Learning from the Little Guy: Innovation Spillover from Private to Public Firms*

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Abstract

Although research commonly focuses on either public or private firms, little is known about interactions between the two. One natural interaction is in the innovation space, since R&D investment creates knowledge spillovers from firms. We construct a novel measure of knowledge spillovers for public firms from young, private firms. Public firms benefit from private firms through increased innovation quantity and novelty. We identify the causal effect of spillovers using changes in the enforceability of non-compete agreements as a shock to the availability of inventors for private firms. Public firms respond to these spillovers by acquiring more venture capital-backed firms and hiring inventors with prior experience at such firms.

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1 Introduction

Public firms account for the majority of patent production in the U.S. (Sørensen and Stuart, 2000), yet a growing body of research highlights the critical role of private firms-especially young firms-in producing novel and high-impact innovations (Gao et al., 2018; Ewens and Marx, 2024). At the same time, firms do not innovate in isolation. Investment decisions often generate spillovers, where knowledge and technology diffuse across firm boundaries (Grennan and Lowry, 2024). Prior studies show that public spillovers lower the cost of innovation (Bloom et al., 2013), but tend to shift innovation output toward more incremental advances (Byun et al., 2021). In this paper, we show that spillovers from private firms-particularly young ones-not only increase innovation output among public firms but also shift it toward more novel innovations. By neglecting such spillovers, prior literature has underestimated the total impact of innovation spillovers on public firms' innovation outcomes.

While spillovers from public firms have been extensively studied, we examine those from private firms for two key reasons. First, public and private firms differ in their regulatory status, which may influence the nature and diffusion of spillovers. Public firms are subject to a high degree of mandatory disclosure, along with greater price efficiency, trade visibility, and scrutiny from analysts and regulators. These features generate a clear benefit for all market participants, who can extract information from public firms' prices, filings, and product decisions (Bennett et al., 2020). In contrast, it is often assumed that public firms have little to learn from private firms, which operate with less transparency and limited public reporting. However, we argue that patenting is itself a form of technological disclosure, and that even unlisted firms contribute meaningfully to the public information environment, particularly in an era where firms with high levels of intangible capital often choose to remain private (Stulz, 2020).

The second reason relates to the firm's life cycle. Public firms tend to be older, larger, and more established incumbents that benefit from economies of scale and strong market positions. In contrast, younger firms benefit from a more concentrated investor base and are therefore more likely to explore novel and untested ideas (Ewens and Marx, 2024). As a result, the types of spillovers public firms are exposed to from younger firms may differ significantly than those they experience from other firms at a similar stage in the life cycle. Given public firms' market power and resources, they may also be in a better position to absorb and respond to innovations emerging from younger entrants. We therefore study these spillovers from the perspective of the public firm to better understand how knowledge flows between incumbents and entrants shape innovation dynamics from the market leaders' perspective.

Ex ante, it is unclear how spillovers from young firms affect the innovation behavior of public firms.

These effects may manifest along two dimensions: innovation quantity, which reflects the overall intensity of knowledge output, and innovation novelty, which captures the degree to which the innovation is breakthrough or disruptive. We propose two competing hypotheses to frame the potential responses of public firms: the Value Hypothesis and the Schumpeterian Hypothesis. Under the Value Hypothesis, public firms respond to spillovers from young firms by increasing their innovation activity. In this view, knowledge spillovers act as a positive externality - providing public firms with access to novel technologies, processes, or ideas without requiring them to bear the full cost of discovery (Bloom et al., 2013). This reduces the marginal cost of innovation and allows firms to build upon the cumulative nature of technological progress (Jaffe, 1986; Griliches, 1991). Consistent with prior work on public-to-public spillovers, this hypothesis suggests that public firms should similarly benefit from knowledge generated by young, private firms.

Alternatively, public firms operating in a similar knowledge space to young firms may lead to a cycle of "creative destruction" (Schumpeter, 1942). Under this Schumpeterian Hypothesis, young firms drive economic progress through technological advancements and new business models that render older industries or companies obsolete. As entrants introduce breakthrough innovations, public firms may experience a decline in market share, profitability, and future innovation output (Aghion et al., 2005). Thus, while spillovers by young firms provide new knowledge, they may also create a competitive challenge for public firms operating in closely related industries.

To test these two alternative hypotheses, we construct a novel measure of technology spillover from private firms to public firms. Following the approach of Bloom et al. (2013), we measure the distribution of public and private firms patenting across technology fields. We then scale the technological overlap by the number of inventors in each private firm and aggregate by public firm-year. We validate this measure by showing that spillovers lead to more patent citations and active information acquisition by public firms about private firms.

To distinguish more clearly between different stages of the firm life cycle, we consider two types of private firms: entrepreneurial firms, defined as those three years or younger, and venture capital (VC) -backed firms[1]. Entrepreneurial firms produce more novel innovations than other firms (Ewens and Marx, 2024), suggesting they have high potential for producing valuable spillovers. On the other hand, VC-backed firms develop patents that are more highly cited than other firms (Ewens and Marx, 2024). This suggests that other inventors may be more aware of VC-backed private firms as they have undergone investor screening, reducing information asymmetry of their innovations. Thus while entrepreneurial firms may produce more novel innovations than VC-backed firms on average, public firms may be more aware of VC-backed innovations.

[1] VC-backed firms can also be classified as entrepreneurial firms and vice versa if firms three years or younger receive venture financing.

To examine whether public firms benefit differently from these two groups, we construct separate measures of private-to-public technology spillovers: spillovers from VC-backed firms and spillovers from entrepreneurial firms.

Our first set of tests examines the impact of young firm spillovers on public firms' innovation output, proxied by patents produced and the number of citations received. The results support the Value Hypothesis: public firms with larger spillovers from private firms experience an increase in subsequent innovation output. This indicates that larger spillovers lower the cost of innovation, consistent with the positive externalities created by spillovers between public firms (Bloom et al., 2013). Economic magnitudes are larger for VC spillovers than for entrepreneurial spillovers, suggesting that public firms may be more attuned to VC-backed innovations, which face lower information asymmetry.

Next, we examine whether technology spillovers influence public firms' innovation quality and novelty, specifically distinguishing between exploitative and exploratory innovation. Exploitative innovation builds on existing ideas, while exploratory innovation involves pursuing unknown knowledge, which requires both a tolerance for failure and a significant commitment of resources (Manso, 2011). Previous literature finds that larger spillovers among public firms tend to shift innovation efforts toward more incremental advancements (Byun et al., 2021), as these spillovers reduce the cost of exploitative innovation relative to exploratory innovation. However, young private firms are more likely to generate novel and breakthrough innovations than their public counterparts (Gao et al., 2018). Consequently, greater spillovers from young firms may reduce the cost of exploratory innovation relative to exploitative innovation. Our findings support this prediction: public firms with larger technology spillovers from private firms produce more novel innovations and fewer incremental innovations, with the effect being stronger for VC spillovers, consistent with VC-backed firms facing lower information asymmetry than entrepreneurial firms.

To mitigate concerns that our results are driven by transitory shocks simultaneously affecting technology spillovers and innovation output, we construct an instrumental variable for our main spillover measure. Specifically, we exploit exogenous changes in the availability of inventors to private firms resulting from variations in non-compete enforceability laws as our primary identification strategy. Non-compete laws are governed at the state level and vary significantly across states and over time (Starr et al., 2018). For a given public firm, we measure its private firm peers' exposure to non-compete laws based on their headquarters' locations.

Prior literature finds that non-compete agreements (NCAs) negatively impact labor mobility (Marx et al., 2009), entrepreneurial innovation (Johnson et al., 2023), and entrepreneurial entry (Marx, 2022). As a result, private firms are differentially affected by non-compete laws depending on their location and the timing of legal changes. These differences influence private firms' inventor stock, which in turn affects the focal public firm's technology spillovers (relevance criterion). Since public firms experience spillovers from numerous young firms across different states, the aggregated spillover—instrumented by the private firms' state locations—should be exogenous to any single public firm's corporate decisions (exclusion criterion). Using this instrumental variables approach, we establish a causal link between private firm spillovers and public firm innovation.

After showing that private firm innovation has positive spillovers on public firm innovation, and these effects are causal, we next test the channel through which spillovers occur. A well-established literature identifies labor mobility as a key channel for knowledge transfer (e.g. Bloom et al., 2020). Consistent with this, we find that greater VC spillovers are associated with an increase in both the number and proportion of newly hired inventors from VC-backed firms. However, we do not observe a significant effect for entrepreneurial spillovers. Together with our findings on spillovers and innovation output, this suggests a distinct role for VC-backed firms in facilitating public firm innovation from young firms.

Rather than hiring inventors, public firms may also invest in private firms through corporate venture capital (CVC) or outright acquisitions. Our findings indicate that larger VC spillovers are associated with an increase in VC-backed acquisitions. This suggests that public firms actively manage these spillovers by acquiring innovation when there is overlap in their technological base. In contrast to acquisitions, Ma (2020) suggests that public firms tend to invest in private firms when there is no overlap in knowledge base, aiming to learn more about new technologies to enhance their innovation efforts. Consequently, we find no significant relationship between private firm spillovers and CVC investments.

Our paper contributes to three strands of literature. First, we contribute to a growing literature on spillovers between firms. Spillovers arise because innovation is inherently a public good (Arrow, 1972). In a seminal paper, Jaffe (1985, 1986) first defines the technological space of firms by classifying their patents in different technology classes. Building upon this, Bloom et al. (2013) examine the interaction between technological spillovers and product market spillovers. Intuitively, although innovation has a positive externality on other firms, it may also take away product market share from less innovative competitors. The authors find that the technological spillover effect exceeds product market effects. Yet, the prospect of competitors benefiting from in-house innovation may discourage firms from expending resources on R&D. Arora et al. (2021) and Antón et al. (2024) provide further evidence on the heterogeneous impact of knowledge spillovers on innovative firms' incentives and show that for some firms, the benefit of R&D outweighs the cost from spillovers. Importantly, firms with large spillovers continue to produce more R&D, but this innovation is more incremental, rather than breakthrough innovation (Byun et al., 2021). Whereas prior papers have focused on spillovers between publicly traded firms,[2] we contribute to this literature by constructing an

[2]Notable exceptions include Matray (2021) who finds spillover effects from public firms to local entrepreneurship.

analogous measure with young, private firms. Our results are different from prior findings: Public firms are more likely to have breakthrough innovation when they are in the same technological space as innovative private firms.

Second, our paper contributes to the literature on cross firm dynamics in public and private markets. There are several avenues for interactions between mature and young firms. On the one hand, mature firms whose innovation has slowed down can benefit from knowledge from young, innovative firms. For example, Ma (2020) explores how public firms actively seek innovation improvement through CVC investment. Similarly, Lerner (2012) suggests collaboration between public and private firms through a "hybrid" model in which corporate R&D labs work with VC-backed startups. Mergers may also improve innovation outcomes, depending on technological overlap (Bena and Li, 2014). On the other hand, if innovative firms pose a product market threat, public firms can leverage their market power to influence innovative practices. Cunningham et al. (2021) show that public firms acquire competitors through "killer acquisitions." We contribute to this literature by showing another mechanism through which public firms benefit from private firms - knowledge spillovers - without direct investment or acquisition.

Lastly, our paper contributes to the literature on private and public firm innovation. Several papers have examined differences in innovation across public and private firms. Ewens and Marx (2024) highlight that firms produce their most innovative patents when they are young. Similarly, Gao et al. (2018) show that private firms' patents are more exploratory and Bernstein (2015) finds a decrease in innovation post-IPO, with some heterogeneity across public firms' financial dependence (Acharya and Xu, 2017). We show that public firms' innovation improves when private firms are in the similar technology space as they provide valuable knowledge transfers.

2 Hypotheses

R&D activity generates two types of spillovers for firms: technology or knowledge spillovers and product market rivalry spillovers. Seminal work by Bloom et al. (2013) develops a methodology to identify the separate effects of these two types of spillovers. This methodology has been used in subsequent work to test how firms respond to these two types of spillovers (e.g. Qiu and Wan, 2015; Byun et al., 2021; Eldar et al., 2023).

An important observation is that these measures are limited to spillovers between *public* firms. While public firms produce the majority of patents, young, private firms are more likely to produce more novel innovation (Gao et al., 2018) and are more dominant in the early years of an industry (Ewens and Marx, 2024). Since private firm innovation is different from public firms, it is unclear how spillovers from young firms may impact public firm innovation. In line with prior literature on public spillovers, public firms may also benefit from private firm spillovers and increase their innovation. Alternatively, public firms operating in a similar knowledge space to young firms may lead to a cycle of "creative destruction" whereby young firms drive economic progress, rendering older industries or companies obsolete. We refer to these two alternatives as the Value Hypothesis and the Schumpeterian Hypothesis. We describe the hypotheses below.

2.1 The Value Hypothesis

The existing literature, including Jaffe (1986) and Bloom et al. (2013), shows that large technology spillovers promote innovation output. The Value Hypothesis posits that knowledge spillovers from private firms lower the cost of research and development for public firms, thereby enhancing their capacity to innovate. According to this view, larger spillovers act as a positive externality, allowing public firms to access new technologies, processes, or knowledge without bearing the full costs of development (Bloom et al., 2013). This diffusion of ideas leads to increased productivity and higher innovation output as firms can build on existing entrepreneurial innovations, leveraging the cumulative nature of technological progress (Jaffe, 1986; Griliches, 1991). Therefore the Value Hypothesis predicts that larger spillovers with young, private firms increases public firm innovation output.

2.2 The Schumpeterian Hypothesis

In contrast, the Schumpeterian Hypothesis draws on the concept of "Creative Destruction" (Schumpeter, 2013), which suggests that public firms operating in the same technological or market space as entrepreneurial firms may face disruption rather than benefit from spillovers. Young firms produce more novel patents and are dominant in the early years of an industry (Ewens and Marx, 2024). Therefore, the influx of innovative ideas from startups may accelerate competition, threatening incumbents by rendering their existing technologies or business models obsolete.[3] As startups introduce breakthrough innovations, public firms may experience a decline in market share, profitability, and future innovation output (Aghion et al., 2005). Thus, while spillovers by young firms provide new knowledge, they may also create a competitive challenge for public firms operating in closely related industries. Therefore the Schumpeterian Hypothesis predicts that larger spillovers with young, private firms decreases public firm innovation output.

[3] For example, Blackberry and Nokia were dominant players in the mobile phone market in the early 2000s. However, the emergence of private firms like Android Inc., which developed an open-source mobile operating system in 2003, began to shift the landscape. By offering a flexible and customizable platform, Android lowered the barriers for hardware makers such as Samsung, LG, and Motorola to enter and compete in the smartphone space without building their own operating systems. As Android matured, it enabled rapid innovation and user-driven customization. Meanwhile, Blackberry and Nokia, reliant on their proprietary systems and slow to adopt touch interfaces and app ecosystems, struggled to keep pace. Despite their early leadership, both firms failed to adapt to the new mobile paradigm, and as Android became the global standard, they lost market relevance.

3 Data and Measurement

In this section, we discuss the data and measures used in the empirical analysis. First, we explain the construction of the spillover measures. Second, we describe the innovation outcomes utilized in the study. Third, we provide an overview of additional outcomes and control variables. Fourth, we present the sample summary statistics for the firm-year panel spanning 1990 to 2021. Finally, we provide additional background and validation, as well as examples of technology spillovers.

3.1 Technology Spillovers

We measure the level of technology spillovers based on the methodology of Jaffe (1986) and Bloom et al. (2013). These studies theoretically derive technology spillovers as a process of knowledge transfer when firms in similar technology fields interact with each other. The more intensively firms interact and the closer their fields are, the more knowledge that is transferred - i.e. higher technology transfers generated. Based on this framework, the authors employ an empirical proxy to quantify the theoretical model and generate the measure of technology spillovers.

The first step in constructing the technology spillover measure is to calculate the closeness between two firms' technology fields. To capture this component, Bloom et al. (2013) employ the overlap between two firms' patent technology classifications. We obtain firms' patent technology classifications from the USPTO-Patentsview database. This database provides detailed information for more than three million patents granted between 1976 and 2023, including unique identifiers for inventors, assignee, and patent technology classes. To identify patents produced by VC-backed and entrepreneurial firms, we merge in VC identifiers and assignee age from Ewens and Marx (2024) link tables. Ewens and Marx (2024) classify entrepreneurial firms as establishments between 0 and 3 years old. The VC identifier provided is a time invariant identifier if the assignee was ever VC-backed. We therefore fuzzy name match all the VC-backed assignees with Crunchbase data to classify assignees and their patents as VC-backed from the date of their first VC financing until they either exit through IPO or acquisition or two years after their last VC-financing (whichever comes first). We construct three versions of the technology spillover measure: between public firms (used in prior literature), public firms and VC-backed firms and public firms and entrepreneurial firms. The measure captures the technology closeness between two firms i and j as follows:

$$Tech_{ij,t} = \frac{X_{i,t}X'_{j,t}}{(X_{i,t}X'_{i,t})^{0.5}(X_{j,t}X'_{j,t})^{0.5'}} \tag{1}$$

where $X_{i,t} = (X_{i1,t}, X_{i2,t}, ..., X_{i\tau,t}, ..., X_{iT,t})$ is a vector that denotes public firms i's proportion in technology classifications $\tau = 1, 2, ..., T$ over the sample period up to time t and $X_{j,t}$ is defined in a similar way for public firms, VC-backed firms, entrepreneurial firms, and all private firms. $tech_{ij,t}$ therefore measures the correlation of two firms' proportion of patents in each technology classification. The higher the correlation, the closer their technology fields are.

Prior literature interacts $Tech_{ij,t}$ with firm j's R&D stock in year t. As stated by Bloom et al. (2013), firm j's cumulative R&D stock proxies for the level of firm j's cumulative R&D input and, hence, the intensity of technology diffusion between firms j and i. However, private firms do not have to disclose their R&D expenses. In addition, young private firms such as entrepreneurial firms and VC-backed firms typically do not have a separate R&D department as the purpose of the new firm is for a new product. Therefore instead of interacting $tech_{ij,t}$ with firm j's R&D stock, we multiply it by the cumulative number of unique inventors working for firm j up until time t ($Inventors_{j,t}$). The intuition is that human capital is the channel through which knowledge transfers occur and, like R&D inputs, the more inventors employed by a firm, the higher the intensity of technology diffusion between firms. Because inventors leave the firm, we "depreciate" the cumulative number of inventors until $t - 1$ by 15%, similarly to Antón et al. (2024). Therefore the spillover measure is constructed as follows for each public firm i:

$$SpillTech_{i,t} = \sum_{j \neq i} tech_{ij,t} \times Inventors_{j,t} \tag{2}$$

Figure 1 shows a time series of natural log of the various spillover measures: VC spillover (blue bars) and entrepreneurial spillover (red bars) in Panel A and public spillovers (purple bars) in Panel B.

It is important to note that the technology spillover measure captures potential *knowledge* spillovers between two firms. Bloom et al. (2013) identify a second spillover effect from a firm's innovative activity: the market rivalry effect. The market rivalry effect arises from the product market competition between two firms whereas knowledge transfer between two firms results from the overlapping of technology fields. While distinct from each other, there may be overlap as firms that have similar technology fields may also compete in similar markets and thus is necessary to control for the product market rivalry effect.

To capture product market rivalry spillovers, we use data from Hoberg and Phillips (2016). The authors determine the cosine similarity of words contained in the Business Description section of 10-K statements. Hoberg and Phillips (2016) build a vocabulary of 61,146 words that firms use to describe the characteristics of their products. Based on this vocabulary, the produce for each firm i a vector of word frequencies where each entry of the vector corresponds to the number of times a word appears in firm i's product description. $SpillPM_{i,j}$ is the cosine similarity between firm i and j and ranges between 0 (no overlap in word frequencies) and 1 (perfect overlap). Hoberg and Phillips (2016) show that these cosine similarity scores correctly identify industry groupings and predict competitive relationships between firms better than standard industry classifications.

Analogously to the technology spillover measure, we construct the pool of product market spillovers for firm i in year t as:

$$SpillPM_{i,t} = \sum_{j \neq i} PM_{ij,t} \times Inventors_{j,t} \tag{3}$$

We only construct $SpillPM_{i,t}$ between public firms as VC-backed and entrepreneurial firms do not file 10-Ks. Figure 1 shows a time series of the natural log of product market spillovers (orange bars) in Panel B.

3.2 Product Market Spillovers

Whereas technological progress has positive spillovers on peers in the same technology space, it may also have a business-stealing effect (Bloom et al., 2013). Under the creative destruction hypothesis, more innovative firms obtain market share from less innovative firms. We would expect this effect to be stronger when firms are in the same product market space. In their seminal paper, Bloom et al. (2013) calculate product market spillover analogously to technological spillover, but using sales-weighted SIC categories rather than patent-weighted patent classes. However, SIC classifications and sales are not readily available for private firms. We therefore classify private firms into 2-digit SIC classes using a TF-idf model in four steps. First, we collect all 10K description data from public firms in 2010, 2016, and 2020 using the "Edgar" package in R.[4] We then merge these descriptions to compustat on cik to obtain SIC classifications and complete our training data. Second, we clean the text data by dropping the most commonly used words ("and", "to") and apply a tf-idf vectorizer to the cleaned text data. The vectorizer scores each word in a document by multiplying the word term frequency (TF) by the inverse document frequency (IDF). This procedure assigns a greater importance to less commonly used words, so that for example technical jargon receives greater weight for classification than more commonly used words. Third, we use this vectorized data to train a Support Vector Machine (SVM) classifier, which is 76% accurate in its industry classification. Fourth and finally, we apply the trained model to private firm descriptions from Crunchbase, which yields SIC classifications for all VC-backed firms. We use this data to count the number of firms per 2-digit SIC code. In the main tests, the number of firms in a product market negatively affects innovation, but this negative effect does not exceed the positive technology spillover, or learning effect, from private to public firms.

[4] Data to be expanded. Link to Edgar package: `https://www.rdocumentation.org/packages/edgar/versions/2.0.7/topics/getBusinDescr`

3.3 Innovation Outcomes

We use two proxies to determine a firm's innovation output: $PatentCount$ and $CitationCount$. $PatentCount$ is the total number of patents a firm applies for in a given year. We use the filing year as this captures when the innovation actually occurs, as opposed to when the patent is granted (on average, nearly 3 years after filing). We also calculate the number of citations each patent receives and aggregate it to the firm level. This is commonly considered to be a patent's "impact" (Hall et al., 2005). To account for the truncation bias of patent citations and the differing size and types of technology classes in innovation, we scale a patent's citations by the mean number of citations received by patents in the same technology class and filing year.

In addition, we construct proxies to characterize the nature of public firms' patents, distinguishing between more incremental and more breakthrough innovations. Our first proxy captures the degree of disruptiveness in a particular patent. Specifically, we use Bowen III et al. (2023) data on Rapidly Evolving Technology (RETech). Bowen III et al. (2023) identify words in patent descriptions that are used with increasing frequency in given technology areas, and demonstrate that patents intensely using these words are at the forefront of technological waves. Intensive use of newly advancing words produces high positive values of RETech, while use of words on the decline produce low or negative values. We use firms' $RETech/Patent$ to identify how disruptive their innovation output is on average.

Our second proxy focuses on how incremental the patent is to prior innovation output. We use the backward similarity measure created by Arts et al. (2023), which measures for each patent the average cosine similarity between the focal patent and all patents filed in the five years before based on keywords retrieved from the title, abstract and claims of the patent. The intuition is that patents with high backward similarity are similar to existing patent stock, and are therefore less novel and more incremental. We therefore use firms' $BackwardSimilarity/Patent$ to identify how incremental their innovation output is on average.

3.4 Other Outcomes and Controls

In addition to innovation outcome measures, we also examine firms' acquisition and venture activity. We use data from Crunchbase to calculate the number of VC-backed firms acquired by public firm i in year t as well as the number of corporate venture capital (CVC) investments public firm i conducts in year t.

Throughout our analyses, we control for a number of firm characteristics, including $R\&D$ (R&D expenditure scaled by assets), $ln(Size)$ (natural log of total book value of assets), $ln(Age)$ (natural log of firm age), $Leverage$ (total book value of debt divided by total assets)$Capex$, $Cash$ (both scaled by total assets), M/B (total assets plus market value of equity minus book value of equity, scaled by total assets), and ROA (net income divided by total book value of assets).

3.5 Summary Statistics

Table 1 provides summary statistics at the firm-year level. Patent and citation data is skewed, with an average of 18.62 patents and 12.48 citations, but one patent and no cites at the median. The average patent has a RETech score of 1.43 and backward similarity score of 3.07. Firms rarely acquire VC-backed startups or conduct CVC investments with the average firm acquiring 0.02 VC-backed startups and investing in 0.15 startups per year. The mean technology spillover measure between public firms is 9.85, comparable to Antón et al. (2024).[5] The mean technology spillovers measures between public and VC backed firms and public and entrepreneurial firms is 5.58 and 5.01 respectively. These are smaller than the public spillover measure, however this is unsurprising as public firms produce the majority of patents. The mean product market rivalry measure is 3.09. In terms of firm characteristics, an average firm in our sample has total assets of $1.1 billion and an age of 19 years. It has R&D expenditure of $240 million, leverage ratio of 0.24, a capex-to-assets ration of 0.05, a market-to-book ratio of 2.73, a cash-holdings-to-assets ratio of 0.25 and an ROA of -0.15. These magnitudes are consistent with existing studies.

3.6 Validation and Interpretation of the Technology Spillover Measure

To aid interpretation of our measure and results, we now provide some intuition for the construction of the spillover measure, closely following Bloom et al. (2013). The spillover measure captures the total amount a firm can learn from others. Knowledge spillovers occur when scientists encounter each others' work. The likelihood that scientists learn from each other is greater when they work in similar technological spaces. These technology spaces are defined by firms' patent classifications. Because the measure is cumulative over time, patenting activity during a given year does not need to fully represent a firm's technology space.

When a firm's technology space has large spillovers, the firm is exposed to innovation of others. This exposure may lower the cost of innovation to the firm (Byun et al., 2021). We therefore think of technology spillovers as an "input" to the production function of firms' innovation. This is different from citations, which are "outputs" of research and development. The goal of our paper is to examine how novel innovation inputs from private firms affect public firm innovation. Therefore, spillovers are a more appropriate measure for our setting than citations.

However, the mere existence of spillovers does not necessarily mean that firms utilize such spillovers. For example, it is possible that a firm observes a new entrant's innovation and decides to take their innovation in a different direction. To verify directly that firms utilize spillovers, we conduct three tests. First, we

[5] Antón et al. (2024) scale spillovers by R&D expense, leading to an average ln(spilltech) measure of 11.74 while we scale spillovers by the number of inventors, leading to an average ln(public spillover) value of 9.85.

examine whether public firms actively collect information when spillovers are high. To do this, we collect clicks by public firms on private firms' form D filings on the SEC EDGAR website. Clicks are a measure of information acquisition. If spillovers are a proxy for learning, we expect information acquisition to increase as spillover, or potential learning, increases. Table 2 presents results. As VC spillover increases, public firm clicks on private firms also increase (columns (1) and (2)). The same is not true for public firm spillover (column (3)). This supports our assumption that spillovers improve public firms' information about recent innovation in their technology space.

Second, if public firms are learning from private firms, we expect similarity across patents to increase. To verify this, we use data from Whalen et al. (2020).[6] The authors calculate similarity scores for each citing-cited patent combination using a cosine distance measure. In columns 1-3 (4-6) of Table 3 we limit our sample to public firm patents and VC (entrepreneurial) firm patents that cite each other. We then run the following OLS regression in columns 1,2,4, and 5:

$$Similarity_{ijt} = \beta Spillover_{ijt} + X_{it} + \alpha_i + \alpha j + \alpha_t + \epsilon \tag{4}$$

where i is the public firm, j is the private firm, t is measured in years, and *Spillover* is the natural log of spillover. Columns 1 and 2 include VC firms, while columns 4 and 5 include entrepreneurial firms. Columns 1 and 4 do not include control variables X, while columns 2 and 5 do. All columns show that spillover and patent similarity are strongly positively related. Public firms that face higher spillover with a private firm also have patents that are more similar to this private firm.

Since all other tests use spillover not at the public-private firm level, but aggregate to the public level, we also test whether VC and entrepreneurial spillover at the public-firm-level is associated with higher similarity scores. That is, we aggregate VC spillover and Entrepreneurial spillover as described in equation (2) and drop private-firm fixed effects α_j. Columns 3 and 6 show results for VC and entrepreneurial spillovers, respectively. Results continue to show that greater spillover is associated with greater similarity. We conclude that although the spillover measure does not measure learning itself, it is correlated with direct measures of information acquisition.

Third, we use the number of citations of VC-backed and entrepreneurial firm patents. If public firms utilize knowledge from private firms, citations should increase. To mitigate concerns that public firms cite old patents from formerly private firms that were VC or entrepreneurial at the time of filing, we limit the citations to the previous 6 years. We conduct the same regression analysis as Equation 7, using a Poisson model as our outcome variables are count variables, left censored at zero and skewed. The results are

[6] Data downloaded from https://zenodo.org/records/3552078

displayed in Table 4.

The outcome variable in columns (1) through (3) are the number of citations of VC-backed patents in the last 6 years. In column (1), we only include $Log(PublicSpillover)$. The coefficient is positive and statistically significant at the 10% level, and can be interpreted as a 10% increase in public spillover leads to a 3% increase in VC citations. In column (2), we replace $Log(PublicSpillover)$ with $Log(VCSpillover)$. The coefficient is positive and statistically significant at the 1% level and can be interpreted as a 10% increase in vc spillover results in a 3.7% increase in VC-backed citation count. In column (3) we include $Log(PublicSpillover)$ as a control and the magnitude size and significant largely goes away on $Log(PublicSpillover)$. This indicates that the increase in citation count is entirely driven by VC spillovers.

In columns (4) through (6), we replace the outcome variable with the number of citations of entrepreneurial firms in the previous 6 years. We find no significant effect on $Log(EntrepSpillover)$ on the number of entrepreneurial citations. The coefficient on $Log(PublicSpillover)$ is positive and statistically significant in columns (4) and (6), suggesting further that VC spillovers provide a particular source of knowledge spillover distinct from other types of young firms.

There are three reasons why we use technology spillovers rather than citations to measure learning. First, and most importantly, spillovers represent a change to the cost of input into innovation, whereas citations are an output of innovative activity. Second, citations are binary constructs, and do not measure nuances such as the type of information learned (e.g. which tech space) or the amount of information learned (e.g. the overlap between cited and citing patent) (Whalen et al., 2020). Third, it is important to distinguish between technological knowledge spillovers and product market spillovers among firms, as they generate different predictions for hoe firms respond to spillover. However, this distinction is not possible when relying solely on patent citations. Firms may cite a patent either because they operate in a similar product market or because they utilize a technology that is unrelated to their product. While a more detailed analysis of these two spillovers is provided by Bloom et al. (2013), our technology spillover measure specifically isolates the knowledge spillover effect from the product market spillover.

We next examine spillover measures in greater detail. We construct new measures for VC spillover and entrepreneurial spillover. These measures are correlated with public spillover, as shown in Table 5. Intuitively, there are strong industry effects. For example, firms in more innovative industries such as pharmaceuticals have more patents, greater R&D expenses, more inventors, and more VC-backed firms. Product market spillovers are additionally positively correlated with all technological spillover measures (0.34 for entrepreneurial, 0.38 for VC, and 0.37 for public spillovers).

However, our measure does capture a novel aspect of interactions between private and public firms beyond industry effects. Table 6 provides a list of firms with the largest spillovers for each decade. There are at least two notable takeaways. First, spillovers and firms benefiting from such spillovers change over time. While Hitachi is ranked 1st in public spillovers in 1990, it is ranked 10th in 2000, and is not in the top 10 in 2019. Similarly, Biogen is ranked 5th among VC spillovers in 1990, but is not in the top 10 in 2000, 2010, or 2019. Second, there is large industry variation across time period. In 1990 and 2000, firms that benefit most from public spillovers are more likely to be large, stable, manufacturing firms (e.g. General Motors, Intercontinental Rubber, and HP) and firms with larger VC spillovers are more likely to be in a biotech sector (e.g. Biogen, Amgen, Sanofi, Genentech, Genzyme, and Transkaryotic Therapies). However, in 2010 and 2019, this switches to the tech sector for both public and VC spillover. Apple, Microsoft, and Oracle are in the top 10 public spillover list in both 2010 and 2019. Similarly, there is a shift from biotech to software companies in the top 10 VC spillover list (e.g. Intel, Oracle, and Progress Software). Overall, this table shows that public firm spillovers are very different from private firm spillovers.

4 The Effect of Private Firm Technology Spillovers on Public Firm Innovation

4.1 Innovation Quantity

Prior literature shows that large technology spillovers between public firms promote innovation output (Jaffe, 1986; Bloom et al., 2013). The innovation output of private firms, particularly among young firms, comprises a significant amount of economically important novel innovations (Ewens and Marx, 2024). However, it is unclear whether large spillovers with young, private firms have a positive or negative externality on public firm innovation output. Similar to public firm spillovers, technology spillovers between private and public firms could increase innovation output as spillovers create valuable knowledge exposure and thus lower the cost to innovate for public firms. Alternatively, larger spillovers with private firms could lead to a decrease in innovation output. Schumpeterian competition theory highlights the cyclical nature of "creative destruction" (Schumpeter, 2013; Aghion, 1990), whereby new firms and technologies displace older ones. Since young, private firms are dominant in terms of patent output in the early years of an industry (Ewens and Marx, 2024), public firms with a larger technological overlap may be at risk of displacement, and consequently, lower innovation output.

To test these predictions, we conduct the following regression analysis:

$$Innovation_{i,t} = \beta \ln TechnologySpillover_{i,t-1} + X_{i,t-1} + \alpha_i + \alpha_t + \epsilon_{i,t} \tag{5}$$

$Innovation_{i,t}$ captures the total number of patents produced and the total number of citations received by firm i in year t. The independent variable of interest is $TechnologySpillover_{i,t-1}$, which measures either public to public or private to public firm technology spillovers faced by firm i during year t. The vector $X_{i,t-1}$ is the set of firm i's characteristic controls including, public firm market rivalry, R&D expenditure, size, age, leverage, market-to-book ratio, capital expenditures, cash and ROA. We include firm fixed effects to control for any time invariant firm characteristics and year fixed effects to control for time trends. We cluster standard errors at the firm level. We estimate a Poisson model as our outcome variables are count variables, left censored at zero and skewed.

Table 7 presents the results. In Panel A, we use $PatentCount$ as the main innovation output variable. Columns (1) and (2) replicate the findings in existing studies regarding how public technology spillovers affect firms' patent counts and find consistent results: larger public to public technology spillovers have a positive effect in firms' patenting output. The coefficient result in column (2) can be interpreted as a 10% increase in public spillover results in a 5.4% increase in patent count, an increase of approximately one patent per year. In columns (3) and (4) we replace the main independent variable with $Log(VCSpillover)$. The coefficients are positive and statistically significant. The coefficient estimate on column (4) can be interpreted as a 10% increase in VC spillover results in a 2.3% increase in patent count, an increase of roughly 0.4 patents per year. Columns (5) and (6) display similar results when replacing VC spillover with entrepreneurial spillover. These results support the "value" hypothesis: public firms benefit not only from other public firms' innovation, but also from private firms' patents.

Next, we conduct a similar analysis with the number of citations received in Panel (B). This measure captures not only innovation quantity, but also quality. Columns (1) and (2) find consistent results with prior literature. Larger public technology spillovers lead to more citations received by public firms, indicating a positive externality of knowledge transfers. We also find similar results to patent counts when we replace public spillover with VC spillover in columns (3) and (4) and entrepreneurial spillover in columns (5) and (6). The coefficient estimates on column (4) can be interpreted as a 10% increase in VC spillover translates to a 1.82% increase in citation count, which is equivalent to an increase of 1 citation per year. Similar magnitudes are found when looking at entrepreneurial spillover in column (6). Overall, the results indicate that larger spillovers with young, private firms lead to higher innovation output (as proxied by patent count) and innovation impact (as proxied by patent citations). This supports the hypothesis that technological spillovers to young, private firms create valuable knowledge exposure for public firms, as it lowers their cost to innovate and consequently increases their innovation output.

4.2 Novelty of Innovation Output

While the above results show that technological spillovers with young, private firms increase innovation output, the economic increase is not as large as that of public spillovers. This is unsurprising as public firms are prolific patenters, representing 58.2% of patents issued and thus, have a larger opportunity for technological overlap. We therefore further explore the impact of technological spillover with young firms by examining the disruptiveness and novelty of innovation produced. Prior literature finds that larger spillovers between public firms lower the cost of incremental innovation relative to breakthrough innovation (Byun et al., 2021). However, young firms produce more novel patents (Ewens and Marx, 2024) and thus a larger exposure to young firm innovation may lower the cost to more breakthrough innovation.

We use $RETech/Patent$ to proxy for the average disruptiveness of a firm's patenting activity. $RETech$ captures how early in a technology life cycle a patent occurs (Bowen III et al., 2023). We conduct the same regression analysis as Equation 7, using an OLS model. The results are displayed in Table 8. Column (1) shows the results for public firm spillovers. The coefficient on $Log(PublicSpillover)$ is negative and statistically significant, indicating that larger public firm spillovers leads to less disruptive innovation. This is consistent with prior literature, that spillovers lower the cost of incremental innovation relative to breakthrough innovation (Byun et al., 2021). In column (2), we replace the spillover measure with spillovers between public and VC-backed firms. The coefficient is positive and statistically significant, and can be interpreted as a 10% increase in VC spillover results in a 0.6% increase in firm i's average RETech. In column (3), we add $Log(PublicSpillover)$ to control for firms with larger patenting activity having both high spillovers with both public firms and VC-backed firms. The coefficient increases substantially, indicating the distinct effects of public versus VC spillovers for public firm's future innovation quality. In column (4), we replace the spillover measure with $Log(EntrepSpillover)$. The coefficient is largely insignificant. In column (5), we include $Log(PublicSpillover)$ as a control and the coefficient becomes positive and statistically significant, indicating that, after controlling for public firm spillover, firms with large spillovers to entrepreneurial firms produce more disruptive innovation.

In columns (6) through (10), we use $Backward\ Similarity/Patent$ as our main outcome variable. This measure captures how similar firm's innovation output is to prior innovation. The result for public spillover is displayed in column (6). Consistent with prior literature, the coefficient on $Log(PublicSpillover)$ is positive and statistically significant, indicating that larger spillovers between public firms lead to less novel innovation output. In column (7), we replace the public spillover with VC spillover. The coefficient is negative but statistically insignificant. However, when we add $Log(PublicSpillover)$ as a control in column (8), the coefficient is negative and statistically significant and increases largely in magnitude, indicating that after controlling for public spillover, firms with larger VC spillover produce more novel innovation. This provides evidence that firms respond differently to differing spillovers. In columns (9) and (10) we replace the spillover measure with $Log(EntrepSpillover)$. The coefficient is positive and statistically significant in column (9) but becomes insignificant after controlling for public spillover in column (10). Taking these results together, firms with larger VC spillovers tend to produce more breakthrough and less incremental innovations. Firms with larger entrepreneurial spillovers tend to produce more novel but not necessarily less incremental innovations. This may speak to the large variation in entrepreneurial innovations. In addition, the results show that firms may be subject to multiple spillovers, which can lead to competing innovation responses.

5 Endogeneity

As discussed in Section 3.6, we take both a public firm's innovation space and private firms' entry (or exit) decisions as exogenously given. The primary concern is that private firms may enter a space due to unobserved transitory shocks, which could also lead to an increase in public firm innovation. For example, a sudden rise in the profitability of a technology could simultaneously attract new entrants and stimulate innovation among incumbents. In other words, an unobserved, correlated omitted variable could be driving our results. To address this concern, we conduct a variety of tests.

First, we employ a more comprehensive set of fixed effects compared to prior literature. Second, we identify exogenous changes in the availability of private firm spillovers. We discuss both approaches in detail below.

5.1 Additional Fixed Effects for Industry-Related Shocks

Prior literature primarily addresses omitted variable concerns by employing firm and year fixed effects to control for time-invariant firm characteristics and overall time trends. However, transitory events, such as industry-related shocks, can simultaneously drive public firm innovation and increase the number of entrants, thereby amplifying spillovers. Such shocks may arise from sudden changes in technology profitability, shifts in consumer demand, or regulatory adjustments that impact an entire sector. Standard fixed-effect specifications may therefore not fully account for industry-wide fluctuations that influence both public and private firms operating within a shared knowledge space. To mitigate this concern, we incorporate industry-by-year fixed effects, which more effectively control for industry-specific shocks that could confound our results. We repeat our main results for technology spillover from private firms on the impact on public firm innovation novelty and quality. The results remain robust and are displayed in Table A1. with the VC spillover results in Panel and A and the entrepreneurial results in Panel B.

5.2 Instrumental Variable Approach: Noncompete Agreements

While industry-by-year fixed effects help control for industry-related shocks, they may not fully address all sources of endogeneity. In particular, unobserved time varying firm-level factors or broader economic trends could still drive both public firm innovation and private firm spillovers, raising concerns about reverse causality or omitted variable bias. To establish a stronger causal link, we seek exogenous variation in spillovers across firms. Specifically, we utilize changes in the availability of inventors to private firms caused by non-competition enforceability laws.

5.2.1 Non-Competition Agreement Institutional Background

Non-compete agreements (NCAs) are contractual clauses that prevent employees from joining or establishing competing firms. Employers use NCAs to protect trade secrets, proprietary information, and reduce labor turnover while also imposing deterrent costs on competitors. Since NCAs are part of employment contracts, their enforceability is governed at the state level, leading to substantial variation across states and over time. In states with high enforceability, courts uphold long-duration and broad geographic restrictions with minimal negotiation or additional compensation. For example, after Ohio strengthened NCA enforceability in 2004, firms were no longer required to provide consideration (e.g., compensation, training, or promotion) when requiring existing employees to sign an NCA. In contrast, states with low enforceability impose stricter limitations, making it difficult to uphold NCAs in court. A non-compete agreement must be deemed reasonable by a court to be legally binding.

Prior research finds that changes in NCA enforceability influence labor mobility, innovation, and entrepreneurship. States that increase (decrease) NCA enforceability experience lower (higher) inventor mobility (Marx et al., 2009), higher (lower) out-migration of inventors (Chen et al., 2023), reduced (enhanced) firm innovation (Stuart and Sorenson, 2003; Starr et al., 2018; Jeffers, 2024), and lower (higher) rates of entrepreneurial entry (Johnson et al., 2023; Marx, 2022). Thus, shifts in NCA enforceability create an exogenous shock to the number of inventors able to join or establish young firms at the state-level, influencing knowledge spillovers from private to public firms.

5.2.2 Empirical Approach

We use time-varying state-level changes in NCA enforceability to causally estimate the impact of knowledge spillovers from private to public firms. Specifically, we utilize a year-by-year index of non-compete enforceability at the state level created by Marx (2022)[7] from 1991 to 2014. The non-compete enforceability scores by state-year by Marx (2022) can be found in Table A2. The index ranges from 0 (North Dakota) which indicates no NCA enforceability to 470 (Florida) which is the state with the highest level of NCA enforceability. Following Marx (2022), we normalize the index to a [0,1] interval.

For a given public firm, we measure its exposure to state-level NCA enforceability through its private firm peers, based on the headquarters state of each private firm. The underlying premise is that NCA enforceability influences young firms' ability to (a) enter the market and (b) attract inventors. Consequently, the location of a public firm's private peers determines these peers' inventor stock, which in turn affects the level of technology spillovers they generate to the public firm. The introduction and revision of state NCA enforceability laws primarily reflect broader economic policy shifts, often balancing the interests of employers, employees, and economic growth. Since the focal public firm experiences technology spillovers from numerous young firms across different states, the aggregated spillover -instrumented by the private firms' state locations - should be uncorrelated with the firm's corporate decisions. This ensures that our instrument reasonably satisfies the exclusion criterion.

To construct the instrumented technology spillover measure, we first predict private firm inventor stock for a given year. We identify each private firm's headquarter location (proxied by the location of their inventors) and regress their inventor stock on their headquartered states' NCA normalized enforceability index level:

$$Inven\hat{tor}s_{j,s,t} = \beta NoncompeteEnforceability_{s,t} + \alpha_t + \epsilon \tag{6}$$

The results are displayed in panel B of Table A3. In column (1), we regress the level of inventor stock in VC-backed firms on their states' normalized enforceability index. The coefficient on $NoncompeteEnforceability$ is negative and statistically significant, indicating that VC-backed firms in states with a higher enforceability index experience a decrease in inventor stock. We find a similar effect in column (2), where we predict the inventor stock at the entrepreneurial firm-year level.

Next, we use all the private firms' predicted inventor stock to calculate the predicted technology spillover the public focal firm faces, using the same equation as Equation 2. This predicted variable (denoted as $Log(VC\ \hat{S}pillover)$ or $Log(Entre\hat{p}\ Spillover)$) is our instrument for technology spillovers. Table A4 reports the summary statistics for the instrumented measures.

We report the results of our instrumented regressions in Table 9. Panel A reports the first and second

[7] Marx (2022) created this index by extending state-by-state indexes from Bishara (2010), who originally created the index from 1991 to 2009. Marx (2022) determined the index values up until 2014 by using state-level non-compete policy shifts from Garmaise (2011) and Ewens and Marx (2018).

stage results for the VC technology spillover regressions and Panel B reports the first and second stage results for the entrepreneurial technology spillover regressions. In the first stage, we conduct the following specification:

$$\ln VCSpillover_{i,t} = \beta \ln VCS\hat{pillover}_{i,t} + X_{i,t-1} + \alpha_i + \alpha_t + \epsilon_{i,t} \tag{7}$$

The results are presented in column (1). The coefficient on $\ln VCS\hat{pillover}$ is positive and statistically significant, with an F-statistic of 1,486, supporting the relevance criterion and indicating that our instrument is unlikely to be weak. Columns (2) through (4) report the second-stage results for our main analyses: patent count and citation count (columns (1) and (2)) capture innovation quantity, while RETech per patent and backward similarity per patent (columns (3) and (4)) reflect innovation novelty. The coefficient on the instrumented $\ln(VCSpillover)$ confirms our main findings: technology spillovers from VC-backed firms enhance innovation output in public firms (columns (1) and (2)), specifically lowering the cost of more novel innovation (column (3)) and leading public firms to produce innovation that is less incremental (column (4)). Additionally, the coefficient magnitudes remain consistent with our main analysis. Panel B presents similar results, reinforcing the causal impact of entrepreneurial spillovers on public firm innovation quantity and novelty. The above analyses show a causal interpretation for the value hypothesis, that public firms with larger technology spillovers with young firms are more innovative and produce more novel innovations than firms with lower technology spillovers.

5.2.3 Robustness Test for Instrumental Variable Analyses

The instrument for technology spillovers leverages the headquarters locations of peer private firms to identify variation in their inventor stock resulting from changes in state-level NCA enforceability. As long as neither the headquarters locations of peer firms nor changes in state-level NCA enforceability directly affect the focal firm's innovation strategies, the exclusion restriction should be reasonably satisfied.

However, prior literature finds that NCAs influence public firms' R&D investment and innovation (e.g., Johnson et al., 2023). If a focal public firm experiences significant technology spillovers from private firms headquartered in the same state, changes in NCA enforceability could simultaneously affect both private peers and the focal firm's innovation investments, potentially violating the exclusion restriction. Nevertheless, because stronger NCA enforceability tends to have a negative impact on public firm innovation, any resulting bias in our coefficient estimates would be downward. To further address this concern, we repeat the analysis while excluding public-private firm pairs located in the same state when constructing the spillover measure. This ensures that spillovers originate from private firms in different states, which are not subject to the same non-compete enforceability. The results, presented in Table A5, are consistent with our main IV analysis. If anything, the coefficient estimates are slightly larger, suggesting that any bias in our main IV results would be in the conservative direction.

6 Dissemination of Spillovers

So far, the results show that public firms with significant spillovers with young firms exhibit higher innovation output and generate more disruptive and novel innovations, particularly when the young firms are VC-backed. We next test how public firms' capitalize on these spillovers.

6.1 Do larger spillovers lead to hiring more VC-backed inventors?

Given the shift in innovation strategies, how do technology spillovers affect firms' decisions on human capital accumulation? Specifically, do firms prefer to invest in high-skilled human capital to leverage the lower costs of innovation stemming from younger firms' knowledge? We examine this question in this section.

We conduct the same regression analysis as in Equation 7. We replace the outcome variables with the number of inventors hired by public firm i in year t that previously worked at a VC-backed firms in the past 5 years and the the proportion of VC inventors relative to the total number of inventors. Since young firms account for a disproportionately large share of novel innovations (Ewens and Marx, 2024), hiring inventors from these firms may allow established firms to access valuable knowledge.

The results are displayed in Table 10. We first examine whether large spillovers between public firms leads to an increase in VC inventor hires. The coefficient on $Log(PublicSpillover)$ is positive and significant in columns (1), indicating that firms with higher public spillover hire more VC inventors. In column (2), the coefficient on $Log(VCSpillover)$ is also positive and significant, indicating that firm with large VC spillovers hire more VC inventors. In column (3) we include both $Log(VCSpillover)$ and $Log(PublicSpillover)$. The coefficient on $Log(VCSpillover)$ remains significant and increases in magnitude, whereas the coefficient on $Log(PublicSpillover)$ reverses its sign and becomes insignificant. This indicates that firms with larger spillover with VC firms captures most of the variation in new VC inventor hires. In columns (4) and (5), where find the firms with higher spillover with entrepreneurial firms also hire more VC inventors (column (4)), but this effect goes away when including $Log(PublicSpillover)$ (column (5)). In columns (6) through (10), we repeat the same analysis but replace the number of VC inventor hires with the proportion of VC inventor hires relative to all hires in that year. The results remain largely consistent with firms with larger VC spillover hiring more VC inventors relative to other inventors in a given year.

6.2 Do larger spillovers lead to more strategic ventures?

Next we investigate if larger spillovers with young firms lead to strategic ventures such as acquiring VC-backed firms or conducting corporate venture capital investments. Firms with larger knowledge spillovers may acquire VC-backed firms to capitalize on their innovative capabilities and gain access to their novel technologies. Prior literature finds that technological overlap between firms leads to increased incidence of acquisitions and combining innovation capabilities are important drivers of acquisitions (e.g. Bena and Li, 2014). In extreme cases, public firms can acquire young firms to put an end to their innovation practices (Cunningham et al., 2021). We therefore predict that larger spillovers with young firms lead to increased acquisitions of VC-backed firms. To test this, we replace the dependent variable in Equation 7 with the number of acquisitions of VC-backed firms and estimate a Poisson regression. The results are shown in Table 11. Column (1) shows that the effect of $Log(PublicSpillover)$ on the number of VC-backed acquisitions is positive but statistically insignificant. The coefficient is positive but statistically insignificant. In column (2), we replace public spillover with $Log(VCSpillover)$. The coefficient is positive and statistically significant and can be interpreted as a 10% increase in VC-spillover results in a 2% increase in VC-backed acquisition in a given year. In Column (3), we include $Log(PublicSpillover)$ as a control. The coefficient on $Log(VCSpillover)$ increases in size and magnitude, indicating spillovers with VC-backed firms account for all of the variation in VC-backed acquisitions. While smaller in magnitude and significance, we find a similar effect when replacing technology spillover with $Log(EntrepSpillover)$ in columns (4) and (5). We interpret this finding as one channel through which firms benefit from spillovers: Public firms acquire VC-backed firms to improve their own innovative capabilities, especially when innovation occurs in related fields.[8]

Lastly, we test the impact of knowledge spillovers on Corporate Venture Capital (CVC) investments. CVC investments are not conducted for financial motive, but rather for the strategic value that CVC investments may add to the parent firm (Hellmann, 2002; Mathews, 2006), indicating that public firms with larger spillovers may use CVC as method for further knowledge transfer. However, prior literature finds that CVCs select startups with a similar technology focus but with non-overlapping knowledge base (Ma, 2020), suggesting that public firms invest in startups because there is a lack of knowledge spillovers. To test this we replace the dependent variable in Equation 7 with the number of CVC investments made in a public firm-year and conduct a Poisson regression. Across all types of spillovers (public, VC, and entrepreneurial), we find insignificant coefficients, supporting prior literature that CVC investments occur between firms with non-overlapping knowledge base. Interestingly, we do find a positive and statistically significant coefficient

[8] One example includes Amazon's interest in Covariant, a robotics firm. See Bloomberg News from 08/01/2024: https://www.bloomberg.com/news/articles/2024-08-01/robot-software-maker-covariant-gets-takeover-inquiry-from-amazon?sref=CUpXQy6u

on $Log(PMSpillover)$ with a similar magnitude across all five specifications. Prior literature finds that firms with higher product market competition either start or increase their CVC investments, shifting away from internal R&D spending to gain knowledge advantages (Kim et al., 2016). Similarly, we find a positive relationship between the potential for product market rivalry and CVC investments.

7 Conclusion

This paper contributes to our understanding of how young firms influence innovation in incumbent firms by introducing a novel measure of technology spillovers from young, innovative firms to publicly traded incumbents. Our findings show that greater exposure to spillovers from entrants significantly increases innovation activity among incumbents operating in similar technological domains, particularly by spurring more breakthrough rather than incremental innovations. This contrasts with prior research that has largely focused on spillovers among incumbents. We also document that incumbent firms exposed to higher levels of entrant-driven spillovers are more likely to hire or acquire VC-backed inventors and startups, highlighting a key channel through which knowledge diffusion occurs. Overall, this study expands the literature on R&D-driven spillovers by emphasizing the dynamic interplay between entrants and incumbents and the critical role of young, innovative firms in shaping the innovation trajectories of more established players.

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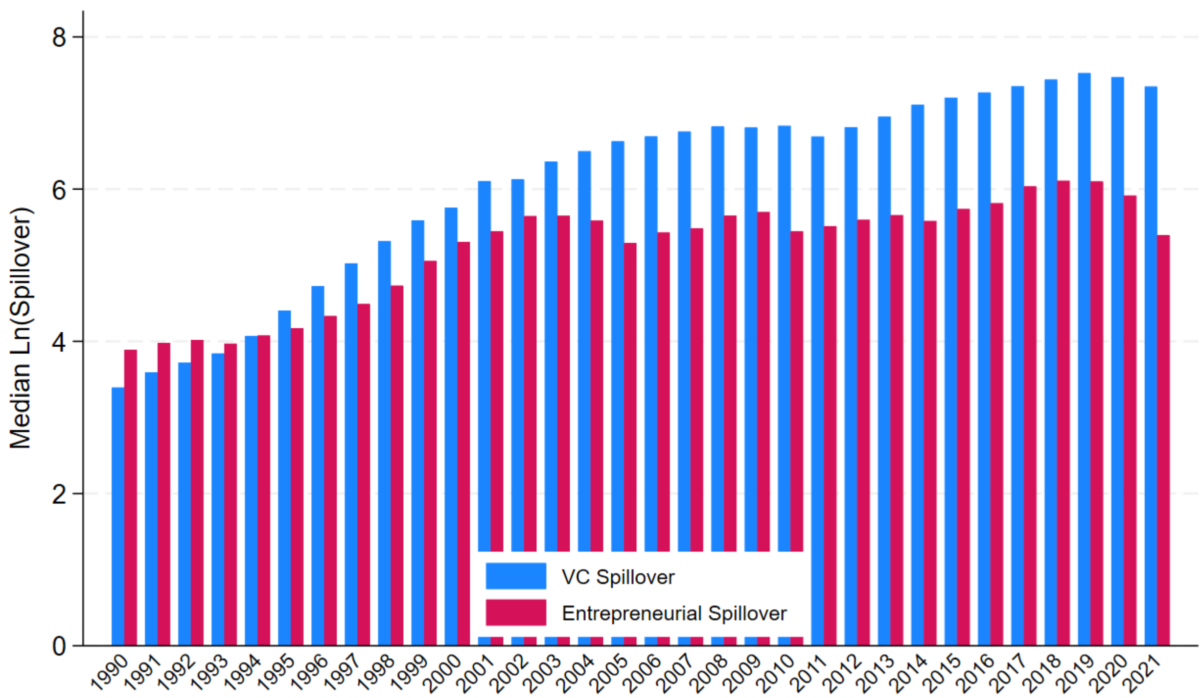
Figure 1: **Technology and Product Market Spillovers 1990 - 2021**

This figure plots a time series of the median natural log of public firm spillovers from 1990 to 2021. Panel (A) displays technology spillovers between public and private firms, specifically with VC-backed firms (blue bars) and entrepreneurial firms (red bars). Panel (B) displays spillovers between public firms, specifically technology spillovers (purple bars) and product market spillovers (orange bars).

(A) VC and Entrepreneurial Spillovers



(B) Public and Product Market Spillovers

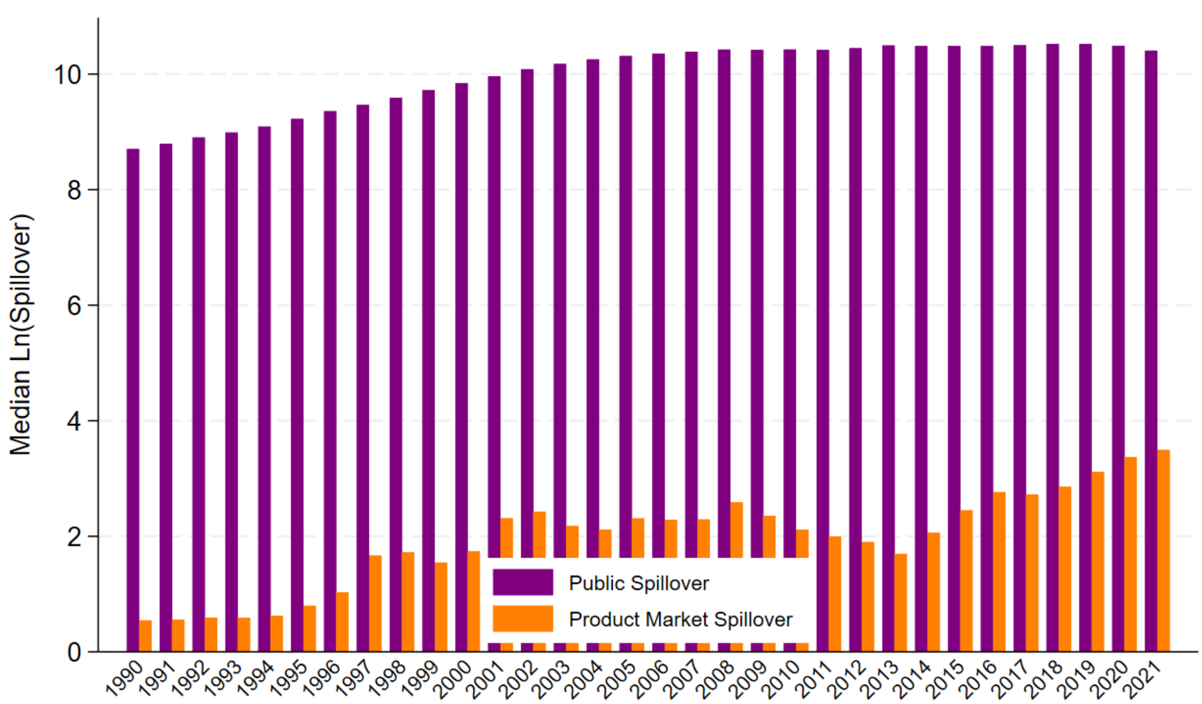


Table 1: **Summary Statistics**

This table reports summary statistics at the public firm-year level.

	Mean	St. Dev.	P1	P25	Median	P75	P99	N
Firm-Year Level								
Patent Count	18.62	67.99	0.00	0.00	1.00	5.00	30.00	84513
Cites	12.48	45.89	0.00	0.00	0.00	2.97	20.93	84513
Cites/Patent	0.45	0.83	0.00	0.00	0.00	0.62	1.31	84513
Retech/Patent	1.43	1.62	-1.06	0.48	1.05	1.94	3.35	41384
Prop Star Inventors	0.12	0.19	0.00	0.00	0.03	0.20	0.33	49663
Prop Star Inventors New Hires	0.13	0.23	0.00	0.00	0.00	0.19	0.40	21609
Prop VC Inventors	0.06	0.18	0.00	0.00	0.00	0.00	0.12	49663
Prop VC Inventors New Hires	0.09	0.23	0.00	0.00	0.00	0.04	0.33	21609
# VC-backed Acquisitions	0.02	0.20	0.00	0.00	0.00	0.00	0.00	84513
# CVC Investments	0.15	3.07	0.00	0.00	0.00	0.00	0.00	84513
Backward Similarity	3.07	1.06	0.82	2.34	3.12	3.75	4.37	38739
Log(VC Spillover)	5.58	2.04	-0.35	4.23	5.82	7.23	7.94	82765
Log(Entrep Spillover)	5.01	1.36	1.45	4.08	5.04	6.05	6.81	82765
Log(Public Spillover)	9.85	1.15	6.82	9.09	9.96	10.65	11.33	82765
Log(PM Spillover)	3.09	2.82	0.00	0.03	2.71	5.57	7.24	84513
VC Spillover Residuals	-0.01	1.04	-2.75	-0.67	-0.01	0.74	1.31	82765
Entrep Spillover Residuals	-0.01	0.84	-2.10	-0.59	-0.02	0.56	1.04	82765
R&D	0.11	0.58	0.00	0.00	0.03	0.11	0.25	84513
Assets - Total	10638.93	85585.64	2.26	53.79	281.47	1970.51	11284.11	84513
Age	19.37	15.88	1.00	7.00	15.00	28.00	44.00	84513
Leverage	0.24	2.14	0.00	0.02	0.16	0.33	0.48	84513
Capex	0.05	0.05	0.00	0.02	0.03	0.06	0.10	84513
M/B	2.73	12.60	0.63	1.16	1.61	2.66	4.70	84513
Cash	0.25	0.26	0.00	0.04	0.14	0.38	0.68	84513
ROA	-0.15	9.72	-2.08	-0.10	0.02	0.07	0.12	84513
Inventor-Year Level								
Patent Count	1.01	1.57	0.00	0.00	1.00	1.00	3.00	3773798
Citations Per Patent	1.18	1.57	0.05	0.31	0.65	1.36	2.70	1529567
Experience	8.14	7.25	0.00	2.00	6.00	12.00	19.00	3773798
VC Inventor	0.04	0.20	0.00	0.00	0.00	0.00	0.00	3773798
Inventor-Hire Event Study								
Patent Count	1.21	2.05	0.00	0.00	0.00	2.00	3.00	1772694
Citations Per Patent	0.46	1.02	0.00	0.00	0.00	0.47	1.38	1772694
Experience	9.08	6.72	0.00	4.00	8.00	13.00	19.00	1772694
VC Inventor	0.09	0.29	0.00	0.00	0.00	0.00	0.00	1772694

Table 2: **Technology Spillovers and Public Firm Clicks**

This table shows the relationship between clicks by public firms on private firms' form D filings and spillovers. The symbols $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	Clicks			
	(1)	(2)	(3)	(4)
Log VC Spillover	0.313***	1.352*		
	(6.464)	(1.647)		
Log Public Spillover			3.329	
			(1.506)	
Log Entrep Spillover				1.283*
				(1.954)
ROA		-0.000	-0.001	-0.000
		(-0.194)	(-0.295)	(-0.210)
CapEx		0.003	0.003	0.003
		(1.111)	(1.087)	(1.079)
Log Age		-0.939	-1.238	-0.900
		(-1.186)	(-1.250)	(-1.180)
Log Size		0.529	0.478	0.540
		(1.501)	(1.519)	(1.469)
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
R-squared	0.001	0.166	0.166	0.166
N	111,550	99,807	99,807	99,807

Table 3: **Technology Spillovers and Similarity Scores**

This table shows the relationship between similarity score by Whalen et al. (2020) and spillover. The test is conditional on public and private firms filing at least one patent during year t and at least one citation during year t.The symbols $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	Similarity Score					
	(1)	(2)	(3)	(4)	(5)	(6)
Log VC Spillover	0.009***	0.009***	0.005***			
	(39.638)	(37.100)	(18.541)			
Log Entrep Spillover				0.009***	0.009***	0.008***
				(25.945)	(24.512)	(0.000)
R&D		0.000	0.000***		0.000	0.000***
		(0.653)	(5.677)		(1.210)	(0.000)
ROA		-0.000*	-0.000		-0.000	-0.000
		(-1.946)	(-0.241)		(-1.386)	(0.490)
CapEx		0.016**	0.005		0.010	-0.005
		(2.072)	(1.253)		(1.426)	(0.428)
Ln Assets		0.004***	0.002***		0.005***	0.003***
		(11.735)	(8.100)		(11.746)	(0.000)
Public Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Private Firm FE	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.354	0.356	0.836	0.404	0.406	0.775
N	981,758	922,526	43,718	467,562	440,686	29,807

Table 4: **Technology Spillovers and VC and Entrepreneurial Citations**

This table examines how technology spillovers impact public firm citations of private firm patents at the public firm-year level. In columns (1) through (3), the outcome variable is the number of citations of VC-backed patents from filed public firm patents. In columns (4) through (6), the outcome variable is the number of citations of entrepreneurial patents from filed public firm patents. Columns (1) and (4) focus on public spillover, columns (2) and (3) VC-spillover and columns (5) and (6) entrepreneurial spillover. All specifications include firm and year fixed effects and time varying firm-level controls. Standard errors are clustered at the public level. We estimate a Poisson Pseudo Maximum Likelihood (PPML) regression. The symbols $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	VC Citation Count			Entrep Citation Count		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(VC Spillover)		0.369***	0.397***			
		(3.76)	(4.09)			
Log(Entrep Spillover)					0.070	-0.005
					(1.63)	(-0.10)
Log(Public Spillover)	0.303*		-0.081	0.240***		0.244***
	(1.93)		(-0.52)	(2.87)		(2.66)
Log(PM Spillover)	0.006	0.007	0.008	-0.008	-0.005	-0.008
	(0.43)	(0.50)	(0.54)	(-0.79)	(-0.46)	(-0.79)
R&D	0.088	0.070	0.071	0.053	0.065	0.053
	(1.21)	(0.99)	(1.01)	(0.56)	(0.67)	(0.56)
Log(Size)	0.296***	0.286***	0.288***	0.354***	0.364***	0.354***
	(6.36)	(6.33)	(6.37)	(11.33)	(11.65)	(11.26)
Log(Age)	-0.365***	-0.348***	-0.336***	-0.204***	-0.158***	-0.205***
	(-3.55)	(-3.46)	(-3.29)	(-3.61)	(-2.81)	(-3.64)
Leverage	-0.092	-0.097	-0.098	-0.106	-0.108	-0.106
	(-0.70)	(-0.74)	(-0.75)	(-1.16)	(-1.16)	(-1.16)
Capex	0.969	1.071*	1.072*	1.691***	1.665***	1.691***
	(1.53)	(1.78)	(1.78)	(4.16)	(4.17)	(4.16)
M/B	0.016***	0.017***	0.017***	0.014***	0.013***	0.014***
	(3.78)	(3.82)	(3.81)	(5.23)	(4.84)	(5.24)
Cash	0.028	-0.019	-0.022	0.135	0.144	0.135
	(0.16)	(-0.11)	(-0.12)	(1.27)	(1.34)	(1.27)
ROA	0.017	0.020	0.019	0.005	0.003	0.005
	(0.34)	(0.42)	(0.39)	(0.14)	(0.09)	(0.14)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.83	0.83	0.83	0.86	0.86	0.86
N	82137	82137	82137	82137	82137	82137

Table 5: **Correlation Matrix**

This table reports a correlation matrix between the natural log of public spillover, VC spillover, entrepreneurial spillover, and product market spillover.

	Log(Public Spillover)	Log(VC Spillover)	Log(Entrep Spillover)	Log(PM Spillover)
Log(Public Spillover)	1.0000			
Log(VC Spillover)	0.8559	1.0000		
Log(Entrep Spillover)	0.7797	0.8618	1.0000	
Log(PM Spillover)	0.3711	0.3829	0.3354	1.0000

Table 6: **Firms with Highest Spillovers over Time**

This table reports the top 10 public firms with the highest spillovers over time. Panel (A) reports the top 10 public firms with spillovers in 1990, Panel (B) in 2000, Panel (C) in 2010, and Panel (D) in 2019. The first column in each panel displays the rank with 1 being the public firm with the highest spillover in that year and 10 being the public firm with the 10th highest spillover. The second column reports the 10 public firms with the highest public to public firm spillover. The third column reports the 10 public firms with the highest VC-backed to public firm spillover. The fourth column reports the 10 public firms with the highest entrepreneurial to public firm spillover. The fifth column reports the 10 public firms with the highest product market public to public firm spillover.

Panel A: Top 10 Firms with Largest Spillovers in 1990				
Rank	Public Spillover	VC Spillover	Entrepreneurial Spillover	Product Market Spillover
1	Hitachi	Harris	Novametrix Medical Systems	Consumlier Engineering
2	General Electric	Research	Cabot Medical	O Sullivan
3	Matsushita Electric	Amgen	Surgical Laser Techs	Mountain Fuel Supply
4	ITT	National Semiconductor	G V Medical	Enercap
5	General Motors	Biogen	Circon	Huntington Bancshares
6	Intercontinental Rubber	Koninklijke Philips Electric	Bank of Boston	Mosinee Paper
7	Sanyo Electric	HP	Everest Medical	Imperial Oil
8	Allied Chemical & Dye	General Instrument	Concept	C S X
9	HP	Biotechnica International	Hitachi	C Tec
10	AT&T	Genzyme	Bard C R	Exabyte
Panel B: Top 10 Firms with Largest Spillovers in 2000				
1	N E C	Sun Microsystems	McAfee Associates	Schering
2	Matsushita Electric	International Business Machs	Trend Micro	3COM
3	Koninklijke Philips Electric	Intel	Compuware	Mitel
4	Sanyo Electric	Chiron Y	Microsoft	Phoenix Technologies
5	AT&T	Genentech	Intellisync	Extended Systems
6	Lucent Technologies	Cardinal Distribution	Keynote Systems	Osicom Technologies
7	Intercontinental Rubber	Amgen	Entrust	Broadcom
8	International Business Machs	Sanofi	C N E T	Santa Cruz Operation
9	L S I	Transkaryotic Therapies	Serena Software	Merck
10	Hitachi	Millennium Pharmaceuticals	Intervu	Sun Microsystems
Panel C: Top 10 Firms with Largest Spillovers in 2010				
1	Apple	Sun Microsystems	Facebook	Oracle
2	Advanced Micro Devices	International Business Machs	Satyam Computer Services	Informatica
3	Ericsson	Oracle	SalesForce	Red Hat
4	Hitachi	Intel	Appfolio	Sun Microsystems
5	Intel	B M C Software	Acxiom	Cisco Systems
6	L S I	Informatica	Alibaba	Ikanos Communications
7	3COM	Progress Software	Alphabet	Adobe
8	Sun Microsystems	A D P T	Ipass	Marvell Technology
9	Oracle	E M C	Progressive Software	NVIDIA
10	Microsoft	Gen Digital	A O L	Broadcom
Panel D: Top 10 Firms with Largest Spillovers in 2019				
1	Apple	Northern Trust	Oracle	Oracle
2	Advanced Micro Devices	Acxiom	Microsoft	Microsoft
3	Intel	Oracle	Northern Trust	Adobe
4	Northern Trust	Microsoft	Microsoft	Cisco Systems
5	Interdigital Communications	Adobe	Adobe	Citrix Systems
6	Acxiom	Gen Digital	Verisign	Open Text
7	Oracle	Cisco Systems	Amazon	Extreme Networks
8	Microsoft	Progress Software	Progress Software	Juniper Networks
9	Adobe	Gartner Group	Cisco Systems	Red Hat
10	Cadence Design Systems	NetApp	Gartner Group	International Business Machs

Table 7: **Technology Spillovers and Innovation Output**

This table examines how technology spillovers impact public firm innovation output at the public firm-year level. In Panel A, the outcome variable is the number of patents filed by the public firm. In Panel B, the outcome is the number of forward citations the patents filed by the public receive. Columns (1) and (2) focus on public spillover, columns (3) and (4) VC-spillover and columns (5) and (6) entrepreneurial spillover. All specifications include firm and year fixed effects and even numbered columns include time varying firm controls. Standard errors are clustered at the public level. We estimate a Poisson Pseudo Maximum Likelihood (PPML) regression. The symbols $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Outcome:	**Innovation Output**					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Patent Count						
Log(Public Spillover)	0.850***	0.540***				
	(9.33)	(6.11)				
Log(VC Spillover)			0.389***	0.231***		
			(8.58)	(6.02)		
Log(Entrep Spillover)					0.294***	0.170***
					(7.58)	(5.25)
Log(PM Spillover)	0.015**	0.001	0.035***	0.010	0.037***	0.010
	(2.04)	(0.18)	(4.55)	(1.28)	(4.73)	(1.32)
R&D	-0.051	0.231***	-0.074	0.253***	-0.079	0.267***
	(-1.17)	(3.51)	(-1.33)	(3.69)	(-1.29)	(3.80)
Panel B: Citation Count						
Log(Public Spillover)	0.658***	0.387***				
	(7.58)	(4.49)				
Log(VC Spillover)			0.318***	0.182***		
			(6.85)	(4.52)		
Log(Entrep Spillover)					0.274***	0.157***
					(7.15)	(4.67)
Log(PM Spillover)	0.005	-0.001	0.020***	0.004	0.021***	0.005
	(0.77)	(-0.16)	(2.75)	(0.48)	(2.97)	(0.54)
R&D	-0.016	0.346**	-0.028	0.357**	-0.026	0.372**
	(-0.51)	(2.44)	(-0.80)	(2.47)	(-0.76)	(2.55)
Firm Controls	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.87	0.88	0.86	0.88	0.86	0.88
N	89326	82137	89326	82137	89326	82137

Table 8: **Technology Spillovers and Innovation Novelty**

This table examines how technology spillovers impact public firm innovation novelty at the public firm-year level. In columns (1) through (5), the outcome variable is RETech Per Patent. In columns (6) through (10), the outcome variable is Backward Similarity Per Patent. Columns (1) and (6) focus on public spillover, columns (2), (3), (7), and (8) VC-spillover and columns (4), (5), (9) and (10) entrepreneurial spillover. All specifications include firm and year fixed effects and time varying firm-level controls. Standard errors are clustered at the public level. The symbols $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	RETech Per Patent					Backward Similarity Per Patent				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(VC Spillover)		0.058***	0.163***				-0.007	-0.074***		
		(3.25)	(7.57)				(-0.52)	(-4.99)		
Log(Entrep Spillover)				-0.009	0.062***				0.055***	0.014
				(-0.44)	(2.76)				(4.39)	(0.97)
Log(Public Spillover)	-0.156***		-0.331***		-0.212***	0.138***		0.217***		0.126***
	(-4.67)		(-8.36)		(-5.43)	(5.95)		(7.76)		(4.67)
Log(PM Spillover)	-0.015***	-0.018***	-0.014**	-0.018***	-0.015***	0.009**	0.011***	0.008**	0.010***	0.009**
	(-2.66)	(-3.11)	(-2.45)	(-3.02)	(-2.65)	(2.54)	(3.08)	(2.38)	(2.90)	(2.55)
R&D	-0.010	-0.017	-0.009	-0.015	-0.010	0.022	0.027	0.022	0.026	0.022
	(-0.22)	(-0.39)	(-0.21)	(-0.34)	(-0.22)	(0.76)	(0.94)	(0.74)	(0.89)	(0.76)
Log(Size)	0.002	-0.011	0.001	-0.006	0.001	0.007	0.016	0.008	0.011	0.007
	(0.14)	(-0.63)	(0.07)	(-0.35)	(0.06)	(0.71)	(1.56)	(0.80)	(1.09)	(0.67)
Log(Age)	-0.302***	-0.334***	-0.296***	-0.325***	-0.299***	0.076***	0.098***	0.074***	0.092***	0.077***
	(-10.01)	(-11.18)	(-9.92)	(-10.92)	(-9.94)	(4.07)	(5.30)	(4.00)	(4.97)	(4.10)
Leverage	-0.072**	-0.067**	-0.070**	-0.070**	-0.071**	-0.021	-0.024	-0.022	-0.021	-0.021
	(-2.14)	(-2.03)	(-2.07)	(-2.08)	(-2.10)	(-1.15)	(-1.29)	(-1.23)	(-1.15)	(-1.13)
Capex	0.410*	0.464**	0.394*	0.450**	0.410*	-0.430***	-0.467***	-0.422***	-0.452***	-0.430***
	(1.83)	(2.07)	(1.76)	(2.00)	(1.83)	(-3.79)	(-4.11)	(-3.74)	(-3.99)	(-3.79)
M/B	0.008***	0.008***	0.008**	0.008***	0.007**	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(2.58)	(2.63)	(2.55)	(2.62)	(2.53)	(-3.78)	(-3.86)	(-3.73)	(-3.98)	(-3.82)
Cash	0.144*	0.130*	0.130*	0.138*	0.142*	-0.041	-0.035	-0.035	-0.040	-0.042
	(1.88)	(1.70)	(1.71)	(1.81)	(1.85)	(-0.98)	(-0.84)	(-0.83)	(-0.94)	(-0.99)
ROA	-0.009	-0.009	-0.009	-0.010	-0.009	-0.011	-0.010	-0.011	-0.010	-0.011
	(-0.60)	(-0.61)	(-0.56)	(-0.62)	(-0.60)	(-1.21)	(-1.20)	(-1.24)	(-1.20)	(-1.21)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.43	0.42	0.43	0.42	0.43	0.64	0.64	0.64	0.64	0.64
N	39380	39380	39380	39380	39380	36872	36872	36872	36872	36872

Table 9: **Technology Spillovers IV**

Panel A: VC Spillover					
	Log(VC Spillover)	Patent Count	Citation Count	RETech / Patent	Backward Similarity / Patent
	(1)	(2)	(3)	(4)	(5)
Log(VC $\hat{\text{S}}$pillover)	0.862***				
	(51.37)				
Log(VC Spillover) - Instrumented		0.245***	0.162**	0.116**	-0.083***
		(3.35)	(2.26)	(2.40)	(-3.16)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Model	OLS	Poisson	Poisson	OLS	OLS
F-Statistic	1486				
R-squared	0.97	0.02	0.02	0.02	0.01
N	61046	61046	61046	30985	30724

Panel B: Entrepreneurial Spillover					
	Log(Entrep Spillover)	Patent Count	Citation Count	RETech / Patent	Backward Similarity / Patent
	(1)	(2)	(3)	(4)	(5)
Log(Entre$\hat{\text{p}}$ Spillover)	0.265***				
	(31.48)				
Log(Entrep Spillover) - Instrumented		0.575***	0.473***	0.797***	-0.234***
		(5.64)	(5.14)	(9.79)	(-5.29)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Model	OLS	Poisson	Poisson	OLS	OLS
F-Statistic	1308				
R-squared	0.97	0.88	0.92	0.02	0.01
N	61046	61046	61046	30985	30724

Table 10: **Spillovers and Hiring VC Inventors**

This table examines how technology spillovers impact public firm acquisitions and corporate investments of VC-backed firms at the public firm-year level. In columns (1) through (5), the outcome variable is the number VC-backed firms acquired by the public firm. In columns (5) through (10), the outcome variable is the number of CVC investments made by the public firm. Columns (1) and (6) focus on public spillover, columns (2), (3), (7) and (8) VC-spillover and columns (4), (5), (9) and (10) entrepreneurial spillover. All specifications include firm and year fixed effects and time varying firm-level controls. Standard errors are clustered at the public level. We estimate a Poisson Pseudo Maximum Likelihood (PPML) regression. The symbols $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	# VC Inventor New Hires					Prop VC Inventor New Hires				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(VC Spillover)		0.274***	0.281***				0.013***	0.019***		
		(4.99)	(4.24)				(3.29)	(3.58)		
Log(Entrep Spillover)				0.091**	0.001				0.005	0.005
				(2.15)	(0.03)				(1.35)	(1.18)
Log(Public Spillover)	0.251***		-0.018		0.250**	0.005		-0.015*		0.000
	(2.91)		(-0.17)		(2.38)	(0.75)		(-1.71)		(0.05)
Log(PM Spillover)	-0.013	-0.013	-0.012	-0.009	-0.013	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.28)	(-1.21)	(-1.20)	(-0.91)	(-1.28)	(-0.18)	(-0.18)	(-0.03)	(-0.17)	(-0.17)
R&D	0.271***	0.271***	0.272***	0.290***	0.271***	0.009	0.008	0.009	0.009	0.009
	(2.87)	(2.75)	(2.74)	(2.97)	(2.86)	(0.48)	(0.45)	(0.50)	(0.50)	(0.50)
Log(Size)	0.216***	0.211***	0.212***	0.228***	0.216***	0.008**	0.007*	0.008**	0.008**	0.008**
	(7.32)	(7.27)	(7.22)	(7.59)	(7.31)	(2.13)	(1.92)	(2.10)	(2.12)	(2.10)
Log(Age)	-0.333***	-0.313***	-0.311***	-0.302***	-0.333***	-0.021***	-0.021***	-0.019***	-0.020***	-0.020***
	(-5.59)	(-5.40)	(-5.22)	(-5.23)	(-5.52)	(-3.16)	(-3.25)	(-2.93)	(-3.16)	(-3.11)
Leverage	-0.475***	-0.469***	-0.469***	-0.483***	-0.475***	-0.002	-0.002	-0.002	-0.002	-0.002
	(-3.97)	(-3.91)	(-3.91)	(-4.00)	(-3.97)	(-0.17)	(-0.16)	(-0.16)	(-0.16)	(-0.16)
Capex	1.120***	1.115***	1.112***	1.092***	1.120***	0.026	0.026	0.021	0.026	0.026
	(2.83)	(2.82)	(2.81)	(2.75)	(2.83)	(0.54)	(0.53)	(0.44)	(0.54)	(0.55)
M/B	0.001	0.001	0.001	-0.001	0.001	0.000	0.001	0.000	0.000	0.000
	(0.13)	(0.18)	(0.16)	(-0.14)	(0.13)	(0.68)	(0.71)	(0.68)	(0.64)	(0.64)
Cash	0.107	0.079	0.080	0.120	0.107	0.010	0.009	0.009	0.010	0.010
	(0.84)	(0.64)	(0.64)	(0.93)	(0.84)	(0.58)	(0.48)	(0.48)	(0.57)	(0.57)
ROA	-0.026	-0.008	-0.008	-0.023	-0.026	-0.009	-0.008	-0.008	-0.009	-0.009
	(-0.38)	(-0.11)	(-0.11)	(-0.33)	(-0.38)	(-1.16)	(-1.09)	(-1.11)	(-1.13)	(-1.13)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.47	0.47	0.47	0.47	0.47	0.28	0.28	0.28	0.28	0.28
N	21273	21273	21273	21273	21273	21273	21273	21273	21273	21273

Table 11: **Spillovers and VC Acquisitions and CVC Investments**

This table examines how technology spillovers impact public firm acquisitions and corporate investments of VC-backed firms at the public firm-year level. In columns (1) through (5), the outcome variable is the number VC-backed firms acquired by the public firm. In columns (5) through (10), the outcome variable is the number of CVC investments made by the public firm. Columns (1) and (6) focus on public spillover, columns (2), (3), (7) and (8) VC-spillover and columns (4), (5), (9) and (10) entrepreneurial spillover. All specifications include firm and year fixed effects and time varying firm-level controls. Standard errors are clustered at the public level. We estimate a Poisson Pseudo Maximum Likelihood (PPML) regression. The symbols $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	VC-Backed Acquisitions					CVC Investments				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(VC Spillover)		0.200**	0.317***				0.145	-0.144		
		(2.08)	(2.58)				(0.53)	(-0.36)		
Log(Entrep Spillover)				0.127*	0.139				0.145	0.012
				(1.72)	(1.49)				(0.68)	(0.08)
Log(Public Spillover)	0.117		-0.232		-0.027	0.485		0.675		0.473
	(0.72)		(-1.05)		(-0.13)	(0.79)		(0.78)		(0.79)
Log(PM Spillover)	0.010	0.009	0.010	0.011	0.011	0.060*	0.065**	0.064**	0.067*	0.060
	(0.45)	(0.41)	(0.44)	(0.48)	(0.49)	(1.65)	(2.07)	(1.97)	(1.91)	(1.63)
R&D	-0.104	-0.105	-0.093	-0.091	-0.089	1.101	1.104	1.066	1.002	1.096
	(-0.46)	(-0.48)	(-0.44)	(-0.42)	(-0.40)	(0.84)	(0.85)	(0.85)	(0.74)	(0.83)
Log(Size)	0.473***	0.477***	0.483***	0.475***	0.476***	0.776***	0.777***	0.764***	0.765***	0.776***
	(5.50)	(5.56)	(5.64)	(5.57)	(5.54)	(5.02)	(5.14)	(5.58)	(5.19)	(5.02)
Log(Age)	-0.339**	-0.344**	-0.320**	-0.314**	-0.310*	-0.197	-0.143	-0.197	-0.115	-0.195
	(-2.12)	(-2.16)	(-1.99)	(-1.98)	(-1.94)	(-1.10)	(-0.86)	(-1.09)	(-0.58)	(-1.08)
Leverage	-1.152***	-1.137***	-1.143***	-1.160***	-1.162***	-0.650	-0.683	-0.656	-0.701	-0.651
	(-3.66)	(-3.63)	(-3.65)	(-3.70)	(-3.70)	(-0.87)	(-0.95)	(-0.87)	(-0.94)	(-0.87)
Capex	2.213*	2.342*	2.388*	2.237*	2.236*	0.078	0.342	-0.066	0.265	0.083
	(1.70)	(1.79)	(1.83)	(1.72)	(1.72)	(0.04)	(0.16)	(-0.03)	(0.13)	(0.04)
M/B	0.040***	0.040***	0.040***	0.039***	0.039***	0.070*	0.068**	0.068**	0.065**	0.070*
	(4.16)	(4.19)	(4.25)	(4.24)	(4.21)	(1.95)	(1.99)	(1.97)	(1.98)	(1.96)
Cash	0.509	0.493	0.494	0.515	0.516	0.565	0.531	0.593	0.589	0.567
	(1.39)	(1.34)	(1.34)	(1.40)	(1.40)	(1.12)	(1.14)	(1.14)	(1.11)	(1.11)
ROA	0.390	0.403	0.407	0.401	0.402	-0.601***	-0.555***	-0.599***	-0.482**	-0.596***
	(1.52)	(1.53)	(1.54)	(1.56)	(1.56)	(-3.71)	(-3.63)	(-3.76)	(-2.42)	(-3.67)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.60	0.60	0.60	0.60	0.60	0.81	0.81	0.81	0.81	0.81
N	82137	82137	82137	82137	82137	2056	2056	2056	2056	2056

Internet Appendix

A Robustness Tests

Table A1: **Technology Spillovers Robustness**

Panel A: VC Spillover				
	Patent Count	Citation Count	RETech / Patent	Backward Similarity / Patent
	(1)	(2)	(3)	(4)
Log(VC Spillover)	0.230***	0.206***	0.121***	-0.058***
	(6.23)	(5.65)	(6.10)	(-3.62)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Model	Poisson	Poisson	OLS	OLS
R-squared	0.91	0.89	0.59	0.65
N	82137	82137	39380	36872
Panel B: Entrepreneurial Spillover				
	Patent Count	Citation Count	RETech / Patent	Backward Similarity / Patent
	(1)	(2)	(3)	(4)
Log(Entrep Spillover)	0.189***	0.186***	-0.003	0.024
	(5.27)	(5.42)	(-0.14)	(1.50)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Model	Poisson	Poisson	OLS	OLS
R-squared	0.91	0.89	0.59	0.65
N	82137	82137	39380	36872

Table A2: Non-compete Enforceability Scores, by state-year

This table is from Marx (2022)

State	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
AL	373	373	373	373	373	373	373	373	373	373	373	373	373	373	373	373	373	373	373	373	373	373	373	373
AK	251	250	249	249	248	248	247	247	246	246	245	245	244	244	243	243	242	242	241	241	241	241	241	241
AZ	296	297	298	299	300	301	302	303	304	305	306	307	308	309	310	311	312	313	316	316	316	316	316	316
AR	220	221	222	222	223	223	224	224	225	225	226	226	227	227	228	228	229	229	230	230	230	230	230	230
CA	39	39	38	38	37	37	36	36	35	35	34	34	33	33	32	32	31	31	31	31	31	31	31	31
CO	360	360	360	360	360	360	360	360	360	360	360	360	360	360	360	360	360	360	360	360	410	410	410	410
CT	418	419	420	421	422	423	424	425	426	427	428	429	430	431	432	433	434	435	435	435	435	435	435	435
DE	318	320	322	324	326	328	330	332	334	336	338	340	342	344	346	348	350	352	360	360	360	360	360	360
DC	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310
FL	435	435	435	435	435	470	470	470	470	470	470	470	470	470	470	470	470	470	470	470	470	470	470	470
GA	370	367	364	361	358	355	352	349	346	343	340	337	334	331	328	325	322	319	285	385	385	385	385	385
HI	286	290	294	298	302	306	310	314	318	322	326	330	334	338	342	346	350	354	358	358	358	358	358	358
ID	336	336	336	336	336	336	336	336	336	336	336	336	336	336	336	336	336	429	429	429	429	429	429	429
IL	410	411	412	413	414	415	416	417	418	419	420	421	422	423	424	425	426	427	430	430	430	480	480	480
IN	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370	370
IA	352	356	360	364	368	372	376	380	384	388	392	396	400	404	408	412	416	420	425	425	425	425	425	425
KS	397	400	403	406	409	412	415	418	421	424	427	430	433	436	439	442	445	448	455	455	455	455	455	455
KY	395	396	397	398	399	400	401	402	403	404	405	406	407	408	409	410	411	412	415	415	415	415	415	415
LA	285	285	285	285	285	285	285	285	285	285	380	380	380	285	285	285	285	285	285	285	285	285	285	285
ME	345	346	347	348	349	350	351	352	353	354	355	356	357	358	359	360	361	362	370	370	370	370	370	370
MD	348	350	352	354	356	358	360	362	364	366	368	370	372	374	376	378	380	382	379	379	379	379	379	379
MA	405	403	401	399	397	395	393	391	389	387	385	383	381	379	377	375	373	371	375	375	375	375	375	375
MI	367	367	368	368	369	369	370	370	371	371	372	372	373	373	374	374	375	376	379	379	379	379	379	379
MN	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340	340
MS	340	341	342	343	344	345	346	347	348	349	350	351	352	353	354	355	356	357	360	360	360	360	360	360
MO	425	425	425	425	425	425	425	425	425	425	425	425	425	425	425	425	425	425	425	425	425	425	425	425
MT	257	257	257	257	257	257	257	257	257	257	257	257	257	257	257	257	257	257	259	259	259	259	259	259
NE	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281
NV	309	309	309	309	309	309	309	309	309	309	309	309	309	309	309	309	309	309	309	309	309	309	309	309
NH	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	311	311	311	311
NJ	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385	385
NM	409	409	409	409	409	409	409	409	409	409	409	409	409	409	409	409	409	409	409	409	409	409	409	409
NY	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310	310
NC	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335
ND	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OH	340	340	340	340	340	340	340	340	340	340	340	340	340	390	390	390	390	390	390	390	390	390	390	390
OK	267	267	267	267	267	267	267	267	267	267	267	267	267	267	267	267	267	267	267	267	267	267	267	267
OR	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	211	211	211	211	211	211	211
PA	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335
RI	299	299	299	299	299	299	299	299	299	299	299	299	299	299	299	299	299	299	299	299	299	299	299	299
SC	285	285	285	285	285	285	285	285	285	285	285	285	285	285	285	285	285	285	245	245	245	245	245	245
SD	367	367	367	367	367	367	367	367	367	367	367	367	367	367	367	367	367	367	367	367	367	367	367	367
TN	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361	361
TX	354	354	354	354	354	354	354	354	354	354	354	354	354	354	354	404	404	404	404	404	404	454	454	454
UT	428	428	428	428	428	428	428	428	428	428	428	428	428	428	428	428	428	428	428	428	428	428	428	428
VT	310	310	310	310	310	310	310	310	310	310	310	310	310	310	360	360	360	360	360	360	360	360	360	360
VI	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335
WA	400	400	400	400	400	400	400	400	400	400	400	400	400	400	400	400	400	400	400	400	400	400	400	400
WV	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281	281
WI	319	319	319	319	319	319	319	319	319	319	319	319	319	319	319	319	319	319	419	419	419	419	419	419
WY	322	322	322	322	322	322	322	322	322	322	322	322	322	322	322	322	322	322	322	322	322	322	322	322

Table A3: **Predicted Inventor Stock Using Non-Compete Enforceability Index**

This table reports summary statistics at the public firm-year level with the IV Sample.

Panel A: Summary Statistics	Mean	St. Dev.	P1	P25	Median	P75	P99	N
VC-Backed Firm-Year Level								
Enforceability Index	233.70	167.11	31.00	32.00	335.00	375.00	404.00	80381
Enforceability Index Normalized	0.49	0.35	0.06	0.07	0.70	0.78	0.84	80381
Entrepreneurial Firm-Year Level								
Enforceability Index	227.33	167.99	31.00	33.00	316.00	375.00	404.00	37841
Enforceability Index Normalized	0.47	0.35	0.06	0.07	0.66	0.78	0.84	37841

Panel B: Predicted Inventor Stock Regression		
Outcome:	**Inventor Stock**	
	VC-Backed Firm	**Entrepreneurial Firm**
	(1)	(2)
Enforceability Index Normalized	-3.071***	-0.792***
	(-6.65)	(-5.01)
Year FE	Yes	Yes
R-squared	0.01	0.02
N	80381	37841

Table A4: **Summary Statistics**

This table reports summary statistics at the public firm-year level with the IV Sample.

	Mean	St. Dev.	P1	P25	Median	P75	P99	N
Firm-Year Level - IV Sample								
Patent Count	18.65	68.11	0.00	0.00	1.00	5.00	30.00	61873
Cites	14.60	49.91	0.00	0.00	0.00	4.06	27.44	61873
Retech/Patent	1.44	1.64	-1.06	0.47	1.04	1.95	3.43	32131
Backward Similarity/Patent	3.01	1.01	0.83	2.30	3.07	3.68	4.25	31846
Log(Predicted VC Spillover)	4.68	1.85	-0.36	3.38	4.72	6.13	7.13	61873
Log(Predicted Entrep Spillover)	2.36	2.24	-4.30	1.07	2.63	4.06	5.01	59731
Firm-Year Level - IV Sample Robustness								
Patent Count	18.65	68.11	0.00	0.00	1.00	5.00	30.00	61873
Cites	14.60	49.91	0.00	0.00	0.00	4.06	27.44	61873
Retech/Patent	1.44	1.64	-1.06	0.47	1.04	1.95	3.43	32131
Backward Similarity/Patent	3.01	1.01	0.83	2.30	3.07	3.68	4.25	31846
Log(Predicted VC Spillover)	4.53	1.82	-0.46	3.26	4.55	5.90	6.94	61873
Log(Predicted Entrep Spillover)	2.19	2.22	-4.39	0.95	2.46	3.84	4.81	59638

Table A5: **Technology Spillovers IV - Robust**

Panel A: VC Spillover					
	Log(VC Spillover)	Patent Count	Citation Count	RETech / Patent	Backward Similarity / Patent
	(1)	(2)	(3)	(4)	(5)
Log(VC $\hat{\text{Spillover}}$)	0.813***				
	(58.91)				
Log(VC Spillover) - Instrumented		0.254***	0.152**	0.118**	-0.090***
		(3.41)	(2.08)	(2.27)	(-3.21)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Model	OLS	Poisson	Poisson	OLS	OLS
F-Statistic	1940				
R-squared	0.97	0.91	0.88	0.02	0.01
N	49968	49968	49968	25348	25149

Panel B: Entrepreneurial Spillover					
	Log(Entrep Spillover)	Patent Count	Citation Count	RETech / Patent	Backward Similarity / Patent
	(1)	(2)	(3)	(4)	(5)
Log($\widehat{\text{Entrep}}$ Spillover)	0.245***				
	(30.64)				
Log(Entrep Spillover) - Instrumented		0.329***	0.182*	0.839***	-0.189***
		(3.36)	(1.88)	(9.73)	(-4.11)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Model	OLS	Poisson	Poisson	OLS	OLS
F-Statistic	2407				
R-squared	0.92	0.90	0.88	0.00	0.01
N	48115	48201	48201	25057	24862

B Spillover Construction

We follow Byun et al. (2021), Bloom et al. (2013), and Jaffe (1986) in constructing our spillover measure. We provide an example calculation below. Imagine three firms, A,B,C in three tech spaces, T1, T2, T3.

We calculate vectors for each firm in tech space $\begin{bmatrix} T1 \\ T2 \\ T3 \end{bmatrix}$ by calculating $\frac{n_{i1}}{n_1}$, where n_{i1} is the number of firm i's patents in tech space T1 up until time τ, and n_1 is the total number of patents in tech space T1 up until time τ. For example, if Firm A had 6 patents in T1, 2 patents in T2, and 2 patents in T3, and each tech space had a total of 10 patents at time τ, then Firm A's tech space vector is $\begin{bmatrix} \frac{6}{10} \\ \frac{2}{10} \\ \frac{2}{10} \end{bmatrix}$.

If in the next year, tech space T1 has 20 total patents, and firm A had 12 of them, but all other tech spaces are unchanged, then firm A's tech space vector is $\begin{bmatrix} \frac{12}{20} \\ \frac{2}{10} \\ \frac{2}{10} \end{bmatrix}$. The tech space is therefore a cumulative measure of public firm i's technology exposure.

To illustrate the spillover measure, assume that Firm A has vector $\begin{bmatrix} 0.6 \\ 0.2 \\ 0.2 \end{bmatrix}$, Firm B has vector $\begin{bmatrix} 0.1 \\ 0.7 \\ 0.2 \end{bmatrix}$, and Firm C has vector $\begin{bmatrix} 0.3 \\ 0.1 \\ 0.6 \end{bmatrix}$. In this example, 60% of patents in tech space 1 are filed by firm A, 10% are filed by firm B, and 30% are filed by firm C.

We begin by calculating spillover between A and B. To calculate $X_{i,t}X'_{j,t}$ for the numerator of the $Tech$ measure, we take A*B': $\begin{bmatrix} 0.6 \\ 0.2 \\ 0.2 \end{bmatrix} * \begin{bmatrix} 0.1 & 0.7 & 0.2 \end{bmatrix} = 0.24$.

The denominator of $Tech$ is calculated as $\sqrt{AA'} * \sqrt{BB'} =$
$$\sqrt{\begin{bmatrix} 0.6 \\ 0.2 \\ 0.2 \end{bmatrix} * \begin{bmatrix} 0.6 & 0.2 & 0.2 \end{bmatrix}} * \sqrt{\begin{bmatrix} 0.1 \\ 0.7 \\ 0.2 \end{bmatrix} * \begin{bmatrix} 0.1 & 0.7 & 0.2 \end{bmatrix}} = \sqrt{0.44} * \sqrt{0.54}.$$

The total $Tech_{ijt}$ measure is then equal to $\frac{0.24}{\sqrt{0.44} * \sqrt{0.54}} = 0.49$. We follow the equivalent steps for similarities between A,C and B,C. $Tech_{A,C} = 0.71$ and $Tech_{B,C} = 0.57$.

Next, we multiply each $Tech_{ij}$ measure by the number of inventors of firm j before summing at the focal-firm level. The number of inventors proxies for firm j's innovation input and thus the intensity for the technology diffusion between firms i and j. Assuming firm A has 10 inventors, firm B has 3 inventors, and firm C has 1 inventor,

$Spilltech_A = Spill_{A,B} * 3 + Spill_{A,C} * 1 = 0.49 * 6 + 0.71 * 1 = 3.65$.

$Spilltech_B = Spill_{B,A} * 10 + Spill_{B,C} * 1 = 0.49 * 10 + 0.57 * 1 = 5.47$.

$Spilltech_C = Spill_{C,A} * 10 + Spill_{C,B} * 3 = 0.71 * 10 + 0.57 * 3 = 8.81$.

Based on these calculations, firm C benefits most from spillovers because it has high similarity with firm A, which also has many scientists working in this space. This measure is not merely capturing the number of technology fields the focal firms patents cover, but rather the correlation between a firm's technology fields and others. The interacted inventors portion of the spillover measure the intensity of the technology exposure between two firms and together, the knowledge transfer between the two firms.