On the shoulders of giants: Financial spillovers in innovation networks*

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Abstract

Do financial markets price knowledge spillovers? We find evidence that patent grants influence the stock returns of firms that are connected through technological knowledge dependencies. In particular, patents granted to a firm's technologically upstream companies significantly boost its abnormal stock returns during the week of the grant. This contrasts with the gradual fade-out of returns from a firm's own patent grants, indicating a gradual diffusion of information in markets. We find that these financial spillovers are predominantly localized within a firm's immediate technological connections. Additionally, we provide a novel empirical decomposition of financial spillovers due to patent grants by distinguishing those emerging from knowledge spillovers, with those emerging from product market rivals (negative effect) and suppliers (positive effect). Our findings are robust to suggest that knowledge spillovers create important market-priced ties between firms that are not fully captured by traditional product market relationships.

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"If I have seen further, it is by standing on the shoulders of giants."

— Isaac Newton[1]

1 Introduction

Innovations in the form of intellectual property are a key, intangible asset of publicly traded companies. They generate the prospect of monopoly rents and reflect a firm's potential for future growth (Aghion and Howitt, 1992, Aghion et al., 2014). However, innovations are not produced in isolation; instead, they build upon preexisting knowledge and, in turn, become inputs for future technological breakthroughs (Hall et al., 2001). These knowledge dependencies convey useful information about a firm's potential for future growth: innovations from important knowledge sources of a firm's R&D can amplify their use cases for it and provide new ideas to develop subsequent downstream innovations (Acemoglu et al., 2016b, Liu and Ma, 2021).

Despite the fundamentally networked nature of knowledge creation in producing new innovations, existing literature, to our knowledge, has not examined the relationship between firms' technological knowledge dependencies and their stock returns. One of the best works that connects innovation with financial returns comes from Kogan et al. (2017) who use ticks in stock prices (measured by actual return excess of market return) on dates of patent grant to estimate the market value generated by patents to the innovating firm. However, innovations do generate large value for other firms through "knowledge spillovers", and an extensive literature shows their role in diffusion of new knowledge for both rivals and partners (see Bloom et al., 2013). This paper takes a different approach and aims to bridge the gap in literature by studying and quantifying "financial spillovers", namely the stock returns generated for a firm due to innovation by its sources of technological knowledge. Given upstream advances spur downstream innovations, do financial markets account for technological knowledge dependencies? If securing a patent raises the returns of an innovating firm, does it also heighten investor sentiment towards another firm that stands to benefit from the new knowledge?

To answer these questions, we exploit the exogenous variation in the timing and quality of patent grants to a firm and its knowledge neighbors using administrative data on granted utility patents from the USPTO and detailed financial metrics of publicly listed firms in the US. We use the patent data to estimate knowledge dependencies between firms using patent citations, and construct a dynamic, directed innovation network, a la

[1] Retrieved from Historical Society of Pennsylvania's webpage on October 14, 2023.

Acemoglu et al. (2016b), for all listed firms in the US timed every month from 1988 to the present. In our innovation network, the nodes represent firms, and the directed edges between them represent the share of patent citations a target firm makes to a source, innovating firm. These edge weights correspond to "knowledge input shares" at the extensive margin, and reflect how important a firm finds another firm in crafting new innovations. We call the set of firms with a positive weight in the five years preceding a reference date as its neighborhood. Since patent grants by the USPTO to particular patents filings are exogenous to firms and their investors on a given date, we construct a measure of exposure shocks faced by each firm on each date in the innovation network due to patent grants to other firms in its neighborhood weighted by their corresponding knowledge input shares to the focal firm. We use this measure of shock from a firm's neighborhood, and the value of a firm's own patent grants on each day, to assess whether a firm's stock returns rise when its knowledge upstream firms are granted patents. We are able to identify the effects of patent grants on each date using the fact that the USPTO grants patents only on Tuesdays. To ensure that our results are not sensitive to our measurement of the shock itself, we use various measures of quality and incidence of patent grant.[2]

Since stock returns of firms are affected by firm fundamentals and several events, we estimate their daily abnormal returns ("alpha") using an industry adjusted 5-factor Fama-French model (Fama and French, 1992, 1993, 2015), augmented with the momentum factor (Carhart, 1997), as our main outcome variable of interest throughout the paper. This measure of stock returns provides a stringent threshold to find any positive results in our analysis since it filters out returns driven by most considerations by investors that drive firms' returns. To ensure that our analysis is not driven by noise, we further use returns averaged over three days since the reference date of patent grants in our main analysis. Since financial markets may react slowly, we test our results using daily returns over the same day, three days, and a working week from the reference date.

We find that, first, stock returns increase when a firm's upstream innovators are granted patents, and these increases in stock returns are directly proportional to the quality of patent granted to their upstream innovators. Moreover, we find that these financial spillovers are pronounced when the upstream makes a technological breakthrough. These elevated abnormal returns are statistically significant, and robust to a number of controls and alternative specifications. Our baseline quantification of financial spillovers suggests that 1 percent increase in the market value of patents granted to a firm's upstream neighbors is associated with an additional 0.5 basis point daily abnormal return within three

[2]While our preferred measure comes from the market value of patents granted estimated by Kogan et al. (2017), we further use the raw number of patents, and the number of technological breakthroughs granted to demonstrate that our results continue to hold.

days of their grant. In comparison, a percent increase in the market value a firm's own patents is associated with about 2.5 basis points of daily abnormal returns within three days of their grant. Therefore, the financial spillovers generated are quantitatively large, and constitute about 20 percent of the additional returns associated with new innovations at the extensive margin.[3] Moreover, the returns generated from a firm's own patent grants fade-out over the course of the week, whereas those emerging from the neighborhood's grants increase over the week throughout our specifications. Moreover, restricting our analysis to cross industry patent citations among firms in the innovation network, to avoid contamination from within industry effects on returns or patent grants, does not alter the persistence of financial spillovers. These findings align with predictions from gradual information diffusion in the financial market. Thus, the stock returns generated from upstream firms are quantitatively and qualitatively large for firms reliant on their technological knowledge for producing new innovations.

Second, while firm linkages through technological knowledge dependencies explain observed increase in returns, alternative linkages between firms, such as their relationship supply chains, or the degree of product-market rivalry, could potentially overlap or confound with our estimates. On the one hand, when a competing firm secures a patent, it could depress investor sentiment about a firm since the firm loses its potential to earn monopoly rents from the invented technology, in line with Bloom et al. (2013). On the other hand, when a firm's suppliers secure patents, investors may expect it to benefit from enhanced inputs or lower costs. Indeed, prior work has shown that news about sellers affects the stock prices of buyer firms (Cohen and Frazzini, 2008). To investigate this channel, we use Hoberg and Phillips (2010, 2016) and Frésard et al. (2020) microdata of directed pairwise firm relationships, and construct daily exposure to each firm of patents granted to their knowledge upstream firms, weighted instead by their degree of product-market competition and potential vertical integration. In their augmented version, we include the shock from technological knowledge relationship to assess if our main estimates of financial spillovers change. In line with predictions, we find that innovation by suppliers further boosts the returns of downstream firms, whereas competitors who also double as knowledge sources depress stock returns of downstream firms. However, interestingly, including these product market relationships does not affect financial spillovers estimated from knowledge input channel measured using patent citations. This suggests

[3] Our estimates of generated stock returns effectively use equal weighting of the firm's degree of reliance on its own knowledge versus that of other listed firms since we add them as independent controls. Total knowledge input shares to firms include a firm's self citations, and citations to private firms and public institutions such as universities and national labs. Therefore, an accurate measurement of the spillover returns would rely on the share of patent citations that a firm makes to itself, versus the pool of other listed firms it cites.

that patent citations between firms may capture a link that is empirically uncorrelated with product market relationships in financial markets.

Finally, we secure our results further in two ways. One, we test the degree to which knowledge input shares matter by performing a placebo test using uniform weights for each firm within a firm's neighborhood (instead of patent citation shares from innovation network). Using shocks computed from placebo weights, we find that the estimates are indistinguishable from zero. This suggests that the technological knowledge input shares estimated in the innovation network convey important information about how a firm's prospect is valued. Two, since shocks generated by news of patent grants may propagate through the innovation network and contaminate our results, we test the effects of patent grants to second-degree neighbors of a firm, and similarly find null results. This suggests that the effect of shocks generated by patent grants on investor sentiment about firms are localized to first-degree connections in the innovation network.

Our results speak to literature on knowledge spillovers, valuation of patents, and firm linkages. Spillovers of innovation can be traced back to early theories emphasizing the importance of R&D externalities across firms and industries (Griliches, 1979). The idea that technological advancements in one firm or sector can influence the economic outcomes in another has been prominent in economic literature, particularly in endogenous growth theory (Romer, 1986, 1990). R&D activities not only provide direct benefits to the innovating firm but also offer indirect benefits to other firms by expanding the knowledge frontier (Aghion et al., 2005, 2013, 2014, Cohen and Levinthal, 1989). Innovations generate knowledge spillovers that extend beyond product market rivalry, and firms often benefit from external R&D even when they don't directly invest in it Bloom et al. (2013). The diffusion of new knowledge through these spillovers aids in fostering more innovations across industries. Acemoglu et al. (2016b) and Liu and Ma (2021) build on the networked nature of innovation and demonstrate that breakthroughs in one technology spur technological advancements in their downstream technologies. This not only establishes the interconnectedness of innovations, but also highlights the importance of recognizing technological dependencies between firms. Our paper contributes to this literature by studying these spillovers in financial markets. Moreover, our results mirror their findings of localization of shocks at the technology level but provide a much granular analysis at the level of firms in the financial market within the course of days of patent grants.

Lastly, our work provides a new perspective on the effects of innovation on financial markets and their efficiency. If markets efficiently account for innovation dependencies, changes in investor expectations about a firm's prospects due to innovations by other firms should be reflected in asset prices. By examining these price movements, we can infer whether information about innovation spillovers is integrated into market valuations. This approach builds on the work of Kogan et al. (2017), who assess the financial market reaction to patent grants to estimate the value these patents create for the innovating firm. Our study extends this by evaluating the broader spillover effects of innovation. We posit that because innovation can affect not only the innovating firm's profits and growth but also those of other firms, the aggregate value of an innovation may well surpass the individual value realized by the innovating firm alone. Our findings suggest that investors effectively account for these technological knowledge dependencies. However, whether these spillovers are attributable directly to knowledge inputs, or whether these knowledge inputs serve as a reliable proxy for business partnerships in technology (Fadeev, 2023) that investors in practice are attentive to deserves further scrutiny.

The paper is organized as follows: section 2 describes the data sources, and characteristics of the patent and financial market data used in our analysis. In section 3, we describe our method of constructing the innovation network and determining technological knowledge input shares (weights) using directed patent citations between firms. Section 4 presents the main empirical findings of our study. First, we present the findings from a baseline model in section 4.1 showing that patents granted to a firm (measured by their economic value), as well as to its external sources of technological knowledge (neighborhood), are positively and significantly associated with its returns. We show that our results continue to hold under alternative measurements of patenting activity. Second, in sections 4.2 and 4.3, we show that these financial spillovers are orthogonal to those generated by market relationships between firms, such as vertical relationships in product supply-chain or by product-market competition. Lastly, we discuss two potential threats to our identification in sections 4.4 and 4.5, namely the relevance of patent citation weights between firms using placebo weights, and the propagation of shocks beyond immediate connections, and show evidence that suggests neither may be driving our results. Finally, we conclude.

2 Data and measurement

To assess the relationship between technology networks and stock returns, we combine data on patents and stock returns at the firm level, as we describe below.

2.1 Patent data

We use the universe of patent data derived from USPTO's PatentsView administrative database, which allows us to uniquely track patents granted to firms (i.e., assignees) from 1976 to present, and their application and grant dates Further, our data allow us to track prior patents cited by every patent granted by the USPTO. Throughout this paper, the date of a patent will correspond to its grant or publication date, unless specified otherwise. We combine the data on patent citations with patent-assignee match to build a dynamic, firm-level innovation network based on patent citations dated every month.

Since stock returns are observable only for publicly listed firms, we disambiguate and uniquely track public and non-public firms in our patent data. To do so, we use the patent-firm match from the full sample of Kogan et al. (2017)'s data and combine it with our patent-assignee match to generate a firm-assignee match. Their data allows us to match the *assignee* identifier of a firm from PatentsView data with its corresponding *permno* identifier on the Center for Research in Security Prices (CRSP) database, which allows us to track the firms' stock performance over time. Note that since stock returns are available for a firm only after it goes public, all dates prior to its IPO contain only its patent information, and are thus excluded from our sample.

We use various measures of patent value to study the effect of technological innovations on financial spillovers. The traditional approach has been to use patent citations in the first few years since a patent's publication as a measure of patent value. Since our network is measured using citation networks, our firm-level network is endogenous to technological influence measured by citations. Kogan et al. (2017) measure the market value of a patent based on its assignee's stock performance upon the news of its grant, which provides an alternative way to assess its influence. Another approach comes from Kelly et al. (2021), who measure the "breakthroughness" of a patent based on the degree of its text's similarity with subsequent body of literature versus prior literature. While both measures correlate with a patent's citations, they provide different ways of measuring its impact on subsequent innovations. Our main results on estimating spillovers use the market value of patents as the measure of their value. However, we also use the raw count of patents granted, and the number of top 10 percent patents granted to a firm in terms of their market value and novelty of their text in alternative tests.

For all measures of patent grants and quality, we use their logged values throughout our analysis. To ensure we do not discard patents with zero value in the data, we use the log of 1 plus the raw patent value.

2.2 Industry- and firm-level financial data

Throughout this paper, our outcome variable of interest is the abnormal returns ("alpha") of firms. We follow Carhart (1997) and Fama and French (2015) to measure abnormal returns using the industry-adjusted version of the Fama-French 5-factor plus momentum factor model for each day of listed firms in the US.

The Fama-French 5-factor model (Fama and French, 2015) provides a broad understanding of stock returns by incorporating profitability and investment. The addition of these two factors reflects the empirical observation that more profitable firms tend to deliver higher returns and that firms with conservative investment strategies, relative to aggressive ones, outperform in the long-run. Coupled with the momentum factor from Carhart (1997), this model's granularity captures a robust representation of market forces that influence stock returns. Inclusion of these factors not only broadens the accounting of various risk exposures, but also underscores the importance of accounting for intrinsic firm characteristics. Thus, it enhances the precision with which abnormal returns can be measured, allowing for a more granular understanding of firm performance in financial markets.

Furthermore, firms within a given industry or sector often show correlated stock return behavior, largely attributable to shared economic risk exposure and synchronous reactions to macroeconomic events (Ross, 1976). By controlling for industry-specific returns, our approach systematically captures and neutralizes the underlying influences exerted by an industry on the returns of its constituent firms. Moreover, it accounts for cross-industry return correlations. As such, our computation of alpha offers a rigorous benchmark, in line with modern literature, and covers a broad spectrum of determinants that shape the stock performance of publicly traded firms.

We source the stock returns and market values data from CRSP. To obtain firm-specific book-to-market ratios, we rely on data from Compustat. While the market values are observed on a monthly basis, the book-to-market ratios are only available quarterly for listed firms. Finally, we obtain the pricing factors from Wharton Research Data Services (WRDS) database. Empirical measurement of abnormal returns using our data presents a few choices given the constraints of available data. First, we use the daily return and factor data to compute the abnormal returns. Our preferred rolling window is 252 days where a minimum of 200 observations are available. We use the stringent conditions to reduce noise in our estimates. Second is the case of missing values for any of the variables in estimating alpha on a given date, leading to its missing values. To partly address this concern, we estimate the average alpha within every week using data on all dates within the week for which we can estimate the abnormal returns. In particular, we compute one day, three-day averaged and weekly averaged alpha, where we observe the abnormal return for at least three days. Second, the USPTO publishes information on the patents it grants in their Official Gazette for Patents every Tuesday.[4] Throughout this paper, we exploit this fact, and define the calendar week to begin on Tuesday and end on Monday in measuring α. Thus, α_{it} will denote the average of abnormal returns for firm i calculated within week t.

2.3 Product-market linkages between firms

> *"There is a bubbling cauldron of innovation... It is super hard to decide who is a competitor and who is collaborator, because there is so much going on in this space. In the technology industry, we have thrived on open standard innovation, where we get to stand on the shoulders of the work that has gone before us, something we deeply believe in. But it has also thrived on 'coopertition', because it is not clear some days who is going to be a competitor and who is going to be your customer the next day."*
>
> — Patrick Gelsinger, Intel CEO[5]

Technological innovations produced by one firm can benefit other firms by expanding the knowledge base on which they can build new innovations, thereby raising investors' expectations of them due to complementarity. At the same time, innovating firms block their competitors from earning monopoly rents from the technologies they produce, which in turn diminishes the relative value of investors' expectations of the competitors' future returns due to substitution. Since we wish to study the financial spillovers generated by an innovating firm on others, we disentangle the two effects by utilizing the text-based network industry classifications (TNIC) data produced by Hoberg and Phillips (2010) and Hoberg and Phillips (2016) who measure the similarity in products produced by pairs of publicly listed firms from 1989 to 2020[6] and reported in their 10-K filings. Throughout this paper, $Comp_{ijt} \in [0, 1]$ will refer to the measure of between-firm product-market competition among firms i and j at time t using Hoberg-Phillips. Higher values on Hoberg-Phillips horizontal measures indicate higher levels of competitiveness.

A different source of relationship between firms is via vertical integration in the supply chain of the product market. Firms provide inputs to other firms in the production process, thereby forging business relationships through sales and purchases. If a source

[4]Retrieved from the USPTO Official Gazette webpage on October 14, 2023.

[5]Excerpts from Patrick Gelsinger's address, *Manufacturing at MIT Distinguished Speaker Series*. Retrieved from YouTube on December 15, 2023.

[6]We consider the innovation network within this time period as well.

firm innovates, then its downstream firms in the supply chain are likely to benefit from investors' expectations of their returns through improved inputs or reduced costs. Therefore, in addition to horizontal measures of relationships between firms, we account for the effects induced by their vertical integration in the product market in our measurements of financial spillovers. While the ideal data to measure this should include sales and purchases between all pairs of firms, such data are unfortunately unavailable to us. The best data available to us that approximates that ideal are the Compustat inter-firm sales, which report observations only when the buyer firm constitutes over 10 percent of the seller firm's share in a year. There are at least two reasons why this data may not be suitable for our purposes: one, the inter-firm sales are measured yearly and do not provide enough variation for our granular weekly measures of stock returns and patenting activity; and two, they comprise only a handful of highly selected observations over synergies between firms, which can bias our results.

Therefore, as the second-best option, throughout this paper, we use the granular data produced by Frésard et al. (2020) as a measure of directed vertical integration among pairs of firms using the text of product descriptions in their 10-K filings. For simplicity of expression, we will call the upstream firm in this data a "supplier" and the downstream firm a "customer." Firm i can be a customer as well as a supplier to another firm j, and thus i can have different values of vertical integration depending on its role relative to j. We use $Vert^S_{ijt} \in [0, 1]$ to denote the degree to which firm j is a supplier to a focal firm i. Higher levels of Frésard-Hoberg-Phillips measures indicate a higher potential of vertical integration in the supply chain.

2.4 Summary statistics

In the patent citation data, we have 4,827 cited firms and 4,885 citing firms. We have 134,768 pairs of (cited firm, citing firm) and 101,747 unique ordered pairs. Comparing these two numbers shows that most of the citations are in one direction.

In Table A.1, we present the summary statistics for the study's key variables. Figure B.2 illustrates the number of unique technology classes that a specific firm has cited in its patents from another, upstream firm in the innovation network over its lifetime. Moving on, Figure B.3 depicts the duration, in days, for which each pair of firms (citing firm and cited firm) appears in our dataset. Turning to edge weights, Figure B.4a displays the distribution for those pairs where the upstream node is ranked within the top 10 percent in terms of market value. In a contrasting perspective, Figure B.4b portrays the edge-weight distribution when the upstream node is positioned within the bottom 10 percent by market value. Lastly, Figure B.6 showcases the number of patents published by the subset of firms' upstream neighbors that are connected to the firm with an edge weight greater than zero.

3 The innovation network

Knowledge by its nature is non-rival (Romer, 1990). Although patents provide intellectual property rights for the processes and products that a firm innovates, the knowledge embodied in a patent can be utilized by any other firm to further build upon it. This allows for the creation of a sufficiently distinct process or product that can in turn earn intellectual property rights for itself (Jaffe et al., 1993). Knowledge that a firm prefers to keep private is typically maintained as a trade secret, which raises barriers to entry into a technology (Anton and Yao, 2004).[7]

Patent citations capture an important source of knowledge diffusion between firms that is distinct from production networks. Recent work by Acemoglu et al. (2016b) and Liu and Ma (2021) uses patent citations to construct knowledge flows based on upstream (cited) and downstream (citing) technologies and to demonstrate that advances in the upstream technology field generate positive knowledge spillovers on the downstream technologies by spurring new innovations of higher quality. This follows the predictions of standard models of technological change, where innovations in an upstream technology provides new knowledge inputs to a firm operating in the downstream technology, thereby decreasing the arrival time of new downstream innovations and increasing their quality. Under perfect markets, this prospect of growth of the downstream firms should raise investors' expectations about their future.

Other works have measured technological knowledge exposure of firms through horizontal measures. Following canonical literature, Bloom et al. (2013) for instance construct a technological similarity measure between firms using the vector of technology classes in which firms' patent. In their measure, higher overlap in R&D activity across technologies corresponds to a higher exposure to knowledge between firms. While this approach has several advantages given it directly measures similarity in the technology profile of firms, it fails to capture the direction of knowledge flows in crafting new innovations, which patent citations do. This directed relationship is important since it represents an asymmetric relationship between firms; shocks to one firm affect another firm depend-

[7]Patents, conversely, are often filed to block others from accessing or utilizing a technology. Thus, they reflect the competitive landscape a firm navigates, especially when the risk of keeping knowledge as a secret outweighs the benefits of public disclosure (Hall et al., 2001).

ing on the direction of their relationship. Furthermore, advances in one technology can lead to new applications in a different technology, which the similarity in technological profiles of firms does not capture.

Moreover, a nascent literature suggests that patent citations between firms capture synergies in knowledge sharing between them, which are particularly evident when firms cite each other heavily (Fadeev, 2023). Such dynamics make it more intuitive for us to rely on patent citations to estimate directed knowledge flows since we expect a firm's stock price to rise when their business partner gains a patent, and to interpret the financial spillovers other firms experience when the firms they extensively cite secure new IP. These spillovers become particularly significant when the market is informed that the cited firm has secured intellectual property rights over new products and processes, thereby raising investors' sentiments about the firm (Kogan et al., 2017).

3.1 Empirical construction of the innovation network

In this section, we describe the construction of an innovation network and its associated variables. The administrative data on patents includes details of citations among patents granted by the USPTO, such as the unique IDs of citing and cited patents, their exact dates of publication, and the assignees to which the patents were granted. We combine this data with Kogan et al. (2017) to uniquely identify the public firms associated with the cited and citing patents through their *permno*. Here is an example of a few rows from the matched data:[8]

Cited patent	Citing patent	Cited firm	Citing firm	Cited patent grant	Citing patent grant
US8179370	US9842105	Google	Apple	15 May 2012	12 Dec 2017
US8209183	US9842105	Google	Apple	26 Jun 2012	12 Dec 2017
US8943423	US9842105	IBM	Apple	27 Jan 2015	12 Dec 2017

This example illustrates that patent US9842105, granted on 12 December 2017 to Apple Inc., cites in its text a previously issued patent US8179370 that was granted to Google Inc. on 15 May 2012.

Using data on the universe of patent citations between pairs of firms, we generate an innovation network among firms, which evolves over time. The source node of each edge represents the cited firm, while the target node represents the citing firm. The edge itself captures the incidence of a patent citation. We include nodes for every firm that appears at least once in our dataset. Thus, the dynamics of the edges and their corresponding

[8]For clarity of exposition, we replace the *permno* by the firm's name.

weights captures the evolving nature of the network.

We measure directed edge weights based on the share of backward citations coming to a focal firm. In producing new innovations, a firm can either cite its own patents or cite patents granted to other firms. Since we aim to capture the financial spillovers generated by innovations on other firms, we exclude firms' self-citations. This approach enables a more accurate representation of the innovation network's properties and better quantifies knowledge input shares from other firms. We define the edge weight based on backward citations between cited firms j (upstream) and citing firms $i \neq j$ (downstream) at each month t as the share of references made to patents granted to firm j by i relative to all references by i in its patents up to time t:

$$g_{i,j,t} = \frac{\text{Patent citations } (j \rightarrow i) \text{ up to time } t}{\sum_{k(\neq i)} \text{Patent citations } (k \rightarrow i) \text{ up to time } t} \tag{3.1}$$

The backward citations weight $g_{i,j,t}$ measures the knowledge input share of firm j toward producing innovations by firm i.[9]

Citations between firms could happen in different technology classes. Due to computational capacity, we did not compute weights based on each technology class. Also, it could be that in one day one firm grants two different patents with two different technology categories; in this case, deciding which technology weight between two firms must be considered in that day would be challenging as well. Figure B.2 shows the cumulative distribution function of the number of unique technologies one specific firm has cited from one of its upstream firms during its lifetime. As the figure illustrates, there is a 60 percent chance that a given firm cites another given firm in only two technology classes during its lifetime. Therefore, not considering technological weights in this analysis could not have a huge impact on the results.

As technologies and industry structure evolve, the inputs to innovations firms seek from others change over time in creating new products.[10] Previously strong knowledge influence between two firms may shift to others. Therefore, to avoid contaminating our measures of directed edge weights by potentially non-persistent relationships, we restrict our analysis to those citations made within the past five years of our reference months.[11]

[9] For instance, $g_{i,j,t} = 1$ implies that outside of citing itself, firm i's patents rely entirely on firm j's patents for technological inputs.

[10] For instance, Apple replaced Intel processors with ARM in their laptops in 2020, a marked shift from their longstanding partnership with Intel but in line with prior iPhone and iPad architectures.

[11] Five-year citations are highly predictive of long-run citations while being sufficiently close to the technological frontier. While citations within the first few years following immediately after a patent's grant reflect its high relevant to new technologies, they are less predictive of its long-run impact. In contrast, later-year citations tend to strongly predict long-run impact but do not necessarily reflect closeness to con-

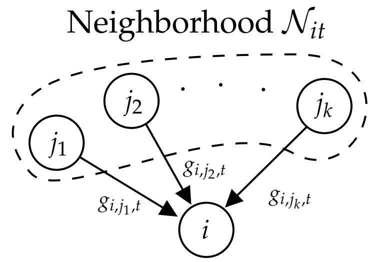

Figure 3.1: Directed innovation network among firms

Notes: This figure illustrates the directed innovation network among firms represented through patent citations between them. Self-citations of firms are excluded. This figure illustrates the citations made by a firm i in its patents toward patents granted to other firms in the five years preceding the month of date t. These other firms $(j_1, j_2, \cdots, j_k)$ constitute a neighborhood $\mathcal{N}_{it}$ specific to firm i at time t. The values $g_{i,j_1,t}, g_{i,j_2,t}, \cdots, g_{i,j_k,t}$ reflect the firms' respective edge weights as defined in equation (3.1).

This ensures contemporary technological relevance while providing sufficient sample size to measure innovation inputs between firms.

The backward citation network at each time t can be represented as an adjacency matrix. We denote these matrices by G_t, which have N rows and columns each, where N corresponds to the number of unique firms in our data. Since we rule out self-citations, the diagonal elements of G_t are 0. For a focal firm i, these rows will be denoted by G_{it}. Since the (i, j)'th elements of G_t are $g_{i,j,t}$, the rows add up to 1. At all times, each firm i has a neighborhood of firms it has cited at least once before in its patents. We call this neighborhood $\mathcal{N}_{it}$, which corresponds to a subset of columns in G_t for row i (see Figure 3.1 for illustration). Indeed, the row weights of only those firms in the neighborhood also add up to 1:

$$\mathcal{N}_{it} = \left\{ j \mid \exists t' \leq t : g_{ijt'} > 0 \right\} \qquad \sum_{j \in \mathcal{N}_{it}} g_{ijt} = 1 \tag{3.2}$$

Note that it is possible that the weight of a firm in a neighborhood is 0 at a time t if it has not been cited for over 5 years preceding t. We will use these row weights of a focal firm to study their association with the abnormal returns generated by its neighbors. This captures any lingering relationship that a firm which transitions out of influence for a given downstream innovator carries in affecting its returns. For a firm, its neighborhood represents the stock of external knowledge upon which it draws to develop new ideas and produce innovations.

In measuring the edge weights empirically, we require that pairs of technologically up-

temporary technologies. However, we use 10-year and cumulative reference periods to test for long-run persistence.

stream and downstream firms appear at least once together in our patent citation dataset. Thus, for every pair of downstream firm i and upstream firm j, our data begins the first time i cites j, and we observe them to the most recent date for which financial data are available for both. This excludes firms that have never been cited.[12] However, we allow a firm in a neighborhood as long as it previously had or subsequently will have a positive edge weight. This method of selecting firm pairs in our data helps us capture any lasting financial relationship between firms that may arise from a knowledge partner transitioning out of their technological influence.

For testing the robustness of our results, we subset the full innovation network using only citations between firms operating across different industries and develop a cross-industry innovation network. For all analyses, we use the Fama-French 48-industry classification using their Standard Industrial Classification (SIC) codes to identify cross-industry patent citations among firms. We denote the adjacency matrices of innovation networks produced using this subset as G_t^{ind} for each month t. Their matrix entries are calculated for only cross-industry citations, and we retain all notations by analogy. Since firms operating in the same industry may have correlated financial or innovation shocks, our cross-industry network ameliorates these effects for the study of financial spillovers generated in firms in one industry arising from innovations in another.[13]

4 Financial spillovers in innovation networks

The prospect of monopoly rents through new innovations is an important driver for firms to develop new technologies and gain an edge over their competitors (Aghion et al., 2014). In line with this prediction, Kogan et al. (2017) show that the news of a patent grant raises stock returns of publicly listed firms, and they use the size of the difference in observed market return to measure the value of patents. However, whether innovation by one firm is associated with stock returns in other firms has, to the best of our knowledge, not been studied.

In this section, we demonstrate that patent grants to technologically upstream firms are associated with elevated stock returns of their technologically downstream firms. To show the existence of these "financial spillovers," we exploit the directedness of our inno-

[12]This method maintains computational efficiency and assumes that many relationships between firms prior to citing one another are not directly affecting stock co-movements arising from knowledge sharing. Thus, our data is selected for those firm pairs where there has been at least one incident of patent citation between them.

[13]In this paper, we adjust stock returns to remove the industry factor. This approach ensures we address any industry-specific outcomes and also eliminates correlations arising from cross-industry interactions.

vation network and measure the technological knowledge dependency (i.e., input shares) of firms on other firms using equation (3.1). These knowledge input shares reflect the potential value innovations by an upstream firm bring to its downstream. Our hypothesis is that when an upstream firm is granted a patent, investors' expectations about the downstream firm grow and translate into a return proportional to the knowledge input share.

4.1 Financial spillovers through innovation in neighborhoods

Firms rarely innovate in isolation; instead, they depend on other firms for new knowledge upon which they further build new technologies (Hall et al., 2001). Nor do firms rely on others independent of their full set of knowledge sources; instead, firms rely on the synergies they share with their full set of partners and competitors for new ideas to develop technological innovations. Thus, the neighborhood of upstream innovators of a firm captures the total stock of external knowledge it relies upon for new ideas. The neighborhoods represent an idiosyncratic, complementary source of knowledge, acting as one unit, to the focal firm. Knowledge dependence of a firm on another specific firm can vary over time, and the composition of knowledge inputs within the neighborhood typically evolves over time. Therefore, to capture the returns generated by all external knowledge sources, we study the financial spillovers arising from firms' neighborhoods.

To understand the impact of neighborhoods, we concentrate on how a firm i relies on knowledge from its upstream innovators. Recall that patents are granted and published by the USPTO in their *Official Gazette* only on Tuesdays. Thus, on every Tuesday at time t, each downstream firm i has a specific neighborhood $\mathcal{N}_{it}$ consisting of upstream firms j that contribute, or have contributed, knowledge input to firm i (which we infer from firm i having cited their patents at any previous time). The row vector G_{it} (from the adjacency matrix G_t of our innovation network) represents the knowledge input shares of each firm j to firm i at time t. The significance of knowledge input from firm j within firm i's neighborhood is determined by its weight $g_{ijt} \in [0, 1]$ (see equation 3.1). This weight is updated based on data from the preceding month. The downstream firm experiences a shock when their upstream innovators acquire new patents. We thus calculate firm i's exposure to new innovations at time t using the weighted average of patenting activity $\mathcal{P}_{jt}$ from its neighborhood firms j using patent citation shares within the extensive margin g as follows:

$$\mathcal{P}^{g}_{\mathcal{N}_{it}} = \sum_{j \in \mathcal{N}_{it}} g_{ijt} \mathcal{P}_{jt} \tag{4.1}$$

Our preferred measure is the (logged) value of patents as derived from Kogan et al. (2017).[14] This measure is based on the portion of an upstream firm's stock return that reflects only the value of the patent it grants at each time t. It does not account for the idiosyncratic component of the upstream firm's return or any other pricing factor; however, we use alternative definitions of $\mathcal{P}_{jt}$, which include incidence of patent grants and other measures of patent quality, in our robustness checks.

To estimate the contribution of innovations in a firm's neighborhood to its abnormal returns, we use the specification in (4.2). Our outcome variable of interest is the abnormal return α_{it} of downstream firm i at date t:

$$\begin{aligned}\alpha_{it} = c + \beta_1 \mathcal{P}^{g}_{\mathcal{N}_{it}} + \beta_2 \mathcal{P}_{it} + \\ \underbrace{\mu_i + \mu_{\text{Ind}_i} + \delta_1 \alpha_{i,t-1} + \delta_2 V_{i,t-1} + \delta_3 BM_{i,t-1}}_{\text{Firm } i\text{-related controls}} + \delta_1 V_{\mathcal{N}_{i,t-1}} + \tau_t + \epsilon_{it}\end{aligned} \tag{4.2}$$

where α_{it} are the abnormal returns of firm i on date t, $\mathcal{P}^{g}_{\mathcal{N}_i}$ is the exposure to new patent grants of its upstream neighbors, and $\mathcal{P}_i$ is patenting activity by firm i. In Appendix C, we show that Kogan et al., 2017 patent values for the downstream firms are strongly and positively correlated with our measure of abnormal return. μ_i, μ_{Ind_i}, and τ_t account for variation by firm-, firm's industry-, and date-specific characteristics, respectively, and $\alpha_{i,t-1}$ is the lagged return from the previous week that accounts for mean-reversing autocorrelation. Our preferred measure of α_{it} is the three-day averaged abnormal returns from date t, and $\mathcal{P}$ is the value of patents granted during the week using Kogan et al. (2017).[15] However, we include other measures of patenting activity for robustness.[16] $\mathcal{P}$ is 0 on days on which there is no granted patent, and positive whenever it generates any excess returns.

Following Fama and French (1992, 1993), we include the lag of market value ($V_{i,t-1}$) and book-to-market value ($BM_{i,t-1}$) of the firm (in log scale) in a fuller specification to

[14] To ensure we do not throw away zeros, throughout this paper, we use log of 1 plus patent values.

[15] This measure of the value of patents captures the value of excess returns attributed to news about patent grants in the three days from the date of date of grant, which are directly relevant to our outcome measure. Note that Kogan et al. (2017) measure the value generated within three days of patent grant, which aligns with our preferred measure of abnormal returns.

[16] These include their incidence on the date, the number of patents granted on the date, their level of technological breakthroughness (Kelly et al., 2021), and their impact on subsequent literature measured using patent citations in the years subsequent to their publication. Considering various measures of patenting activity is useful for both conceptual and statistical reasons. First, they allow for alternative measurements that capture different aspects of technological change and R&D activity of a firm. Second, large R&D-intensive firms, such as IBM or Apple, could potentially be always in treatment if we consider only incidence of patenting activity or have a similar number of patents granted on all dates, thereby not providing sufficient variation for useful estimation. Alternative measures allow variation.

account for factors that affect abnormal returns. We use the lagged values to avoid contaminating our results with simultaneity. For market value, we use the preceding month's data, and for book-to-market, we use the reported values from the previous year.[17] In all subsequent specifications, we simply denote the lagged returns, market value, and book-to-market terms collectively as firm i-specific controls.

Our coefficient of interest β_1 estimates whether patenting in the neighborhood is associated with higher abnormal returns for firm i.[18] We let the neighborhood be idiosyncratic to a firm given that firms are never perfect substitutes and have distinct market positioning.[19] In a fuller specification, we also account for the market size of the neighborhood $V_{\mathcal{N}_{i,t-1}}$, defined as the sum of logged market values of firms in the neighborhood in the preceding month. The total market size of the upstream firms accounts for whether a focal firm is positioned in a niche or an established market. The error term ϵ_{it} captures the idiosyncratic component of the abnormal return.

We present the results of estimating (4.2) in Table 4.1. We find that exposure of a firm to an innovation shock from its upstream neighbors is positively and significantly correlated with a higher abnormal return. Regardless of the duration of reference for measuring abnormal return, our results suggest that a one-percent increase in value generated by patents in the neighborhood is associated with at least a 0.53 basis point increase in the daily abnormal returns on average during the week. Our results, therefore, suggest the existence of financial spillovers, measured by returns produced by sources of technological knowledge, due to innovation. These effects are quantitatively large, and are as high as one-fifth of the returns produced by a firm itself when it is granted a patent.

As explained in Section 3.1, to further eliminate industry-specific effects, we constructed an innovation network among firms operating in different industries. Table A.2 presents the results of the regression analysis (regression 4.2) applied to this cross-industry network. As Table A.2 shows, the results hold even for the cross-industry network.

We attempt to secure our results in two ways. One, we restrict our analysis to only cross-industry knowledge dependencies. Since firms operating in the same industry are more likely to face correlated shocks over those firms operating across different industries, restricting our innovation network to cross-industry relationships helps eliminate the concern. In estimating this version of (4.2), we use cross-industry knowledge input

[17] Book-to-market values are reported annually in the Compustat dataset we use in our analysis.

[18] The exact timing of patent grants and their values should ideally be uncorrelated among firm i and its upstream neighbors.

[19] Although overlaps in neighborhoods can be high between downstream firms, the relative importance of specific upstream neighbors varies between them.

Table 4.1: Effect of patent grants to upstream innovators on abnormal returns of downstream firms

Dependent Variables:	Same day α			Three-day averaged α			Weekly averaged α		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Patent value of upstream innovators ($\mathcal{P}^{g}_{\mathcal{N}_{it}}$)	0.440	0.561*	0.560*	0.429***	0.529***	0.532***	0.544***	0.580***	0.580***
	(1.50)	(1.85)	(1.83)	(2.74)	(3.24)	(3.24)	(4.28)	(4.43)	(4.38)
Patent value ($\mathcal{P}_{it}$)	2.27***	2.30***	2.27**	2.27***	2.44***	2.53***	1.64***	1.66***	1.65***
	(10.1)	(7.43)	(2.56)	(16.7)	(13.0)	(5.93)	(15.2)	(11.4)	(4.97)
Interaction term ($\mathcal{P}_{it} \times \mathcal{P}^{g}_{\mathcal{N}_{it}}$)			0.016			-0.044			0.003
			(0.036)			(-0.209)			(0.018)
Lagged market value of firm	-12.1***	-14.7***	-14.7***	-12.1***	-14.0***	-14.0***	-11.7***	-13.3***	-13.3***
	(-16.1)	(-17.9)	(-17.9)	(-25.5)	(-26.7)	(-26.7)	(-31.3)	(-32.0)	(-32.0)
Lagged book-to-market ratio	-57.9***	-80.9***	-80.9***	-52.8***	-72.0***	-72.0***	-53.3***	-73.6***	-73.6***
	(-6.30)	(-6.90)	(-6.90)	(-9.19)	(-9.99)	(-9.99)	(-10.9)	(-11.5)	(-11.5)
Lagged abnormal return		-0.191***	-0.191***		-0.099***	-0.099***		-0.064***	-0.064***
		(-19.6)	(-19.6)		(-23.3)	(-23.3)		(-19.5)	(-19.5)
Lagged market value of upstream innovators		0.002	0.002		0.001	0.001		0.003**	0.003**
		(0.866)	(0.872)		(0.885)	(0.871)		(2.37)	(2.37)
Fixed-effects									
Date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	2,455,122	2,103,957	2,103,957	2,360,075	2,021,949	2,021,949	2,280,273	1,954,160	1,954,160
R^2	0.00591	0.01221	0.01221	0.00826	0.01415	0.01415	0.01073	0.01559	0.01559
Within R^2	0.00044	0.00637	0.00637	0.00150	0.00692	0.00692	0.00251	0.00675	0.00675

Clustered (Date) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents the results of estimating (4.2). Our outcome variables of interest are the same-day (columns 1 to 3), three-day averaged (columns 4 to 6) and weekly averaged abnormal returns (columns 7 to 9). The values of patents are borrowed from Kogan et al. (2017). They are 0 when there is no patent granted on a date and positive whenever an excess return is generated to the patenting firm. The exposure to patents by upstream innovators is captured in the value of neighbors' patents ($\mathcal{P}^{g}_{\mathcal{N}_{it}}$) computed using equation (4.1). The lagged market value of a firm is derived from the log of the previous month's market value of the firm, the lagged book-to-market value corresponds to the log of the previous year's book-to-market ratio, and the lagged abnormal return is the average of the preceding week's abnormal returns. The lagged market value of neighbors is the sum of the logged market values of firms in the neighborhood of the focal firm. We rescale the abnormal returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate.

shares in measuring exposure to patent grants of neighbors. Note that this captures the intensive margin within the cross-industry neighbors. Two, we consider alternative measurements of patent grant activity $\mathcal{P}$ using the number of technological breakthroughs granted on the reference date. We expect that more breakthroughs granted produces higher returns for the innovating firm, and breakthroughs granted to important sources of a firm's technological knowledge positively affect its returns. Empirically, we identify technological breakthroughs as the top 10 percent of patents by their value (from Kogan et al., 2017) and by their level of knowledge advancement (from Kelly et al., 2021). We compute the innovation shock from technological breakthroughs using (4.1) by defining $\mathcal{P}_{jt}$ as the number of breakthrough patents granted to a firm j, and we estimate (4.2) using this new definition of the shock. As a further robustness test, we include results for an alternative definition of $\mathcal{P}_{jt}$ as the raw number of patents granted to firm j. This is a highly noisy measure of patenting activity since most patents tend to be of low quality.

The results of these estimations for three-day averaged and weekly averaged returns are presented in Tables A.2 and A.3. Our preferred estimations are the three-day version since they balance the signal from patenting and noise from other events over the course of the week. We find that cross-industry knowledge input shares highly and significantly predict the abnormal returns, despite the rescaling of weights away from neighbors within industry. Second, the numbers of patents and breakthroughs granted on a date are significantly and positively associated with additional abnormal returns. And lastly, their grants to firms that provide technological knowledge generate an additional return that is not fully explained by the firm's own patenting. Technological breakthroughs are associated with an additional return of 2 to 15 basis points for a firm, and upstream breakthroughs, adjusted by their importance to a firm, are associated with a return that is 15 to 20 percent of their size. These findings highlight that new innovations granted to knowledge sources generate quantitatively large financial spillovers in firms.

In the subsequent section, we consider two other important relationships that firms share, namely their position in the supply chain and their role as competitors, and compare their shocks with the knowledge input weighted shocks.

4.2 Financial spillovers through vertical integration of firms

While prior literature has shown that news about seller firms generates predictable returns for buyer firms (see Cohen and Frazzini, 2008), we consider the case of when the news pertains to successfully securing patents for new innovations. When a firm j innovates, it may improve product quality, enhance efficiency, or reduce production costs. As a consequence, firm i that is technologically downstream to, as well as a customer of firm j in the product market, benefits from better inputs at a lower cost, thereby improving its scope for growth and profitability. When upstream firms in the innovation network innovate, investors are likely to increase their growth expectations for the downstream firms, both from new knowledge input and through supply chain channels.

An ideal test for this hypothesis would require complete data on sales and purchases between firms across various sectors. However, such data are unavailable to us for listed US firms. To best approximate these relationships, we use the directed Frésard et al. (2020) measure of vertical integration of all pairs of listed firms in the product market (described in Section 2.3). Unlike knowledge input shares, vertical integration measures do not add up to 1 for firms in the neighborhood of a firm as they measure the potential for a firm being vertically upstream to each of the other firms. We avoid normalization within the neighborhood to ensure that we capture the extensive margin on the product market and instead use their raw values. We measure the innovation shock experienced by a firm i at date t as patenting activity by firms in its neighborhood weighted by their degree of being a supplier to firm i:

$$\mathcal{P}^{S}_{\mathcal{N}_{it}} = \sum_{j \in \mathcal{N}_{it}} Vert^{S}_{ijt} \mathcal{P}_{jt} \tag{4.3}$$

where $Vert^{S}_{ijt} \in [0, 1]$ is the Frésard et al. (2020) potential of a firm $j \in \mathcal{N}_{it}$ being seller to firm i in the product market and $\mathcal{P}$ is the value of patents granted at date t. To empirically test this relationship, we estimate (4.2) using weights of vertical integration in place of knowledge input shares:

$$\alpha_{it} = c + \beta_1 \mathcal{P}^{S}_{\mathcal{N}_{it}} + \beta_2 \mathcal{P}_{it} + \text{Firm } i\text{-related controls} + \delta_1 V_{\mathcal{N}_{i,t-1}} + \tau_t + \epsilon_{it} \tag{4.4}$$

Our coefficient of interest remains β_1, which measures whether an increase in exposure to innovations based on vertical relationships in the product market are associated with higher abnormal return. We report the estimates for (4.4) in the columns 1, 3, and 5 of Table 4.2.

Our estimates suggest that innovations by suppliers in the neighborhood of a firm are indeed strongly and significantly associated with predicting its abnormal returns. In particular, if a firm secures patents, then the returns of its customer firm rise proportionally to how valuable the upstream firm is as a supplier and to the market value generated by their patents. A unit increase in the exposure to the patents granted to suppliers in the neighborhood is associated with an increase of over 2.16 basis points in the daily abnor-

Table 4.2: Exposure to patent grants to product-market suppliers and abnormal returns

Dependent Variables:	Same day α		Three-day averaged α		Weekly-averaged α	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Patent value of upstream innovators ($\mathcal{P}^{g}_{\mathcal{N}_{it}}$)		0.567^{*}		0.537^{***}		0.584^{***}
		(1.87)		(3.28)		(4.45)
Patent value ($\mathcal{P}_{it}$)	2.38^{***}	2.39^{***}	2.50^{***}	2.51^{***}	1.71^{***}	1.72^{***}
	(7.68)	(7.72)	(13.4)	(13.5)	(11.8)	(11.9)
Patent value of suppliers ($\mathcal{P}^{S}_{\mathcal{N}_{it}}$)	3.24^{**}	3.15^{**}	2.06^{***}	1.97^{***}	2.20^{***}	2.10^{***}
	(2.40)	(2.33)	(2.70)	(2.58)	(3.67)	(3.51)
Lagged market value of firm	-14.7^{***}	-14.7^{***}	-13.9^{***}	-14.0^{***}	-13.3^{***}	-13.3^{***}
	(-17.9)	(-18.0)	(-26.7)	(-26.8)	(-32.1)	(-32.1)
Lagged book-to-market ratio	-81.1^{***}	-81.3^{***}	-72.0^{***}	-72.3^{***}	-73.6^{***}	-73.8^{***}
	(-6.92)	(-6.93)	(-10.0)	(-10.0)	(-11.5)	(-11.6)
Lagged abnormal return	-0.191^{***}	-0.191^{***}	-0.099^{***}	-0.099^{***}	-0.064^{***}	-0.064^{***}
	(-19.6)	(-19.6)	(-23.3)	(-23.3)	(-19.5)	(-19.5)
Lagged market value of upstream innovators	-0.0003	-0.001	-0.0005	-0.001	0.002	0.001
	(-0.088)	(-0.291)	(-0.207)	(-0.522)	(0.995)	(0.560)
Fixed-effects						
Date	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,103,957	2,103,957	2,021,949	2,021,949	1,954,160	1,954,160
R^2	0.01221	0.01221	0.01415	0.01415	0.01558	0.01559
Within R^2	0.00637	0.00637	0.00692	0.00692	0.00674	0.00675

Clustered (Date) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents the results of estimating (4.4). Our outcome variables of interest are the same-day (columns 1 to 2), three-day averaged (columns 3 to 4) and weekly averaged abnormal returns (columns 5 to 6). The values of patents are borrowed from Kogan et al. (2017). They are 0 when there is no patent granted on a date and positive whenever an excess return is generated to the patenting firm. The exposure to innovation shock from vertically related supplier firms in the neighborhood is computed using (4.3). We control for innovation shock the firm faces from its technological knowledge sources (computed using 4.1) and its interaction with the firm's patent values. The lagged market value of a firm is derived from the log of the previous month's market value of the firm, the lagged book-to-market value corresponds to the log of the previous year's book-to-market ratio, and the lagged abnormal return is the average of the preceding week's abnormal returns. The lagged market value of neighbors is the sum of the logged market values of firms in the neighborhood of the focal firm. We rescale the abnormal returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate. The coefficient for the vertical relationships is not directly comparable to the coefficient of knowledge relationships. To make them comparable, the coefficient of the vertical relationships should be divided by 10, as the average vertical values for active neighbors at each time are a tenth of the average knowledge weights.

mal returns of a firm.

To find whether it is the vertical relationships in the product market that drive the results we observe in Table 4.1, we combine the covariates of (4.2) and (4.4) and report them in columns 2, 4, and 6 of Table 4.2 in a full specification. We find that the shock from knowledge sources continues to be strongly and significantly associated with generation of the downstream firm's abnormal returns beyond the relationships a firm shares in the supply chain. The coefficients of patent value of upstream innovators ($\mathcal{P}^{g}_{\mathcal{N}_{it}}$) do not change significantly in comparison to the specification that only accounts for technological and not supply chain relationships between firms (Table 4.1); in fact, they slightly dampen the effect of vertical relationships. Although the effects captured by the shock from vertical relationships appear quantitatively larger than those of knowledge relationships, the metric of the average vertical relationship a firm shares with its neighbors is a tenth of that of the knowledge input shares.[20]

In conclusion, we find that news about patent grants to firms that provide technological knowledge constitutes an important, exogenous explanation for abnormal returns of firms. These financial spillovers are large and persist despite accounting for the potential business partnerships that firms share with others.

4.3 The effects of product-market competition

Technological knowledge produced by firms, captured in their patents, provides useful information about the frontier to their peers. Although peer firms cannot directly capitalize this knowledge due to protections given to intellectual property, they can utilize it to create further technological advances which lead to growth (Romer, 1990, Aghion and Howitt, 1992). Therefore, when a firm innovates, it produces two effects: one, it benefits other firms that stand to use the knowledge of the technology to produce subsequent innovations, and two, it depresses the prospect of growth for the firm's rivals since it blocks them from benefiting from the technology itself. The dual effects of innovation on encouraging and discouraging rival firms have been well studied in the Schumpetarian paradigm (Aghion et al., 2014), and prior literature has tried to directly capture the two effects through the lens of knowledge spillovers (Bloom et al., 2013). We take a different approach and consider the financial spillovers arising from innovation by rival firms.

So far, we demonstrated that innovation by knowledge sources raises returns. The same firms that serve as sources of technological knowledge could also compete with a

[20]Therefore, we prefer to interpret the coefficients for the shock from vertical relationships as being roughly a tenth of the reported values to compare them with shock from knowledge relationships.

firm.[21] Therefore, we expect that a firm facing competition by its neighbors may have diminished returns when they patent influential innovations, whereas their role as knowledge sources contributes positively to that firm. To estimate the financial spillovers arising from rivals in a firm's neighborhood, we construct a measure of exposure to innovation by rivals. A rival firm is identified by the similarity of its products relative to a reference firm. We use the yearly text-based product similarity (Hoberg and Phillips, 2010, 2016) values ($Comp_{ijt} \in [0,1]$) between all pairs of firms (i and j) as a measure of their product-market competition at date t. We distinguish the role of overall competition faced by a firm from its knowledge sources from that arising from them being granted patents. More firms producing similar products correspond to a higher degree of competition faced by a firm. We construct a measure of overall competition faced by a firm as a simple sum of their competition:

$$Comp_{it} = \sum_{j \in \mathcal{N}_{it}} Comp_{ijt} \tag{4.5}$$

Second, we compute the competition-weighted innovation shock to a firm i as:

$$\mathcal{P}^c_{\mathcal{N}_{it}} = \sum_{j \in \mathcal{N}_{it}} Comp_{ijt}\mathcal{P}_{jt} \tag{4.6}$$

where $\mathcal{P}_{jt}$ is the patent grant activity of an upstream firm j on date t. Using the values of (4.5) and (4.6), we estimate the following specification:

$$\begin{aligned}\alpha_{it} = c + \beta_1 \mathcal{P}^c_{\mathcal{N}_{it}} + \beta_2 \mathcal{P}_{it} + \\ \text{Firm } i\text{-related controls} + \delta_1 V_{\mathcal{N}_{i,t-1}} + \delta_2 Comp_{it} + \tau_t + \epsilon_{it}\end{aligned} \tag{4.7}$$

For our main analysis, $\mathcal{P}$ is the value of patents granted borrowed from Kogan et al. (2017), $V_{\mathcal{N}_{i,t-1}}$ is the total market value of the neighborhood $\mathcal{N}_i$ of firm i in the preceding month, τ_t is the date fixed effect, $Comp_{it}$ is the total market competition faced by the firm, and firm-related controls include the lagged abnormal returns (preceding week), market value of the firm (preceding month), and book-to-market value (preceding year). Our coefficients of interest are δ_2, which captures the abnormal returns associated with steeper product-market competition from technological knowledge sources, and β_1, which estimates whether competition-weighted innovation shocks affect returns.

We present the results of estimating (4.7) in Table 4.3. Columns 2, 5, and 8 show

[21] For instance, Apple's patents could be a useful source of knowledge for Samsung's innovations in mobile phone technology. However, the two firms have been fierce competitors on the mobile phone market since the 2010s.

Table 4.3: Effect of exposure to patent grants to product-market rivals on abnormal returns

Dependent Variables:	Same day α			Three-day averaged α			Weekly-averaged α		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Patent value of upstream innovators ($\mathcal{P}^{g}_{\mathcal{N}_{it}}$)			0.530*			0.479***			0.529***
			(1.75)			(2.93)			(4.03)
Patent value ($\mathcal{P}_{it}$)	2.30***	2.29***	2.31***	2.42***	2.42***	2.43***	1.64***	1.64***	1.65***
	(7.44)	(7.41)	(7.46)	(13.2)	(13.1)	(13.2)	(11.5)	(11.4)	(11.6)
Patent value of competitors ($\mathcal{P}^{c}_{\mathcal{N}_{it}}$)	-6.54*	-6.62*	-6.22*	-10.1***	-10.1***	-9.75***	-9.89***	-9.89***	-9.49***
	(-1.92)	(-1.94)	(-1.82)	(-4.94)	(-4.94)	(-4.75)	(-6.05)	(-6.04)	(-5.78)
Product market competition		2.00**	1.89**		2.63***	2.52***		2.54***	2.43***
		(2.18)	(2.05)		(4.78)	(4.59)		(5.78)	(5.51)
Lagged market value of firm	-14.6***	-14.8***	-14.8***	-13.9***	-14.0***	-14.1***	-13.3***	-13.4***	-13.4***
	(-17.8)	(-17.9)	(-18.0)	(-26.8)	(-26.8)	(-26.8)	(-32.0)	(-32.1)	(-32.1)
Lagged book-to-market ratio	-81.2***	-81.3***	-81.5***	-72.0***	-72.0***	-72.2***	-73.3***	-73.5***	-73.7***
	(-6.92)	(-6.92)	(-6.93)	(-10.0)	(-9.99)	(-10.0)	(-11.5)	(-11.5)	(-11.6)
Lagged abnormal return	-0.191***	-0.191***	-0.191***	-0.099***	-0.099***	-0.099***	-0.064***	-0.064***	-0.064***
	(-19.6)	(-19.6)	(-19.6)	(-23.3)	(-23.3)	(-23.3)	(-19.5)	(-19.5)	(-19.5)
Lagged market value of upstream innovators	-0.0006	-0.0007	-0.001	0.003	0.003	0.002	0.005***	0.006***	0.005**
	(-0.149)	(-0.169)	(-0.340)	(1.22)	(1.17)	(0.894)	(2.84)	(2.87)	(2.48)
Fixed-effects									
Date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	2,103,967	2,103,957	2,103,957	2,021,957	2,021,949	2,021,949	1,954,167	1,954,160	1,954,160
R^2	0.01219	0.01221	0.01221	0.01413	0.01416	0.01417	0.01557	0.01561	0.01562
Within R^2	0.00636	0.00637	0.00637	0.00692	0.00693	0.00694	0.00675	0.00677	0.00678

Clustered (Date) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents the results of estimating varying specifications of (4.7). Our outcome variables of interest are the same-day (columns 1 to 3), three-day averaged (columns 4 to 6) and weekly averaged abnormal returns (columns 7 to 9). The values of patents are borrowed from Kogan et al. (2017). They are 0 when there is no patent granted on a date and positive whenever an excess return is generated to the patenting firm. *Product market competition* is the total competition faced by a firm measured using (4.5), and *patent value of competitors* is computed using (4.6). We control for innovation shock the firm faces from its technological knowledge sources (computed using 4.1) and its interaction with the firm's patent values. The lagged market value of a firm is derived from the log of the previous month's market value of the firm, the lagged book-to-market value corresponds to the log of the previous year's book-to-market ratio, and the lagged abnormal return is the average of the preceding week's abnormal returns. The lagged market value of neighbors is the sum of the logged market values of firms in the neighborhood of the focal firm. We rescale the abnormal returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate. The coefficient of the competition effect is not directly comparable to the coefficient of knowledge relationships. To make them comparable, the coefficient of the competition effect should be divided by 5, as the average competition values for active neighbors at each time are a fifth of the average knowledge weights.

that innovation shocks weighted by competition are negatively associated with abnormal returns of firms; the abnormal returns decline with every additional unit of the shock. Firms exposed to innovations by stronger competitors or to more breakthroughs granted to those competitors face lower returns. On the other hand, firms facing higher competition on the product market have higher overall returns; firms with 10 additional competitors, which each share a 10 percent overlap in the product space, have approximately 2 additional basis points of daily abnormal return. This may indicate selection, since being a listed firm in a highly competitive product space indicates strong fundamentals that allow the firm to survive in the first place.

Furthermore, including knowledge-source-weighted innovation shock in our analysis (columns 3, 6, and 9) changes neither its own coefficient relative to estimations from prior specifications (4.2 and 4.4; about 0.5 basis points), nor does it affect the coefficients of the competition-weighted shock (less than -10 basis points).[22] Our results concur broadly with prior literature that highlights the business-stealing effects of innovation on competitors, and our quantification demonstrates their prevalence in stock returns and highlights that while the positive financial spillovers generated from knowledge sources remain large, their overall effect on a firm depends on the competition they face from those upstream firms.

4.4 Robustness check using uniform placebo weights

An important concern in our analysis is about the validity of our exposure weights. Specifically, we want to ensure that the abnormal returns we observe for firms are driven by their exposure to upstream firms proportional to their knowledge inputs, not by spurious correlations or other unobserved factors. In other words, the draw of weights measured using equation (3.1) for a firm should matter. One way to test the robustness of our results is by redoing our analysis by using placebo weights. If the results persist with placebo weights, then our case weakens; conversely, if we observe no effects with placebo weights, our results strengthen.

In this section, we test our results by using a uniform weight of $1/|\mathcal{N}_{it}|$ for each upstream firm, instead of their true knowledge input shares g_{ijt}, where $|\mathcal{N}_{it}|$ is the number of firms in firm i's neighborhood at date t. These firms are selected for having been cited by firm i at least once before t, and the placebo weights may coincide with (or be close

[22]Note that the coefficients of competition-weighted shock are not directly quantitatively comparable to knowledge-input-share-weighted shock since the weights are constructed differently and measure qualitatively different aspects of relationships between firms.

to) their true weight g_{ijt} for some upstream firms.[23] We calculate the exposure of firm i to patent grants of its upstream innovators using placebo weights as:

$$\mathcal{P}_{\mathcal{N}_{it}}^{\text{Placebo}} = \sum_{j \in \mathcal{N}_{it}} \frac{1}{|\mathcal{N}_{it}|} \mathcal{P}_{jt} \tag{4.8}$$

where $|\mathcal{N}_{it}|$ is the number of neighbors of firm i at time t, and $\mathcal{P}_{\mathcal{N}_{it}}^{\text{Placebo}}$ represents a uniform average of patent activities of firm i's neighbors at that time.

The modified regression incorporating this placebo weight is given by

$$\alpha_{it} = c + \beta_1 \mathcal{P}_{\mathcal{N}_{it}}^{\text{Placebo}} + \beta_2 \mathcal{P}_{it} + \text{Firm } i\text{-related controls} + \delta_1 V_{\mathcal{N}_{i,t-1}} + \tau_t + \epsilon_{it} \tag{4.9}$$

where our coefficient of interest is β_1. We expect that the placebo weights should generate attenuation if indeed the knowledge input shares capture information in the association with a downstream firm's abnormal return.

The results from estimating (4.9) are presented in Table 4.4 in columns 1, 3, and 5. In a fuller version, presented in columns 2, 4, and 6, we include as controls the shock faced by a firm through patent grants to its neighborhood using weights of competition and vertical relationships. We find that the coefficient of exposure to innovation by upstream firms using placebo weights (0.36 for three-day return) is smaller than the coefficients in Table 4.1 (0.43 for three-day return), and the association is not statistically significant. The size and significance of the coefficient are further diminished in the fuller specification. The results align with our prediction despite the selection of firms being upstream at least one point. This test highlights the role of the particular knowledge input shares of each firm in capturing its exposure to patent grants to other firms; in particular, knowledge input shares capture important information about what affects a firm's abnormal returns
.

4.5 Assessing the role of second-degree connections

Our results so far suggest that (1) news about patent grants to a firm generate abnormal returns for the firm, and (2) direct exposure to patent grants to sources of technological knowledge of a firm is associated with its higher abnormal returns. This implies that shocks in the innovation network generate a positive and detectable effect at degrees 0 and 1. However, shocks in the network need not remain localized within first-degree

[23] This way, we assign a positive weight to those firms in the neighborhood of a firm that have been cited in the distant history but not in the five years preceding the reference date.

Table 4.4: Exposure to patent grants to upstream innovators using uniform weights

Dependent Variables:	Same day α		Three-day averaged α		Weekly-averaged α	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Patent value of upstream innovators ($\mathcal{P}^{\text{Placebo}}_{\mathcal{N}_{it}}$)	0.770	0.708	0.366	0.287	0.340	0.263
	(1.60)	(1.45)	(1.32)	(1.07)	(1.45)	(1.16)
Patent value ($\mathcal{P}_{it}$)	2.39***	2.32***	2.50***	2.43***	1.72***	1.65***
	(6.92)	(6.54)	(7.86)	(7.86)	(6.95)	(6.80)
Patent value of suppliers ($\mathcal{P}^{S}_{\mathcal{N}_{it}}$)		3.16		2.51*		2.69**
		(1.61)		(1.97)		(2.39)
Patent value of competitors ($\mathcal{P}^{c}_{\mathcal{N}_{it}}$)		-6.54*		-10.2***		-10.0***
		(-1.95)		(-4.50)		(-5.54)
Product market competition		1.89**		2.59***		2.50***
		(2.21)		(4.30)		(5.55)
Lagged abnormal return	-0.191***	-0.191***	-0.099***	-0.099***	-0.064***	-0.064***
	(-13.6)	(-13.6)	(-23.1)	(-23.1)	(-20.6)	(-20.6)
Lagged market value of firm	-14.7***	-14.8***	-13.9***	-14.0***	-13.3***	-13.4***
	(-16.3)	(-16.4)	(-19.4)	(-19.6)	(-20.9)	(-21.1)
Lagged book-to-market ratio	-80.9***	-81.9***	-71.9***	-72.4***	-73.4***	-73.9***
	(-5.52)	(-5.59)	(-4.25)	(-4.31)	(-3.50)	(-3.53)
Lagged market value of upstream innovators	0.002	-0.0008	0.0008	0.003	0.003	0.005
	(0.434)	(-0.180)	(0.278)	(0.653)	(1.39)	(1.60)
Fixed-effects						
Date	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,103,957	2,103,957	2,021,949	2,021,949	1,954,160	1,954,160
R^2	0.01221	0.01221	0.01415	0.01417	0.01558	0.01562
Within R^2	0.00637	0.00638	0.00692	0.00694	0.00674	0.00677

Clustered (Date) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents the results of estimating (4.9). Our outcome variables of interest are the same-day (columns 1 to 2), three-day averaged (columns 3 to 4) and weekly averaged abnormal returns (columns 5 to 6). The values of patents are borrowed from Kogan et al. (2017). They are 0 when there is no patent granted on a date and positive whenever an excess return is generated to the patenting firm. The knowledge input shares (innovation edge weights) are simply equal over all firms in a focal firm's neighborhood. We measure a firm's exposure to patent grants to firms in its neighborhood using uniform placebo weights ($1/\mathcal{N}_{it}$) defined in (4.8). The lagged market value of a firm is derived from the log of the previous month's market value of the firm, the lagged book-to-market value corresponds to the log of the previous year's book-to-market ratio, and the lagged abnormal return is the average of the preceding week's abnormal returns. The lagged market value of neighbors is the sum of the logged market values of firms in the neighborhood of the focal firm. We rescale the abnormal returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate.

connections alone. Indeed, it is possible that they have a cascading effect in generating returns across the second- and further-degree connections.[24] In this section, we determine whether the financial market response to news about an innovation by a firm extends beyond its immediate connections. We do so by examining the role of second-degree relationships in the innovation network.

A firm i is directly connected in the innovation network to upstream firms $j \in \mathcal{N}_{it}$. Consider a firm $s \notin \mathcal{N}_{it}$ that is granted patents $\mathcal{P}_{st}$ at date t. In our previous analysis, this firm was omitted in the measurement of exposure to shock to firm i since its weight g_{ist} was 0. Suppose that this firm $s \in \mathcal{N}_{jt}$ is directly upstream to firm $j \in \mathcal{N}_{it}$ in the innovation network. Firm s has an indirect effect on firm i in knowledge inputs through firm j. We denote the set of all such firms in the second-degree neighborhood of firm i at time t by $\mathcal{N}_{it}^{2nd}$ (see Figure 4.1).

One simple way to measure the effective knowledge input weight from firms s in the second-degree neighborhood to firm i is to take the product of their weights: $g_{ijt} \times g_{jst}$. However, some firms upstream to firm j may also be directly upstream to firm i. Therefore, the weights may not add up to 1 and may vary across firms. To enable comparison of knowledge exposure weights across firms in this intensive margin, we normalize each weight by dividing it by the total sum of all weights. This normalization ensures that the normalized second-degree knowledge weights for each individual downstream firm add up to 1.

Using this effective weight, we compute the exposure of firm i at time t of patent grants to firms that are its second-degree connections as

$$\mathcal{P}_{\mathcal{N}_{it}^{2nd}} = \frac{1}{\sum_{j \in \mathcal{N}_{it}} \sum_{s \in \mathcal{N}_{it}^{2nd}} g_{ijt} \times g_{jst}} \sum_{j \in \mathcal{N}_{it}} \sum_{s \in \mathcal{N}_{it}^{2nd}} g_{ijt} \times g_{jst} \mathcal{P}_{st} \tag{4.10}$$

where $\mathcal{P}$ is the value of patents granted at date t, g_{ijt} is the knowledge input share of firm i from firm j, and g_{ijt} is the same of firm j from firm s, and firms $j \in \mathcal{N}_{it}$ and $s \in \mathcal{N}_{it}^{2nd}$ are one and two degrees away, respectively, from firm i in the innovation network. To empirically test the exposure to patent grants in the second degree, we estimate:

$$\alpha_{it} = c + \beta_1 \mathcal{P}_{\mathcal{N}_{it}^{2nd}} + \beta_2 \mathcal{P}_{it} + \text{Firm } i\text{-related controls} + \delta_1 V_{\mathcal{N}_{i,t-1}^{2nd}} + \tau_t + \epsilon_{it} \tag{4.11}$$

where $\mathcal{P}$ is the value of patents granted, whose preferred measure is their market value that we borrow from Kogan et al. (2017), $V_{\mathcal{N}_{i,t-1}^{2nd}}$ is the total market value of the second-degree neighborhood $\mathcal{N}_i^{2nd}$ of firm i in the preceding month, τ_t is the date fixed effect,

[24] See Acemoglu et al. (2016a) for a discussion on the propagation of shocks in the macroeconomy.

Table 4.5: Patent grants to second-degree connections in innovation network

Dependent Variables:	Three-day averaged α			Weekly averaged α		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Patent value of 2nd deg. neighborhood ($\mathcal{P}_{\mathcal{N}_{it}^{2nd}}$)	0.389	0.402	0.324	0.235	0.260	0.220
	(0.634)	(0.655)	(0.523)	(0.476)	(0.522)	(0.440)
Patent value ($\mathcal{P}_{it}$)	2.30***	2.46***	2.49***	1.67***	1.77***	1.79***
	(16.9)	(18.0)	(18.3)	(15.4)	(16.3)	(16.5)
Lagged market value of firm	-12.4***	-13.4***	-13.4***	-12.3***	-12.9***	-12.9***
	(-24.7)	(-26.1)	(-26.0)	(-31.0)	(-32.0)	(-31.9)
Lagged book-to-market ratio	-54.8***	-59.7***	-59.6***	-57.6***	-60.9***	-60.8***
	(-9.49)	(-10.3)	(-10.3)	(-11.9)	(-12.5)	(-12.5)
Lagged abnormal return		-0.096***	-0.096***		-0.064***	-0.064***
		(-24.6)	(-24.6)		(-23.8)	(-23.8)
Lagged market value of neighbors			-0.0003*			-0.0001
			(-1.96)			(-1.26)
Fixed-effects						
Date	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,022,118	2,022,039	2,022,039	1,953,812	1,953,735	1,953,735
R^2	0.00900	0.01413	0.01413	0.01139	0.01531	0.01531
Within R^2	0.00159	0.00676	0.00677	0.00268	0.00663	0.00664

Clustered (Date) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents the results of estimating (4.11). Our outcome variables of interest are the three-day averaged (columns 1 to 3) and weekly averaged abnormal returns (columns 4 to 6). The values of patents are borrowed from Kogan et al. (2017). They are 0 when there is no patent granted on a date and positive whenever an excess return is generated to the patenting firm. The exposure to patents by second-degree upstream innovators is captured in the value of second-degree neighbors' patents ($\mathcal{P}_{\mathcal{N}_{it}^{2nd}}$) computed using equation (4.10). The lagged market value of a firm is derived from the log of the previous month's market value of the firm, the lagged book-to-market value corresponds to the log of the previous year's book-to-market ratio, and the lagged abnormal return is the average of the preceding week's abnormal returns. The lagged market value of neighbors is the sum of the logged market values of firms in the neighborhood of the focal firm. We rescale the abnormal returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate.

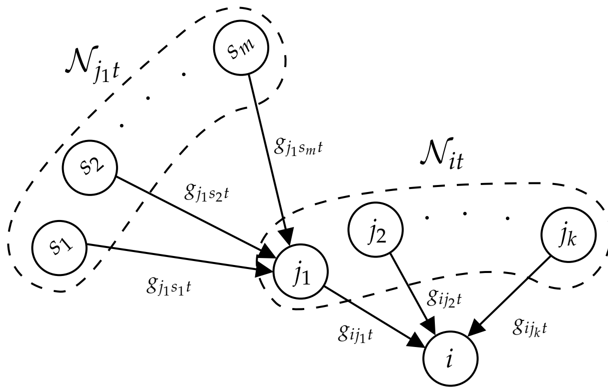

Figure 4.1: Second-degree innovation connections among firms

Notes: This figure illustrates second-degree connections within the innovation network at a given time t for a given firm i. Firms $j_1, \cdots, j_k$ belong to the neighborhood $\mathcal{N}_{it}$ of firm i, meaning firm i has cited each of them at least once in its patents before time t. Firms $s_1, \cdots, s_m$ belong to the neighborhood of firm j_1 that do not belong to firm i's neighborhood. The effective knowledge contribution that firm s_1 provides to firm i is calculated by multiplying $g_{j_1 s_1 t}$ (the knowledge share from firm s_1 to an intermediary firm j_1) by $g_{ij_1 t}$ (the knowledge share from intermediary firm j_1 to firm i). This product (weight) is then normalized by the aggregate of all the knowledge shares that firm i receives from all firms in its second degree connections in the innovation network.

and firm-related controls include the lagged abnormal returns (preceding week), market value of the firm (preceding month), and book-to-market value (preceding year). Our coefficient of interest, β_1, estimates whether patenting in the second-degree neighborhood is associated with higher abnormal returns for firm i.

We present the results of our estimating (4.11) in Table 4.5. We find that the coefficients of the second-degree connections are statistically indistinguishable from 0, suggesting that a firm's exposure to new patent grants to second-degree neighbors does not significantly correlate with its abnormal returns. We interpret this as some evidence to suggest that financial spillovers of innovation are localized to firms that are directly connected in the innovation network. These findings are in line with Acemoglu et al. (2016b) and Liu and Ma (2021) who find that advances in a technological area generate spillovers localized to technologies that are its direct downstream.

5 Discussion and conclusion

In this paper, we identify financial spillovers from upstream innovators to technologically downstream firms. Based on the efficient market hypothesis, market prices must reflect information about knowledge spillovers stemming from an innovation. By extracting this information from the market prices, we identify and measure the spillover value of patent grants to a firm. Our results show that not only do a firm's own patent grants generate abnormal returns to itself proportional to their total value, but so do patent grants to a firm's sources of technological knowledge (upstream firms). The exposure of a firm to each upstream knowledge source is measured by the firm's share of non-self-citations made to their respective patents in its innovations. The magnitude of the downstream firm's gains is proportional to the quality of patents granted. These effects continue to hold after using alternative measures of the value of patent grants and after accounting for product-market competition and vertical relationships with the technologically upstream firms. However, the effects fail to be detected when we consider placebo weights, and they do not extend to second-degree relationships in the innovation network. Our findings, in parallel with past literature on knowledge spillovers and financial market response to innovation, suggest that the benefits of innovation are not limited to an innovating firm alone; rather, firms that technologically depend on it also stand to benefit in the financial market from those innovations.

More broadly, our findings speak to a broader literature on attention by investors, and raises questions about the mechanisms through which the shocks in the innovation network translate to abnormal returns. First, whether the spillover effects emerge due to investors leveraging information on knowledge input shares per se, or whether these knowledge input shares proxy well for an unobserved knowledge partnership between businesses that investors usually pay attention to, is not easily testable. The best evidence on this subject so far comes from Fadeev (2023) who suggests that the intensity of patent citations do indeed correspond to knowledge sharing between firms, an interpretation that aligns with our results. Second, throughout our specifications, we find that abnormal returns generated by news of a firm's own patent awards fade out over the course of the week in which patents are granted, whereas they rise in the same duration when its upstream firms are granted patents, an observation that falls in line with investors' limited attention to new information. The lag with which investors react to innovation by upstream innovators also suggests the potential for a trading strategy.

Given that this paper concerns only listed firms, our analysis serves as a measure of the effects at the intensive margin limited to few sources of technological knowledge inputs. The edge weights we compute in the innovation network of firms will decrease if we were to include non-listed firms, public institutions, and self-citations, thereby raising our estimates if the results continue to hold. Indeed, non-public firms tend to develop breakthroughs that listed firms may stand to benefit from (Akcigit et al., 2021), and a firm's own reliance on its prior innovation tends to be large. In further research, we hope to factor in these knowledge input weights and examine whether patent grants by non-public firms also generate a similar financial spillover in listed firms. Second, we pool our results for firms that vary by their R&D productivity. For firms that produce very few, intermittent innovations, the knowledge input shares may not convey rich information that could be leveraged by investors and that may lead to financial spillovers. Accounting for the R&D productivity may therefore lead to a better estimation of spillovers. Third, the firms we observe in our final data are selected with stringent criteria for measuring the abnormal returns and observability of controls in the specifications. Although this omits few among all listed firms, our results can be tested on a larger pool of firms by relaxing some of these criteria and controls. Fourth, mechanisms that explain the results can be tested using higher frequency and granular data on stock movements and detailed data on firm ownership by investors. Although we are able to quantify the association in upstream patenting on stock returns, establishing their causal relationship is a natural next step. Although this paper estimates the partial equilibrium effects on a firm of upstream firms collectively as a neighborhood, we see further research quantifying the general equilibrium effects of patent grants on financial markets and measuring the spillovers generated by each innovation.

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A Tables

Table A.1: Summary Statistics

Variable	Observations	Mean	Std. dev.	Min	Pctl. 25	Pctl. 75	Max
Directed edge weights in innovation network (knowledge input shares)							
Weight g	92,835,710	0.02	0.071	0	0	0.011	1
Number of firms in neighborhoods							
Full neighborhood	2,754,709	34	68	1	3	31	880
Subset with $g > 0$	2,356,870	29	58	1	3	28	775
Subset with $g > 0.1$	1,641,370	2.3	1.5	1	1	3	9
Firm characteristics							
Downstream innovator market value	92,182,373	27,340	67,946	0.031	821	21,212	1,187,463
Upstream innovator market value	92,182,373	26,515	65,902	0.041	748	20,375	1,187,463
Downstream innovator book-to-market	87,258,986	0.011	0.11	0.00000013	0.00026	0.00078	5.9
Upstream innovator book-to-market	87,258,986	0.011	0.11	0.000000012	0.00027	0.00079	5.9
Upstream firms' patent characteristics							
Number of breakthroughs	2,695,440	0.062	0.66	0	0	0	77
1 year citations	2,695,440	0.13	1.9	0	0	0	590
3 year citations	2,695,440	1.3	14	0	0	0	3,354
5 year citations	2,695,440	2.9	28	0	0	0	6,374
Market value of patents	2,695,440	8.3	56	0	0	0	2,657
Downstream firms' patent characteristics							
Number of breakthroughs	2,754,709	0.061	0.66	0	0	0	77
1 year citations	2,754,709	0.13	1.9	0	0	0	590
3 year citations	2,754,709	1.2	14	0	0	0	3354
5 year citations	2,754,709	2.8	28	0	0	0	6374
Value of patents	2,754,709	8.1	56	0	0	0	2657
Hoberg-Phillips and Fresard-Hoberg-Phillips values of between firm relationships							
Product market competition	92,835,710	0.031	0.048	0	0	0.047	0.97
Potential of vertical integration	92,835,710	0.0023	0.0058	0	0	0.00057	0.1
Frequency of ordered firm pairs	204,956	453	389	1	147	646	1670

Notes: This table provides a summary of the data. The market value of patents are borrowed from Kogan et al. (2017). The count of breakthroughs follows the methodology of Kelly Kelly et al. (2021). The product market competition which is based on Hoberg and Phillips (2010, 2016) and is a text-based product similarity measure, gauges the competitive intensity between two firms. The vertical integration, as defined by Frésard et al. (2020), evaluates the extent to which a firm in the innovation network's upstream also serves as a supplier for the downstream.

Table A.2: Upstream patenting activity in other industries and abnormal returns of downstream firms

Dependent Variables:	Same day α			Three-day averaged α			Weekly averaged α		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Patent value of upstream neighborhood ($\mathcal{P}^{g,\text{CrossInd}}_{\mathcal{N}_{it}}$)	0.354	0.425	0.427	0.352**	0.391***	0.414***	0.345***	0.351***	0.369***
	(1.20)	(1.45)	(1.43)	(2.34)	(2.60)	(2.72)	(2.83)	(2.88)	(2.99)
Patent value ($\mathcal{P}_{it}$)	2.24***	2.46***	2.50***	2.23***	2.36***	2.84***	1.60***	1.59***	1.96***
	(9.90)	(10.8)	(3.98)	(16.6)	(17.1)	(9.15)	(14.8)	(14.5)	(7.86)
Interaction term ($\mathcal{P}_{it} \times \mathcal{P}^{g}_{\mathcal{N}_{it}}$)			-0.017			-0.257			-0.200
			(-0.048)			(-1.50)			(-1.45)
Lagged market value of firm	-11.8***	-13.6***	-13.6***	-12.0***	-12.9***	-12.9***	-11.6***	-12.2***	-12.2***
	(-15.7)	(-17.8)	(-17.8)	(-25.4)	(-26.5)	(-26.5)	(-31.2)	(-32.0)	(-32.0)
Lagged book-to-market ratio	-57.3***	-66.8***	-66.8***	-52.6***	-57.2***	-57.2***	-52.5***	-55.6***	-55.7***
	(-6.23)	(-7.28)	(-7.28)	(-9.11)	(-9.95)	(-9.96)	(-10.7)	(-11.3)	(-11.3)
Lagged abnormal return		-0.191***	-0.191***		-0.097***	-0.097***		-0.063***	-0.063***
Lagged market value of neighbors		0.001	0.001		0.0008	0.0006		0.002***	0.002***
		(1.22)	(1.18)		(1.10)	(0.776)		(3.90)	(3.56)
Fixed-effects									
Date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	2,342,744	2,331,164	2,331,164	2,252,060	2,240,763	2,240,763	2,175,928	2,165,055	2,165,055
R^2	0.00588	0.01185	0.01185	0.00826	0.01345	0.01346	0.01055	0.01447	0.01447
Within R^2	0.00044	0.00643	0.00643	0.00150	0.00671	0.00671	0.00250	0.00643	0.00643

Clustered (Date) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents the results of estimating (4.2) for cross-industry network. Our outcome variables of interest are the same day (columns 1 to 3), three-day averaged (columns 4 to 6) and weekly averaged abnormal returns (columns 7 to 9). The value of patents are borrowed from Kogan et al. (2017), which are 0 when there is no patent granted on a date, and positive whenever an excess return is generated to the patenting firm. The exposure to patents by upstream innovators operating across industries different from firm i's is captured in $\mathcal{P}^{g,\text{CrossInd}}_{\mathcal{N}_{it}}$, that is computed using the cross industry version of equation (4.1). The lagged market value of a firm is derived from the log of the previous month's market value of the firm, the lagged book-to-market value corresponds to the log of the previous year's book-to-market ratio, and the lagged abnormal return is the average of the preceding week's abnormal returns. The lagged market value of neighbors is the sum of the logged market values of firms in the neighborhood of the focal firm. We re-scale the abnormal returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate.

Table A.3: Effect of patent grants and technological breakthroughs by upstream innovators on abnormal returns

Measure of patent value $\mathcal{P}$:	No. of top 10% patents by market value				No. of top 10% patents by breakthroughness				Number of patents			
Dependent variables:	Three-day averaged α		Weekly averaged α		Three-day averaged α		Weekly averaged α		Three-day averaged α		Weekly averaged α	
Variables												
Patent value of upstream innovators ($\mathcal{P}^{g}_{\mathcal{N}_{it}}$)	2.68**	3.07***	2.71***	2.85***	0.284*	2.93***	0.320**	0.298**	0.363	0.439	0.522**	0.501**
	(2.47)	(2.79)	(3.02)	(3.12)	(2.22)	(2.25)	(3.10)	(2.86)	(1.26)	(1.48)	(2.32)	(2.17)
Patent value ($\mathcal{P}_{it}$)	12.9***	11.6***	9.41***	7.94***	0.447**	2.79***	0.343*	1.68**	1.24***	1.60***	1.11***	1.02**
	(16.3)	(7.83)	(15.2)	(6.75)	(2.64)	(3.76)	(2.53)	(2.89)	(3.87)	(3.04)	(4.38)	(2.49)
Lagged market value of firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged book-to-market ratio	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged abnormal return		Yes		Yes		Yes		Yes		Yes		Yes
Lagged market value of neighbors		Yes		Yes		Yes		Yes		Yes		Yes
Fixed effects												
Date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics												
Observations	2,360,075	2,021,949	2,280,273	1,954,160	1,755,960	1,509,218	1,693,932	1,456,498	2,360,075	2,021,949	2,280,273	1,954,160
R^2	0.00823	0.01411	0.01069	0.01555	0.00820	0.01410	0.01067	0.01555	0.00820	0.01410	0.01066	0.01554
Within R^2	0.00146	0.00688	0.00247	0.00671	0.00144	0.00688	0.00246	0.00670	0.00143	0.00687	0.00245	0.00670

Clustered (Date) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents the results of estimating varying specifications of (4.2) for innovation breakthroughs. Our outcome variables of interest are three-day averaged (columns 1,2,5,6,9, and 10) and weekly averaged abnormal returns (columns 3,4,7,8,11, and 12). In the first four columns our definition of breakthrough is related to patent values reported by Kogan et al. (2017), which are 0 when there is no patent granted on a date, and positive whenever the patent value belongs to top ten percent docile of all patent values has been published within the same year. In the second four columns our definition of breakthrough is related to Kelly et al. (2021), which are 0 when there is no patent granted on a date, and positive whenever the patent is identified as a breakthrough. In the last four columns we re-run the analysis using the raw number of patents as our main independent variable. We control for innovation shock the firm faces from its technological knowledge sources (computed using 4.1) and its interaction with the firm's patent values. The lagged market value of a firm is derived from the log of the previous month's market value of the firm, the lagged book-to-market value corresponds to the log of the previous year's book-to-market ratio, and the lagged abnormal return is the average of the preceding week's abnormal returns. The lagged market value of neighbors is the sum of the logged market values of firms in the neighborhood of the focal firm. We re-scale the abnormal returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate.

B Figures

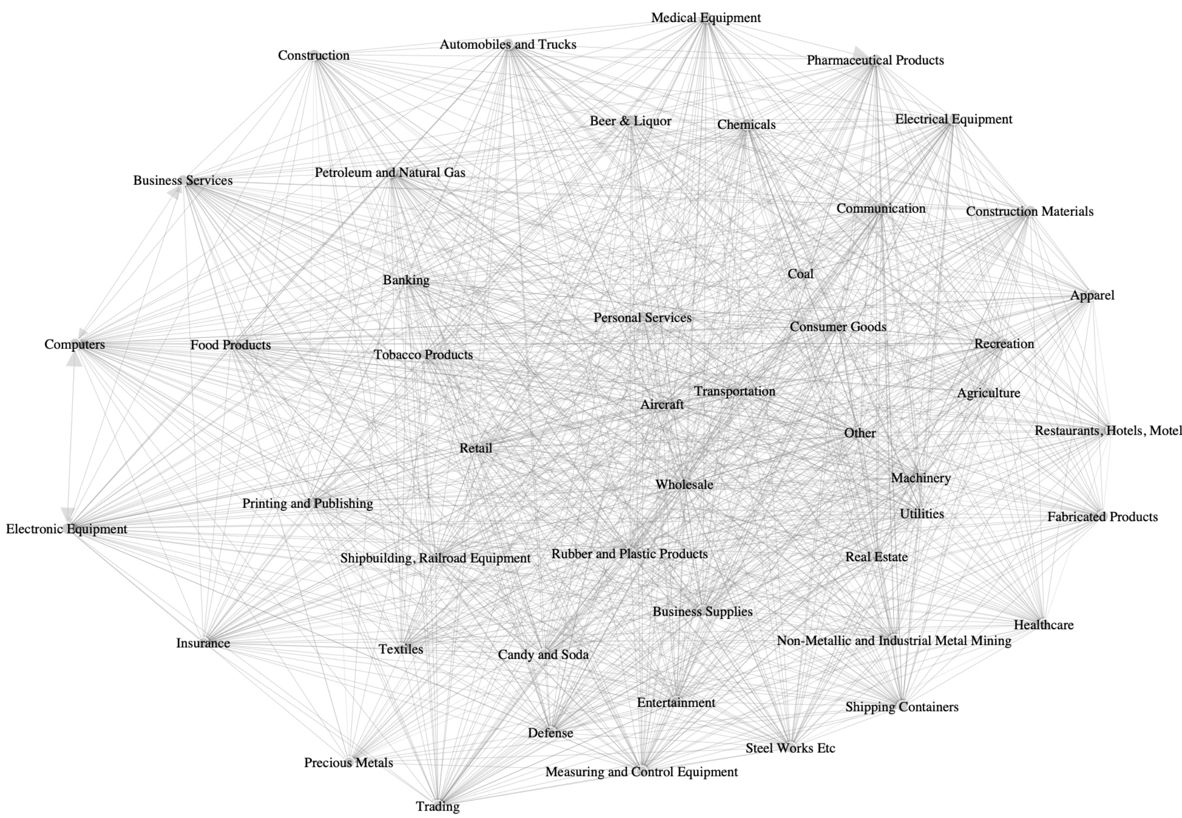


Figure B.1: Directed innovation network across industries

Notes: This figure illustrates the directed innovation network among firms operating across different industries by their SIC classifications as of 2020. For clarity of presentation, we aggregate firm level observations at the level of their main SIC industry using the 48 industry classification code. The directed edges from one upstream industry (say J) to a focal downstream industry (say I) are weighted by the share of patent citations made toward industry J by industry I in its patents.

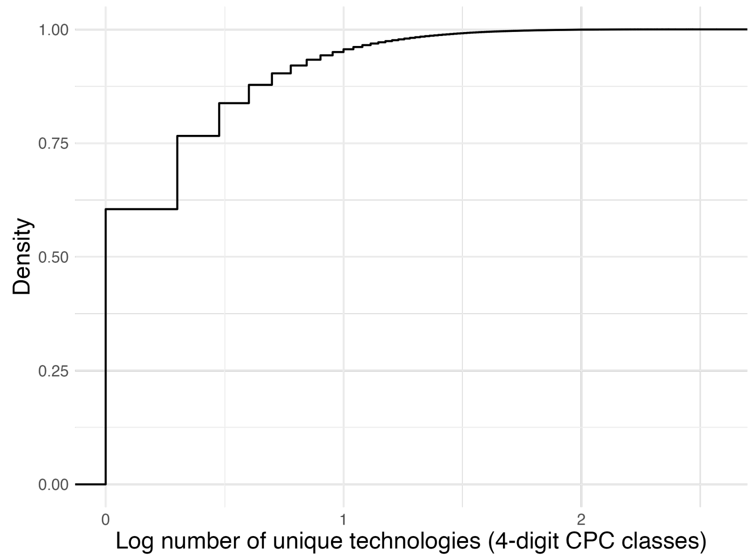


Figure B.2: Distribution of the number of distinct technologies cited by firms

Notes: This figure shows the cumulative distribution of the number of distinct 4-digit CPC technology sub-classes cited by publicly listed firms in their portfolio of patents from a given upstream firm over their observed lifetime. The x-axis is in log scale with base 10. Despite over 600 available CPC sub-classes, most firms (over 60 percent) cite just 1 technology in their patents in their lifetime, and over 75 percent cite just 2 technologies.

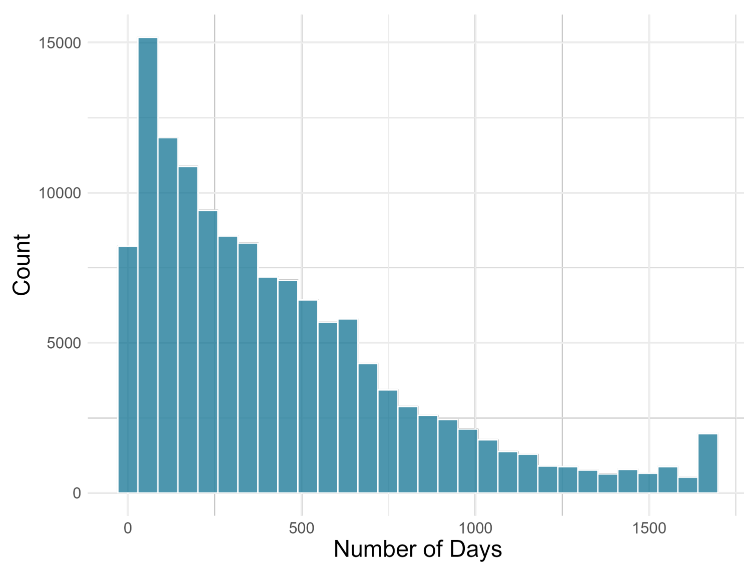
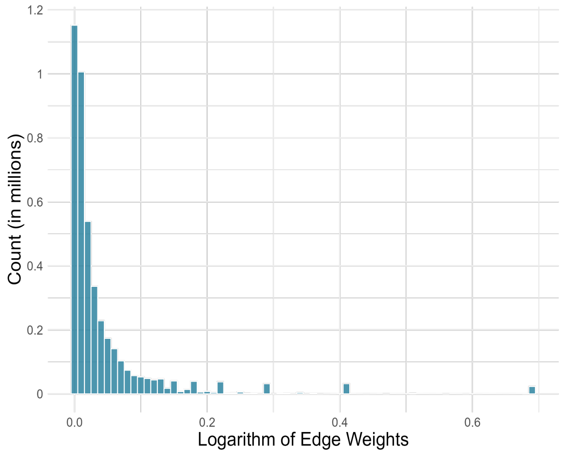
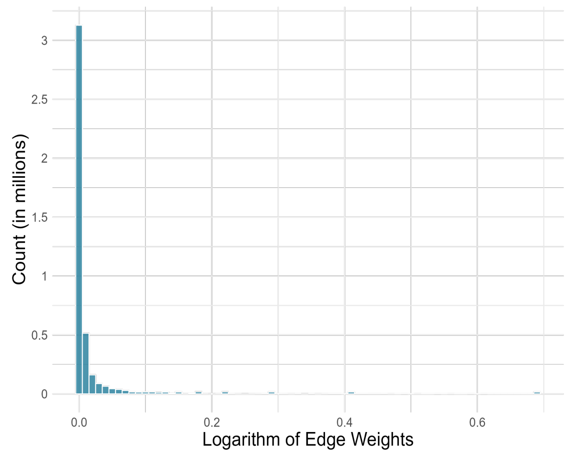


Figure B.3: Frequency of unique pairs of firms appearing in our final dataset

Notes: This figure shows the frequency with which ordered pairs of firms occur in our matched dataset of patent citations and listed firms occur over all Tuesdays. (Patents are published in the USPTO's Official Gazette only on Tuesdays.) This includes the dates on which a firm does not cite a previously cited firm.



(a) Top 10% firms by market value



(b) Bottom 10% firms by market value

Figure B.4: Edge weight distributions by market value of upstream firms

Notes: Figure B.4a displays the edge weight distribution in patent grants where the upstream firms are ranked within the top 10% of firms ranked by their market value. Figure B.4b displays the edge weight distribution in innovation where the upstream firms are ranked within the bottom 10% by their market value.

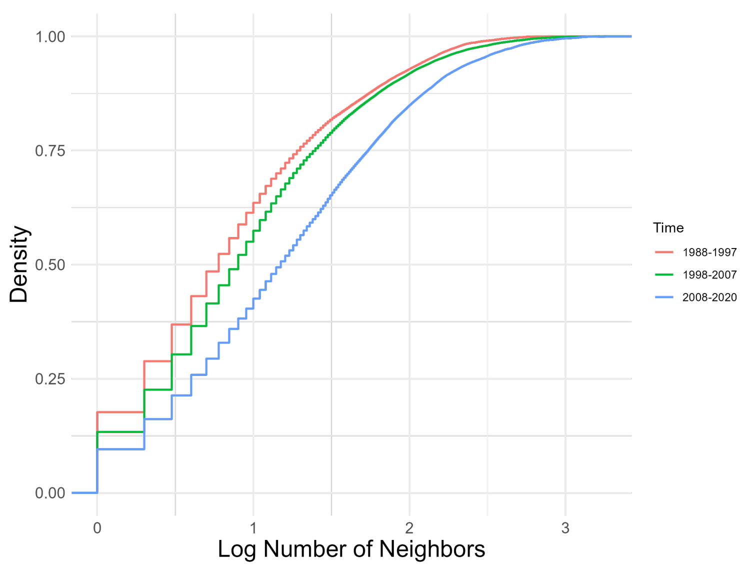


Figure B.5: Distribution of the size of neighborhoods of firms

Notes: This figure presents the cumulative distribution of the number of neighbors of firms, i.e. the number of firms cited by firms in their patents excluding themselves, across three time periods, namely years 1988 to 1997, 1998 to 2007 and 2008 to 2020. We note that the number of firms cited by firms in their patents has been growing over time.

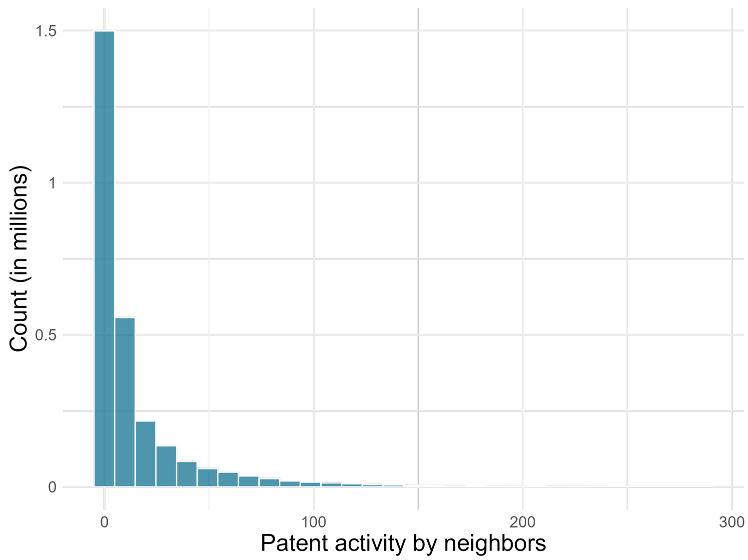


Figure B.6: Frequency of patent grants to upstream firms

Notes: For each firm that cites another, we identify the dates when the connection weight was non-zero and the cited firm was granted a patent. We then aggregate this data by the citing firm and date. As a result, this variable indicates the number of times the connected portion of a firm's network was active with patent activity. This figure underscores the observation that patent activity (the treatment) is not consistently present in our dataset.

C Patent grants and abnormal returns of firms

In this section, we provide justification for our choice of specific abnormal returns used in this study. We present a straightforward specification to examine the positive correlation between a firm's abnormal returns and the news of its own patents grants weighted by their market values borrowed from Kogan et al. (2017):

$$\alpha_{it} = c + \beta_1 \mathcal{P}_{it} + \mu_i + \mu_{\text{Ind}_i} + \delta_1 \alpha_{i,t-1} + \delta_2 \ln(V_{i,t-1}) + \tau_t + \varepsilon_{it} \tag{C.1}$$

Here α_{it} are the abnormal returns of firm i on date t; $\mathcal{P}$ represents patent grant activity on date t (such as incidence of patent grant, the number of patents granted, or the quality of patents granted on the date); τ_t account for variation by date specific characteristics. Firm i related controls contains $\alpha_{i,t-1}$ which is the lagged return from the previous week that accounts for mean reversing autocorrelation, laged market value of firm i, lagged book-to-market, and firm fixed effect. Our preferred measures of α_{it} and $\mathcal{P}$ are the three day averaged abnormal returns from date t, and the market value of patents granted during the week using Kogan et al. (2017), respectively.[25] The market values of patents measure the value of excess returns attributed to news about patent grants in the three days from the date of date of grant, which are directly relevant to our outcome measure. However, we include other measures of patenting activity for robustness.[26] $\mathcal{P}$ is 0 on days on which there is no granted patent, and positive whenever it generates any excess returns. In line with Kogan et al. (2017), we expect that patenting activity of a firm is positively correlated with its abnormal returns in the same week, i.e. β_1 is positive in estimating (C.1). The term ε_{it} comprises omitted variables that affect the abnormal return and idiosyncratic shocks on date t.

The results of estimating (C.1) are presented in Table C.1 for same day abnormal return (columns 1 to 3), its three-day average (columns 5 to 7) and weekly average values (columns 9 to 11). We demonstrate that, in line with literature, our estimated abnormal returns are significantly associated with lagged returns, market value and book-to-market ratios. (See columns 1, 5 and 9) Columns 2, 5 and 9 show that the market value of patents

[25]Note that Kogan et al. (2017) measure the market value generated within three days of patent grant, which aligns with our preferred measure of abnormal returns.

[26]These include their incidence on the date, the number of patents granted on the date, their level of technological breakthroughness (Kelly et al., 2021), and their impact on subsequent literature measured using patent citations in the years subsequent to their publication. Considering various measures of patenting activity are useful for both conceptual and statistical reasons. First, they allow for alternative measurements that capture different aspects of technological change and R&D activity of a firm. Second, large research R&D intensive firms, such as IBM or Apple, could potentially be always in treatment if we consider only incidence of patenting activity or have similar number of patents granted on all dates, thereby not providing sufficient variation for useful estimation. Alternative measures allows variation.

Table C.1: Patent grants to firms and their abnormal returns

Dependent Variables:	Same day α			Three-day averaged α			Weekly averaged α		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Patent value ($\mathcal{P}_{it}$)		0.564***	2.57***		0.566***	2.43***		-0.037	1.75***
		(2.67)	(11.4)		(4.34)	(17.9)		(-0.349)	(16.2)
Lagged market value of firm	-13.2***		-13.6***	-12.4***		-12.9***	-11.9***		-12.2***
	(-17.9)		(-18.2)	(-26.3)		(-26.7)	(-31.8)		(-32.1)
Lagged book-to-market ratio	-66.3***		-66.5***	-57.0***		-57.3***	-56.0***		-56.1***
	(-7.22)		(-7.25)	(-9.86)		(-9.90)	(-11.3)		(-11.4)
Lagged abnormal return	-0.187***	-0.183***	-0.187***	-0.096***	-0.094***	-0.096***	-0.063***	-0.061***	-0.063***
	(-20.3)	(-21.9)	(-20.3)	(-23.7)	(-23.1)	(-23.7)	(-20.0)	(-20.1)	(-20.0)
Fixed-effects									
Date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	2,455,039	2,682,421	2,455,039	2,359,993	2,580,175	2,359,993	2,280,193	2,492,114	2,280,193
R^2	0.01155	0.01118	0.01158	0.01325	0.01224	0.01332	0.01444	0.01245	0.01451
Within R^2	0.00613	0.00533	0.00616	0.00653	0.00495	0.00660	0.00627	0.00370	0.00634

Clustered (Date) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents the results of estimating (C.1). Our outcome variables of interest are the same day (columns 1 to 3), three-day averaged (columns 4 to 6) and weekly averaged abnormal returns (columns 7 to 9). The value of patents are borrowed from Kogan et al. (2017), which are 0 when there is no patent granted on a date, and positive whenever an excess return is generated to the patenting firm. The lagged market value of a firm is derived from the log of the previous month's market value of the firm, the lagged book-to-market value corresponds to the log of the previous year's book-to-market ratio, and the lagged abnormal return is the average of the preceding week's abnormal returns. The lagged market value of neighbors is the sum of the logged market values of firms in the neighborhood of the focal firm. We re-scale the abnormal returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate.

granted to a firm are indeed positively and significantly correlated with abnormal returns, thereby concurring with Kogan et al. (2017). Controlling for other factors related to firms, the effect of patenting activity continues to be strongly and significantly associated with abnormal returns. Moreover, it does not take away the effects driven by the auto-correlation or by its size and book-to-market value. Our preferred estimation comes from the three-day averaged return (reported in column 6) which suggests that a percentage change in the market value of patents is associated with a 2.43 basis point increase in the daily abnormal return. We note that the effects are the strongest on the same day return, and become progressively weaker over the duration of the week. However, the effects are no less than 1.75 daily basis points, which are quantitatively large. We interpret the results as a further validation of our measurement of abnormal returns in our analysis.

Although the estimates presented here are limited to using the value of patents, the results of estimating (C.1) continue to hold when we use alternative measures of patent value $\mathcal{P}$, such as the raw number of patents and the number of breakthrough patents granted on date t, in line with Table A.3.