	0.32	0.00
Originality	0.21	0.26	0.05	0.00	0.08	0.46	0.38	0.00
Scaled originality	0.18	0.21	0.03	0.00	0.07	0.39	0.32	0.00
I(Best 50% of citations)	0.57	0.63	0.06	0.00	0.22	1.23	1.01	0.00
I(Best 5% of citations)	0.10	0.15	0.06	0.00	0.04	0.29	0.25	0.00
# patents					0.30	1.45	1.16	0.00

Note: This table shows summary statistics for start-ups and for established companies per patent (columns 1 to 4) and per dollar spent (columns 5 to 8). "Forward citations" is the total number of forward citations a patent receives over all years. To calculate the "scaled forward citations", we scale the citations of each patent by the average number of citations a patent in same technology class and filing year receives. Then we aggregate at the company level. “Generality” is the generality of a patent and “originality” is the originality of a patent as defined by Hall et al. (2001). “Scaled generality” and “scaled originality” are the generality or orginality of a patent standardized of the average generality or originality of a patent in the same technology class and filing year. “I(Best 50% of citations)” and “I(Best 5% of citations)” are indicators specifying whethr the patent is in the best 50% or best 5% of the citation distribution. The p-value refers to a t-test of difference of means of the two groups, assuming unequal variance.

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 do not, however, provide causal evidence on the spillovers originating from these patents or how citations are related to patent production in other companies.

[12]Measured by the average citation-augmented proximity, they are also at least as central in technology space as established companies (Table 1.). This contrasts with the finding of Bloom et al. (2013) who report that small companies on average usually work in technological niches.

3 Empirical Strategy

Knowledge spillovers may arise when scientists from different companies meet and exchange ideas, when a firm hires scientists previously employed by another firm, or when a firm learns via scientific publication or by reverse engineering of 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. Unfortunately, the knowledge created in a firm cannot be observed, nor can we observe the knowledge flows between companies. Thus, we need to estimate the reduced form impact of investment in firm i onto the patent production in firm j. To make our estimates comparable with the literature we use the same reduced form function $h(.)$ as Bloom et al. (2013):

$$ln(Patents_j) = \gamma \cdot ln(\sum_{j \neq i} \omega_{ji} \cdot VC_i) + \cdots + \varepsilon_i \tag{1}$$

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.

Since knowledge flows between companies are unobservable, we do not know which knowledge flow of which start-up influences the patent production of a particular company. 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 data set of 500 companies receiving and 500 start-ups generating spillovers, this would require the estimation of 250,000 ω-parameters. This curse of dimensionality precludes us from estimating all the ω_{ji}s from the data (Azoulay et al., 2015).

Instead, we follow the literature and address this problem by constructing the knowledge flow graph from auxiliary data. Jaffe (1986) and Bloom et al. (2013), for example, 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 et al. (2015) use citations as a direct indicator of knowledge flows, measuring which patents cite and hence apparently benefit from knowledge published 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

$$\Gamma = E\left[\frac{\partial Patents_j}{\partial VC_i}\right] = \gamma \cdot E\left[\omega_{ji} \cdot \frac{Patents_j}{\sum_{j \neq i} \omega_{ji} \cdot VC_i}\right] \tag{2}$$

and therefore a function of ω_{ji}. 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 were not the case we should be worried that our results are not a stable feature of the data but potentially driven by our modeling choices.

3.2 Constructing the knowledge flow graph

In the following, we describe three different ways to construct the knowledge flow graph and discuss their respective advantages and disadvantages. In Appendix A we use the axiomatic approach suggested by Bloom et al. (2013) to compare the different approaches.

Method 1: Using citations directly The most direct evidence of a knowledge flow between a start-up and an established company is 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 et al., 2015; Jaffe and Trajtenberg, 2002).[13] To construct the ωs using citations directly, we collect for each patent all cited patents that are not 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

$$\omega_{ji,t-1}^{Citation} = \frac{\#Citations_{ji,t-1}}{\#Patents_{i,t-1}} \tag{3}$$

where $\#Citations_{ji,t-1}$ denotes how many times the patents of firm j cite patents of firm i up to $t-1$. For example, if an established company j cites one out of ten patents of a

[13] Azoulay et al. (2015) 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 et al. (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.

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 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 flows 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

$$\omega_{ji,t-1}^{Jaffe} = s'_{j,t-1} s_{i,t-1} \tag{4}$$

where $s_{i,t-1}$ is the standardized patent share vector of company i in the year $t-1$. To arrive at $s_{i,t-1}$, we first calculate for each company i and for each point in time the patent stock of a company in each technology class τ. The patent stock is the accumulated number of patents in the technology class τ up to the year $t-1$. Then we calculate for each company the share of the patent stock, $S_{i,\tau,t-1}$, in each technology class τ and combine it to a share vector for the company $S_{i,t-1} = (S_{i,1,t-1}, S_{i,2,t-1}, ..., S_{i,386,t-1})$, where 386 is the total number of technology classes with a positive patent count. In the last step, we standardize this share vector by the firm's patent share dot product, $s_{i,t-1} = \frac{S_{i,t-1}}{(S_{i.t-1}S'_{i,t-1})^{\frac{1}{2}}}$. 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 of past patents rather than actual patent citations is that current patenting behavior has no influence on the construction of the knowledge flow matrix.[14] However, a drawback of the Jaffe measure is that it assumes that companies only learn from companies active in the same technology classes. This

[14]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 specifications, we employ company fixed effects controlling for the possibility that a company generally employs better researchers which might influence the technological position, e.g. by patenting in more diverse technological classes.

assumption does not seem innocuous given that the literature suggests that high-quality innovations often come from the recombination of ideas from different technological fields (Uzzi et al., 2013; Weitzman, 1998).

Method 3: Augmenting the Jaffe proximity measure 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.[15] The resulting "citation-augmented proximity measure" between company i and company j is given by

$$\omega_{ji,t-1}^{Cit.aug.} = s'_{i,t-1} W^{Cites} s_{j,t-1} \tag{5}$$

where $s_{i,t-1}$ and $s_{j,t-1}$ are the standardized patent share vectors of companies i and j in the year $t-1$.[16]

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

$$w_{B,A} = \frac{\#Citations_{B,A}}{\sum_M \#Citations_{M,A}} \tag{6}$$

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}.[17]

We plot the matrix W^{Cites} in Figure 2a.[18] 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 2b).[19] 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 2c).

This citation-augmented proximity measure has two advantages. First, it allows to capture knowledge flows between companies that are not necessarily close in technology space,

[15] Bloom et al. (2013) modify the Jaffe proximity with a weighting matrix based on collocation of patent classes.

[16] Bloom et al. (2013) uses the average share of patents per firm in each technology class over the period 1970 to 1999 to calculate technological proximity. Our results are robust using this approach.

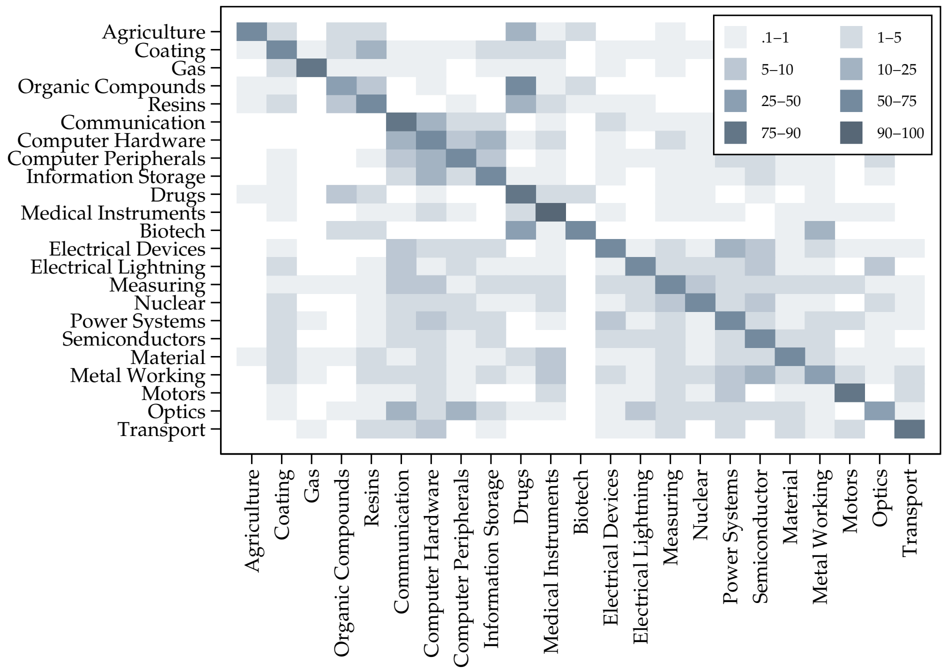
[17] A similar cross-citation matrix is used by Acemoglu et al. (2016) to predict future patenting.

[18] 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 et al. (2001).

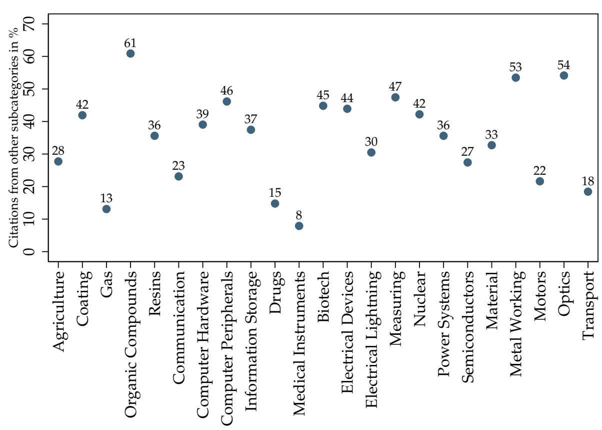
[19] One can see "clusters" of patent citations between similar technologies, as for example in computer hardware and software, comprising communication, computer periphery, and information storage. Another such cluster is drugs with organic compounds, resins, medical instruments and coating.

Figure 2: Citation Patterns of Technology Classes

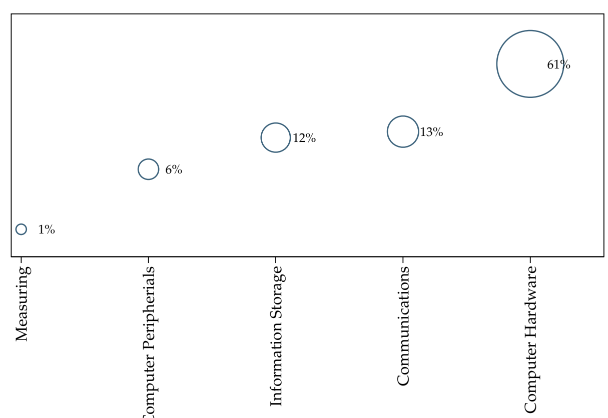
(a) Cross Citation Matrix in %



(b) Share of Citations from other Technological Subcategories

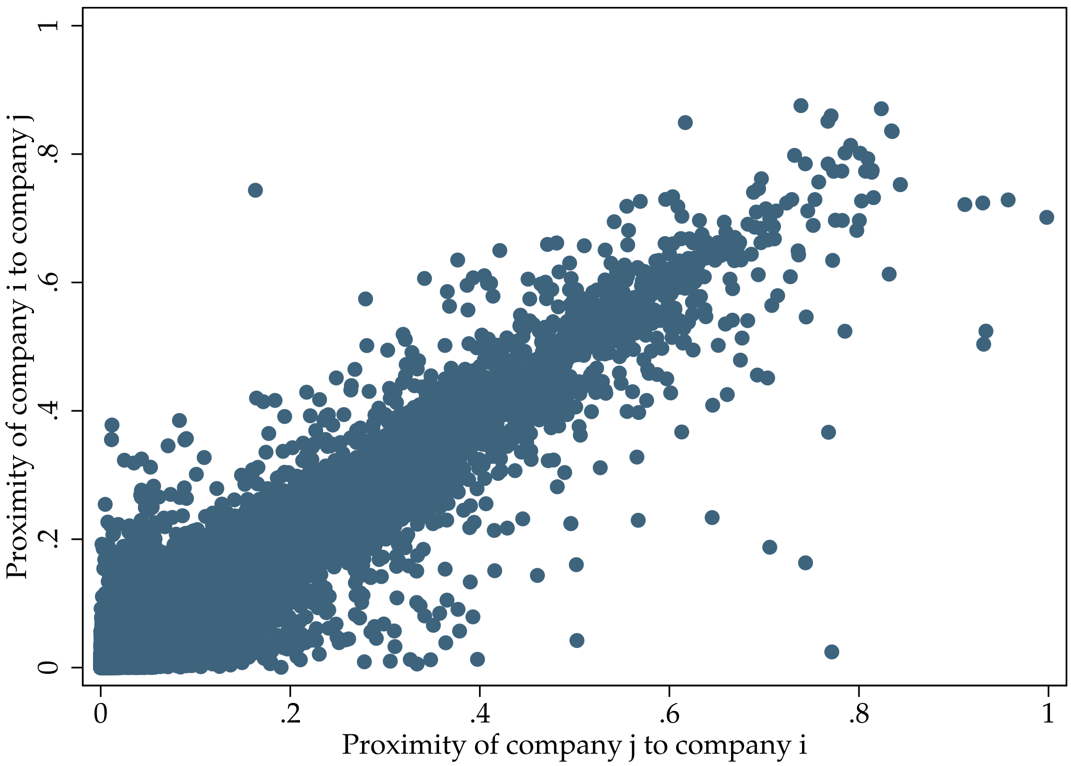


(c) Citations of Computer Hardware and Software



Note: Subfigure a) shows the share of cross citations between patents in broad technology subcategories in %. We use the broad subcategories defined by Hall et al (2005) instead 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 add up 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 3: 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 presents 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 0.016. The average difference between the proximity from i to j (and vice versa) is 0.005 or 33%. To simplify visualization we delete 3 observations (of 133 thousand) with a proximity larger than 1.

but that have a (backward citation) proven record of learning from each other. Second, it allows the spillover flows between companies to be asymmetric while by construction the Jaffe measure is symmetric. In Figure 3, we plot the pairwise proximities between companies 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

To measure the effect of knowledge spillovers we use the following estimation equation

$$
\begin{aligned}
ln(Patents_{j,t}+1) = \beta_0 &+ \beta_1 \cdot ln\left[Spillover^{VC}_{j,t-1}+1\right] \\
&+ \beta_2 \cdot ln\left[Spillover^{R\&D}_{j,t-1}+1\right] \\
&+ \beta_3 \cdot ln[VC_{j,t-1}+1] + Controls + \varepsilon_{j,t} \qquad (7)
\end{aligned}
$$

where $Patents_{j,t}$ is the number of scaled forward citation-weighted patents and $VC_{j,t-1}$ is the stock of venture capital investment of a venture capital-financed company j at time $t-1$. The spillover term for venture capital investment, $Spillover^{VC}_{j,t-1}$, is the proximity weighted venture capital investment in other starts-ups

$$Spillover^{VC}_{j,t-1} = \sum_{j \neq i} \omega_{j,i,t-1} \cdot VC_{i,t-1}. \qquad (8)$$

Correspondingly, the spillover term for R&D investment, $Spillover^{R\&D}_{j,t-1}$, is the proximity-weighted R&D investment of other established companies

$$Spillover^{R\&D}_{j,t-1} = \sum_{j \neq i} \omega_{j,i,t-1} \cdot R\&D_{i,t-1}. \qquad (9)$$

As companies might differ in their unobserved research productivity, we use as controls pre-sample mean scaling to account for firm-fixed effects. In robustness checks, we also use de-meaning to control for firm fixed effects (Appendix B.1). In addition, we include a complete set of year and industry dummies. For the subsample of established companies, we replace $VC_{j,t-1}$ by $R\&D_{j,t-1}$, i.e., the stock of R&D investment of company j at time $t-1$.[20] We estimate equation 7 with a linear instrumental variables regression model. In Appendix B.1, we repeat the main part of our analysis using a negative binomial model.

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.[21] Therefore we instrument the two spillover terms.[22]

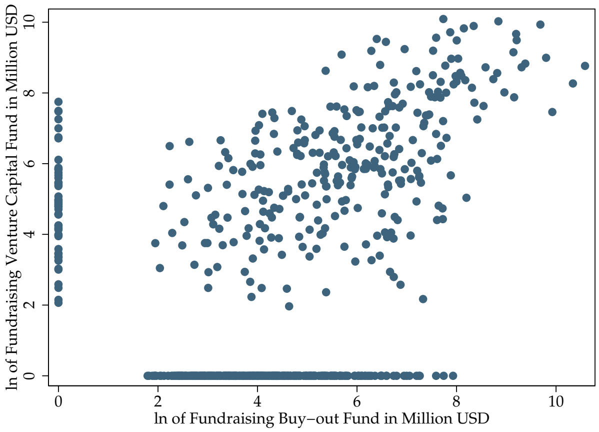
[20] To calculate Venture Capital and R&D stocks we use a perpetual inventory method with a 15% depreciation rate following inter-alia Hall et al. (2005). We keep the established companies in the data if they have reported R&D spending. Venture Capital financed start-ups are from the date of the first investment till two years after the last investment in the data.

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

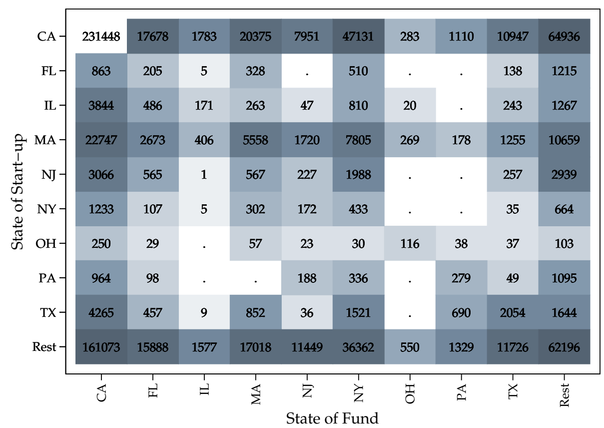
[22] We follow Bloom et al. (2013) in instrumenting only the spillover terms.

Figure 4: Venture Capital Instrument

(a) Correlation between VC and Buy-out Fundraising



(b) Fund-flows between U.S. States



Note: Subfigure a) shows the correlation between the natural logarithm of buy-out 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.

To construct an instrument for venture capital investment, we use fundraising of leveraged buyout funds lagged by eight quarters, following Gompers and Lerner (2000) and Nanda and Rhodes-Kropf (2013). 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 buy-out funds. This mechanically results in an increase in investment in VC and in buy-out funds and in a strong correlation between the two (Figure 4a). 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.

We follow two more steps to convert fundraising data into a start-up-specific instrument. 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.[23] Fundraising often takes place where the institutional investor is located. Therefore, to predict how much funding is available in each state, we weight the buy-out-fundraising with the historical fund-flows in venture capital. Figure 4b depicts the absolute fund flows in the sample period for a selected number of states. In the second step, we follow Bloom et al. (2013) and weight the available funds in a state according to the locations of the venture capital investee companies.[24]

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:

$$Z_{i,t}^{VC} = P'_{i,\sigma} X'_{\sigma,\sigma'} Fundraising_{\sigma',t-2} \tag{10}$$

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 $Fundraising_{\sigma',t-2}$ is the fundraising of buy-out-funds. The instrument is, therefore, the pool of funding available at a particular location.

To construct an instrument for R&D expenditures, we use local supply-side shocks caused by the staggered introduction of R&D tax credits across states in the U.S. These tax credits lower the cost of conducting R&D and, therefore, in equilibrium should increase its optimal level. The literature surveyed by Bloom et al. (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 the fundraising and the tax policy instruments to predict the venture capital and R&D investment. Then, following Bloom et al. (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 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

[23] For example, Chen et al. (2010) document that venture capital funds and investment companies are highly concentrated in the US.

[24] 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 files 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 et al. (2013) and to the instrument for R&D spending below.

Table 3: Regression of VC and R&D Expenditure on Instruments

	(1)	(2)	(3)	(4)	(5)
Dependent:	ln(VC Investment+1)				ln(R&D+1)
VC Fundraising	3.64***				
	(1.25)				
Buy-out		1.98			
		(1.48)			
Buy-out / Cross-state			4.27***		
			(0.97)		
Buy-out / Cross-state / Firm specific				5.27***	
				(1.09)	
R&D Costs					-4.62***
					(1.49)
F-Value	8.52	1.79	19.49	23.47	9.65
R2	0.13	0.13	0.13	0.13	0.80
N	1869	1430	2003	2003	9947

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. In the first column, the instrument is venture capital fundraising in a state and year. In the second column, we use the fundraising of buy-out funds. In the following two columns, we weight buy-out fundraising with the distribution of fund flows across states and with the distribution of states where a company produces its patents. In the last column, 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.

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. For our instrumental variables strategy, we use the instruments specified in columns 4 and 5. The F-values in these two columns are around or above 10, suggesting that the instruments used in the analysis are suitable for the estimation.[25]

[25]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 quantify the spillovers generated by VC-backed start-ups and provide causal evidence that these spillovers are larger than the spillovers of corporate R&D. We estimate the patent production function in equation 7 with three different technological proximity 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 4 to 6, we report the results of the instrumental variable regressions for the three different specifications.

Table 4 shows that the knowledge spillovers resulting from venture capital investment in start-ups have a positive influence on the patent production of established companies. This result holds independent of the employed proximity measure. Our results suggest that venture capital investment in start-ups makes the innovation efforts of established companies in similar technologies more productive. All estimated elasticities are different from zero at conventional levels, and the results are similar for both OLS and IV specifications.

In addition, we find the expected positive spillover effect of R&D expenditures of other established companies and a positive direct effect of own R&D investment on own patenting. Compared with the OLS specification in the study of Bloom et al. (2013), our estimated elasticity of 0.15 for the spillover of established companies with the Jaffe metric is smaller than their elasticity of 0.47, while our R&D elasticity of 0.41 is larger than their estimate of 0.22.[26] Other estimates for the R&D elasticity in the literature range from 0.2 to 0.9 (Hall et al., 2001; Hausman et al., 1984).[27]

[26]These numbers refer to column 2 in Table IV on page 1371 in Bloom et al. (2013).

[27]The main difference between the Bloom et al. (2013) study and ours is that we do not control for product market spillovers, and we use linear regressions instead of a negative binomial model. Furthermore, Bloom et al. (2013) do not control for the spillovers of start-ups. In Table B.1 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 almost the same as in Bloom et al. (2013). We still find a larger direct effect of R&D spending.

Table 4: Measurement of Spillovers - Established Companies

	(1)	(2)	(3)	(4)	(5)	(6)
	Scaled Forward Citation-Weighted Patents					
	OLS			IV		
	Direct citations	Jaffe proximity	Citation-augmented	Direct citations	Jaffe proximity	Citation-augmented
Ln(Spillover Est.)	7.4***	15.2***	31.1***	8.2***	18.6***	37.2***
	(1.0)	(3.4)	(6.5)	(1.1)	(3.6)	(6.6)
Ln(Spillover VC.)	15.9***	6.1***	8.3**	8.0*	5.9***	7.8**
	(4.7)	(1.8)	(3.5)	(4.7)	(1.9)	(3.6)
ln(R&D Stock)	40.5***	41.4***	39.4***	40.3***	40.9***	38.7***
	(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	.	.	.	196.25	153.43	155.68
R2	0.46	0.45	0.46	0.46	0.45	0.46
N	9947	9947	9947	9947	9947	9947

Note: This table shows the results of estimating equation 7 for the subsample of established companies and for the three definitions 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.

For the subsample of VC-financed start-ups, we find the expected positive direct effect of own venture capital investment on the patent production of a start-up firm. Furthermore, we confirm the expected positive spillover effects of R&D investment of established companies onto the patent production of start-ups. In contrast, the measured spillover effects of venture capital investment are not significantly different from zero at conventional levels for any of the three proximity measures. There could be several reasons why the spillover effects are small for VC-financed firms. First, they might be less precisely measured than 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 a 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).

Table 5: Measurement of Spillovers - Start-ups

	(1)	(2)	(3)	(4)	(5)	(6)
	Scaled Forward Citation-Weighted Patents					
	OLS			IV		
	Direct citations	Jaffe proximity	Citation-augmented	Direct citations	Jaffe proximity	Citation-augmented
Ln(Spillover Est.)	1.2***	19.2***	60.0***	1.3***	23.9***	72.1***
	(0.4)	(3.6)	(8.8)	(0.4)	(4.2)	(9.9)
Ln(Spillover VC.)	-0.2	1.4	2.5	-2.4	0.1	0.2
	(2.1)	(1.7)	(3.3)	(2.6)	(1.9)	(4.1)
ln(VC Stock)	18.1***	16.0***	14.7***	18.1***	15.9***	14.5***
	(2.7)	(2.7)	(2.6)	(2.7)	(2.8)	(2.6)
Pre-sample FE	3.8***	4.0***	3.9***	3.9***	4.0***	3.8***
	(0.5)	(0.6)	(0.6)	(0.5)	(0.6)	(0.7)
F-Value	.	.	.	44.40	51.37	78.87
R2	0.03	0.05	0.08	0.03	0.05	0.08
N	5999	5999	5999	5999	5999	5999

Note: This table shows the results of estimating equation 7 for the subsample of venture capital-financed start-ups and for the three definitions 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.

As elasticities are hard to interpret quantitatively, we use equation 2 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 for the different proximity measures. The results are presented in Table 6.The average direct effect of venture capital investment on the own patent production is larger than the average direct impact of R&D investment (Table 6, column 1). The results imply that increasing the venture capital investment by 1 million dollars yields directly between 0.12 and 0.16 patents with the average number of citations. This translates into costs per patent between 6.6 and 8.3 million dollars in venture capital funding. The corresponding number for R&D expenditures of established companies is around 12 million dollars.

The estimates for the external effect vary more widely (Table 6, column 2). 1 million dollars more venture capital yield between 0.02 and 0.19 patents of average quality. Therefore it requires between 5 and 50 million dollars in venture capital to generate a patent in another company, while it requires between 47 and 588 million dollars investment in R&D. If we take

Table 6: Counterfactual Increase in Forward Citation-Weighted Patents when Spending 1 Million Dollars More on...

	(1)	(2)	(3)	(4)
Direct citations	Own company	Other companies	Total	Multiplier
R&D	8.47	0.16	8.64	
Venture Capital	16.07	1.89	17.97	2.07
Jaffe proximity	Own company	Other companies	Total	Multiplier
R&D	8.60	1.00	9.60	
Venture Capital	14.12	18.73	32.85	3.41
Citation-augmented	Own company	Other companies	Total	Multiplier
R&D	8.14	2.12	10.26	
Venture Capital	12.87	20.32	33.20	3.24
Citation-augmented - adjusted	Own company	Other companies	Total	Multiplier
R&D	8.14	2.12	10.26	
Venture Capital	13.14	13.11	26.25	2.55

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 Tables 4 and 5 and the equation 2 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, established firms and VC-financed start-ups. In column 3, 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 by the total effect of an increase in venture capital. To increase the readability of the table, we multiply each estimate by 100.

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

In our main estimation, we consider only start-ups that have at one point in their life cycle filed 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 the venture capital investment by a correction factor such that the investment in each industry and year in our sample matches the total investment in this industry and year in the economy. Then we repeat the estimation of the patent production function in equation 7 (the regression table is Table B.3 in Appendix B.2) and recalculate the marginal effects. On the basis of these marginal effects, we 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 all other specifications.

There are no estimates for the external effect of venture capital in the literature with which to compare these results. However, these estimates appear to be of a sensible magnitude as they imply that the total return of venture capital is between 2.07 and 3.41 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.

The average marginal effects 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 start-ups generate relatively more knowledge spillovers and which companies benefit most.

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. A product is complex if it needs the input of numerous separately patentable elements, while it is discrete if it requires only few of such inputs (Cohen et al., 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, we would expect spillovers to be weakly smaller in discrete than in complex product industries.[28]

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

We test this hypothesis by measuring separately the spillovers originating from 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.[29]

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 that have less ("discrete"). We find that established firms experience relatively larger spillovers from VC-firms in complex product 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 product 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 spillover effect of venture capital that is significantly different from zero onto start-ups in complex or discrete product industries although the mean estimate is larger in complex product industries (columns 7 and 8).

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

[29]Thus, we classify 715 established companies and 871 start-ups as active in complex product industries, whereas 506 established companies and 335 start-ups are active in discrete product industries.

Table 7: Spillovers by the Complexity of the Product Industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Scaled Forward Citation-Weighted Patents - IV							
	Established companies				Start-ups			
Subsample	Full	Full	Dis-crete	Com-plex	Full	Full	Dis-crete	Com-plex
Ln(Spillover Est.)	37.2***	34.9***	26.8**	45.2***	72.1***	73.5***	93.1***	66.5***
	(6.6)	(6.2)	(11.4)	(7.1)	(9.9)	(9.7)	(13.0)	(12.1)
Ln(Spillover VC.)	7.8**		6.5	11.8***	0.2		-0.6	4.1
	(3.6)		(6.5)	(3.4)	(4.1)		(7.8)	(5.4)
discrete		-0.2				-3.8		
		(3.2)				(3.4)		
complex		12.7***				6.2**		
		(3.5)				(3.0)		
ln(R&D Stock)	38.7***	38.2***	37.3***	39.5***				
	(2.3)	(2.3)	(3.6)	(2.7)				
ln(VC Stock)					14.5***	14.1***	7.8***	17.4***
					(2.6)	(2.8)	(2.9)	(3.8)
Pre-sample FE	3.2***	3.2***	2.9***	4.1***	3.8***	3.8***	7.9***	3.0***
	(0.5)	(0.5)	(0.6)	(1.1)	(0.7)	(0.7)	(0.6)	(0.6)
F-Value	155.68	129.25	89.94	120.98	78.87	60.41	46.73	42.81
R2	0.46	0.46	0.46	0.45	0.08	0.08	0.10	0.09
N	9947	9947	4617	5330	5999	5999	1763	4236

Note: This table shows the results of estimating equation 7 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 significance at the 1%, 5% and 10% level, respectively. To increase the readability of the table we multiply each estimate by 100.

4.3 Spillovers depending on characteristics of the start-up

We investigate next whether the strength of knowledge spillovers varies systematically with ex-ante characteristics of the start-ups. Prior research suggests that both the founder team and access to prior technology may play an important role in the success of a venture (Kaplan et al., 2009; Gompers et al., 2010). The question is whether this is also true for the spillovers generated by venture capital-financed start-ups. If we can find pre-determined characteristics of start-ups that exhibit large knowledge spillovers, this would be important information for policy makers who want to use subsidies to account for the positive external effects of venture capital investment on innovation.

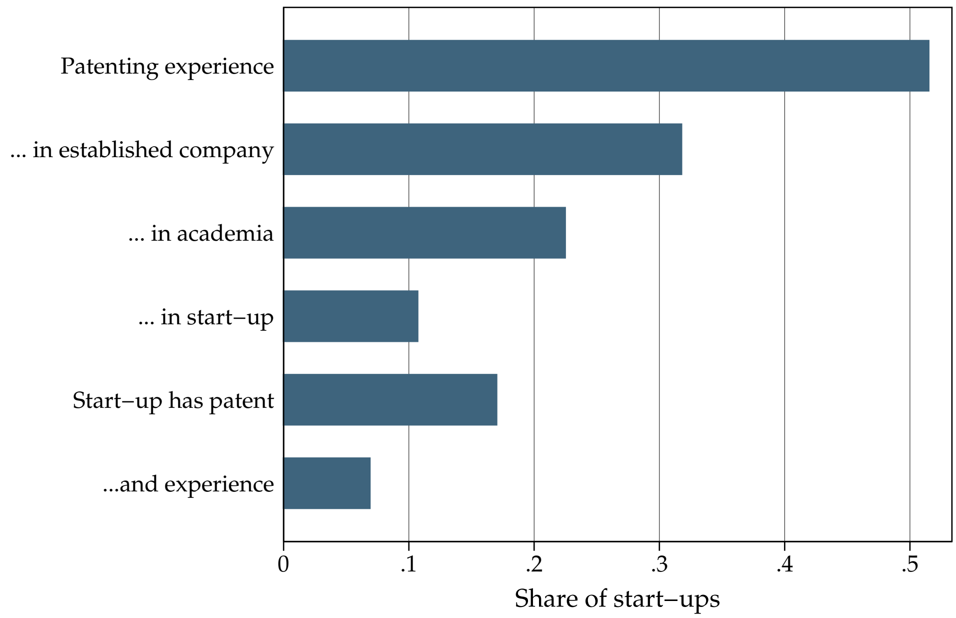
Founders may differ in a number of characteristics. One characteristic studied in the literature is the experience from previous employments. The literature on entrepreneurial spawning, for example, emphasizes that a prior affiliation with a start-up may help entrepreneurs learn how entrepreneurship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

Entrepreneurs with prior experience in a large corporation instead may have access to a technology the established company is reluctant to commercialize (the "Xerox view" - e.g. Gompers et al. 2005; Klepper and Sleeper 2005). Similarly, entrepreneurs with a prior affiliation with a university may be able to commercialize technology developed at universities (e.g. Gregorio and Shane, 2003; Nerkar and Shane, 2003). Experience in start-ups may thus improve the entrepreneurial skills of the founders (skills hypothesis), while experience in established companies or universities 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. We do not have a complete curriculum vitae of each inventor, so we cannot directly observe experience from previous employments. Instead, we follow the literature by using prior patenting as an indicator for a movement between employers (Marx et al., 2009). We check whether the inventor of the first patent of the start-up already patented before joining the start-up and whether she did so at an established company or a start-up or at a university.

In Figure 5, we show the share of the start-ups that have at least one inventor on the first patent with prior patenting experience or that have a patent at the time of the first funding round. Around 51% of the start-ups have at least one inventor with prior patenting experience. 31% have an inventor who patented before in an established company, 22% have one who patented before for a university, and 11% have one who patented before for a start-up. 17% of all start-ups in our sample have a patent at the time of the first investment

Figure 5: Share of Start-ups with Experience and Prior Patents



Note: This figure shows the share of the 1206 start-ups in our sample that have an inventor on the first patent with prior patenting experience. We separate inventors into having any patenting experience (bar 1), patenting experience in established companies (bar 2), in academia (bar 3) or in start-ups (bar 4). In bar 5, we show the share of start-ups with a patent filed before the first investment, and in bar 6, we show the share of start-ups with a patent and with inventors with prior patenting experience.

round, and 7% have both a patent and an inventor with prior patenting experience.

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 Table 8. For expositional convenience, we only report the results for the instrumental variables regressions, and only for the citation-augmented proximity measure. In columns 1 to 3, we split spillover generating start-ups in inventors with any 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.

Overall, in complex industries, start-ups with experienced inventors generate significantly more spillovers onto established firms than inexperienced ones (Table 8, column 3). For established firms, the spillover effect seems to be mostly driven by inventors with a background in established companies and in academia, lending support to the commercialization hypothesis. For VC-financed firms, the effect is strongest for inventors with a background in start-ups. This observation would be consistent with the skills hypothesis.

To dig deeper into this question of whether any of the two hypotheses has particular merit, we use the information on 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., if experience matters because it improves the inventor's skills we would expect the 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. In our data, 205 start-ups have a patent assigned to the start-up before the first investment round, and 83 have both a patent and a team with prior patenting experience.

The results are presented in Table 9. Again, we report only the results for the instrumental variables regressions, and only for the citation-augmented proximity measure. According to Table 9, 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 established and onto VC-financed firms. Furthermore, if we split the sample of VC-financed start-ups in four categories with regard to patent holding and experience, we find that spillovers are significantly stronger for start-ups that have an experienced inventor team and 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.

To summarize, we find that spillovers are stronger for start-ups with an experienced inventor teams, in particular, if start-ups already hold a patent at the time of the first investment. This suggests that the commercialization hypothesis has particular merit. An increase in venture capital has the biggest external impact if it goes to a firm that already has a patent. This points to a complementary 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.

Table 8: Spillovers by Patenting Experience of Inventor Team

	Scaled Forward Citation-Weighted Patents - IV											
	1	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Established companies											
Split by	Prior experience			Start-up inventor			Established inventor			Academic inventor		
	Full	Dis-crete	Com-plex	Full	Dis-crete	Com-plex	Full	Dis-crete	Com-plex	Full	Dis-crete	Com-plex
ln(Spillover VC)												
wo experience	4.6	9.1	-1.1	6.5	4.8	6.5	5.1	11.5	-1.3	8.8**	20.9**	2.3
	(5.7)	(10.8)	(7.2)	(4.5)	(6.3)	(6.3)	(5.0)	(10.5)	(5.1)	(4.5)	(10.5)	(5.1)
w experience	4.1	-1.1	13.9*	2.0	2.1	5.5	3.6	-4.4	13.7**	1.8	-8.5	14.3***
	(6.7)	(10.0)	(7.5)	(4.8)	(6.2)	(7.1)	(6.3)	(10.6)	(6.3)	(4.8)	(8.7)	(4.4)
N	9947	4617	5122	9947	4617	5122	9947	4617	5122	9947	4617	5122
	Panel B: Start-ups											
ln(Spillover VC)												
wo experience	-7.9**	1.3	-6.9	-8.0**	0.9	-7.2	-5.5	0.3	-1.0	4.4	13.3	1.6
	(3.8)	(11.2)	(5.1)	(3.4)	(7.6)	(4.8)	(4.2)	(11.5)	(5.3)	(4.0)	(12.5)	(4.8)
w experience	8.4*	-1.4	11.7**	9.7***	-3.3	11.7***	7.1	0.2	5.1	-4.1	-7.5	1.9
	(4.5)	(8.7)	(5.8)	(3.3)	(9.5)	(4.1)	(4.7)	(11.1)	(4.2)	(3.8)	(9.4)	(4.4)
N	5999	1763	4090	5999	1763	4090	5999	1763	4090	5999	1763	4090

Note: This table shows the instrumental variable results of estimating equation 7 for the subsample of established companies (Panel A) and start-ups (Panel B) and the citation-augmented proximity measure. In all regressions, we control for the spillovers of R&D and the direct effect of R&D or venture capital investment as well as industry and year fixed effects. 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 active in a discrete product industry. All standard errors are clustered on the four digit industry-year 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 9: Spillovers by Prior Patent

	(1)	(2)	(3)	(4)
	Scaled Forward Citation-Weighted Patents - IV			
	Established		Start-ups	
ln(Spillover Est.)	37.6***	37.0***	69.1***	70.0***
	(6.3)	(6.4)	(9.1)	(9.5)
ln(Spillover VC)				
wo patent	-1.6		-8.8*	
	(3.9)		(5.0)	
w patent	15.3***		14.4***	
	(5.7)		(4.2)	
w patent wo experience		9.0*		0.8
		(4.7)		(3.8)
w patent with experience		10.6**		15.0***
		(5.4)		(5.3)
wo patent wo experience		9.3		-2.5
		(6.5)		(2.9)
wo patent with experience		-10.4*		-7.4
		(6.2)		(6.2)
ln(R&D stock)	39.4***	39.2***		
	(2.3)	(2.3)		
ln(VC stock)			15.2***	14.9***
			(2.5)	(2.6)
Pre-sample FE	3.3***	3.3***	2.3***	2.4***
	(0.5)	(0.5)	(0.5)	(0.5)
N	9947	9947	5999	5999

Note: This table shows the instrumental variable results of estimating equation 7 for the subsample of established companies (columns 1-2) and for venture capital-backed start-ups (columns 3-4). For conciseness, 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. All standard errors are clustered on the four digit industry-year 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.

4.4 Robustness

As a robustness check, we investigate whether the mechanism described above is stable with respect to the sample period and the choice of the outcome variable.[30] The two robustness checks are visualized in Figure 6. 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.[31] The sample period does not seem to matter, the spillover effect is - except for a dip in the mid-1980s and at the end of the sample period - stable over time. Yet, taking each period separately the coefficient is often not significant at the 10% level (Figure 6a). The spillover effect is also stable if we use different patent related outcome measures (Figure 6b).

In Appendix B.1, we re-do our main regression using de-meaning instead of pre-sample mean scaling to control for firm fixed effects and estimating specifications using negative binomial regressions with control functions to show that our results are robust. In Appendix B.3, we show how the results vary depending on the location of the start-ups and the established company.

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 onto other firms' quality weighted patent production. 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 employ 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 differ. This confirms that our findings are robust to different specifications.

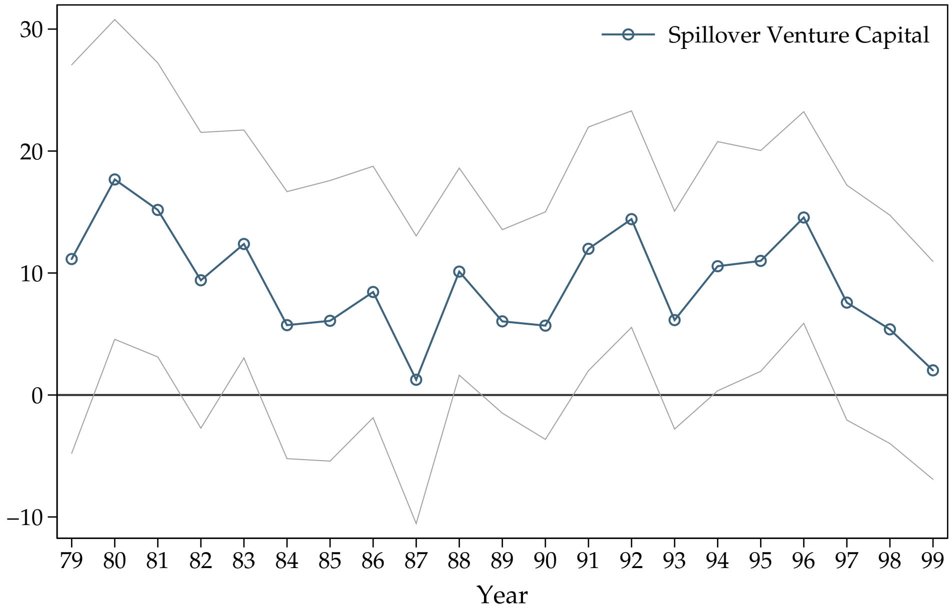
Our analysis allows us to paint a nuanced picture of venture capital-induced spillovers. The effects are heterogenous, depending on what type of start-up increases its VC investment and who is affected by the potential spillover. In general, complex product industries tend to be more conducive to spillovers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

[30] We thank Mark Schankerman for suggesting most of the additional specifications.

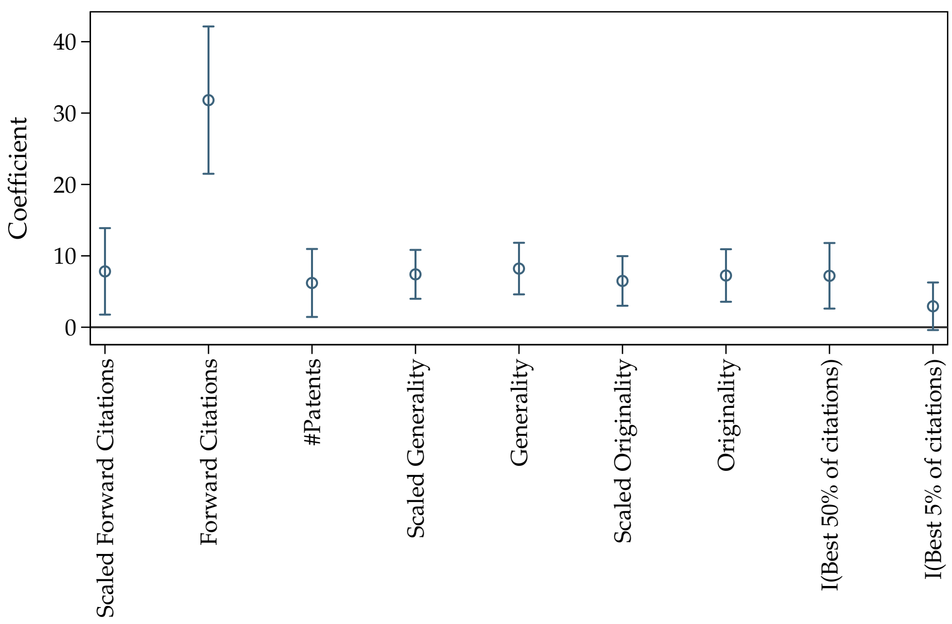
[31] All underlying figures and tables are available from the authors upon request.

Figure 6: Robustness Checks

(a) Time-Pattern



(b) Alternative Outcomes



Note: This figure plots the coefficient of the venture capital spillover measure for the subsample 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. The 90% confidence intervals displayed in each picture are derived from standard errors clustered on the four digit SIC code level.

discrete product 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 stronger for investments in a small set of start-ups that are characterized by an inventor team with prior patenting experience and 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 innovation and economic growth.

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

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Appendix

A Comparison of Spillover Measures

In the paper, we use a variety of different spillover measures to show that our conclusions are robust. In this section, we discuss whether the employed measures for technological proximity have desirable properties. The desirable properties proposed by Bloom et al. (2013) are

1. Economic Microfoundation (EMF): The measure has an economic microfoundation.

2. Invariance to Re-Scaling (SCALE): The measure is invariant (up to a monotone transformation) to rescaling the number of units. This means the rankings of firm pairs in terms of proximity does not depend on the units in which R&D is measured.

3. Within-field overlap (WFO): The measure increases in the degree of R&D overlap within a technology field (within-field overlap). Holding constant the share of firm j's R&D in technology field A, firm i is more likely to enjoy a knowledge spillover from firm j the larger is the share of firm i's R&D in field A.

4. Between-field overlap (BFO): The measure increases in the degree of R&D overlap in technologically related fields (between-field overlap). For a given share of firm j's R&D in technology field A, firm i is more likely to enjoy a knowledge spillover from firm j in field A if it does more R&D in field B whenever fields A and B are technologically related.

5. Non-overlapping fields (NOF): The measure is invariant to the allocation of R&D by firm i in fields where firm j does no R&D and which are not technologically related to those in which firm j is active.

6. Invariance to aggregation over non-active fields (AGG): The measure is invariant to aggregation of technology fields in which neither firm i nor firm j does R&D.

7. Robustness to aggregation of active fields (ROB): The measure is robust to the aggregation of technology fields in which either firm i or firm j does R&D.

In addition, we propose an 8th property

8. Directionality of knowledge flows (DIR): The measure takes into account that knowledge flows (potentially) only in one direction between companies active in different technologies. This implies that the proximity from firm i to firm j is not necessarly

Table A.1: Desirable Properties of Distance Measures

Model	Definition	Economic Microfoundation EMF	Invariance to Re-Scaling SCALE	Within-field overlap WFO	Between-field overlap BFO	Non-overlapping fields NOF	Invariance to aggregation to over non-active fields AGG	Robustness to aggregation of active fields ROB	Directionality of knowledge flows DIR
Jaffe	$s'_{j,t-1} s_{i,t-1}$	O	X	X	O	O	X	X	O
Direct Citation	$\frac{\#Citations_{ji}}{\#Patents_i}$	X	X	O	O	X	X	X	X
Citation-augmented	$s'_{j,t-1} W^{Cites} s_{i,t-1}$	O	X	X	X	O	X	X	X
Mahalanobis	$s'_{j,t-1} W^{Mal} s_{i,t-1}$	O	X	X	X	O	X	X	O

Note: In this table, we compare the different technological distance measures employed in this paper along eight criteria outlined in the text. 'X' implies that the measure posses the criteria while 'O' implies that it does not. In the definition of the distance measures we use the following abbreviations: $s_{j,t-1}$ is the standardized patent share vector of copmany j using patent stock up to the period $t-1$. W^{Cites} is a weighing matrix based on average cross-technology class citations. W^{Mal} is the weighing matrix defined in Bloom et al. (2013) based on cross-firm patent holdings.

equal to the proximity from j to i. This property allows to capture that some companies are engaged in basic/upstream and some in applied/downstream technologies.

In Table A.1, we compare the four different proximity measures employed in this paper along with the Mahalanobis proximity measure of Bloom et al. (2013): (1) the Jaffe proximity measure, (2) the Direct Citation measure, (3) the Citation-augmented proximity measure and (4) the Mahalanobis proximity measure. An 'X' denotes that the proximity measure in that row has the property designated in the column, an 'O' denotes that it does not have the property.

The results from using this axiomatic approach to evaluate proximity measures are reported in Table A.1. According to this analysis, the Citation-augmented proximity measure dominates the Mahalanobis measure because it additionally takes the directionality of knowledge flows into account. If we use only the first seven properties suggested by Bloom et al. (2013), both measures have the same advantages and disadvantages.

We cannot rank unambiguously the Direct Citation measure relative to the other measures because this measure does not use technology classes to calculate technological proximity. The Direct Citation measure has an economic microfoundation as citations are directly connected to knowledge flows, and it is insensitive to any kind of aggregation of technology classes. On the other hand, it does not necessarily increase with increasing overlap of technologies (AFO and BFO). As we do not have a metric to compare the relative importance of the different criteria we cannot decide whether the Direct Citation measure is better or worse than Mahalanobis or the Citation-augmented measure.

Besides comparing the theoretical properties of the proximity measures, we can also compare how well the different measures predict citations between companies. Citations are a direct measure of knowledge flows, but they also have several drawbacks discussed in the literature (e.g. Alcacer and Gittelman, 2006). In Table A.2, we compare how much citations between companies correlate with the different proximity measures. A better measure of technological proximity should correlate more with citations.

For this analysis, we first count the number of citations from each start-up and each established company to each other start-up/established company and match it with the value of the Jaffe, Mahalanobis and Citation-augmented proximity measures. Then we assign in the first three columns of Table A.2 a one to a company pair if company j cites at least one patent of company i. In the next three columns, we use only company pairs with at least one citation and use the total number of citations between j and i as outcome. In the last column, we use simultaneously all three measures as explanatory variables and the number of citations as outcome. In all regressions, we standardize the three distance measures to a mean of zero and a standard deviation of one to account for potentially different scaling.

For the intensive margin, the extensive margin, and using partial correlations, we find that the Citation-augmented proximity measure correlates more with actual citations than the Jaffe or the Mahalanobis measure. The reason is two-fold: first, the citation-augmented measure is by construction asymmetric and thus has an advantage predicting directional citation flows. Second, the citation-augmented measure uses citation data as an input. Yet, the advantage of the citation-augmented measure is not mechanical as we only use average citation flows between technology classes to construct the proximity between companies.

Table A.2: Comparison of Different Spillover Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Extensive Margin			Intensive Margin			Partial Correlation
Dependent:	I[Citations>0]*100			# Citations if >0			# Citations
Jaffe	0.18***			3.02***			-0.09***
Mahalanobis		0.20***			3.35***		0.07***
Cit.-aug.			0.21***			3.66***	0.11***
Constant	0.07***	0.07***	0.07***	22.88***	21.24***	19.94***	0.02***
N	22184095	22184095	22184095	15787	15787	15787	22184095

Note: In this table, we calculate the correlation between citations and three different technological proximity measures, the Jaffe measure, the Mahalanobis measure and the Citation-augmented measure. The proximity measures are standardized to a mean of 0 and a standard deviation of 1. In the first three columns, we use as dependent variable an indicator equal to one if there is at least one citation between the company pairs, multiplied by 100. In columns 4 to 6, we use the number of citations between the companies given that there is at least one. In column 7, we use a simple citation count as outcome.

B Robustness

B.1 Estimation methods

In our main analysis, we use a linear instrumental variable regression as empirical specification. The obvious alternative empirical specification is to use a negative binomial model with control functions as employed by Bloom et al. (2013). In Table B.1, we show the results for our main analysis using this approach. The qualitative conclusions from this specification are similar to our main results. There are significant spillovers of venture capital on innovation and the effects are stronger for start-ups with a patent and for start-ups with experienced inventors. There are no spillovers of venture capital investment on start-ups on average (column 7), but there are some spillovers measurable from start-ups with experienced inventors and start-ups with a patent.

Another alternative empirical specification is to use de-meaning to account for firm fixed effects instead of using pre-sample mean scaling. Pre-sample mean scaling uses pre-sample periods to calculate the firm fixed effects. For the subsample of start-ups, this is the appropriate choice since we observe 16% of all start-ups only for one year (Figure B.1). For that reason using de-meaning would induce a selection bias for the start-up subsample as all start-ups with only one year in the data would drop from the sample. Also for all other start-ups there is only little variation to identify the firm fixed effects as start-ups are on average only 4 years in the data. In contrast, each established company is on average 8 years in the data. So de-meaning is sensible in this sample.

Despite these caveats, we present in Table B.2 results using de-meaning to account for firm fixed effects for both subsamples. For established companies, we find significant spillovers from venture capital investment, in particular in complex industries. In contrast to our main results we find stronger spillovers from start-ups with an experienced inventor team (column 4) but none from start-ups with a patent prior to the first investment. The results for start-ups are different from our main specification. Here we find significant spillovers from venture capital investment and in particular in discrete technology fields. As before, we find stronger effects for start-ups with a patent and with an experienced inventor team.[32]

B.2 Adjusted venture capital investment

One concern might be that we overestimate the effects of venture capital investment because we use only start-ups that have at least one patent. To addresse this issue we re-scale the

[32] Since for our main estimation sample we extend the survival of the start-up to two years after the last investment we do not lose many observations. But these two years of extended observation are not independent and hence do not help to identify the fixed effect.

Table B.1: Measurement of Spillovers: Negative Binominal Model and Control Functions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Scaled Forward Citation-Weighted Patents											
	Established companies						Start-ups					
Subsample	Full	Discrete	Complex	Full	Full	Full	Full	Discrete	Complex	Full	Full	Full
Ln(Spillover Est.)	0.5***	0.4**	0.7***	0.5***	0.5***	0.6***	1.4***	1.3***	1.5***	1.2***	1.4***	1.2***
	(0.12)	(0.21)	(0.14)	(0.13)	(0.12)	(0.14)	(0.16)	(0.22)	(0.21)	(0.12)	(0.15)	(0.11)
Ln(Spillover VC.)	0.2**	0.1	0.2***				-0.1	0.1	-0.1			
	(0.08)	(0.14)	(0.09)				(0.08)	(0.13)	(0.14)			
wo experience				-0.2						-0.4***		
				(0.17)						(0.09)		
with experience				0.2						0.4***		
				(0.19)						(0.11)		
wo Patent					0.1						-0.3**	
					(0.07)						(0.11)	
w patent					0.2**						0.3***	
					(0.09)						(0.08)	
w patent wo experience						-0.1						0.1
						(0.12)						(0.08)
w patent with experience						0.4***						0.4***
						(0.14)						(0.09)
wo patent wo experience						-0.0						-0.3***
						(0.14)						(0.07)
wo patent with experience						-0.2						0.0
						(0.16)						(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)	(0.07)	(0.05)	(0.06)	(0.05)
Pre-sample fixed effects	0.0***	0.0***	0.0***	0.0***	0.0***	0.0***	0.1***	0.1***	0.0***	0.1***	0.1***	0.1***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
N	9947	4825	5122	9947	9947	9947	5999	1909	4090	5999	5999	5999

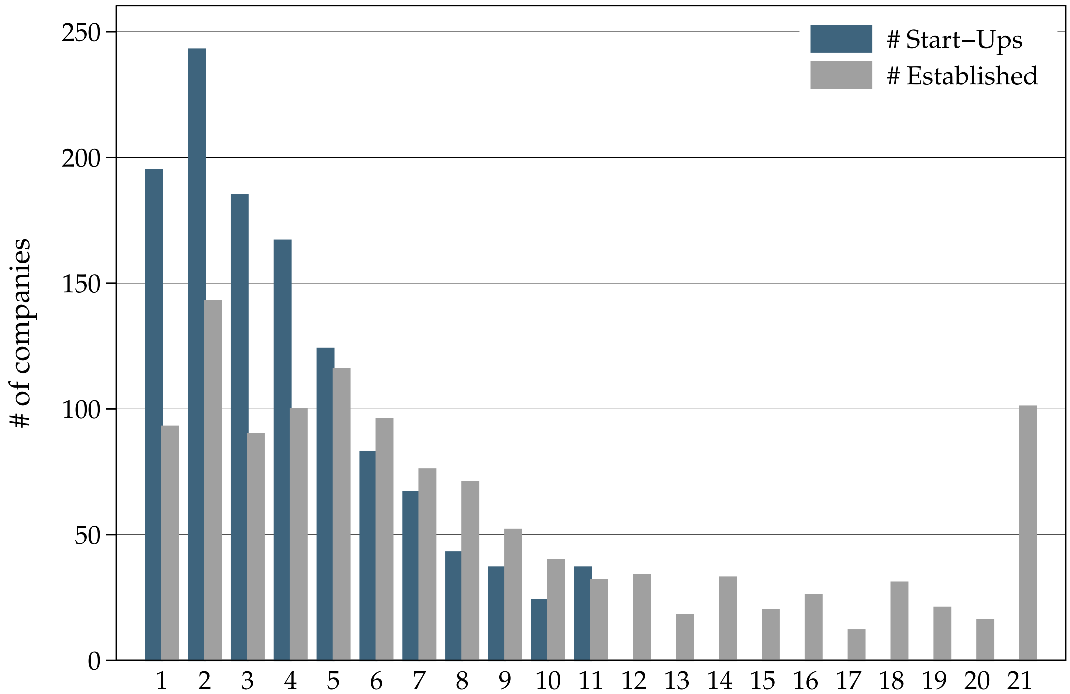
Note: This table shows the results of estimating equation 7 with a negative binomial model, control functions, pre-sample fixed effects and the citation augmented proximity measure. The first six columns show the results for established companies and the following six columns for the sample of start-ups. For the description of the sample splits please refer to the text. All standard errors are clustered on the 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 B.2: Measurement of Spillovers: De-meaning as Firm-Fixed Effects and IV

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Scaled Forward Citation-Weighted Patents											
	Established companies						Start-ups					
Subsample	Full	Discrete	Complex	Full	Full	Full	Full	Discrete	Complex	Full	Full	Full
ln(spillover est.)	25.3***	24.2**	35.2***	27.0***	24.8***	25.5***	79.7***	51.5**	96.3***	77.6***	76.8***	75.5***
	(7.9)	(11.3)	(10.8)	(7.9)	(7.7)	(7.6)	(12.4)	(23.9)	(15.4)	(12.5)	(12.2)	(12.3)
ln(spillover VC)	8.8**	3.7	13.6**				17.2***	39.5***	5.1			
	(4.3)	(7.1)	(6.0)				(6.4)	(12.2)	(8.4)			
wo experience				-5.1						-4.9		
				(5.4)						(6.9)		
with experience				13.0**						23.9***		
				(5.4)						(6.8)		
wo patent					7.8*						10.1	
					(4.4)						(6.5)	
w patent					2.0						12.1**	
					(4.7)						(5.8)	
w patent wo experience						-1.2						2.5
						(4.3)						(4.7)
w patent with experience						5.6						12.8**
						(4.3)						(5.2)
wo patent wo experience						-0.0						-7.9
						(5.2)						(6.1)
wo patent with experience						6.4						17.4***
						(5.4)						(6.6)
ln(R&D stock)	46.0***	45.7***	47.4***	45.9***	45.9***	45.6***						
	(4.2)	(6.8)	(5.3)	(4.2)	(4.2)	(4.2)						
ln(VC stock)							17.2***	5.9	22.5***	17.1***	17.3***	17.1***
							(4.1)	(6.3)	(5.3)	(4.1)	(4.1)	(4.1)
N	9854	4832	5022	9854	9854	9854	5947	1830	4117	5947	5947	5947

Note: This table shows the results of estimating equation 7 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.

Figure B.1: Number of Companies by Years in the Data



Note: This figure shows the number of companies (y-axis) in our data that survive for a given number of years (x-axis). For start-ups, we count the years between the first and the last investment. For established companies, we count all years with reported R&D spending. All start-ups and all established companies have at least one patent.

venture capital investment of each company such that the investment in our sample matches the total investment in each year and four-digit industry combination.

In Table B.3, we report the results from estimating our main specification in equation (7) using the adjusted VC spending. The estimated elasticities are similar to our main specification. In Table 6, we show that the quantitative impact of venture capital investment on innovation of other companies using these estimates is smaller than in our main specification, but still larger than the spillovers from R&D.

B.3 Variation by geographic location

In this section, we show how effects vary by the geography of the financed start-up and the receiving company. In particular, we analyse whether the results are different for California and Massachusets, the two most important states for venture capital and entrepreneurship in the U.S. For this exercise, we report both, spillovers originating from start-ups residing in a particular state and spillovers received by companies in that state. The results are reported in Figure B.2. Start-ups from Massachusets seem to be the source of few spillovers

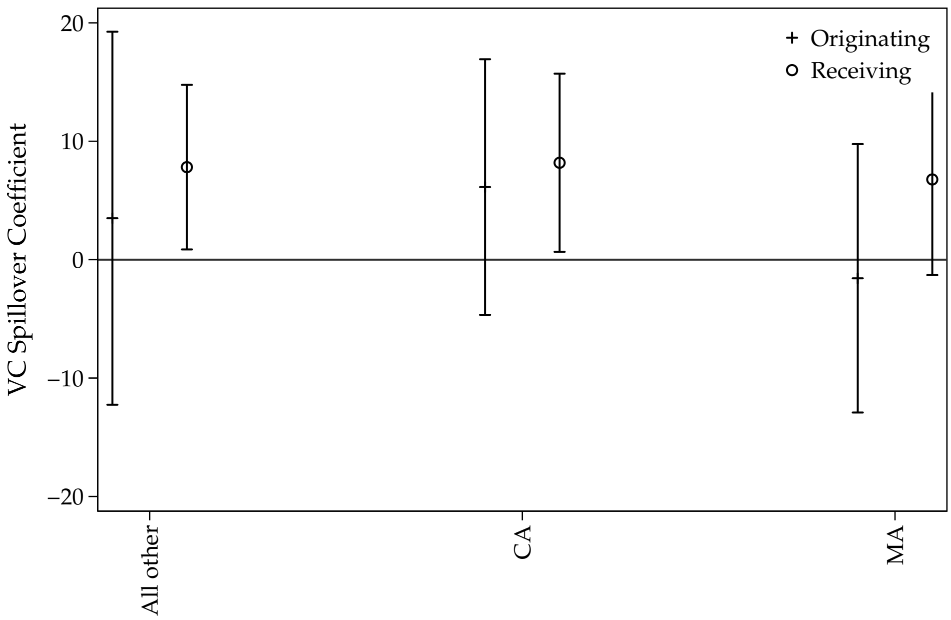
Table B.3: Results for Adjusted VC Spending

	(1)	(2)	(3)	(4)
	Scaled Forward Citation-Weighted Patents			
	Established companies		Start-ups	
	OLS	IV	OLS	IV
Ln(Spillover Est.)	30.8***	37.0***	61.0***	73.1***
Ln(Spillover VC.)	8.5***	8.3**	1.3	-1.7
ln(R&D Stock)	39.4***	38.5***		
ln(VC Stock)			14.8***	14.8***
Pre-sample FE	3.2***	3.2***	3.9***	3.8***
F-Value	.	159.91	.	76.83
R2	0.46	0.46	0.08	0.08
N	9947	9947	5999	5999

Note: This table shows the results of estimating equation 7 with the citation-augmented proximity measure. Venture capital spending is multiplied by a correction factor such that the total investment matches the investment in our sample in every year and industry. The first and third columns show the OLS results, while the second and fourth columns show the instrumental variable results. 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.

while start-ups from California generate significantly more. But in both cases the effects are imprecisely estimated. The effect on established companies is relatively homogeneous in California, Massachusetts and the rest of the U.S., i.e., established companies all over the U.S. benefit from venture capital spillovers (Figure B.2).

Figure B.2: Spillovers of VC by the State of Start-Up



Note: In this figure, we split the sample by the state of the start-up ("originating") and by the state of the established company ("receiving") and report the coefficient for venture capital spillovers for the subsample of established companies. The 90% confidence intervals displayed in each picture are derived from standard errors clustered on the four digit SIC code level.