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Essays in Finance

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To my beloved wife, Sanaz, whose endless love, patience, and unwavering support have been my guiding light through this journey. Your encouragement has made this accomplishment possible.
To my wonderful mother and father, for their unconditional love, wisdom, and sacrifices. You have been my foundation, and your belief in me has been my greatest strength.

Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

Statement of Conjoint Work: I confirm that Chapter 1 is jointly co-authored with Abhijit Tagade, to which I contributed 80% of the work. Chapter 2 is jointly co-authored with Navid Akbaripour, and I contributed 50% of the work.

I declare that my thesis consists of approximately 23,300 words.

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Abstract

In the first chapter, we study how innovation networks among firms cause interdependencies in their stock returns. Using patent grants and citation data from the United States Patent and Trademark Office, we find that patents generate positive abnormal returns not only for the innovating firm but also for firms that have previously cited them in their own patents. The magnitude of this financial spillover is directly proportional to the quality of the granted patents and the intensity of a firm's reliance on its upstream firms in the innovation network. The spillover effect is diminished when firms compete in the product market, but it is larger when the firms are also interconnected within the supply chain. Additionally, we find that the financial spillovers of innovation are restricted to firms that are directly connected in the innovation network. We quantify the spillovers and find that innovations generate large positive financial externalities on other firms.

The second chapter investigates the strategic behavior of chief executive officers (CEOs) in disclosing discretionary corporate news close to their contract renewal dates. Analyzing 296 fixed-term employment contracts of Standard & Poor's (S&P) 1500 firms covering the period from 2000 to 2009 and using contract length as an instrumental variable (IV), we show that, compared to the baseline, the number of discretionary news items is higher by 1.4 in the quarter preceding the renewal date and by 1.44 in the quarter following it. The sentiment of news items is higher by 0.45 in the quarter before the renewal date and lower by 0.35 in the subsequent quarter. This provides evidence of strategic disclosure of good news before, and clustering of bad news after, the contract renewal dates. This behavior is stronger among CEOs with a history of poor performance and weaker among those who also hold the position of chairman.

In the third chapter, I study the effect of mutual fund managers' learning and experience on their portfolio decisions and performance, with a particular focus on stock-specific experience. Using the total number of quarters a specific stock has been held in a manager's portfolio as a proxy for the manager's stock-specific experience, the findings show that managers consistently generate superior abnormal returns when

dealing with stocks on which they have more experience. The results show that, on average, each additional quarter of experience a manager has with a particular stock in their portfolio predicts a 2.7 basis point higher abnormal return for the stock in the following quarter. Additionally, this experience leads to a 2.06% ex-post increase in the proportionate value that the stock adds to the portfolio in the following quarter. The results not only highlight the effect of stock-specific experience on performance but also underscore the significant impact of industry-specific experience. Specifically, when fund managers with more experience in a given industry add a stock from the same industry that has not previously been in their portfolio, they achieve better performance with that stock in the next quarter compared to their peers.

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Chapter 1

Financial spillovers in innovation networks

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

— Isaac Newton, 1675

1.1 Introduction

Innovations in the form of intellectual property are key intangible assets of publicly traded companies. They generate the prospect of monopoly rents and reflect a firm's potential for future growth (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).

Innovations from important knowledge sources of a firm's research and development (R&D) can provide new ideas to develop subsequent downstream innovations (Acemoglu et al., 2016b, Liu and Ma, 2021). Therefore, innovations can generate large value for other firms through "knowledge spillovers," and an extensive literature shows their role in the diffusion of new knowledge (see Bloom et al., 2013).

This paper studies and quantifies the "financial spillovers" of innovation, namely the stock returns generated for a firm due to innovation by its sources of technological knowledge. Do financial markets account for technological knowledge dependencies? If securing a patent raises the returns of an innovating firm, does it also improve investors' view of other firms that stand to benefit from the knowledge? And if there is a reaction, can we utilize it to measure these spillover effects?

To answer these questions, we use administrative data on granted utility patents from the United States Patent and Trademark Office (USPTO) and detailed financial metrics of publicly listed firms. From the patent citations, we estimate knowledge dependencies between firms and construct a dynamic, directed innovation network à la Acemoglu et al. (2016b) for all listed US firms measured monthly from the 1980s to the present. In our innovation network, the nodes represent firms and the edges represent the share of patent citations a target firm (downstream) makes to a source innovating firm (upstream).[1] These edge weights roughly correspond to "knowledge input shares" and reflect how important a given firm finds another firm in crafting new innovations. On the financial side, throughout the paper, we use firms' returns — averaged over different time intervals since the reference date (patents' grant dates) — as our main outcome variable.

First, we find that the stock returns of technologically dependent firms do increase when a firm's upstream innovators are granted patents, and these increases in stock returns are directly proportional to the quality of the patent granted. These financial spillovers are more pronounced when the upstream firm makes a technological breakthrough.[2] Second, we verify that the results associated with innovation shocks to upstream firms have a larger effect if the upstream innovator is also a supplier of the firm. Third, since a firm securing patents could adversely affect investors' views about their rivals, we estimate the returns associated with the degree to which firms compete in the product market with their upstream innovators. We find that the returns are indeed diminished when firms intensely compete with their sources of technological knowledge, relative to when they do not.

Our quantification suggests that the financial spillovers generated are large, constituting about 20 percent of the additional returns associated with new innovations. A one-standard deviation increase in the value of patents granted to upstream innovators of a firm is associated with an additional 0.5 basis point daily abnormal return within three days of their grant. In comparison, a one-standard deviation increase in the value of a firm's own patent grants is associated with over two basis points of daily abnormal returns within three days of their grant.

Financial spillovers of innovation can be traced back to early theories emphasizing the importance of R&D externalities across firms and industries (Griliches, 1979). The concept that technological advancements in one firm or sector can influence the economic outcomes in another is prominent in the economic literature, particularly

[1]In the paper, we exclusively use "upstream" for source nodes and "downstream" for target nodes in the innovation network.

[2]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).

in endogenous growth theory (Romer, 1986). Here, 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. Bloom et al. (2013) expand upon the idea that innovations do not operate in silos. Firms often benefit from external R&D even when they do not directly invest in it. The diffusion of new knowledge through these spillovers aids in fostering more innovations across the industry.

Acemoglu et al. (2016b) build on the networked nature of innovation. Their research demonstrates the cascading effects of innovations where breakthroughs in one technology field can spur subsequent technological advancements in another. This not only establishes the interconnected landscape of innovations but also accentuates the importance of recognizing these dependencies. However, quantifying these spillovers among firms in financial terms remains a gap, one this study aims to address.

To determine and quantify the effects of innovation on other firms, we analyze the financial market's reaction to patent grants. 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 total value of an innovation may surpass the individual value realized by the innovating firm alone. Hence, we aim to leverage stock market reactions to patent announcements as a means to estimate the overall value of firms' innovation activities.

Using USPTO data, we construct a dynamic innovation network among firms, updated monthly. This network is directed, with edges extending from source firms (upstream firms in the innovation network) to target firms (downstream firms). The weight of an edge at any given time represents the proportion of non-self-citations that an upstream firm has received from a specific downstream firm over the preceding five-year period.

We extend our analysis to include all pairs of firms where one has cited the other at least once in the past. As the USPTO publishes information on the patents it grants in its *Official Gazette* every Tuesday, we incrementally expand the network each Tuesday to include new pairs while maintaining the inclusion of existing pairs, irrespective of the current edge weight between them in the network. Hence, at each time point, we identify a focal firm alongside all other firms that have been previously cited by this focal firm at least once. Based on the edge weights, we aggregate all the upstream firms associated with a given focal firm into a single node, termed as the "neighborhood" throughout this paper. This neighborhood encapsulates all potential upstream firms for a given focal firm and acts as a representative upstream firm.

In the following step, we evaluate the influence of patenting activity by the upstream neighborhood of any focal firm on its abnormal return. We use different measures of patent values published by the upstream firms, aggregate the values using the network weights, and examine the relationship between the patent values of aggregated upstream neighborhoods and the return realized by their downstream firms. To quantify the effect of patent activity on a firm's abnormal return, we control for the firm's return exposure to the Fama-French 3-factors (Fama and French, 1993) and the momentum factor (Carhart, 1997a). Since patenting activity can impact industry returns, and firms tend to exhibit a high degree of co-movement with their industry, we also control for industry returns to isolate the pure effect of patent activity through the innovation network on returns. Our findings show that the patenting activity of a firm's upstream neighborhood has an effect on the firm's abnormal return. A one-standard deviation increase in the value of upstream patents granted is associated with a 2.43 basis point increase in the daily abnormal return. We observe that the effects are most pronounced on the same day and fade out progressively over the course of the week. We redo the analysis with placebo weights and observe no significant effects. We also analyze the second-degree layer of the network and find that the financial spillover of innovation is localized to firms that are directly connected in the innovation network. Patenting activity by second-degree upstream firms does not have any effect on downstream firms' abnormal returns.

There are other channels besides knowledge spillovers through which one firm's innovation could affect other firms. One such channel is the supply chain. A firm that is upstream in the innovation network may also be a supplier and innovations by such a firm might produce more pronounced spillover effects on its dependents. As Cohen and Frazzini (2008) show, positive news for suppliers in the market permeates throughout the supply chain and is subsequently reflected in their customers' stock returns. Thus, the granting of patents to upstream firms in the innovation network that are also suppliers to focal firms might create even more positive externalities for their downstream firms.

A second alternative channel pertains to competition between firms in the product market. When an upstream firm innovates, it might bestow positive knowledge externalities upon its product-market competitors (Aghion et al., 2005). However, competitive forces, as delineated by Cohen and Levinthal (1989), should reduce some of these positive impacts.

To assess how innovation affects firms connected through the supply chain, we utilize the measure of vertical integration of firms from Frésard et al. (2020) as directed edge weights in a product-market network. We measure the innovation shock experienced by a downstream firm at any given time by the patenting activity of firms in its vicinity in this network, weighted by their degree of supplier relation to the firm. Our estimates indicate that, beyond the effects of innovation via knowledge spillover, innovations by suppliers strongly and significantly predict a firm's abnormal returns.

Similarly, using the competition measure introduced by Hoberg and Phillips (2010, 2016), which is a text-based product similarity measure, we examine the competition channel. Our results show that while competitors benefit from knowledge spillover, their competition with upstream firms diminishes the financial benefits they receive from knowledge spillovers.

The paper is organized as follows: Section 1.2 describes the data sources and the characteristics of the patent and financial market data used. In Section 1.3, we describe our construction of the innovation network and how we determine knowledge input shares (weights) based on patent citations between firms. Section 1.4 presents the main empirical findings. First, we present the results from a baseline model where we show how patent grants to a firm, as well as to its sources of technological knowledge, are positively and significantly associated with its returns. We show that our results continue to hold under alternative measurements of patenting activity. Second, we study whether these effects are driven by vertical relationships between firms operating in a supply chain and show that knowledge weights explain part of the unexplained return. Finally, Section 1.6 concludes.

1.2 Data and measurement

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

1.2.1 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.

1.2.2 Industry- and firm-level financial data

We source the stock returns and market values data from CRSP. Following (Carhart, 1997a, Fama and French, 1993), we use four-factor model in order to control for return exposures to pricing factors. The pricing factors were extracted from the Wharton

Research Data Services (WRDS) database.

Firms within a given industry or sector often exhibit correlated stock return behaviors, largely attributable to shared economic risk exposures 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.

The USPTO publishes information on the patents it grants in their *Official Gazette* every Tuesday.[3] We exploit this fact throughout this paper, and we define the calendar week to begin on Tuesday and end on Monday in measuring the betas.

Our industry classification adheres to the Fama-French 48-industry categorization. For the purpose of computing industry returns, we derive daily value-weighted industry returns using this classification framework.

1.2.3 Product-market linkages between firms

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[4] 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 firm innovates, then its downstream firms in the supply chain are likely to benefit from investors' expectations of their returns through improved inputs or

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

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

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.

1.2.4 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 1.1, we present the summary statistics for the study's key variables. Figure 1.4 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 1.5 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 1.6a 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 1.6b portrays the edge-weight distribution when the upstream node is positioned within the bottom 10 percent by market value. Lastly, Figure 1.8 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.

1.3 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).[5]

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 vertical relationship is important since it represents an asymmetric relationship between firms; shocks to one firm affect another firm depending 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.

[5]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).

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).

1.3.1 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:[6]

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 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

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

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:

$$g_{i,j,t} = \frac{\text{Citations } (j \to i) \text{ up to time } t}{\sum_{k(\neq i)} \text{Citations } (k \to i) \text{ up to time } t} \tag{1.1}$$

The backward citations weight $g_{i,j,t}$ measures the knowledge input share of firm j toward producing innovations by firm i.[7]

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 1.4 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.[8] 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.[9] 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

[7]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.

[8]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.

[9]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 contemporary technologies. However, we use 10-year and cumulative reference periods to test for long-run persistence.

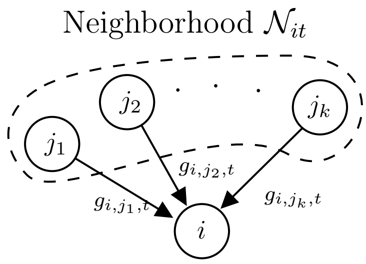


Figure 1.1: Directed innovation network among firms

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 (1.1).

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 1.1 for illustration). Indeed, the row weights of only those firms in the neighborhood also add up to 1:

$$\mathcal{N}_{it} = \{j \mid \exists t' \leq t : g_{ijt'} > 0\} \qquad \sum_{j \in \mathcal{N}_{it}} g_{i,j,t} = 1 \tag{1.2}$$

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 upstream 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.[10]

[10]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

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.[11]

1.4 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 innovation network and measure the technological knowledge dependency (i.e., input shares) of firms on other firms using equation (1.1). 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

patent citation between them.

[11] 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.

to the knowledge input share.

1.4.1 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 1.1). 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:

$$\mathcal{P}^g_{\mathcal{N}_{it}} = \sum_{j \in \mathcal{N}_{it}} g_{ijt} \mathcal{P}_{jt} \tag{1.3}$$

Our preferred measure is the (logged) value of patents as derived from Kogan et al. (2017).[12] 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

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

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 (1.4). Our outcome variable of interest is the return R_{it} of downstream firm i at date t:

$$R_{it} = c + \beta_1 \mathcal{P}^g_{\mathcal{N}_{it}} + \beta_2 \mathcal{P}_{it} + \underbrace{\delta_1 R_{i,t-1} + \delta_2 V_{i,t-1} + \delta_3 R_{\text{Ind}_{it}} + \delta_4 \text{ Exposure to factors} + \mu_i + \mu_{\text{Ind}_i}}_{\text{Firm } i\text{-related controls}} + \tau_t + \epsilon_{it} \tag{1.4}$$

where R_{it} are the excess 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 1.5 we show that Kogan et al. (2017) patent values for the downstream firms are strongly and positively correlated with stock returns in our specification). μ_i, μ_{Ind_i}, and τ_t account for firm-, firm's industry-, and date-specific fixed effects, respectively, and $R_{i,t-1}$ is the lagged return from the previous week that accounts for mean-reversing autocorrelation and $R_{\text{Ind}_{it}}$ is firm i's industry return at time t. We also consider the exposure of each firm's return to market, SMB, HML, and momentum. For example, the exposure to market return at time t would be $\beta_{i,t-1} R_{\text{market},t}$. Our preferred measure of R_{it} is the three-day averaged returns from date t, and $\mathcal{P}$ is the value of patents granted during the week using Kogan et al. (2017).[13] However, we include other measures of patenting activity for robustness.[14] $\mathcal{P}$ 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 ($V_{i,t-1}$) of the firm (in log scale) in a fuller specification to 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. In all subsequent specifications, we simply denote the lagged returns and market value terms collectively as firm i-specific controls.

[13] 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.

[14] 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.

Our coefficient of interest β_1 estimates whether patenting in the neighborhood is associated with higher abnormal returns for firm i.[15] We let the neighborhood be idiosyncratic to a firm given that firms are never perfect substitutes and have distinct market positioning.[16] The error term ϵ_{it} captures the idiosyncratic component of the return.

We present the results of estimating (1.4) in Table 1.2. 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-standard deviation increase in value generated by patents in the neighborhood is associated with at least a 0.58 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 1.3.1, to further eliminate industry-specific effects, we constructed an innovation network among firms operating in different industries. Table 1.3 presents the results of the regression analysis (regression 1.4) applied to this cross-industry network. As Table 1.3 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 (1.4), we use cross-industry knowledge input 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 break-

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

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

throughs using (1.3) by defining $\mathcal{P}_{jt}$ as the number of breakthrough patents granted to a firm j, and we estimate (1.4) 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 1.3 and 1.4. 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 0.5 to 1.5 basis points for a firm, and upstream breakthroughs, adjusted by their importance to a firm, are associated with a return that is 40 to 60 percent of their size. These findings highlight that new innovations granted to knowledge sources generate quantitatively large financial spillovers in firms.

In the subsequent sections, 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.

1.4.2 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 1.2.3). 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:

$$\mathcal{P}^{S}_{\mathcal{N}_{it}} = \sum_{j \in \mathcal{N}_{it}} Vert^{S}_{ijt} \mathcal{P}_{jt} \tag{1.5}$$

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 (1.4) using weights of vertical integration in place of knowledge input shares:

$$R_{it} = c + \beta_1 \mathcal{P}^{S}_{\mathcal{N}_{it}} + \beta_2 \mathcal{P}_{it} + \text{Firm } i\text{-related controls} + \tau_t + \epsilon_{it} \tag{1.6}$$

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 (1.6) in the columns 1, 3, and 5 of Table 1.5.

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 standard deviation increase in the exposure to the patents granted to suppliers in the neighborhood is associated with an increase of over 0.4 basis points in the daily abnormal returns of a firm.

To find whether it is the vertical relationships in the product market that drive the results we observe in Table 1.2, we combine the covariates of (1.4) and (1.6) and report them in columns 2, 4, and 6 of Table 1.5 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 1.2); 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.[17]

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.

1.4.3 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 firm.[18] 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

[17] 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.

[18] 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.

(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 compute the competition-weighted innovation shock to a firm i as:

$$\mathcal{P}^c_{\mathcal{N}_{it}} = \sum_{j \in \mathcal{N}_{it}} Comp_{ijt} \mathcal{P}_{jt} \tag{1.7}$$

where $\mathcal{P}_{jt}$ is the patent grant activity of an upstream firm j on date t. Using the values of (1.7), we estimate the following specification:

$$R_{it} = c + \beta_1 \mathcal{P}^c_{\mathcal{N}_{it}} + \beta_2 \mathcal{P}_{it} + \text{Firm } i\text{-related controls} + \tau_t + \epsilon_{it} \tag{1.8}$$

For our main analysis, $\mathcal{P}$ is the value of patents granted borrowed from Kogan et al. (2017), τ_t is the date fixed effect, and firm-related controls include the lagged returns (preceding week), market value of the firm (preceding month), industry return, firm and industry fixed effects. Our coefficients of interest is β_1, which estimates whether competition-weighted innovation shocks affect returns.

We present the results of estimating (1.8) in Table 1.6. Columns 2, 5, and 8 show 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. A one-standard deviation increase in patent value of competitors decrease the abnormal return of the firm by 0.87 basis point in a daily basis.

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 (1.4 and 1.6; about 0.5 basis points), nor does it affect the coefficients of the competition-weighted shock.[19] 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.

[19]Note that the coefficients of competition-weighted shock are directly quantitatively comparable to knowledge-input-share-weighted shock since the variables are normalized.

1.4.4 Upstream innovators using 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 (1.1) 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 to) their true weight g_{ijt} for some upstream firms.[20] We calculate the exposure of firm i to patent grants of its upstream innovators using placebo weights as:

$$\mathcal{P}_{\mathcal{N}_{it}}^{\text{Placebo}} = \sum_{j\in\mathcal{N}_{it}} \frac{1}{|\mathcal{N}_{it}|}\mathcal{P}_{jt} \tag{1.9}$$

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

$$R_{it} = c + \beta_1\mathcal{P}_{\mathcal{N}_{it}}^{\text{Placebo}} + \beta_2\mathcal{P}_{it} + \text{Firm } i\text{-related controls} + \tau_t + \epsilon_{it} \tag{1.10}$$

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 (1.10) are presented in Table 1.7 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 (0.46 for three-day return) is smaller than the coefficients in Table 1.2 (0.58 for three-day return), and the association

[20] 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.

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 robustness test highlights the role of the particular knowledge input shares in capturing a firm's exposure to patent grants to other firms; in particular, knowledge input shares capture important information about what affects a firm's abnormal returns.

1.4.5 Second-degree connections in the innovation network

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 connections alone. Indeed, it is possible that they have a cascading effect in generating returns across the second- and further-degree connections.[21] 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 1.2).

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

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

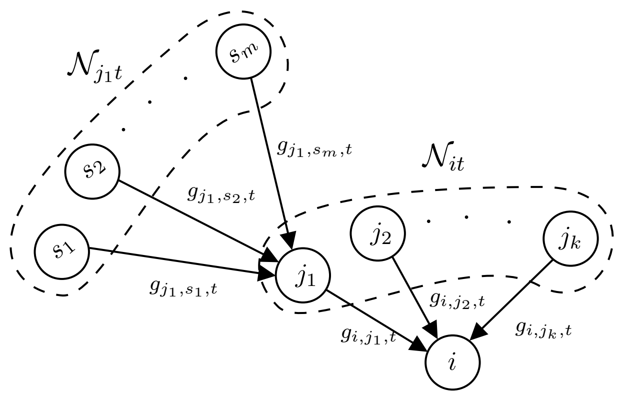


Figure 1.2: Second-degree innovation connections among firms

Notes: This figure illustrates the second-degree connections within the innovation network at time t. Firms $j_1, \cdots, j_k$ belong to the neighborhood $\mathcal{N}_{it}$ of firm i, meaning that 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 but do not belong to firm i's neighborhood. The 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 $g_{i,j_1,t}$ (the knowledge share from intermediary firm j_1 to firm i). This product is then normalized by the aggregate of all the knowledge shares that firm i receives from all firms in the second-degree connections in the innovation network.

grants to firms that are its second-degree connections as

$$\mathcal{P}_{\mathcal{N}_{it}^{2nd}} = \frac{1}{\sum_{j \in \mathcal{N}_{it}} \sum_{s \in \mathcal{N}_{it}^{2nd}} g_{ijt} \times g_{jst}} \sum_{j \in \mathcal{N}_{it}} \sum_{s \in \mathcal{N}_{it}^{2nd}} g_{ijt} \times g_{jst} \mathcal{P}_{st} \tag{1.11}$$

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:

$$R_{it} = c + \beta_1 \mathcal{P}_{\mathcal{N}_{it}^{2nd}} + \beta_2 \mathcal{P}_{it} + \text{Firm } i\text{-related controls} + \tau_t + \epsilon_{it} \tag{1.12}$$

where $\mathcal{P}$ is the value of patents granted, whose preferred measure is their market value that we borrow from Kogan et al. (2017), τ_t is the date fixed effect, and firm-related controls include the lagged returns (preceding week), market value of the firm (preceding month), industry return, firm and industry fixed effects. 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 (1.12) in Table 1.8. 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.

1.5 Patent values and abnormal returns

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 patent grants weighted by their market values, which are borrowed from Kogan et al. (2017):

$$R_{it} = c + \beta_1 \mathcal{P}_{it} + \text{Firm } i\text{-related controls} + \tau_t + \varepsilon_{it} \tag{1.13}$$

Here R_{it} are the 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 accounts for variation by date-specific characteristics. Firm i-related controls contain $R_{i,t-1}$, which is the lagged return from the previous week that accounts for mean-reversing autocorrelation, lagged market value of firm i, firm fixed effects, and industry fixed effects. Our preferred measures of R_{it} and $\mathcal{P}$ are the three-day averaged returns from date t and the market value of patents granted during the week using Kogan et al. (2017), respectively.[22] 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 the grant, which are directly relevant to our outcome measure. However, we include other measures of patenting activity for robustness.[23] $\mathcal{P}$ is 0 on days on which there is no granted patent and positive whenever the firm generates any excess returns.

[22] 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.

[23] 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 the 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.

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, that is, β_1 is positive in estimating (1.13). The term ε_{it} comprises omitted variables that affect the abnormal return and idiosyncratic shocks on date t.

The results of estimating (1.13) are presented in Table 1.9 for same-day return (columns 1 to 3) and its three-day average (columns 4 to 6) and weekly average values (columns 7 to 9). Columns 3, 6, and 9 show that the market value of patents granted to a firm are indeed positively and significantly correlated with 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 returns. Moreover, it does not take away the effects driven by the autocorrelation or by its size. Our preferred estimation comes from the three-day averaged return (reported in column 6) which suggests that a one-standard deviation change in the market value of patents (in logarithm) 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 is quantitatively large.

Although the estimates presented here are limited to using the value of patents, the results of estimating (1.13) 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 1.4.

1.6 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 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.

1.7 Figures

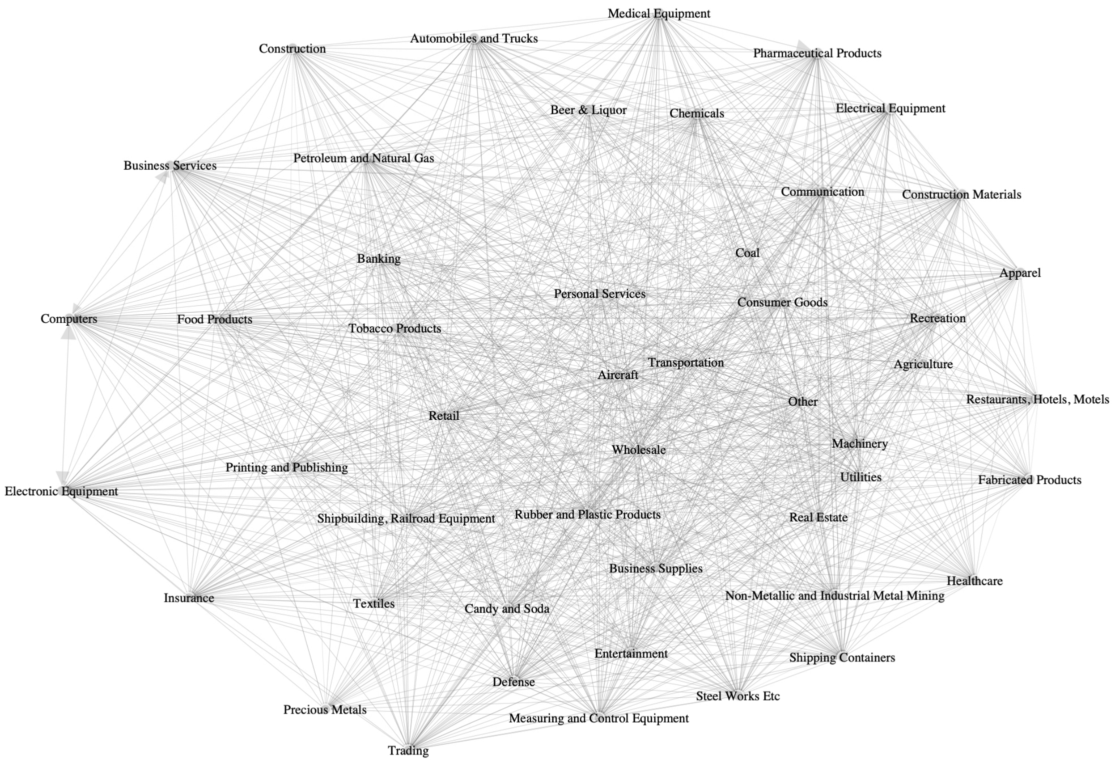


Figure 1.3: Directed innovation network across industries

Notes: This figure illustrates the directed innovation network among firms operating across different industries by their SIC classifications. The network is specific to the last date in our data. 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.

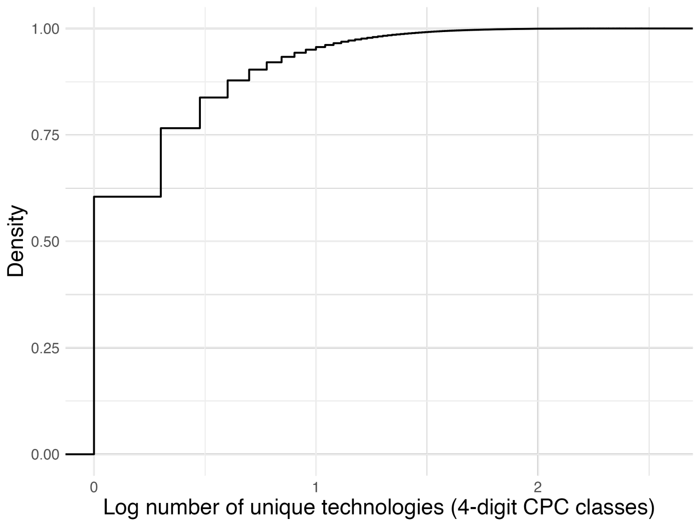


Figure 1.4: Distribution of the number of distinct technologies cited by a firm

Notes: This figure shows the cumulative distribution of the number of distinct 4-digit CPC technology 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 base-10 log scale. Despite over 600 available CPC classes, most firms, over 60 percent, cite just 1 technology in their patents, and over 9 out of 10 firms cite less than 10 distinct technologies in their lifetime.

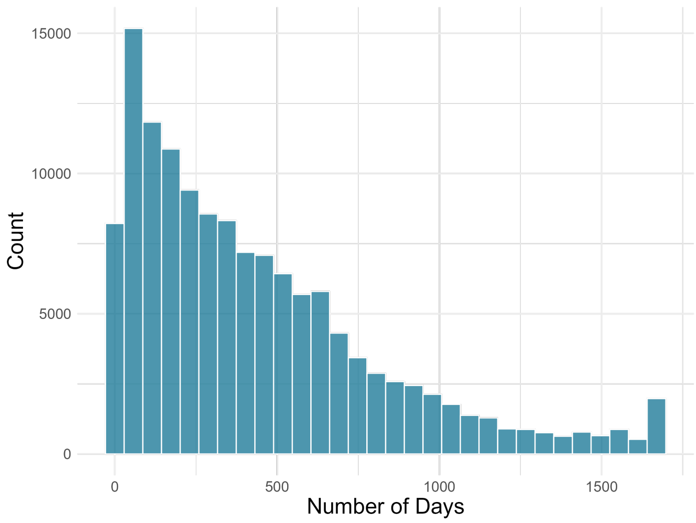
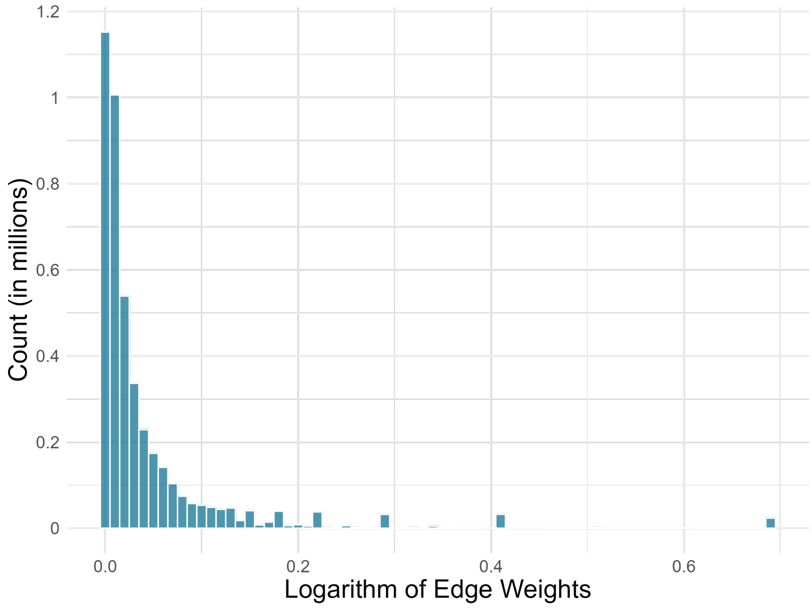
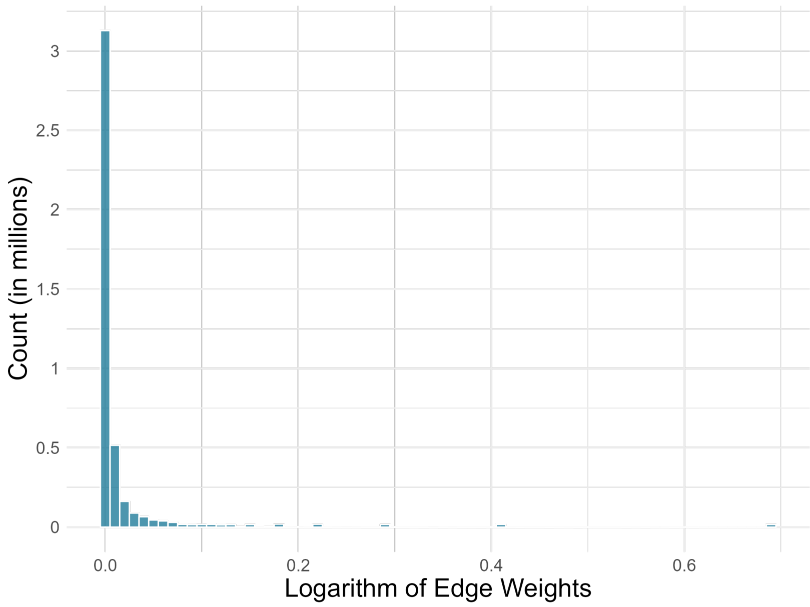


Figure 1.5: Frequency of unique pairs of firms appearing in our final dataset

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 1.6: Edge-weight distributions based on the upstream's market value rankings

Notes: Figure 1.6a displays the edge-weight distribution in innovation where the upstream node ranks within the top 10 percent in terms of market value. Figure 1.6b displays the edge-weight distribution in innovation where the upstream node ranks within the bottom 10 percent in terms of market value.

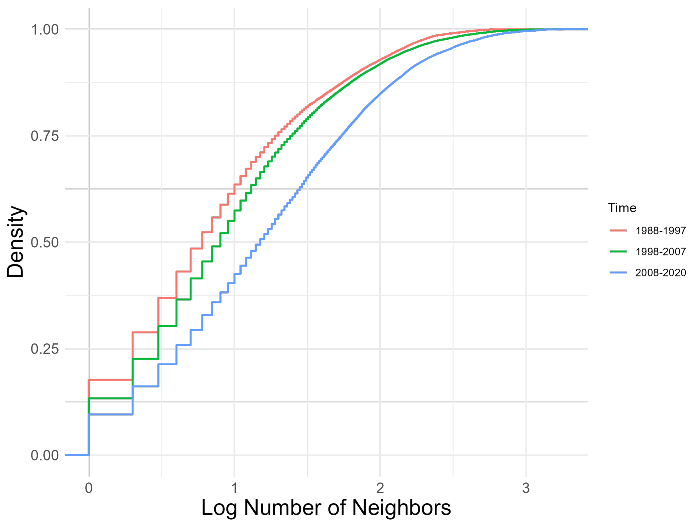


Figure 1.7: Neighborhood size

Notes: Cumulative distribution function of the number of neighbors each firm had during three time periods.

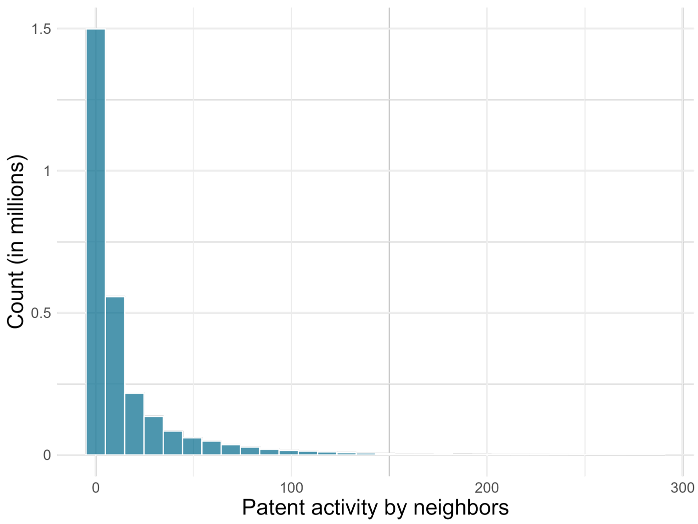


Figure 1.8: Patent activity

Notes: For each firm that cites another, we identify 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.

1.8 Tables

Table 1.1: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Number of firms in neighborhoods							
Full neighborhood	2754709	34	68	1	3	31	880
Subset with $g > 0$	2356870	29	58	1	3	28	775
Subset with $g > 0.1$	1641370	2.3	1.5	1	1	3	9
Directed edge weights in innovation network (knowledge input shares)							
Weight g	92835710	0.02	0.071	0	0	0.011	1
Firm characteristics							
Citing firm market value	92439053	27340	67946	0.031	821	21212	1187463
Cited firm market value	92182373	26515	65902	0.041	748	20375	1187463
Upstream firms' patent characteristics							
Number of breakthroughs	2695440	0.062	0.66	0	0	0	77
1 year citations	2695440	0.13	1.9	0	0	0	590
3 year citations	2695440	1.3	14	0	0	0	3354
5 year citations	2695440	2.9	28	0	0	0	6374
Value of patents	2695440	8.3	56	0	0	0	2657
Downstream firms' patent characteristics							
Number of breakthroughs	2754709	0.061	0.66	0	0	0	77
1 year citations	2754709	0.13	1.9	0	0	0	590
3 year citations	2754709	1.2	14	0	0	0	3354
5 year citations	2754709	2.8	28	0	0	0	6374
Value of patents	2754709	8.1	56	0	0	0	2657
Hoberg-Phillips and Frésard-Hoberg-Phillips values of between-firm relationships							
Product market competition	92835710	0.031	0.048	0	0	0.047	0.97
Potential of vertical integration	92835710	0.0023	0.0058	0	0	0.00057	0.1
Frequency of ordered firm pairs	204956	453	389	1	147	646	1670

Notes: This table provides a summary of the data statistics. The values of patents are borrowed from Kogan et al. (2017). The count of breakthroughs follows the methodology of Kelly et al. (2021). The product-market competition is a text-based product similarity measure based on Hoberg and Phillips (2010, 2016) and 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 1.2: Upstream patenting activity and downstream abnormal returns

Dependent Variables:	Same-day return			Three-day averaged return			Weekly averaged return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Patent value of upstream innovators ($\mathcal{P}^g_{\mathcal{N}_{it}}$)	0.4982	0.4744	0.6003	0.5525**	0.5129**	0.5779***	0.6135***	0.5958***	0.6418***
	(1.228)	(1.194)	(1.510)	(2.487)	(2.393)	(2.683)	(3.341)	(3.395)	(3.650)
Patent value ($\mathcal{P}_{it}$)	2.922***	2.839***	3.295***	3.025***	2.952***	3.198***	2.285***	2.231***	2.399***
	(9.088)	(9.248)	(10.75)	(15.93)	(16.21)	(17.62)	(13.85)	(14.31)	(15.32)
Lagged market value of firm	-28.25***	-27.59***	-31.82***	-28.19***	-27.68***	-29.98***	-28.25***	-27.83***	-29.41***
	(-10.94)	(-11.20)	(-12.87)	(-17.97)	(-18.35)	(-19.73)	(-19.49)	(-20.64)	(-21.59)
Industry return		53.26***	52.80***		33.32***	33.12***		29.46***	29.36***
		(47.95)	(45.77)		(48.66)	(46.72)		(62.25)	(61.13)
Lagged return			-33.25***			-17.78***			-12.18***
			(-22.18)			(-24.16)			(-23.30)
Exposure to market	91.06***	83.72***	82.63***	46.30***	42.30***	41.81***	28.32***	25.52***	25.20***
	(33.99)	(33.84)	(35.69)	(35.49)	(36.05)	(36.78)	(20.16)	(19.31)	(19.68)
Exposure to SMB	36.68***	34.71***	34.96***	24.81***	23.10***	23.53***	17.87***	16.46***	16.82***
	(17.18)	(17.31)	(19.13)	(26.44)	(27.07)	(28.14)	(17.82)	(18.34)	(18.48)
Exposure to HML	30.59***	26.19***	25.92***	19.30***	16.37***	16.29***	12.48***	10.34***	10.39***
	(23.65)	(22.49)	(22.64)	(18.64)	(16.86)	(16.87)	(18.54)	(16.77)	(17.02)
Exposure to Momentum	28.81***	24.34***	24.55***	21.35***	18.28***	18.52***	15.50***	13.15***	13.33***
	(23.75)	(22.86)	(23.23)	(30.07)	(28.94)	(30.21)	(19.44)	(18.07)	(18.01)
Fixed-effects									
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	2,685,931	2,681,008	2,681,008	2,584,435	2,578,831	2,578,831	2,494,464	2,488,837	2,488,837
R^2	0.09	0.09	0.10	0.12	0.12	0.13	0.13	0.14	0.14
Within R^2	0.02	0.03	0.03	0.03	0.04	0.04	0.03	0.04	0.04

Notes: This table presents the results of estimating (1.4). All explanatory variables are normalized. Our outcome variables of interest are the same-day (columns 1 to 3), three-day averaged (columns 4 to 6) and weekly averaged 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 (1.3). The lagged market value of a firm is derived from the log of the previous month's market value of the firm and the lagged return is the average of the preceding week's returns. We rescale the returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate. Standard errors are clustered at the date level. In parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 1.3: Upstream patenting activity in other industries and abnormal returns of downstream firms

Dependent Variables:	Same-day return			Three-day averaged return			Weekly averaged return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Patent value of upstream neighborhood ($\mathcal{P}^{g,\text{CrossInd}}_{\mathcal{N}_{it}}$)	0.4564	0.4772	0.5836	0.4986**	0.4553**	0.5122**	0.4233**	0.3984**	0.4399***
	(1.123)	(1.193)	(1.461)	(2.345)	(2.211)	(2.471)	(2.389)	(2.377)	(2.606)
Patent value ($\mathcal{P}_{it}$)	2.944***	2.859***	3.323***	3.061***	2.986***	3.233***	2.292***	2.236***	2.406***
	(8.906)	(9.066)	(10.57)	(15.88)	(16.17)	(17.55)	(13.61)	(14.08)	(15.08)
Lagged market value of firm	-27.84***	-27.17***	-31.43***	-28.03***	-27.52***	-29.83***	-28.02***	-27.60***	-29.18***
	(-10.67)	(-10.94)	(-12.66)	(-17.80)	(-18.24)	(-19.61)	(-19.36)	(-20.59)	(-21.54)
Industry return		53.67***	53.19***		33.67***	33.47***		29.72***	29.61***
		(47.84)	(45.48)		(49.37)	(47.28)		(62.04)	(60.82)
Lagged return			-33.21***			-17.58***			-12.08***
			(-22.86)			(-25.14)			(-24.08)
Exposure to market	91.10***	83.53***	82.44***	46.44***	42.30***	41.82***	28.27***	25.38***	25.07***
	(33.99)	(33.88)	(35.50)	(34.73)	(35.50)	(36.50)	(20.21)	(19.35)	(19.76)
Exposure to SMB	35.94***	33.83***	34.10***	24.47***	22.60***	23.01***	17.54***	16.00***	16.36***
	(17.79)	(17.89)	(19.90)	(26.40)	(27.26)	(28.51)	(17.94)	(18.58)	(18.71)
Exposure to HML	31.01***	26.56***	26.28***	19.32***	16.34***	16.27***	12.55***	10.37***	10.42***
	(24.00)	(22.83)	(23.03)	(18.16)	(16.36)	(16.37)	(18.68)	(16.89)	(17.12)
Exposure to Momentum	28.71***	24.23***	24.45***	21.29***	18.21***	18.45***	15.53***	13.18***	13.35***
	(23.79)	(22.94)	(23.36)	(30.10)	(28.97)	(30.13)	(18.97)	(17.55)	(17.48)
Fixed-effects									
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	2,561,994	2,557,214	2,557,214	2,465,195	2,459,753	2,459,753	2,379,420	2,373,953	2,373,953
R^2	0.09	0.09	0.10	0.12	0.13	0.13	0.13	0.14	0.15
Within R^2	0.02	0.03	0.03	0.03	0.04	0.04	0.02	0.04	0.04

Notes: This table presents the results of estimating (1.4) for the cross-industry network. All explanatory variables are normalized. Our outcome variables of interest are the same-day (columns 1 to 3), three-day averaged (columns 4 to 6) and weekly averaged 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 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 (1.3). The lagged market value of a firm is derived from the log of the previous month's market value of the firm and the lagged return is the average of the preceding week's returns. We rescale the returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate. Standard errors are clustered at the date level. In parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 1.4: 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:	Same-day return	Three-day averaged return	Weekly averaged return	Same-day return	Three-day averaged return	Weekly averaged return	Same-day return	Three-day averaged return	Weekly averaged return
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Patent value of upstream innovators ($\mathcal{P}^g_{\mathcal{N}_{it}}$)	0.2054	0.4466**	0.4526**	1.148***	0.5574***	0.5320***	0.4386	0.4154*	0.4054**
	(0.5504)	(2.093)	(2.573)	(2.811)	(3.411)	(3.890)	(1.048)	(1.746)	(2.138)
Patent value ($\mathcal{P}_{it}$)	2.205***	2.073***	1.536***	1.444***	0.9685***	0.8654***	0.8752**	0.7155***	0.6187***
	(11.49)	(17.43)	(16.16)	(4.532)	(3.996)	(4.622)	(2.502)	(3.583)	(3.722)
Lagged market value of firm	-31.14***	-29.33***	-28.90***	-42.32***	-38.32***	-37.40***	-30.82***	-29.00***	-28.67***
	(-12.75)	(-19.47)	(-21.47)	(-23.50)	(-41.42)	(-53.82)	(-12.59)	(-19.27)	(-21.32)
Industry return	52.80***	33.12***	29.36***	49.39***	31.24***	28.03***	52.81***	33.13***	29.37***
	(45.77)	(46.75)	(61.15)	(77.77)	(79.49)	(99.79)	(45.78)	(46.73)	(61.15)
Lagged return	-33.23***	-17.76***	-12.17***	-37.50***	-19.61***	-13.45***	-33.23***	-17.76***	-12.17***
	(-22.17)	(-24.14)	(-23.28)	(-26.95)	(-31.90)	(-30.85)	(-22.17)	(-24.14)	(-23.27)
Exposure to market	82.63***	41.82***	25.21***	81.79***	41.87***	24.61***	82.63***	41.82***	25.20***
	(35.69)	(36.80)	(19.70)	(81.90)	(78.07)	(53.57)	(35.70)	(36.81)	(19.70)
Exposure to SMB	34.96***	23.53***	16.82***	34.45***	23.47***	17.18***	34.96***	23.53***	16.82***
	(19.14)	(28.13)	(18.48)	(48.26)	(58.27)	(54.22)	(19.14)	(28.13)	(18.48)
Exposure to HML	25.93***	16.30***	10.39***	25.97***	16.43***	10.58***	25.92***	16.30***	10.39***
	(22.64)	(16.87)	(17.03)	(43.22)	(19.95)	(32.84)	(22.64)	(16.86)	(17.02)
Exposure to Momentum	24.55***	18.52***	13.33***	23.84***	18.37***	13.43***	24.55***	18.53***	13.33***
	(23.23)	(30.21)	(18.02)	(39.16)	(34.52)	(27.49)	(23.23)	(30.21)	(18.01)
Fixed-effects									
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	2,681,008	2,578,831	2,488,837	1,994,383	1,921,464	1,851,545	2,681,008	2,578,831	2,488,837
R^2	0.10	0.13	0.14	0.09	0.13	0.14	0.10	0.13	0.14
Within R^2	0.03	0.04	0.04	0.03	0.04	0.04	0.03	0.04	0.04

Notes: This table presents the results of estimating varying specifications of (1.4) for innovation breakthroughs. All explanatory variables are normalized. Our outcome variables of interest are the same-day (columns 1, 4, and 7), three-day averaged (columns 2,5,and 8), and weekly averaged returns (columns 3,6, and 9). In the first three 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 decile of values of all patents published within the same year. In the second three columns, our definition of breakthrough is related to Kelly et al. (2021), which is 0 when there is no patent granted on a date and positive whenever the patent is identified as a breakthrough. In the last three columns, we rerun 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 1.3) 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 and the lagged return is the average of the preceding week's returns. We rescale the returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate. Standard errors are clustered at the date level. In parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 1.5: Exposure to patent grants to product-market suppliers and abnormal returns

Dependent Variables:	Same-day return		Three-day averaged return		Weekly averaged return	
	(1)	(2)	(3)	(4)	(5)	(6)
Patent value of suppliers ($\mathcal{P}^S_{\mathcal{N}_{it}}$)	1.148***	1.131***	0.4085**	0.3927**	0.3556***	0.3399**
	(3.777)	(3.722)	(2.348)	(2.256)	(2.663)	(2.544)
Patent value of upstream innovators ($\mathcal{P}^g_{\mathcal{N}_{it}}$)		0.5867		0.5760***		0.6389***
		(1.478)		(2.754)		(4.039)
Patent value ($\mathcal{P}_{it}$)	3.273***	3.269***	3.197***	3.194***	2.397***	2.393***
	(13.02)	(13.01)	(21.99)	(21.96)	(21.22)	(21.19)
Lagged market value of firm	-31.81***	-31.84***	-29.95***	-29.99***	-29.37***	-29.41***
	(-22.92)	(-22.95)	(-40.87)	(-40.92)	(-53.37)	(-53.43)
Industry return	52.80***	52.80***	33.12***	33.12***	29.36***	29.36***
	(89.42)	(89.42)	(87.78)	(87.78)	(111.5)	(111.5)
Lagged return	-33.25***	-33.25***	-17.77***	-17.78***	-12.18***	-12.18***
	(-29.14)	(-29.14)	(-40.65)	(-40.65)	(-37.57)	(-37.58)
Exposure to market	82.63***	82.63***	41.81***	41.81***	25.20***	25.20***
	(86.94)	(86.94)	(80.32)	(80.32)	(58.62)	(58.62)
Exposure to SMB	34.96***	34.96***	23.53***	23.53***	16.82***	16.82***
	(51.55)	(51.55)	(62.57)	(62.57)	(58.00)	(57.99)
Exposure to HML	25.92***	25.92***	16.29***	16.29***	10.39***	10.39***
	(43.36)	(43.36)	(20.99)	(20.99)	(34.82)	(34.83)
Exposure to Momentum	24.54***	24.54***	18.52***	18.52***	13.33***	13.33***
	(44.30)	(44.30)	(36.72)	(36.72)	(31.35)	(31.36)
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,681,008	2,681,008	2,578,831	2,578,831	2,488,837	2,488,837
R^2	0.10	0.10	0.13	0.13	0.14	0.14
Within R^2	0.03	0.03	0.04	0.04	0.04	0.04

Notes: This table presents the results of estimating (1.6). All explanatory variables are normalized. Our outcome variables of interest are the same-day (columns 1 to 2), three-day averaged (columns 3 to 4), and weekly averaged 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 (1.5). We control for innovation shock the firm faces from its technological knowledge sources (computed using 1.3) 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 and the lagged return is the average of the preceding week's returns. We rescale the returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate. Standard errors are clustered at the date level. In parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 1.6: Effect of exposure to patent grants to product-market rivals on abnormal returns

Dependent Variables:	Same-day return			Three-day averaged return			Weekly averaged return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Patent value of competitors ($\mathcal{P}^c_{\mathcal{N}_{it}}$)	-0.0879	-0.1419	-0.3799	-0.7063***	-0.7605***	-0.8719***	-0.5063***	-0.5656***	-0.6713***
	(-0.2259)	(-0.3647)	(-0.9338)	(-3.071)	(-3.305)	(-3.617)	(-2.890)	(-3.228)	(-3.651)
Patent value of upstream innovators ($\mathcal{P}^g_{\mathcal{N}_{it}}$)		0.6061	0.5997		0.6088***	0.6058***		0.6647***	0.6619***
		(1.527)	(1.510)		(2.910)	(2.895)		(4.203)	(4.183)
Patent value of suppliers ($\mathcal{P}^S_{\mathcal{N}_{it}}$)			0.7294**			0.3411**			0.3238**
			(2.533)			(2.020)			(2.499)
Patent value ($\mathcal{P}_{it}$)	3.315***	3.318***	3.326***	3.317***	3.321***	3.325***	2.487***	2.491***	2.495***
	(12.99)	(13.00)	(13.03)	(22.46)	(22.49)	(22.51)	(21.61)	(21.65)	(21.67)
Lagged market value of firm	-31.77***	-31.80***	-31.81***	-29.87***	-29.91***	-29.91***	-29.31***	-29.35***	-29.35***
	(-22.87)	(-22.90)	(-22.90)	(-40.73)	(-40.78)	(-40.78)	(-53.18)	(-53.24)	(-53.24)
Industry return	52.80***	52.80***	52.80***	33.12***	33.12***	33.12***	29.36***	29.36***	29.36***
	(89.42)	(89.42)	(89.42)	(87.78)	(87.77)	(87.77)	(111.5)	(111.5)	(111.5)
Lagged return	-33.25***	-33.25***	-33.25***	-17.78***	-17.78***	-17.78***	-12.18***	-12.18***	-12.18***
	(-29.14)	(-29.14)	(-29.14)	(-40.65)	(-40.65)	(-40.65)	(-37.57)	(-37.58)	(-37.58)
Exposure to market	82.63***	82.63***	82.63***	41.81***	41.81***	41.81***	25.20***	25.20***	25.20***
	(86.94)	(86.94)	(86.94)	(80.33)	(80.32)	(80.32)	(58.62)	(58.63)	(58.62)
Exposure to SMB	34.96***	34.96***	34.96***	23.53***	23.53***	23.53***	16.82***	16.82***	16.82***
	(51.55)	(51.54)	(51.55)	(62.57)	(62.57)	(62.57)	(58.00)	(57.99)	(57.99)
Exposure to HML	25.92***	25.92***	25.92***	16.30***	16.30***	16.30***	10.39***	10.39***	10.39***
	(43.36)	(43.36)	(43.36)	(20.99)	(20.99)	(20.99)	(34.83)	(34.83)	(34.83)
Exposure to Momentum	24.54***	24.55***	24.55***	18.52***	18.52***	18.52***	13.33***	13.33***	13.33***
	(44.30)	(44.30)	(44.30)	(36.72)	(36.72)	(36.72)	(31.35)	(31.36)	(31.36)
Fixed-effects									
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	2,681,008	2,681,008	2,681,008	2,578,831	2,578,831	2,578,831	2,488,837	2,488,837	2,488,837
R^2	0.10	0.10	0.10	0.13	0.13	0.13	0.14	0.14	0.14
Within R^2	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.04

Notes: This table presents the results of estimating varying specifications of (1.8). All explanatory variables are normalized. Our outcome variables of interest are the same-day (columns 1 to 3), three-day averaged (columns 4 to 6), and weekly averaged 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. *Patent value of competitors* is computed using (1.7). We control for innovation shock the firm faces from its technological knowledge sources (computed using 1.3) 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 and the lagged return is the average of the preceding week's returns. We rescale the returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate. Standard errors are clustered at the date level. In parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 1.7: Exposure to patent grants to upstream innovators using placebo weights

Dependent Variables:	Same-day return		Three-day averaged return		Weekly averaged return	
	(1)	(2)	(3)	(4)	(5)	(6)
Patent value of upstream innovators ($\mathcal{P}^{\text{Placebo}}_{\mathcal{N}_{it}}$)	0.7669	0.7608	0.4678	0.4450	0.3354	0.3186
	(1.438)	(1.429)	(1.635)	(1.559)	(1.470)	(1.403)
Patent value of suppliers ($\mathcal{P}^{S}_{\mathcal{N}_{it}}$)		0.7338**		0.3485		0.3336*
		(2.016)		(1.604)		(1.771)
Patent value of competitors ($\mathcal{P}^{c}_{\mathcal{N}_{it}}$)		-0.2935		-0.8002**		-0.6010*
		(-0.4513)		(-2.079)		(-1.889)
Patent value ($\mathcal{P}_{it}$)	3.332***	3.348***	3.221***	3.336***	2.418***	2.501***
	(10.89)	(11.33)	(17.85)	(18.79)	(15.58)	(17.10)
Lagged market value of firm	-31.78***	-31.78***	-29.95***	-29.88***	-29.37***	-29.32***
	(-12.86)	(-12.76)	(-19.71)	(-19.57)	(-21.56)	(-21.40)
Industry return	52.80***	52.80***	33.12***	33.12***	29.36***	29.36***
	(45.77)	(45.77)	(46.72)	(46.72)	(61.13)	(61.12)
Lagged return	-33.25***	-33.25***	-17.78***	-17.78***	-12.18***	-12.18***
	(-22.18)	(-22.18)	(-24.16)	(-24.16)	(-23.29)	(-23.29)
Exposure to market	82.63***	82.63***	41.81***	41.81***	25.20***	25.20***
	(35.69)	(35.69)	(36.78)	(36.78)	(19.68)	(19.68)
Exposure to SMB	34.96***	34.96***	23.53***	23.53***	16.82***	16.82***
	(19.13)	(19.13)	(28.14)	(28.14)	(18.48)	(18.48)
Exposure to HML	25.92***	25.92***	16.29***	16.30***	10.39***	10.39***
	(22.64)	(22.64)	(16.87)	(16.87)	(17.02)	(17.02)
Exposure to Momentum	24.55***	24.55***	18.52***	18.52***	13.33***	13.33***
	(23.23)	(23.23)	(30.21)	(30.21)	(18.01)	(18.01)
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,681,008	2,681,008	2,578,831	2,578,831	2,488,837	2,488,837
R^2	0.10	0.10	0.13	0.13	0.14	0.14
Within R^2	0.03	0.03	0.04	0.04	0.04	0.04

Notes: This table presents the results of estimating (1.10). All explanatory variables are normalized. Our outcome variables of interest are the same-day (columns 1 to 2), three-day averaged (columns 3 to 4), and weekly averaged 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 (1.9). The lagged market value of a firm is derived from the log of the previous month's market value of the firm and the lagged return is the average of the preceding week's returns. We rescale the returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate. Standard errors are clustered at the date level. In parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 1.8: Patent grants to second-degree connections in innovation network

Dependent Variables:	Same-day return			Three-day averaged return			Weekly averaged return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Patent value of 2nd deg. neighborhood ($\mathcal{P}_{\mathcal{N}_{it}^{2nd}}$)	0.9766	0.9601	0.9569	0.5189	0.3358	0.4059	0.5797	0.3117	0.3690
	(1.346)	(1.325)	(1.321)	(1.193)	(0.8353)	(1.006)	(1.565)	(0.9058)	(1.064)
Patent value ($\mathcal{P}_{it}$)	3.164***	3.150***	3.627***	3.287***	3.194***	3.437***	2.419***	2.341***	2.505***
	(9.550)	(9.586)	(11.03)	(16.45)	(16.83)	(18.18)	(14.13)	(14.57)	(15.56)
Lagged market value of firm	-29.03***	-28.96***	-33.59***	-28.95***	-28.26***	-30.52***	-28.45***	-27.92***	-29.44***
	(-12.17)	(-12.16)	(-14.19)	(-19.74)	(-20.60)	(-22.35)	(-20.00)	(-21.80)	(-22.99)
Industry return		39.11***	38.93***		34.74***	34.53***		30.51***	30.39***
		(28.08)	(28.20)		(51.74)	(49.44)		(62.57)	(61.61)
Lagged return			-31.71***			-16.03***			-10.91***
			(-23.92)			(-24.22)			(-22.61)
Exposure to market	88.33***	87.83***	86.76***	47.42***	42.94***	42.43***	29.04***	25.96***	25.59***
	(33.20)	(33.21)	(34.35)	(33.80)	(34.82)	(35.28)	(20.34)	(19.58)	(19.80)
Exposure to SMB	35.74***	35.57***	35.71***	25.54***	23.77***	24.13***	18.70***	17.19***	17.52***
	(19.98)	(19.97)	(22.09)	(28.08)	(28.76)	(29.76)	(18.46)	(19.04)	(19.22)
Exposure to HML	27.47***	27.10***	26.91***	19.97***	16.70***	16.62***	12.51***	10.15***	10.18***
	(20.53)	(20.39)	(20.53)	(24.77)	(24.97)	(24.35)	(20.00)	(18.51)	(18.74)
Exposure to Momentum	24.49***	24.11***	24.37***	21.45***	17.99***	18.19***	15.13***	12.49***	12.66***
	(18.85)	(18.78)	(19.29)	(30.89)	(31.64)	(33.08)	(20.60)	(20.09)	(20.17)
Fixed-effects									
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	2,021,419	2,021,419	2,021,419	2,021,419	2,021,419	2,021,419	1,953,196	1,953,078	1,953,078
R^2	0.15	0.15	0.15	0.15	0.16	0.16	0.16	0.17	0.17
Within R^2	0.02	0.02	0.03	0.04	0.05	0.05	0.03	0.04	0.05

Notes: This table presents the results of estimating (1.12). All explanatory variables are normalized. Our outcome variables of interest are the same-day (columns 1 to 3), the three-day averaged (columns 4 to 6), and weekly averaged 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 second-degree upstream innovators is captured in the value of second-degree neighbors' patents ($\mathcal{P}_{\mathcal{N}_{it}^{2nd}}$) computed using equation (1.11). The lagged market value of a firm is derived from the log of the previous month's market value of the firm and the lagged return is the average of the preceding week's returns. We rescale the returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate. Standard errors are clustered at the date level. In parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 1.9: Downstream patenting activity and its abnormal returns

Dependent Variables:	Same day return			Three-day averaged return			Weekly averaged return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Patent value ($\mathcal{P}_{it}$)	2.926***	2.843***	3.300***	3.030***	2.956***	3.202***	2.290***	2.236***	2.404***
	(9.099)	(9.259)	(10.76)	(15.96)	(16.24)	(17.65)	(13.89)	(14.35)	(15.37)
Lagged market value of firm	-28.21***	-27.56***	-31.78***	-28.16***	-27.64***	-29.94***	-28.21***	-27.79***	-29.36***
	(-10.92)	(-11.18)	(-12.86)	(-17.94)	(-18.33)	(-19.71)	(-19.44)	(-20.60)	(-21.56)
Industry return		53.26***	52.80***		33.32***	33.12***		29.46***	29.36***
		(47.95)	(45.78)		(48.65)	(46.72)		(62.25)	(61.13)
Lagged return			-33.25***			-17.77***			-12.18***
			(-22.18)			(-24.16)			(-23.29)
Exposure to market	91.06***	83.72***	82.63***	46.30***	42.30***	41.81***	28.31***	25.52***	25.20***
	(33.99)	(33.84)	(35.69)	(35.48)	(36.04)	(36.78)	(20.16)	(19.30)	(19.68)
Exposure to SMB	36.68***	34.71***	34.96***	24.81***	23.10***	23.53***	17.87***	16.46***	16.82***
	(17.18)	(17.31)	(19.13)	(26.44)	(27.07)	(28.14)	(17.82)	(18.34)	(18.48)
Exposure to HML	30.59***	26.19***	25.92***	19.30***	16.37***	16.29***	12.48***	10.34***	10.39***
	(23.65)	(22.49)	(22.64)	(18.63)	(16.86)	(16.86)	(18.54)	(16.77)	(17.01)
Exposure to Momentum	28.81***	24.34***	24.54***	21.35***	18.28***	18.52***	15.50***	13.15***	13.33***
	(23.74)	(22.86)	(23.23)	(30.07)	(28.94)	(30.21)	(19.43)	(18.07)	(18.01)
Fixed-effects									
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	2,685,931	2,681,008	2,681,008	2,584,435	2,578,831	2,578,831	2,494,464	2,488,837	2,488,837
R^2	0.09	0.09	0.10	0.12	0.12	0.13	0.13	0.14	0.14
Within R^2	0.02	0.03	0.03	0.03	0.04	0.04	0.02	0.04	0.04

Notes: This table presents the results of estimating (1.13). All explanatory variables are normalized. Our outcome variables of interest are the same-day (columns 1 to 3), three-day averaged (columns 4 to 6), and weekly averaged 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 lagged market value of a firm is derived from the log of the previous month's market value of the firm and the lagged return is the average of the preceding week's returns. We rescale the returns so that the coefficients can be interpreted as the change in basis points for each additional unit of the covariate. Standard errors are clustered at the date level. In parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Chapter 2

Do CEOs Manipulate News? Evidence from Fixed-term Employment Contracts

2.1 Introduction

The renewal of a CEO's contract is pivotal for both the firm and its CEO, marking a critical juncture for aligning corporate leadership with shareholder interests. Boards of directors, as representatives of shareholders, rely on performance indicators to make informed decisions about CEO contract renewals. If CEOs can influence these indicators through strategic management of information, this may have significant implications for corporate governance. Understanding the extent and impact of any such manipulation is significant not only for the immediate stakeholders — the CEO and the board — but also for investors, regulators, and the overall market, which depends on transparent and accurate information for its efficient operation. In this paper, we address a critical question: Do CEOs strategically time their news disclosures around their contract renewal dates? Furthermore, if timing of corporate news disclosures is occurring around contract renewals, what strategies are employed?

We use 296 fixed-term employment contracts of S&P 1500 firms, covering the period from 2000 to 2009, to analyze CEOs' strategic behavior close to their contract renewal dates. Our analysis incorporates data from the Capital IQ Key Development dataset, which aggregates information from a diverse range of public sources such as company press releases, regulatory filings, and company websites. We specifically focus on discretionary news items. Employing the Loughran and McDonald (2011) lexicon, we assign sentiment scores to each news item. We use the contract length as an IV for the actual contract renewal date, enabling us to test our main hypothesis: CEOs strategically time good news releases right before the renewal date while clustering and withholding bad news to release after the renewal date.

Our results indicate that CEOs release more discretionary news items around the renewal date of their contracts. The number of news items is higher than the baseline by 1.40 one quarter before and by 1.44 one quarter after the renewal date (the average number of news items per quarter is 5.2). The sentiment of news items rises by 0.45 above the baseline one quarter before the renewal date. In contrast, the sentiment one quarter after the renewal date falls by 0.35 below the baseline (the average sentiment of news items is approximately -0.63 per news item). Hence, we find clear evidence of strategic behavior.[1] The strategic behavior is more pronounced in managers with previous poor performance, and it is less evident in CEOs who are also hold the position of chairman around their contract's renewal date. Previous poor performance may heighten CEOs' incentive to positively influence the board's perception before a renewal decision, while CEOs who also serve as chairman likely have greater control and influence over the renewal process, reducing the need for such short-term strategic disclosures.

Information disclosure can reflect firm performance and, consequently, may influence decisions by the board of directors, such as hiring or firing the CEO. This effect may occur through two distinct channels: firstly, the number and sentiment of news releases can directly impact board decisions, including the continuation or termination of an executive's contract. Secondly, information disclosure can affect stock prices, which are often used as signals by directors. Stock returns serve as proxies for CEO performance, making them one of the main factors boards consider when deciding on contract renewals. Thus, by strategically timing and clustering their information disclosures, CEOs may influence stock prices and increase the likelihood of their contract renewal.

An important concern regarding the potential use of this strategic tool is its efficacy within a rational expectations framework. In other words, can strategic information disclosure by CEOs be effective in the presence of rational investors? If the rational investors fully internalize CEOs potential strategic disclosure, then this behavior would no longer be effective for CEOs. According to the theoretical side of this literature, there are conditions under which investors do not fully internalize strategic disclosure by CEOs, thereby making such disclosure effective for CEOs. For example, Dye (1985)

[1] This strategic behavior may involve the disclosure of good news and clustering of bad news, or increased diligence close to the contract renewal date. We will discuss this in more detail in Section 2.4.

analyzes a scenario in which, given no information disclosure by managers, investors are uncertain whether the non-disclosure is due to the nonexistence of information or its adverse content. This uncertainty on the part of investors deters adverse selection and leads to partial disclosure in equilibrium. Additionally, Lang and Lundholm (1993), Darmouni (2020), and Wagenhofer (1990) predict that, in the presence of uncertainty and disclosure costs, firms whose performance exceeds a certain threshold will disclose, while those below the threshold will not. Therefore, when investors are not fully certain about the existence of information, CEOs could effectively benefit from strategic disclosure of their information.

As shown by Cziraki and Groen-Xu (2020), the time left on a CEO's contract is a strong predictor of turnover. Both the likelihood of turnover and the sensitivity of turnover to performance intensify as the contract nears its expiration. Based on these findings, and considering that a part of news disclosures by CEOs is discretionary and not required by law (as noted by Edmans et al. (2018), "news releases do not occur automatically when corporate events take place but are often a discretionary decision of the CEO"), it is logical to examine CEO behavior as the contract approaches its expiration and renewal date. CEOs may use this period to increase the chances of their contract being renewed, potentially by timing or clustering discretionary news disclosures.

Using corporate news items from the Capital IQ Key Development dataset, the ordinary least squares (OLS) estimates show that, on average, CEOs disclose 1.54 more discretionary news items than the baseline in the quarter preceding the actual renewal date, and 0.87 more in the quarter following it. Additionally, textual analysis of the news items reveals that the sentiment of these discretionary news items is 0.42 higher than the baseline in the quarter leading up to the renewal, yet declines by 0.24 and 0.38 below the baseline in the first and second quarters after the renewal date, respectively.

The main problem with the OLS estimations in analyzing the effects of contract renewal dates on CEO behavior is that the dates may be determined endogenously based on the performance of the firm or CEO. Although employment contracts often state potential dates for extending the contract (See Figure A1 in A.2, panel C), the actual renewal dates may still be endogenously determined. To solve this issue, we use the ex-ante contract length as an instrument for the renewal date. The contract length is determined long before the renewal date (as shown in Figure 2.1). A contract's length may correlate with the CEO's past performance, making the scheduled renewal date endogenous ex-ante. However, it cannot be correlated with new information about the CEO's performance arriving after the contract's start. Therefore, ex-post, the contract length can be used as a pre-determined instrument for the actual renewal date.

Using contract lengths as an exogenous IV, we estimate contract renewal dates and the quarters before and after them. Reduced-form IV estimates show that, on average, the number of discretionary news items disclosed by CEOs is higher than the baseline one quarter before and two quarters after the renewal date. The results also indicate that the sentiment of discretionary news items is above the baseline one quarter before, but falls below the baseline by in the first and second quarters after the expected renewal date, respectively. These results indicate a causal relationship between the actual renewal date, the number of news items, and the sentiment of news items disclosed around that date.

We also run a two-stage least squares (2SLS) specification with all predicted quarter indicators as instruments for the actual quarter indicators (indicators of one and two quarters before, and one and two quarters after, the renewal dates). The results indicate that, on average, CEOs release 1.4 and 1.44 more news items compared to the baseline in the quarter before and the quarter after the actual renewal date, respectively. The sentiment of these news items is 0.45 higher than the baseline one quarter before, but 0.35 lower one quarter after the renewal date.

Therefore, we identify a distinct pattern of news disclosure by CEOs around their contract renewal dates. The pattern shows that CEOs release more discretionary news items around the renewal date of their contracts. Moreover, there is a significant shift in the sentiment of these news items. The sentiment of news items increases before and decreases after the renewal date, compared to the baseline.

There is an extensive empirical literature on executives' strategic behavior, to which this paper contributes. CEOs can leverage strategic information disclosure to influence stock prices and subsequently benefit from those changes. For example, Edmans et al. (2018) show that CEOs tend to reallocate news toward months in which their equity vests and away from adjacent months. Rahman et al. (2020) investigate whether CEOs strategically increase information uncertainty surrounding their insider stock purchases. They find that in the month before and during CEO stock purchases, information uncertainty in their news releases increases, which correlates with lower stock prices. We contribute by providing evidence that CEOs strategically release information to affect the stock price in order to increasing the likelihood of their contract being renewed.

Kothari et al. (2009) focus on strategic timing of information releases by firms, showing that managers delay disclosure of bad news relative to good news. Acharya et al. (2011) show that bad market news can prompt firms to immediately release negative information, while good market news tends to delay the release. Consequently, their model predicts a clustering of negative announcements. Kasznik and Kremer (2014) find that managers strategically time their bad news forecasts around scheduled releases of macroeconomic news. Specifically, they find a significant increase in the frequency of bad news forecasts on days with scheduled releases of the Federal Funds Rate by the FOMC and the Employment Situation Summary by the Bureau of Labor Statistics releases. Dimitrov and Jain (2011) argue that annual shareholder meetings provide an opportunity for shareholders to express their concerns regarding corporate performance. In response to shareholder pressure, managers tend to report positive corporate news prior to these meetings. We contribute by showing evidence of clustering of negative announcements before CEOs' contract renewal date.

The remainder of the paper is structured as follows. Section 2.2 explains the datasets used in our analysis. Section 2.3 discuss the empirical specifications. Section 2.4 presents our empirical results, and Section 2.5 concludes.

2.2 Data

This section describes the variables used in our analysis. Variable definitions are provided in Table A1 in A.1. The initial data on contracts has been collected by Moqi Groen-Xu[2] from regulatory filings exhibits and, when available, from the Corporate Library. The initial dataset contains information on 3,992 fixed-term employment contracts of S&P 1500 firms from 2000 to 2009. Numerous duplicate contracts were identified in the dataset and subsequently excluded from our analysis. Additionally, we identified contracts lacking essential information, such as start dates, renewal dates, or contract lengths. We also found several contracts with incorrect entries, including instances where the start date occurred after the renewal date, contracts with a length of zero, and contracts with a renewal period longer than the contract length. All these erroneous entries are excluded from the analysis. Additionally, part of the data was dropped when we merged the contracts data with the Capital IQ key developments, Stocks returns from Center for Research in Security Prices (CRSP).[3]

For some missing contract terms in the initial dataset, we collect the data summaries of contract terms from proxy filings, 10-Ks, and the Capital IQ key developments. The variables in this dataset are: Ticker, Cusip, company's name, company's

[2]We extend our gratitude to Moqi Groen-Xu for granting access.

[3]We merged the contract dataset with the Capital IQ key developments using the link between Ticker and GVKEY, and then merged it with stock return data using the link between GVKEY and PERMNO.

Address, CEO's first name, CEO's surname, start date, leave date, renewal date, contract length, salary, stock awards percentage, and percentage of total shares owned. After filtering and cleaning the data, the final sample includes 296 different contracts that have been renewed, belonging to 270 different firms and 270 different CEOs.

Our analyses link CEO contracts to news releases. We collect data on news releases from the Capital IQ Key Developments database. Capital IQ Key Developments consist of information from public news sources, company press releases, regulatory filings, call transcripts, investor presentations, stock exchanges, regulatory websites, and company websites. We stratify news into discretionary (where the timing is likely under the CEO's control, such as conferences, client and product announcements, and special dividends) and non-discretionary (such as earnings announcements or annual general meetings). For linking the two datasets, we use the Wharton Research Data Services (WRDS) link file, which assigns a unique GVKEY to each Ticker. Additionally, we only keep news items with announcement dates that fall within the period when the corresponding CEOs were leading the firms.

In order to determine the sentiment of a news item, we use the sentiment lexicon provided by Loughran and McDonald (2011). They find that almost three-fourths of negative word counts in 10-K filings based on the Harvard dictionary are typically not negative in a financial context. By examining all words that occur in at least 5% of the SEC's 10-K universe, they create a list of words that typically have a negative meaning in financial reports, and they show that their negative word list is significantly related to announcement returns. This lexicon contains 2,355 words labeled as Negative and 354 words labeled as Positive.

Another variable in this study is CEO performance. We use the monthly average of CAPM abnormal returns of firms under the control of a CEO from the start of her contract up to two quarters before the contract's renewal date as a proxy for the CEO's performance. The source of our data on monthly stock returns is CRSP. Abnormal returns have been computed using a 36-month rolling regression.

We also use the BoardEx dataset to determine whether the CEOs for whom we have contract details were also chairmen of the board around the time of their contracts' renewal. We link this data to the contract sample using the names of the CEOs and the corresponding corporate names. In 86 out of 296 contracts, the CEOs also held the position of chairman.

Table 2.1 presents summary statistics for the contracts and news. Panel A reports statistics on all contract lengths, renewed contract lengths, the timing of contract renewals (the time between the start date and the renewal date of renewed contracts), the ratio of contract timing to contract length, and the time difference between the actual renewal date and the predicted renewal date based on contract length. 204 contracts out of 296 contracts has been renewed after one year. Panel B shows the distribution of contract lengths. Approximately 58% of contracts have a length of 3 years. Panel B shows the average of contract timing to contract length for different contract lengths. Panel C presents the news statistics. This panel includes the total number of news items, the monthly average of news items, the total number of discretionary news items,[4] and the number of news items corresponding to the categories of annual general meetings, board meetings, and quarterly and yearly earnings announcements. Panel D shows statistics on CEO performance.

Figures 2.2a and 2.2b show the histograms of all contract lengths and renewed contract lengths, respectively. Figure 2.3a illustrates the histogram of the renewal timings. This figure shows most of the contracts has been renewed after one year. Figure 2.3b shows the histogram of renewal timings to contract lengths ratio. Based on this figure, most contracts have been renewed after approximately 40% of the contract length has passed.

Table 2.2 provides examples of news items from the Capital IQ Key Developments. In Panel A, news items 1 and 2 are examples of positive news, and news items 3 and 4 are examples of bad news. Panel B shows examples of non-discretionary news. Item 1 relates to an annual general meeting, number 2 to a board meeting, and number 3 to an earnings announcement. While the main source of CEO contract data used in this paper is SEC filings we obtained some missing information on the start day of contracts in Capital IQ Key Development. Panel C shows examples of news about CEOs contract from this database.

In order to classify news items, we use textual analysis. We read several news items in order to find keywords that the news items usually use to refer to these categories. For example, news headlines announcing annual general meetings often contain the phrase "annual general meeting." We, therefore, treat headlines containing this phrase as news items about annual meetings. We search for "board meeting" within the news headlines to detect board meetings. Finally, when a headline contains all of the words "earning," "quarter or year," and "report," then we assign the corresponding news item to the last non-discretionary category, earning announcements.

[4]Following Edmans et al. (2018), we categorize news as discretionary or non-discretionary, with non-discretionary news including annual general meetings, board meetings, and quarterly and yearly earnings announcements.

2.3 Methodology and regressions

We use two panel regressions in this paper. The panel consists of all daily news items corresponding to each contract, along with the relevant details of each contract. The first regression analyzes the effect of the contract renewal date on the number of news items. As explained in Section 2.2, we exclude non-discretionary news, which consist of all news items about annual general meetings, board meetings, and earning announcement.

$$\text{News Items}_{it} = \alpha + \sum_{j=1}^{2} \beta_j Pre_{itj} + \sum_{j=1}^{2} \theta_j Post_{itj} + \gamma \text{Controls}_{it} + \mu_i + \tau_t + \epsilon_{it} \quad (2.1)$$

News Items_{it} is the total number of news items for firm i in the quarter that includes the day t (The quarters for each contract are defined by their distance from the contract's renewal date). Since we don't aggregate daily observations on a quarterly basis, News Items_{it} has the same value for all days t within a given quarter. To account for the constant value of News Items_{it} across days in a quarter, we run regression 2.1 with weights that are the inverse of the total number of news items (observations) for contract i in the corresponding quarter, applied to each day t. We apply the weighted regression approach in all subsequent regressions where News Items_{it} is the dependent variable.

Pre_{itj} is a dummy that equals 1 when the news item is released j quarter(s) before the renewal date, and zero otherwise. $Post_{itj}$ is a dummy equals 1 when the news item is released j quarter(s) after the renewal date, and zero otherwise.

We control for CEO performance and whether the CEO is also chairman or not as they could be confounding factors that may influence both the number/sentiment of news items and the CEO's incentive to behave strategically close to her contract's renewal date. When a CEO has performed well, she may not find it beneficial to disclose news strategically. On the other hand, relatively poor performance may make it optimal for the CEO to use news disclosure as a strategic tool. From another perspective, performance is an observable and public part of the CEO's action. To derive the pure effect of the strategic disclosure behavior of the CEO (i.e., the unobservable part), we control for the CEO's performance (i.e., the observable part) in our analysis. If a CEO is also the chairman of the board, she may have more influence over the board's decisions, potentially reducing the need for strategic news disclosures. Alternatively, she could feel more pressure to manage perceptions leading up to the renewal.

μ_i and τ_t represent firm and calendar month fixed effects, respectively. In all regressions, when we control for performance and chairman, we drop the firm fixed effect. This is because, out of 296 contracts, we have 270 different firms. So, the firm fixed effect would eliminate the variation in performance for many firms with a single contract in the sample data and is also collinear with performance in some sub-sample analyses.

In the second regression, we analyze the renewal date's effect on the news sentiment. We calculate the number of positive and negative words within the news texts using the sentiment dictionary provided by Loughran and McDonald (2011), and define sentiment of a given news item following Smales (2014):

$$\text{Sentiment} \;=\; \text{Number of Positive Words} \;-\; \text{Number of Negative Words}$$

Then we run the following regression equation:

$$\text{Sentiment}_{it} = \alpha + \sum_{j=1}^{2} \beta_j Pre_{itj} + \sum_{j=1}^{2} \theta_j Post_{itj} + \gamma \text{Controls}_{it} + \mu_i + \tau_t + \epsilon_{it} \qquad (2.2)$$

Sentiment_{it} is the sentiment of a single news item released by the firm corresponding to contract i on day t.

2.3.1 Identification Strategy

To estimate the causal effect of a contract renewal date on the strategic disclosure of news, we face an endogeneity problem. As discussed in the introduction, the timing of the renewal date may be endogenous and, for example, could depend on the news released by the firm or on the CEO's performance. The OLS estimates in (2.1) and (2.2) might therefore be biased. To address this problem, we use contract length—the time between the start date and the expiration date—as an exogenous IV. The timeline of a contract is shown in Figure 2.1. First, the agreement between the board and CEO is written, and the fixed length of the contract is determined. This is long before the expiration (and renewal) date of the contract. A contract's length may also correlate with the CEO's past performance, making the scheduled renewal date endogenous ex-ante. However, it cannot be correlated with new information about the CEO's performance arriving after the contract's start. Therefore, ex-post, the contract length can be used as a pre-determined instrument for the renewal date.

To use contract lengths as a predictor of renewal dates, we first calculate the average ratio of renewal timing to contract length for different contract lengths. Since the number of contracts with lengths of 1 year, 7 years, 8 years, and 10 years is small, we group 1-year and 2-year contracts together, as well as contracts with lengths of more than 5 years. Then we compute the average ratio for each group. The predicted renewal timing for a contract is obtained by multiplying the average ratio by the contract length of the corresponding contract. Consequently, the predicted renewal date would be calculated as follows:

$$\text{Renew}\hat{\text{a}}\text{l Date}_i - \text{Start Date}_i = (\overline{\frac{\text{Renewal Timing}_i}{\text{Contract Length}_i}}) \text{ Contract Length}_i \tag{2.3}$$

Using predicted values from (2.3), we define dummies for the quarters around the predicted renewal date. We analyze a one-year window: two quarters before the renewal date to two quarters after the predicted renewal date.

$$P\hat{o}st_1 = \begin{cases} 1 & \text{if } 0 \leq t - \text{Renew}\hat{\text{a}}\text{l Date} < 1 \\ 0 & \text{otherwise} \end{cases} \qquad P\hat{r}e_1 = \begin{cases} 1 & \text{if } 0 \leq \text{Renew}\hat{\text{a}}\text{l Date} - t < 1 \\ 0 & \text{otherwise} \end{cases}$$
$$P\hat{o}st_2 = \begin{cases} 1 & \text{if } 1 \leq t - \text{Renew}\hat{\text{a}}\text{l Date} < 2 \\ 0 & \text{otherwise} \end{cases} \qquad P\hat{r}e_2 = \begin{cases} 1 & \text{if } 1 \leq \text{Renew}\hat{\text{a}}\text{l Date} - t < 2 \\ 0 & \text{otherwise} \end{cases} \tag{2.4}$$

By taking the average of both sides of (2.3), we can conclude that $\text{Renew}\hat{\text{a}}\text{l Date}$ is an unbiased estimator of the actual renewal date for contracts with a fixed length. As shown in Table 2.1, in our sample, the average difference between the predicted renewal date and the actual renewal date is -2.8 days, which is close to 0. This indicates that the estimated quarter indicators are also unbiased, meaning, for example, that on average $P\hat{r}e_1$ aligns well with Pre_1.

Using the predicted quarter indicators $P\hat{r}e_1$, $P\hat{r}e_2$, $P\hat{o}st_1$, and $P\hat{o}st_2$ as instruments for the actual quarter indicators Pre_1, Pre_2, $Post_1$, $Post_2$, we run the following reduced form IV regressions.

$$\begin{aligned} \text{News Items}_{it} &= \alpha + \sum_{j=1}^{2} \beta_j P\hat{r}e_{itj} + \sum_{j=1}^{2} \theta_j P\hat{o}st_{itj} + \gamma \text{Controls}_{it} + \mu_i + \tau_t + \epsilon_{it} \\ \text{Sentiment}_{it} &= \alpha + \sum_{j=1}^{2} \beta_j P\hat{r}e_{itj} + \sum_{j=1}^{2} \theta_j P\hat{o}st_{itj} + \gamma \text{Controls}_{it} + \mu_i + \tau_t + \epsilon_{it} \end{aligned} \tag{2.5}$$

A positive coefficient β_1 in regression (2.5) shows that, on average, both the number of news items and the sentiment are above the baseline one quarter before the expected renewal date. We similarly can interpret the coefficients β_2, θ_1, and θ_2.

The reduced form IV estimation uses only one instrument for each quarter indicator. In the next specification, for each actual quarter indicator, we use all four instruments to achieve a better fit in the first stage and ,consequently, more efficient causal coefficients. We run the following 2SLS specification:

$$\begin{aligned}
Pre_{1it} &= \alpha + \beta_1 \hat{Pre}_{1it} + \beta_2 \hat{Pre}_{2it} + \theta_1 \hat{Post}_{1it} + \theta_2 \hat{Post}_{2it} + +\gamma \text{Controls}_{it} + \tau_t + \epsilon_{it} \\
Pre_{2it} &= \alpha + \beta_1 \hat{Pre}_{1it} + \beta_2 \hat{Pre}_{2it} + \theta_1 \hat{Post}_{1it} + \theta_2 \hat{Post}_{2it} + +\gamma \text{Controls}_{it} + \tau_t + \epsilon_{it} \\
Post_{1it} &= \alpha + \beta_1 \hat{Pre}_{1it} + \beta_2 \hat{Pre}_{2it} + \theta_1 \hat{Post}_{1it} + \theta_2 \hat{Post}_{2it} + +\gamma \text{Controls}_{it} + \tau_t + \epsilon_{it} \\
Post_{2it} &= \alpha + \beta_1 \hat{Pre}_{1it} + \beta_2 \hat{Pre}_{2it} + \theta_1 \hat{Post}_{1it} + \theta_2 \hat{Post}_{2it} + +\gamma \text{Controls}_{it} + \tau_t + \epsilon_{it}
\end{aligned} \tag{2.6}$$

$$\begin{aligned}
\text{News Items}_{it} &= \alpha + \sum_{j=1}^{2} \beta_j \overline{Pre}_{itj} + \sum_{j=1}^{2} \theta_j \overline{Post}_{itj} + \gamma \text{Controls}_{it} + \mu_i + \tau_t + \epsilon_{it} \\
\text{Sentiment}_{it} &= \alpha + \sum_{j=1}^{2} \beta_j \overline{Pre}_{itj} + \sum_{j=1}^{2} \theta_j \overline{Post}_{itj} + \gamma \text{Controls}_{it} + \mu_i + \tau_t + \epsilon_{it}
\end{aligned} \tag{2.7}$$

In the second stage, our main explanatory variables are the predicted values, $\overline{Pre}_1$, $\overline{Pre}_2, \overline{Post}_1, \overline{Post}_2$ from the first stage. We run the first stage regressions (2.6) simultaneously. Regarding the exclusion restriction, it is a reasonable assumption that the contract length affect news events and news sentiment only through the potential dates for extending the contract (i.e., renewal date).

A positive causal coefficient β_1 in regression (2.7) indicates that when $\overline{Pre}_{it1}$ (the fitted value of the actual quarter indicator Pre_{it1}) is higher—implying a greater likelihood that day t falls within the quarter before the actual renewal date[5]—both the number of news items and sentiment are, on average, higher than the baseline. The interpretation of the coefficients β_2, θ_1, and θ_2 will be similar to the β_1's interpretation.

2.4 Results

Figure 2.4 shows the time difference (in days) between the actual renewal dates and the predicted renewal dates for all renewed contracts. As the figure illustrates, overall,

[5]Meaning it is more likely that $Pre_{jt1} = 1$

most of the predicted renewal dates are close to their corresponding actual renewal dates. Figure 2.5 shows these prediction differences for the different groups of contracts used to calculate the average renewal timing to length ratios.

Figure 2.6 shows the quarterly average number of news items, positive words, negative words, and sentiment for all contracts, spanning ten quarters before and after the actual renewal dates. The red dashed line represents the actual renewal dates, set to 0, while the blue dashed line represents the average predicted renewal dates. The close proximity of the red and blue dashed lines indicates the small magnitude of the average prediction error. As the figure shows, there is an increasing pattern in the average number of news items both before and after the renewal date. The average number of positive words within the news items increases before the renewal date and decreases afterward. The average sentiment follows a similar pattern as the positive words, while the reverse pattern exist for the average number of negative words.

Figures 2.7, 2.8, 2.9, and 2.10 show the same graphs for contracts with a length of 3 years, less than 3 years, more than 3 years, and contracts renewed after one year. Each of these categories constitutes a significant proportion of the sample data.

Table 2.3 shows the simple OLS estimates from regressions (2.1) and (2.2). Our preferred coefficients are from columns with both firm and month fixed effects. The number of news items is significantly higher by 1.54 one quarter before and by 0.87 one quarter after the renewal date compared to the baseline (the number of news items is 5.2 per quarter). The sentiment of news items one quarter before the renewal date is 0.42 points higher than the baseline (the average sentiment is approximately -0.63 per news item). In contrast, the sentiment of news disclosed one quarter and two quarters after the renewal date falls below the baseline by 0.24 and 0.38 points, respectively. Therefore, the OLS results provide significant evidence of more news items being disclosed around the renewal date, with higher sentiment before and lower sentiment after the renewal date.

Table 2.4 shows the results of the reduced form IV (2.5). Although the coefficients are less significant compared to the OLS coefficients, the signs of the coefficients are consistent with those from the OLS regression. Hence, the reduced form regression causally indicates the same pattern in the number of news items and their sentiments before and after the renewal date.

Table 2.5 shows the 2SLS results. Panel A, present the first stage regression results from (2.6). Based on the first-stage results, $\hat{Pre}_2$, $\hat{Pre}_1$, $\hat{Post}_1$, and $\hat{Post}_2$ have significant predictive power for the actual Pre_2, Pre_1, $Post_1$, and $Post_2$. All R-squared values are higher than 50%, except for the $Post_2$ prediction, which is 5%. Panel B shows the second stage results based on (2.7).

The number of news items is higher than the baseline by 1.40 one quarter before and by 1.44 one quarter after the renewal date. The sentiment of news items rises by 0.45 above the baseline one quarter before the renewal date. In contrast, the sentiment one quarter after the renewal date falls below the baseline by 0.35. Therefore, the 2SLS estimates provide significant evidence of more news items being disclosed around the renewal date, with higher sentiment before and lower sentiment after the renewal date.

One caveat that could influence the results is the possibility that CEOs may work harder before the renewal date to increase the likelihood of contract renewal, thereby leading to the disclosure of more positive news items as a result of their efforts. While our analysis cannot entirely rule out this explanation for the higher sentiment before the renewal date, it does not account for the negative news sentiment observed after the renewal date.

2.4.1 Subsample analysis

Since approximately 75% of the sample consists of contracts with a length of 3 years or less, we redo the analysis for a subsample of contracts with a length of more than 3 years to test whether the results are driven by these more frequent contracts or if they hold for the other contracts as well. Therefore, we run all main regressions, but exclusively for contracts longer than 3 years.

Table 2.6 shows the OLS estimates. The number of news items is significantly higher by 1.66 one quarter before the renewal date, but the coefficient for one quarter after the renewal date is not significant. Sentiment is also higher by 0.58 one quarter before the renewal date, but while the coefficient for one quarter after the renewal date is negative, it is not significant.

Table 2.7 shows the reduced form IV results. The coefficient for the number of news items remains the same, but the sentiment is significantly negative one quarter after the renewal date. Table 2.8 shows the 2SLS estimates. The number of news items is significantly higher one quarter before and one quarter after the renewal date. Sentiment is negative one quarter after the renewal date and insignificant one quarter before.

Therefore, the estimates for the subsample are only partly significant, which shows contracts with a length of 3 years or less are important in deriving the main results. This could be due to information loss in the first-stage estimations, as the average and standard deviation of predicted renewal date errors for contracts with a length of more than 3 years are 5 days and 347 days, respectively, while for shorter contracts, these statistics are -0.42 days and 102 days. Additionally, this may be because the potential for strategic disclosure is could be stronger for CEOs with shorter contracts and, consequently, shorter renewal timings. For example, when a contract length is 7 years with a renewal timing of 4 years, disclosing news strategically within 1 year around the renewal date may not be as effective because the renewal decision is likely influenced by long-term performance over several years, making short-term strategic disclosures less impactful.

2.4.2 Cross sectional differences

In this section, we analyze strategic news disclosure conditional on CEO performance between her contract's start date and renewal date, as well as whether the CEO was also the chairman of the board around the renewal date. The idea is that when a CEO has relatively good performance before the renewal date, she may not have an incentive to disclose news strategically close to her contract renewal. Additionally, being the chairman could influence strategic behavior differently; a CEO who also holds the chairman position may have more influence over the board's decisions, potentially reducing the need for strategic news disclosures, or alternatively, could feel more pressure to manage perceptions leading up to the renewal.

We answer these questions by running the following regression:

$$\begin{aligned}\text{News Items}_{it} \text{ or Sentiment}_{it} =& \alpha + \beta_1 Pre_{1it} X_i + \beta_2 Pre_{2it} X_i + \theta_1 Post_{1it} X_i + \theta_2 Post_{2it} X_i \\ &+ \beta_1 Pre_{1it} + \beta_2 Pre_{2it} + \theta_1 Post_{1it} + \theta_2 Post_{2it} \\ &+ \gamma \text{Controls}_{it} + \tau_t + \epsilon_{it} \qquad (2.8)\end{aligned}$$

We run regression (2.8) for interaction variables: X_i = Performance$_i$ and X_i = Chairman$_i$.[6] Tables 2.9, 2.10, and 2.11 show the OLS, reduced form IV, and 2SLS estimations of regression (2.8). The first stage results are reported in Panel A of Table 2.5.

Based on the second stage estimates, higher performance leads to a lower number of news items one quarter before and after the renewal date, as well as a higher number of news items with higher sentiment two quarters after the renewal date. Additionally, for CEOs who are also chairmen of the board, the number of news items is lower with

[6] We run the regression (2.8) using $\{Pre_2, Pre_1, Post_1, Post_2\}$, $\{\hat{Pre}_2, \hat{Pre}_1, \hat{Post}_1, \hat{Post}_2\}$, and $\{\overline{Pre_2}, \overline{Pre_1}, \overline{Post_1}, \overline{Post_2}\}$ as quarter indicators.

higher sentiment around the renewal date, while the number of news items increases with higher sentiment two quarters after the renewal date. This pattern suggests that CEOs with strong performance may feel less pressure to influence perceptions through strategic news disclosures around the renewal date, as their performance speaks for itself. On the other hand, those who also hold the chairman position may have more control over the board's perception and greater confidence in renewing their contracts, which reduces the need for frequent news disclosures.

2.5 Conclusion

This paper analyzes the strategic behavior of CEOs in disclosing news items around the time of their contract renewals. Our analysis provides evidence that CEOs tend to disclose more news items with higher sentiment in the quarter preceding their contract renewal date and more news items with lower sentiment in the quarter following it. Specifically, we find that the number of discretionary news items is significantly higher by 1.4 in the quarter before the renewal date and by 1.44 in the quarter after. Moreover, the sentiment of these news items is higher by 0.45 before the renewal date, indicating a strategic release of favorable information, while the sentiment drops from the baseline by 0.35 in the quarter following the renewal, suggesting a deferral of negative news until after the renewal decision is made.

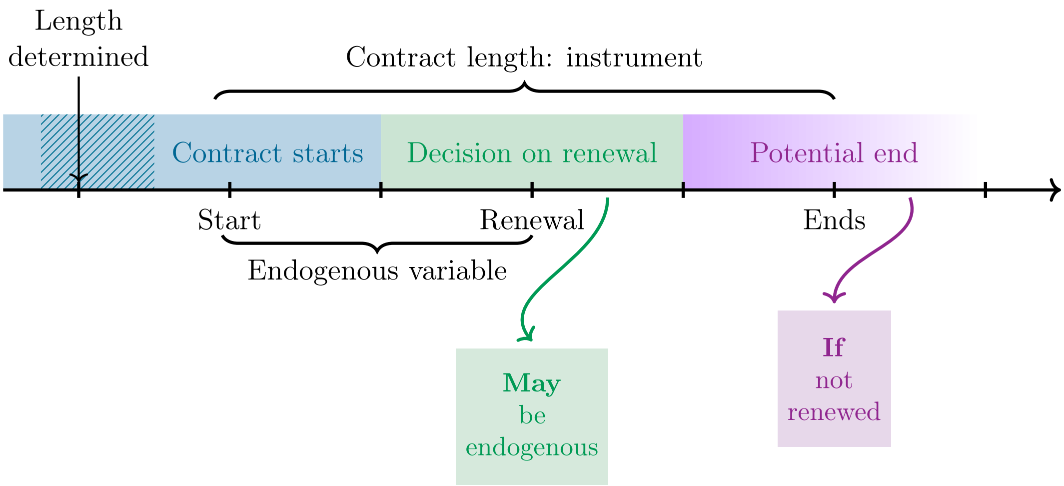
These findings suggest that CEOs may engage in strategic news management to enhance their chances of contract renewal. The behavior appears to be more pronounced among CEOs with shorter contracts and those with a history of poorer performance. The rationale is that shorter contracts and previous poor performance may heighten CEOs' incentive to positively influence the board's perception before a renewal decision. Conversely, this strategic behavior is less evident among CEOs who also serve as the chairman of the board. These dual-role CEOs likely have greater control and influence over the renewal process, reducing the need for such short-term strategic disclosures.

Additionally, while our analysis provides significant evidence of the strategic behavior, it does not fully account for alternative explanations, such as the possibility that CEOs may work harder before the renewal date to secure their positions could lead to genuinely improved performance, which in turn could result in more positive news disclosures before the renewal date. This alternative explanation suggests that the observed patterns in news sentiment might not be solely due to strategic manipulation, but also due to actual improvements in performance leading up to the renewal.

In conclusion, this paper contributes to the understanding of CEO behavior around contract renewals, highlighting the role of strategic news management in influencing renewal outcomes. Future research could further explore the long-term implications of such behavior on firm performance and board governance.

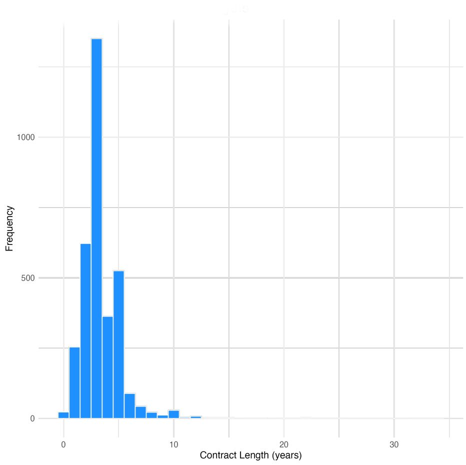
2.6 Figures

Figure 2.1: Timing of a contract

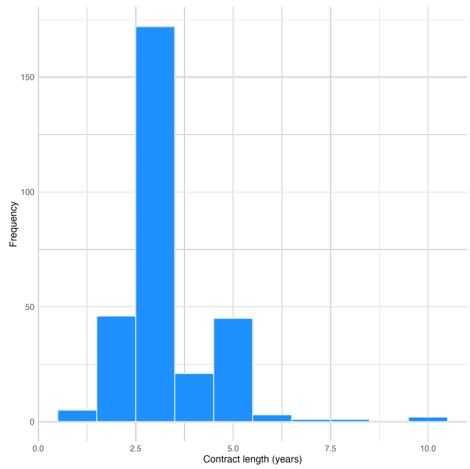


Note: Timing of a contract. The figure shows the chronicle timeline of a contract. First, the contract length is determined, then the contract will start, then the decision based on several factors will be made, and finally, the contract may terminate if it has not been renewed. In this paper, the renewal period, the distance between the start date and the renewal date, is used as an instrument for the contract length, which is the distance between the start date and the expiration date.

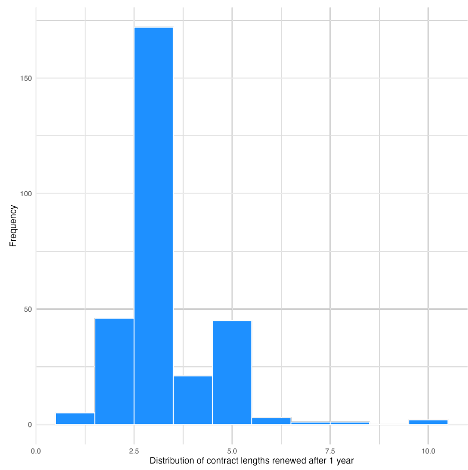
Figure 2.2: Histogram of contract lengths



(a) All contracts



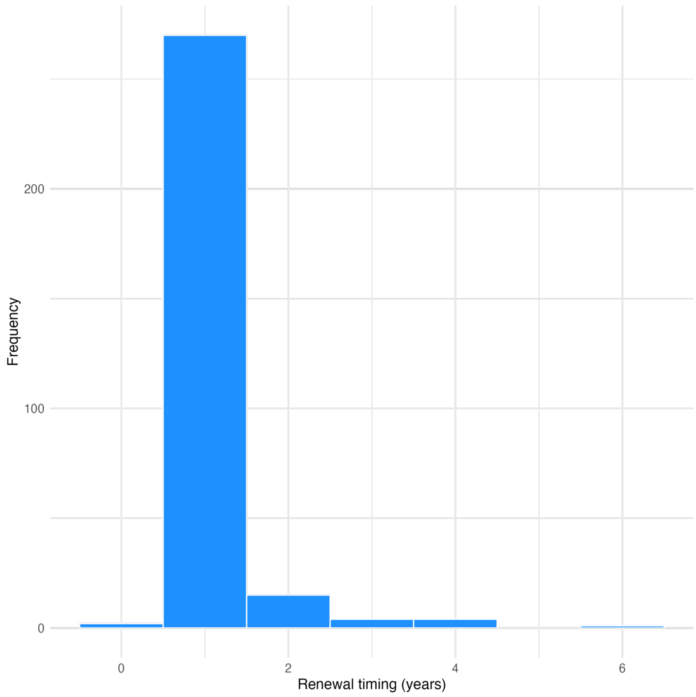
(b) Renewed contracts



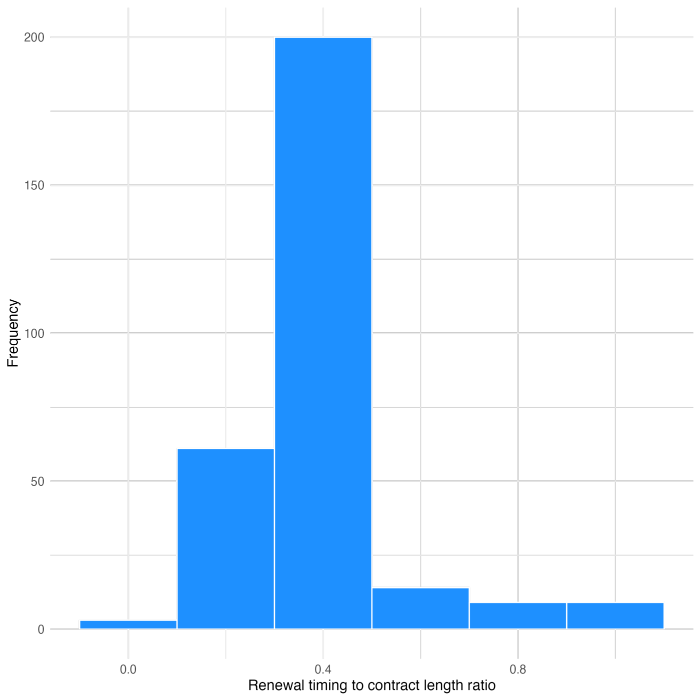
(c) Contracts renewed after 1 year

Note: Histograms of contract lengths for all contracts, contracts that were renewed, and contracts that were renewed 1 year after their start date.

Figure 2.3: Histogram of renewal timings and the ratio of renewal timings to contract lengths



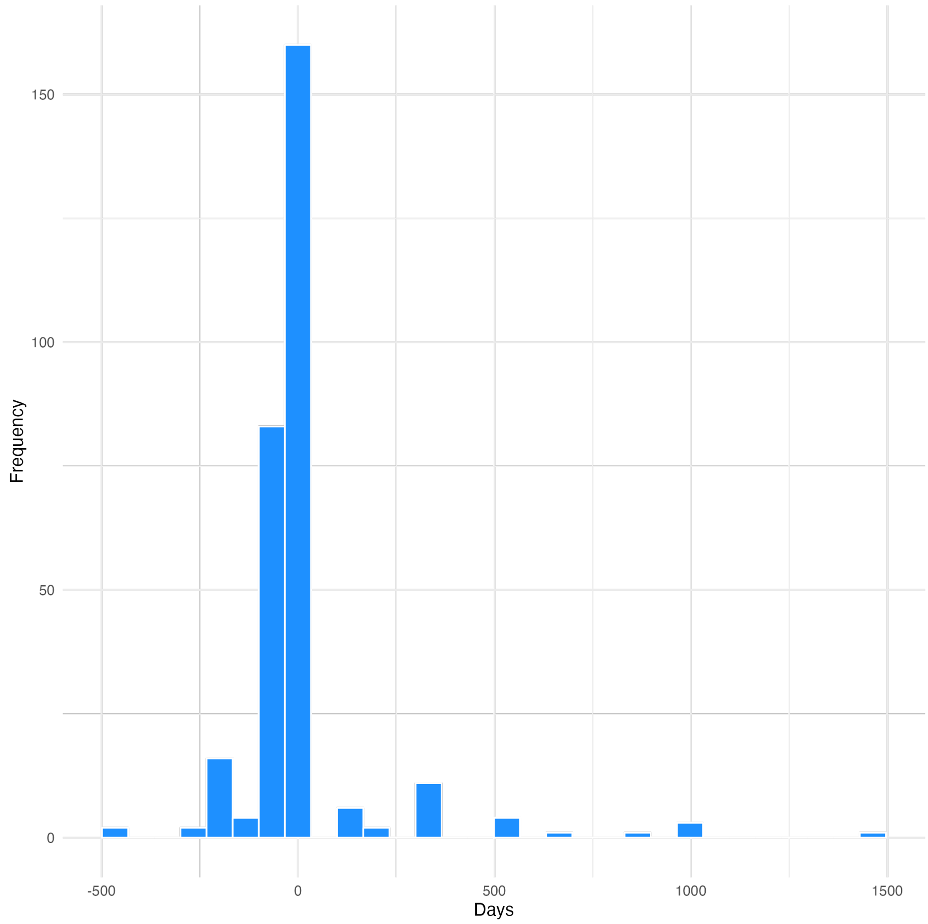
(a) Renewal timings



(b) Renewal timing to contract length ratio

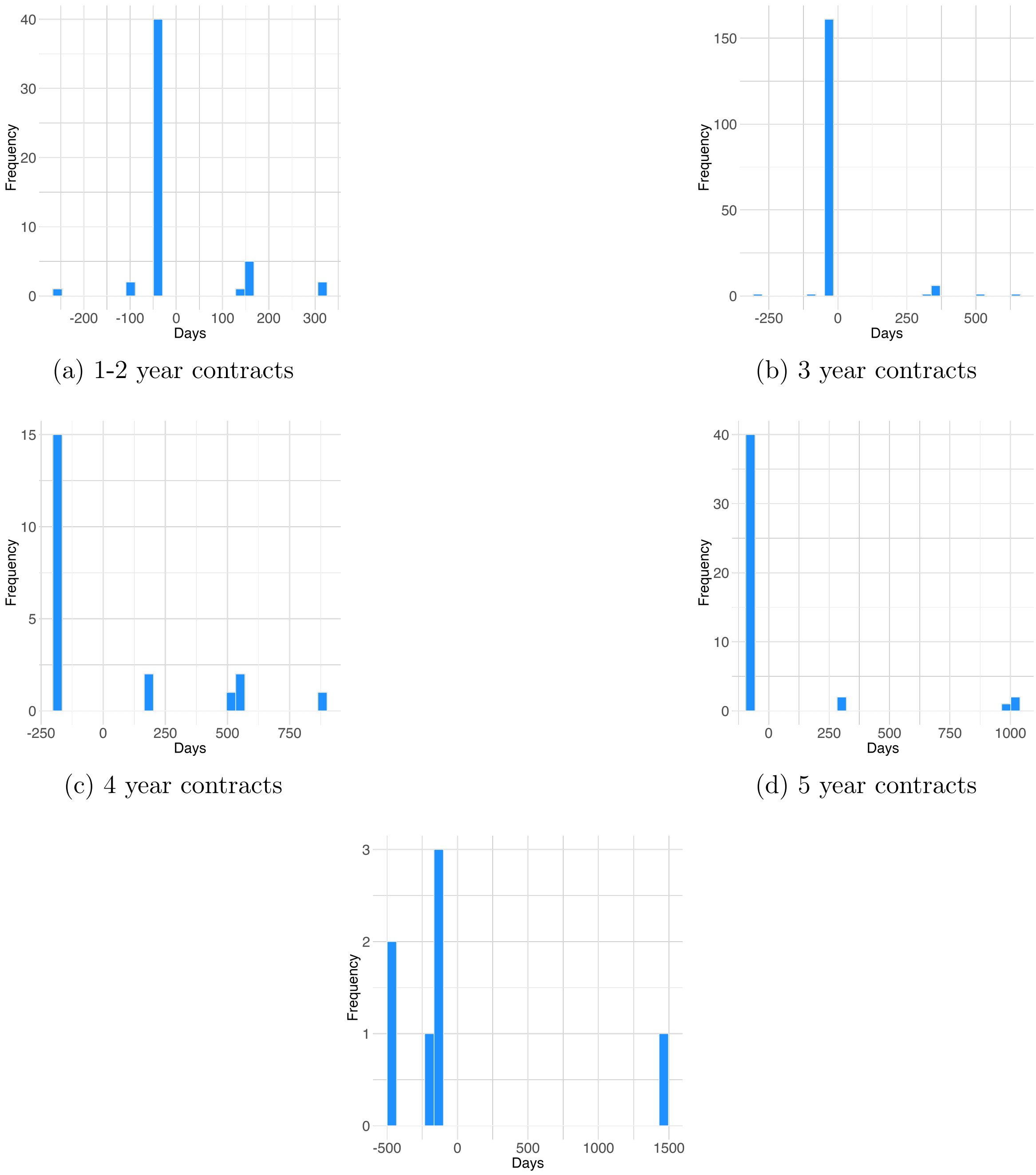
Note: Histograms of renewal timings (the time between the renewal date and the start date) and the ratio of renewal timings to contract lengths.

Figure 2.4: Histogram of the time difference (in days) between the actual and predicted renewal dates for all contracts



Note: Histogram of the time difference (in days) between the actual and predicted renewal dates for all contracts. Predicted renewal dates are derived from (2.3).

Figure 2.5: Histograms showing the time difference (in days) between the actual and predicted renewal dates for contracts of different lengths



(a) 1-2 year contracts

(b) 3 year contracts

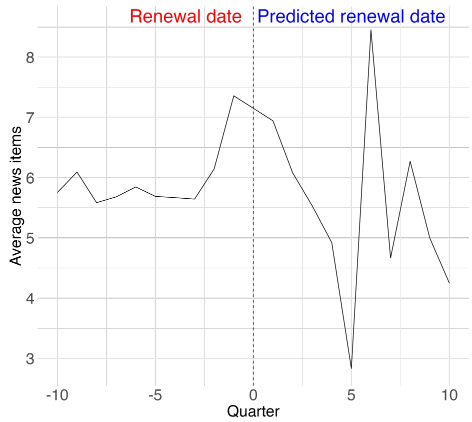
(c) 4 year contracts

(d) 5 year contracts

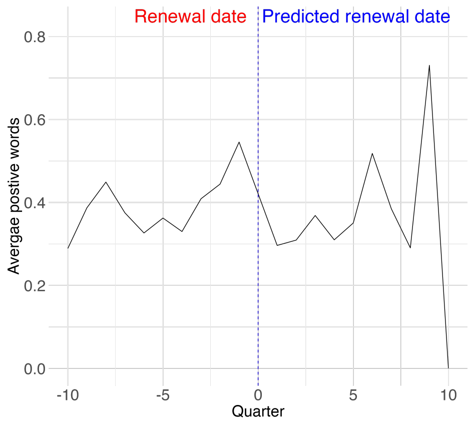
(e) Contracts longer than 5 years

Note: Histograms showing the time difference (in days) between the actual and predicted renewal dates for contracts with lengths of 1 to 2 years, 3 years, 4 years, 5 years, and more than 5 years. Predicted renewal dates are derived from (2.3).

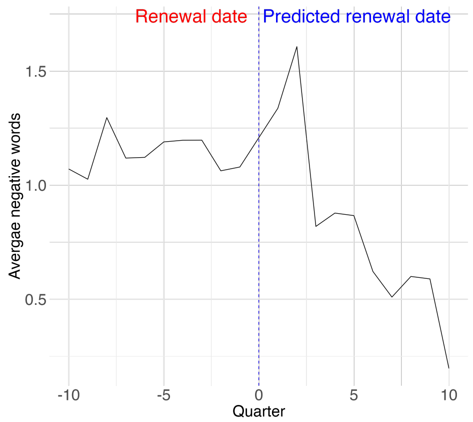
Figure 2.6: Quarterly average number of news items, positive words, negative words, and sentiment for all contracts



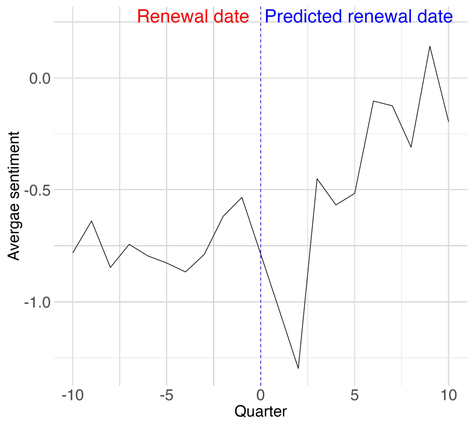
(a) News items



(b) Average positive words



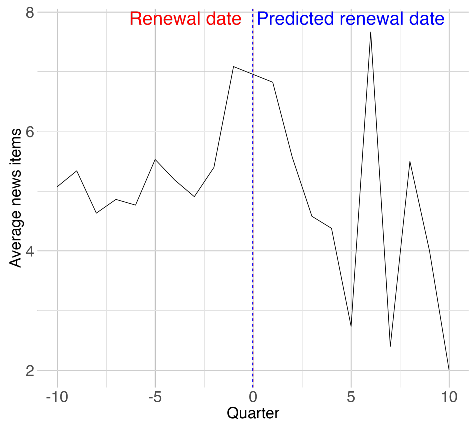
(c) Average negative words



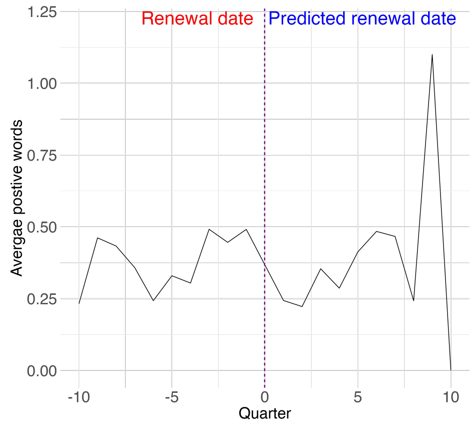
(d) Average sentiment

Note: These figures show the average number of news items, positive words, negative words, and sentiment for all contracts, spanning 10 quarters before and 10 quarters after the contracts' renewal date. The red dashed line corresponds to the actual renewal date, and the blue dashed line represents the average predicted renewal dates derived from (2.3).

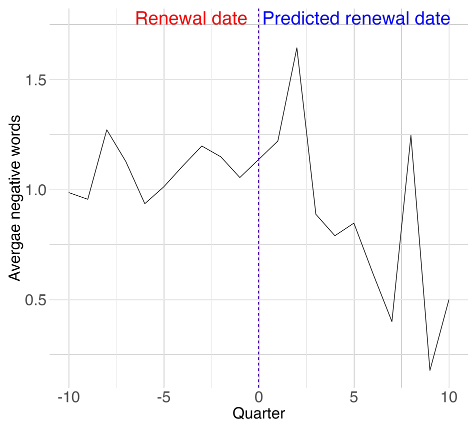
Figure 2.7: Quarterly average number of news items, positive words, negative words, and sentiment for contracts with a length of 3 years



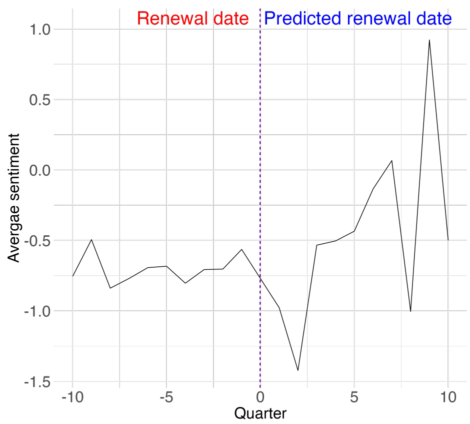
(a) News items



(b) Average positive words



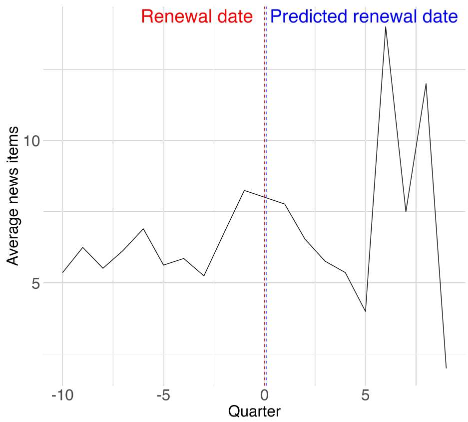
(c) Average negative words



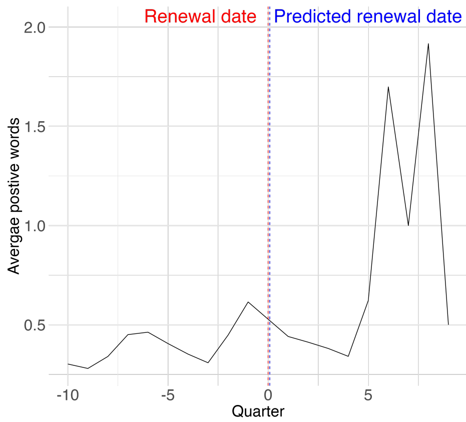
(d) Average sentiment

Note: These figures show the average number of news items, positive words, negative words, and sentiment for contracts with a length of 3 years, spanning 10 quarters before and 10 quarters after the contracts' renewal date. The red dashed line corresponds to the actual renewal date, and the blue dashed line represents the average predicted renewal dates derived from (2.3).

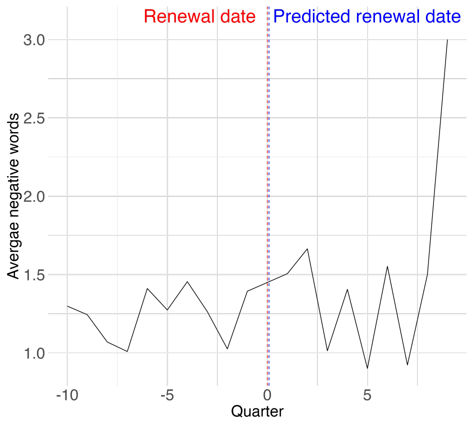
Figure 2.8: Quarterly average number of news items, positive words, negative words, and sentiment for contracts with a length of less than 3 years



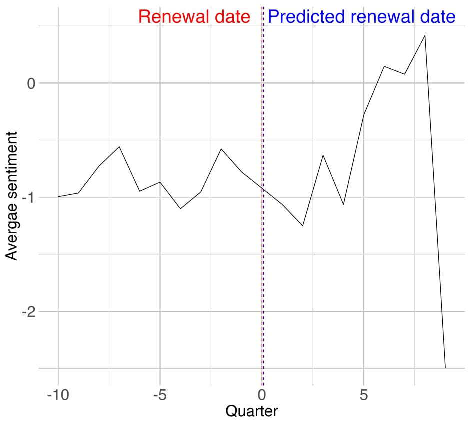
(a) News items



(b) Average positive words



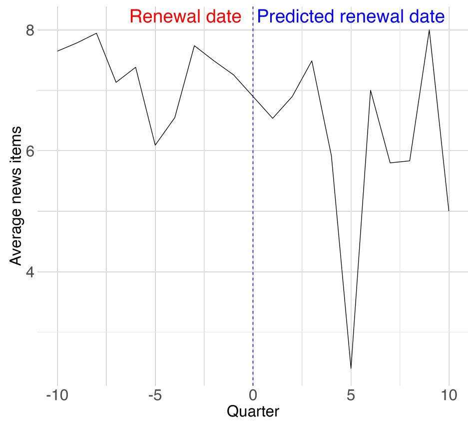
(c) Average negative words



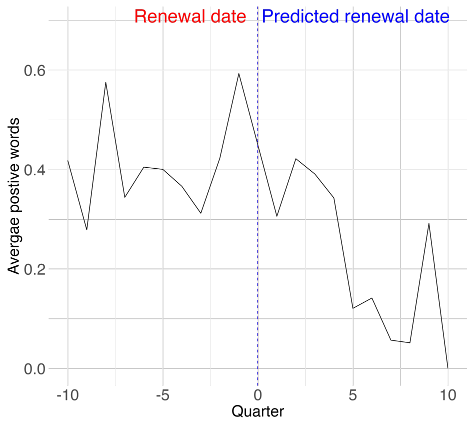
(d) Average sentiment

Note: These figures show the average number of news items, positive words, negative words, and sentiment for contracts with a length of less than 3 years, spanning 10 quarters before and 10 quarters after the contracts' renewal date. The red dashed line corresponds to the actual renewal date, and the blue dashed line represents the average predicted renewal dates derived from (2.3).

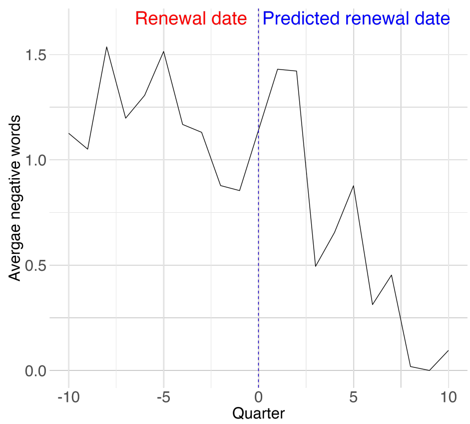
Figure 2.9: Quarterly average number of news items, positive words, negative words, and sentiment for contracts with a length of more than 3 years



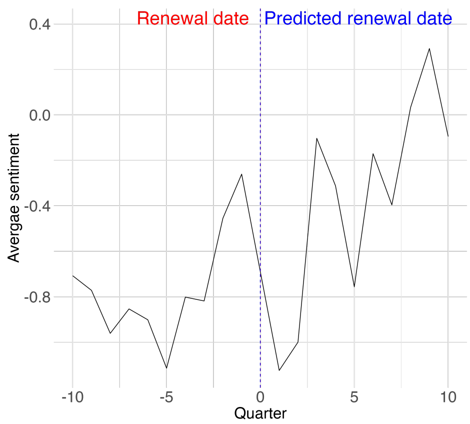
(a) News items



(b) Average positive words



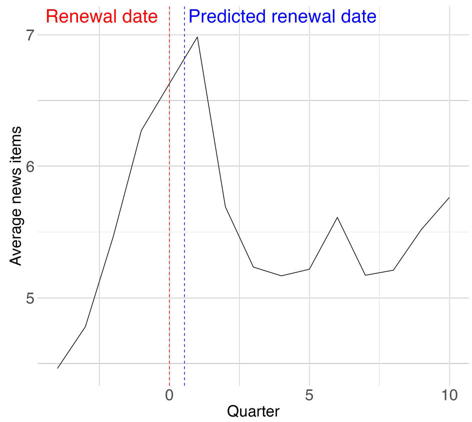
(c) Average negative words



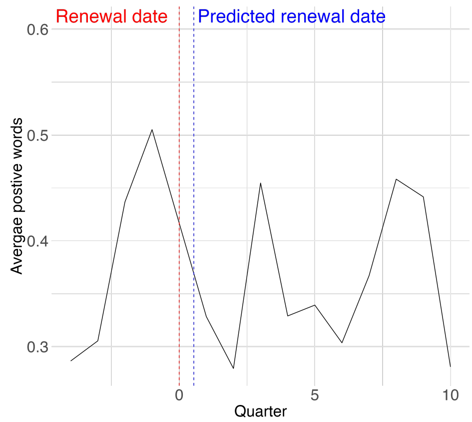
(d) Average sentiment

Note: These figures show the average number of news items, positive words, negative words, and sentiment for contracts with a length of more than 3 years, spanning 10 quarters before and 10 quarters after the contracts' renewal date. The red dashed line corresponds to the actual renewal date, and the blue dashed line represents the average predicted renewal dates derived from (2.3).

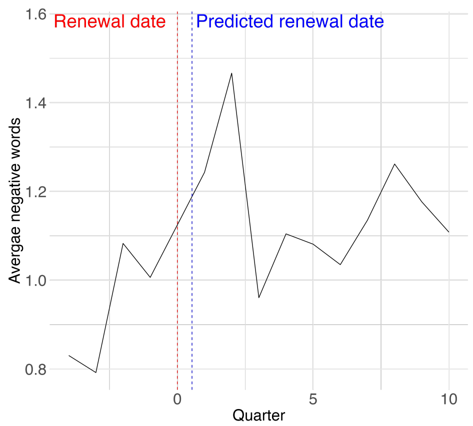
Figure 2.10: Quarterly average number of news items, positive words, negative words, and sentiment for contracts renewed after 1 year



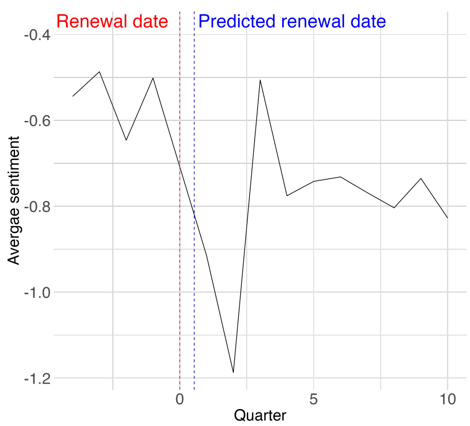
(a) News items



(b) Average positive words



(c) Average negative words



(d) Average sentiment

Note: These figures show the average number of news items, positive words, negative words, and sentiment for contracts renewed after 1 year, spanning 4 quarters before and 10 quarters after the contracts' renewal date. The red dashed line corresponds to the actual renewal date, and the blue dashed line represents the average predicted renewal dates derived from (2.3).

2.7 Tables

Table 2.1: Summary statistics

Panel A: Contract Statistics									
	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max		
Lengths of all contracts (years)	3.4	2.1	1	2	3	4	34		
Lengths of renewed contracts (years)	3.3	1.2	1	3	3	3	10		
Renewal timings (years)	1.1	0.54	0.28	1	1	1	5.8		
Renewal timing to length ratio	0.37	0.17	0.092	0.33	0.33	0.33	1		
Time difference between the actual and predicted renewal dates (days)	-2.8	189	-455	-48	-20	-20	1,474		
Panel B: Distribution of Renewed Contract Lengths									
Length (years)	1	2	3	4	5	6	7	8	10
Number	5	46	172	21	45	3	1	1	2
(Percentage)	(1.6%)	(15.5%)	(58.1%)	(7.1%)	(15.2%)	(1%)	(0.3%)	(0.3%)	(0.6%)
Average renewal timing (years)	1	1.03	1.05	1.51	1.24	1	1	5.83	1
Average renewal timing to contract length ratio	1	0.51	0.35	0.37	0.24	0.16	0.14	0.72	0.1
Panel C: News Disclosures									
	Number of news items	News items per month	Discretionary news items	AGM news items	Board meetings	Earning announcement			
Number	30,516	2.97	27,673	621	243	1,979			
	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max		
Sentiment	-0.63	2.5	-46	-1	0	0	14		
Quarterly average sentiment	-0.73	1.5	-18	-1.1	-0.33	0	14		
Number of news items per day	1.47	0.88	1	1	1	2	14		
Number of news items per quarter	6.1	5.2	1	2.5	5	8	58		
Panel D: CEO Performance									
	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max		
Performance	0.0021	0.055	-0.24	-0.017	0	0.021	0.39		

Table 2.2: Example of good and bad news

Panel A: Examples of good and bad news			
Number	Date	Type	Headline
(1)	2008-11-26	Good	Painted Pony Petroleum Ltd. Announces Operational Accomplishments for the End of Second Quarter of 2008
(2)	2008-01-03	Good	Prometheus Energy Announces Bowerman LNG Plant Achieves Production Targets
(3)	2007-06-04	Bad	Craig K. Townsend, Cheniere Energy Partners LP Vice President and Chief Accounting Officer Begins Leave of Absence
(4)	2007-08-01	Bad	Wells Fargo Accused of Discriminatory Lending

Panel B: Examples of good and bad news			
Number	Date	Type	Headline
(1)	2008-01-02	AGM	Kerry Group plc, Annual General Meeting, May 13, 2008
(2)	2008-01-03	Board	Kirloskar Brothers Ltd., Board Meeting, Jan 19, 2008
(3)	2008-01-02	EA	Voltas Ltd. Reports Earnings Results for the Second Quarter Ended September 2007

Panel C: Examples of news about the contract of the CEO			
Number	Date	Type	Headline
(1)	2008-11-26	CEO	Korea Asset Management Corporation Names Lee Chul-hwi as Chairman and CEO
(2)	2008-01-08	CEO	IAC/InterActiveCorp Appoints Doug Lebda as Chairman and CEO of its Financial Services and Real Estate Businesses

Notes: This table provides some examples of various types of news from Capital IQ Key Developments. In panel A news items 1 & 2 are examples of good news and news items 3 & 4 are examples of bad news. The sentiment analysis is based on the Loughran and McDonald (2011) dictionary. Panel B shows 3 types of non-discretionary news based on textual analysis. Panel C shows examples of news about CEO contracts.

Table 2.3: OLS estimation - All contracts

	News Items	Sentiment	News Items	Sentiment
Pre_2	0.162	0.228	0.041	0.225
	(0.255)	(0.146)	(0.329)	(0.141)
Pre_1	1.54***	0.425***	1.48***	0.448***
	(0.239)	(0.095)	(0.323)	(0.095)
$Post_1$	0.878***	-0.242**	0.851**	-0.237**
	(0.263)	(0.115)	(0.355)	(0.117)
$Post_2$	-0.170	-0.381***	-0.220	-0.396***
	(0.260)	(0.126)	(0.318)	(0.124)
Performance			2.98***	1.51***
			(0.937)	(0.558)
Chairman			-0.147*	-0.091*
			(0.083)	(0.048)
Fixed-effects				
Firm	Yes	Yes	No	No
Calendar month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	27,673	27,673	27,673	27,673
R^2	0.52	0.06	0.27	0.04
Within R^2	0.008	0.002	0.016	0.003

Note: This table shows the OLS estimates of (2.1) and (2.2). In the parentheses, standard errors are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 2.4: Reduced form IV estimation - All contracts

	News Items	Sentiment	News Items	Sentiment
$\hat{Pre}_2$	0.020	0.205	-0.137	0.201
	(0.250)	(0.154)	(0.319)	(0.148)
$\hat{Pre}_1$	1.47***	0.347***	1.48***	0.360***
	(0.275)	(0.128)	(0.398)	(0.122)
$\hat{Post}_1$	1.80	-0.417***	3.47*	-0.270*
	(1.16)	(0.129)	(1.87)	(0.159)
$\hat{Post}_2$	0.704***	-0.219**	0.694**	-0.223**
	(0.237)	(0.110)	(0.312)	(0.109)
Performance			3.03***	1.52***
			(0.937)	(0.558)
Chairman			-0.152*	-0.088*
			(0.082)	(0.048)
Fixed-effects				
Firm	Yes	Yes	No	No
Calendar month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	27,673	27,673	27,673	27,673
R^2	0.52	0.06	0.27	0.04
Within R^2	0.006	0.001	0.016	0.002

Note: This table shows the reduced form IV (2.5) results. The quarter indicators are derived from (2.4). In parentheses, standard errors are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% levels, respectively.

Table 2.5: 2SLS instrumental variable estimation - All contracts

Panel A: First stage				
	Pre_2	Pre_1	$Post_1$	$Post_2$
$\hat{Pre}_2$	0.986***	-0.030***	-0.0003	-0.057***
	(0.007)	(0.004)	(0.001)	(0.007)
$\hat{Pre}_1$	0.134***	0.840***	0.001	-0.060***
	(0.047)	(0.050)	(0.001)	(0.006)
$\hat{Post}_1$	0.006**	-0.017***	1.03***	-0.063***
	(0.003)	(0.004)	(0.005)	(0.008)
$\hat{Post}_2$	0.0010	-0.032***	0.850***	0.086*
	(0.0006)	(0.005)	(0.040)	(0.044)
Performance	-0.002	-0.018	-0.019**	-0.012
	(0.008)	(0.017)	(0.009)	(0.022)
Chairman	0.002*	0.002	-0.002	-0.002
	(0.001)	(0.003)	(0.001)	(0.003)
Fixed-effects				
Calendar month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	27,673	27,673	27,673	27,673
R^2	0.89	0.54	0.87	0.05
Within R^2	0.88	0.52	0.87	0.01

Panel B: Second stage				
	News Items	Sentiment	News Items	Sentiment
$\overline{Pre_2}$	-0.256	0.295*	-1.05	0.227
	(0.398)	(0.170)	(0.835)	(0.172)
$\overline{Pre_1}$	1.40***	0.453***	0.780	0.410**
	(0.473)	(0.171)	(0.724)	(0.169)
$\overline{Post_1}$	1.44**	-0.355***	2.51**	-0.262**
	(0.720)	(0.101)	(1.12)	(0.112)
$\overline{Post_2}$	-5.53	1.60	-16.3	0.539
	(6.90)	(1.01)	(11.1)	(1.05)
Performance			0.527*	0.830*
			(0.303)	(0.478)
Chair			-0.172**	-0.085*
			(0.083)	(0.048)
Fixed-effects				
Firm	Yes	Yes	No	No
Calendar month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	27,673	27,673	27,673	27,673
R^2	0.52	0.06	0.26	0.03
Within R^2	0.006	0.001	0.006	0.001

Note: Panel A, shows the first stage regression (2.6) results. Panel B, represents the second stage (2.7) estimates. In the parentheses, standard errors are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively

Table 2.6: OLS estimation - Contracts with a length of more than 3 years

	News Items	Sentiment	News Items	Sentiment
Pre_2	0.820	0.398*	0.964	0.401*
	(0.644)	(0.227)	(0.683)	(0.205)
Pre_1	1.66***	0.580***	1.61***	0.660***
	(0.499)	(0.167)	(0.509)	(0.166)
$Post_1$	0.872	-0.125	0.898	-0.086
	(0.697)	(0.281)	(0.741)	(0.250)
$Post_2$	0.162	-0.065	0.126	-0.075
	(0.610)	(0.288)	(0.726)	(0.277)
Performance			10.4***	6.63***
			(3.45)	(1.86)
Chairman			-2.87***	-0.127
			(0.191)	(0.107)
Fixed-effects				
Firm	Yes	Yes	No	No
Calendar month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	9,167	9,167	9,167	9,167
R^2	0.50	0.07	0.31	0.05
Within R^2	0.005	0.002	0.011	0.006

Note: This table shows the OLS estimates of (2.1) and (2.2) for a subsample of contracts with length of more than 3 years. In the parentheses, standard errors are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 2.7: Reduced form IV estimation - Contracts with a length of more than 3 years

	News Items	Sentiment	News Items	Sentiment
$\hat{Pre}_2$	0.296	0.295	0.973	0.316
	(0.706)	(0.262)	(0.828)	(0.246)
$\hat{Pre}_1$	1.53*	0.406*	2.23*	0.440*
	(0.838)	(0.238)	(1.18)	(0.219)
$\hat{Post}_1$	2.65	-0.591***	5.99	-0.393*
	(2.81)	(0.124)	(4.49)	(0.203)
$\hat{Post}_2$	0.208	-0.049	0.310	-0.043
	(0.498)	(0.259)	(0.535)	(0.225)
Performance			10.5***	6.89***
			(3.44)	(1.86)
Chairman			-2.80***	-0.136
			(0.191)	(0.107)
Fixed-effects				
Firm	Yes	Yes	No	No
Calendar month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	9,167	9,167	9,167	9,167
R^2	0.50	0.07	0.31	0.05
Within R^2	0.003	0.001	0.016	0.004

Note: This table shows the reduced form IV (2.5) results for a subsample of contracts with length of more than 3 years. The quarter indicators are derived from Equations (2.4). In parentheses, standard errors are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% levels, respectively.

Table 2.8: 2SLS instrumental variable estimation - Contracts with a length of more than 3 years

Panel A: First stage				
	Pre_2	Pre_1	$Post_1$	$Post_2$
$\hat{Pre_2}$	0.938***	-0.046***	0.004	-0.046***
	(0.031)	(0.010)	(0.004)	(0.011)
$\hat{Pre_1}$	0.544***	0.415**	0.002	-0.048***
	(0.146)	(0.159)	(0.004)	(0.011)
$\hat{Post_1}$	0.020***	-0.032***	1.03***	-0.044***
	(0.005)	(0.008)	(0.007)	(0.008)
$\hat{Post_2}$	-0.005**	-0.053***	0.718***	0.222**
	(0.002)	(0.012)	(0.099)	(0.109)
Performance	0.160**	0.011	0.116	-0.036
	(0.064)	(0.089)	(0.072)	(0.042)
Chair	0.008**	0.009	0.010*	-0.001
	(0.003)	(0.009)	(0.005)	(0.007)
Fixed-effects				
Calendar month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	9,167	9,167	9,167	9,167
R^2	0.80	0.15	0.81	0.09
Within R^2	0.79	0.12	0.80	0.05

	News Items	Sentiment	News Items	Sentiment
$\overline{Pre_2}$	0.413	0.419**	0.284	0.435**
	(0.414)	(0.202)	(0.404)	(0.202)
$\overline{Pre_1}$	2.23*	0.475	2.13*	0.519
	(1.20)	(0.525)	(1.17)	(0.525)
$\overline{Post_1}$	4.42***	-0.284*	4.51***	-0.280**
	(0.676)	(0.146)	(0.660)	(0.107)
$\overline{Post_2}$	-12.4	0.914	-13.1	0.954
	(10.54)	(1.07)	(9.48)	(1.07)
Performance			9.8***	4.55***
			(2.18)	(1.25)
Chair			-3.75***	-0.142
			(0.193)	(0.108)
Fixed-effects				
Firm	Yes	Yes	No	No
Calendar month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	9,167	9,167	9,167	9,167
R^2	0.31	0.05	0.34	0.05
Within R^2	0.006	0.001	0.05	0.002

Note: This table shows the 2SLS regression results for a subsample of contracts with length of more than 3 years. Panel A, shows the first stage (2.6) estimates. Panel B, represents the second stage (2.7) results. In the parentheses, standard errors are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively

Table 2.9: OLS estimation - Cross sectional differences

	X = Performance		X = Chairman	
	News Items	Sentiment	News Items	Sentiment
$Pre_2 \times X$	-13.3***	-3.55**	0.286	-0.004
	(3.10)	(1.58)	(0.305)	(0.178)
$Pre_1 \times X$	-9.67***	-0.483	0.301	0.053
	(2.85)	(1.43)	(0.304)	(0.170)
$Post_1 \times X$	-8.96***	3.98***	-0.426	0.081
	(2.82)	(1.48)	(0.308)	(0.183)
$Post_2 \times X$	-3.74	3.91***	0.017	0.145
	(2.91)	(1.44)	(0.315)	(0.187)
Pre_2	0.046	0.217**	-0.047	0.226**
	(0.148)	(0.086)	(0.185)	(0.106)
Pre_1	1.48***	0.431***	1.39***	0.417***
	(0.145)	(0.082)	(0.179)	(0.102)
$Post_1$	0.854***	-0.214**	1.01***	-0.256**
	(0.145)	(0.085)	(0.176)	(0.101)
$Post_2$	-0.216	-0.364***	-0.218	-0.322***
	(0.151)	(0.089)	(0.185)	(0.108)
Performance	1.51	1.39**	2.99***	1.51***
	(0.979)	(0.572)	(0.938)	(0.558)
Chairman	-0.131	-0.093*	-0.155*	-0.091*
	(0.083)	(0.048)	(0.087)	(0.050)
Fixed-effects				
Calendar month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	27,673	27,673	27,673	27,673
R^2	0.26	0.04	0.26	0.04
Within R^2	0.007	0.003	0.006	0.003

Note: This table shows the OLS estimates of (2.8). In the parentheses, standard errors are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 2.10: Reduced form IV estimation - Cross sectional differences

	X = Performance		X = Chairman	
	News Items	Sentiment	News Items	Sentiment
$\hat{Pre_2} \times X$	-11.2***	-3.79**	-0.079	0.031
	(3.16)	(1.63)	(0.313)	(0.187)
$\hat{Pre_1} \times X$	-15.1***	-0.766	0.395	-0.298
	(3.52)	(1.67)	(0.363)	(0.198)
$\hat{Post_1} \times X$	-48.2***	10.3	-4.73***	0.197
	(16.1)	(7.77)	(0.893)	(0.444)
$\hat{Post_2} \times X$	-7.69***	3.52**	-0.566*	0.013
	(2.79)	(1.46)	(0.309)	(0.185)
$\hat{Pre_2}$	-0.132	0.190**	-0.106	0.181*
	(0.151)	(0.089)	(0.189)	(0.110)
$\hat{Pre_1}$	1.48***	0.329***	1.36***	0.441***
	(0.172)	(0.095)	(0.212)	(0.118)
$\hat{Post_1}$	3.69***	-0.267	5.95***	-0.353
	(0.447)	(0.205)	(0.628)	(0.245)
$\hat{Post_2}$	0.696***	-0.200**	0.892***	-0.211**
	(0.145)	(0.086)	(0.175)	(0.101)
Performance	1.78*	1.52***	2.98***	1.54***
	(0.959)	(0.566)	(0.937)	(0.558)
Chairman	-0.135	-0.089*	-0.120	-0.082*
	(0.082)	(0.048)	(0.085)	(0.049)
Fixed-effects				
Calendar month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	27,673	27,673	27,673	27,673
R^2	0.26	0.04	0.26	0.04
Within R^2	0.008	0.002	0.007	0.001

Note: This table shows the reduced form IV (2.8) estimates. In the parentheses, standard errors are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 2.11: 2SLS instrumental variable estimation - Cross sectional differences

	X = Performance		X = Chairman	
	News Items	Sentiment	News Items	Sentiment
$\overline{Pre_2} \times X$	-4.67	-0.766	0.270	0.381*
	(2.98)	(1.69)	(0.342)	(0.201)
$\overline{Pre_1} \times X$	-11.5***	2.49	0.640	0.108
	(3.62)	(1.89)	(0.441)	(0.241)
$\overline{Post_1} \times X$	-19.2***	1.68	-1.39***	0.621***
	(3.89)	(2.21)	(0.408)	(0.229)
$\overline{Post_2} \times X$	60.5***	34.1**	4.04	7.69***
	(22.1)	(13.5)	(2.55)	(1.40)
$\overline{Pre_2}$	-1.05***	0.236*	-1.24***	0.133
	(0.230)	(0.122)	(0.265)	(0.139)
$\overline{Pre_1}$	0.824***	0.413***	0.469	0.410**
	(0.272)	(0.142)	(0.313)	(0.164)
$\overline{Post_1}$	2.61***	-0.268**	3.11***	-0.084
	(0.277)	(0.129)	(0.329)	(0.146)
$\overline{Post_2}$	-16.7***	0.584	-19.2***	-1.57
	(2.88)	(1.37)	(3.12)	(1.42)
Performance	5.36***	1.54***	2.48***	0.073
	(0.735)	(0.454)	(0.571)	(0.333)
Chairman	-0.105	-0.088*	-0.191*	-0.336***
	(0.085)	(0.049)	(0.115)	(0.068)
Fixed-effects				
Calendar month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	27,673	27,673	27,673	27,673
R^2	0.26	0.04	0.26	0.04
Within R^2	0.007	0.002	0.006	0.002

Note: This table shows the second stage (2.8) results. The first stage estimates are reported in Panel A of Table (2.5). In the parentheses, standard errors are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Chapter 3

Dynamic Learning in Mutual Fund Management: The Impact of Stock-Specific Experience

3.1 Introduction

Every public company and industry possesses unique characteristics that are crucial for investors or fund managers to understand in order to assess a company's future potential. For instance, when making trading decisions regarding Nvidia, an investment manager requires an in-depth understanding of the company's structure, ongoing projects, the technology industry landscape, and so on. The depth of the manager's knowledge about the specific details of the firm directly impacts their ability to make well-informed decisions. However, fund managers do not inherently possess this level of expertise; they acquire it through experience in investing in companies. The more involvement a manager has in making decisions regarding a specific company or sector, the greater their understanding and knowledge of that firm or sector will be. As a result, this heightened knowledge will contribute to better-informed decision-making by the manager. This paper explores whether mutual fund managers with extensive experience and knowledge in specific stocks or industries outperform their peers who have less experience in those areas.

To address this question empirically, I measure the number of cumulative quarters a specific stock has remained in a manager's portfolio as a proxy for the manager's experience with that stock. Given that managers continuously make decisions regarding stocks in their portfolios and engage in regular analysis, this metric serves as an effective representation of their experience with individual stocks. In addition, I analyze managers' learning within different industries by assessing the relationship between a manager's expertise within a specific industry and the performance of new stocks (previously not included in their portfolio) from that industry added to the manager's portfolio.

The findings show that managers with extensive experience in a specific stock consistently generate higher abnormal returns on that stock compared to their peers. Each additional quarter of experience with a specific stock is associated with an average of 2.7 basis points higher abnormal returns that the manager achieves on that stock in the following quarter. Additionally, this experience leads to a 2.06% increase in the proportionate value that the stock contributes to the portfolio in the following quarter. The results also show that when the next period ex-post alpha of a specific stock is higher, experienced managers increase the stock's weight in their portfolio in the current quarter, reflecting their more accurate expectations of the stock's future abnormal returns. Furthermore, the findings demonstrate that managers with extensive industry experience consistently outperform in those industries and, when they add a new stock from that industry to their portfolio, tend to outperform their less experienced peers.

Making more informed decisions by fund managers can be improved through their learning over time about the assets they are trading. When fund managers track and make decisions on a particular stock for a longer period, they become more informed about the stock's unique characteristics and more experienced in analyzing the company's structure, ongoing projects, and the technology industry as a whole. Increased involvement in decision-making about a specific company or sector enhances a manager's skill, leading to better-informed decisions.

Measuring a manager's stock specific experience presents a significant challenge, since it is not directly observable. I use the number of cumulative quarters that a specific stock has been held in a fund manager's portfolio as a proxy of the manager's experience with the stock. This involves calculating the number of quarters during which a stock appears in a manager's portfolio from beginning of the managers' career. From an economic standpoint, using the total number of quarters that a manager holds a particular stock as an indicator of experience can be justified for several reasons: First, familiarity with the stock: The longer duration over which managers hold a stock allows them to become more acquainted with aspects such as company operations, financial performance, and industry dynamics. This deeper understanding can lead to enhanced investment decisions. Second, the learning curve: Holding onto stocks for multiple quarters exposes managers to various market events and company-specific news, contributing to practical learning experiences that enhance their decision-making abilities over time. Third, monitoring costs: Managers holding stocks for extended periods are likely to have lower monitoring costs due to increased focus on researching and understanding individual stocks rather than continuously seeking new opportunities.

It is important to recognize that the chosen proxy for managerial experience could be correlated with other factors influencing performance over time, such as age or investment strategy. Consequently, controlling for these potential confounding factors becomes crucial in empirical analysis.

Drawing on this proxy for a fund manager's experience in a specific stock, I assess the fund's performance on individual stocks using stocks risk-adjusted return measured by four-factor model. Specifically, my analysis shows that when managers with greater experience in a stock hold that stock in the current quarter, it will have a 2.7 basis points higher abnormal return and a 2.06% higher proportionate value that the stock adds to the portfolio in the next quarter. Furthermore, I find evidence suggesting that experience and its implication to predict future abnormal returns may influence the current weight of a stock in the portfolio. This implies that managers with deep-seated knowledge are inclined to increase their allocation to a specific stock when the true abnormal return is positive in upcoming period. Therefore, the results suggest that fund managers with more experience with a specific stock are able to predict its abnormal return more accurately. I also find evidence that when more analysts cover a stock or when the stock size is larger, the stock-specific experience effect on performance diminishes. The potential reason for this observation is that when more analysts cover a stock or when a stock is bigger, the stock's information is more accessible to the public, making experience less effective.

Moreover, a similar argument holds for managers focus on specific industries. By focusing on a limited number of industries, portfolio managers can acquire more knowledge of those sectors compared to their peers with broader investments across multiple fields. This heightened knowledge may offer the manager a competitive advantage in forecasting trends and making well-informed choices within their specialized industries. Thus, alongside exploring the effects of stock-specific experience, this study also delves into how mutual fund managers' in-depth knowledge of specific industries contributes to their ability to outperform.

It is well-documented in the literature that mutual funds sometimes deviate from well-diversified portfolios to hold concentrated ones. For instance, Kacperczyk et al. (2005) demonstrated that mutual fund managers who focus their holdings in fewer industries can achieve higher risk-adjusted returns. Additionally, Coval and Moskowitz (1999, 2001) found that mutual funds exhibit a strong preference for investing in locally headquartered firms where they appear to have informational advantages. This raises the question: why do mutual fund managers deviate from the established diversification principle to hold concentrated portfolios?

Van Nieuwerburgh and Veldkamp (2010) provide a theoretical framework to rationalise the under-diversification phenomenon observed in the data. In their model, the authors suggest that the optimal allocation of investors' limited attention resources leads to a concentrated portfolio composition. Specifically, their analysis reveals that investors focus their attention on the assets that exhibit the highest Sharpe ratio ex-ante. However, the static nature of the model fails to account for the potential influence of learning and the acquisition of experience by fund managers and investors on the investment process over time. In B.1, I extend their theoretical model by integrating the dynamic aspects of skill development and learning into portfolio management. This not only rationalizes holding more concentrated portfolios to gain its learning advantages, but also provides a more thorough comprehension of the underlying causes for the observed concentration in mutual fund portfolios and its potential long-term effects on investors and the financial market.

The performance of mutual fund managers has been extensively studied in the literature, with skill being decomposed into natural ability and a learned component. However, there remains a significant gap in understanding how managers' skills evolve through ongoing learning and experience over time.

This paper contributes to the literature on mutual funds performance in several ways. First, it contributes to the literature on the impact of learning and experience accumulation on managers' and investors' skills over time. To the best of my knowledge, the sole paper in this line of literature is Kempf et al. (2017). The authors contend that as mutual fund managers gain more experience within a specific industry, they are presumed to deliver superior performance compared to other managers in the same industry. Thus, their perspective demonstrates industry-specific learning by fund managers while this paper evaluates stock-specific experience. Furthermore, their approach and the measure of experience they use differ significantly from those used in this study. Kempf et al. (2017) identify instances when an industry's return falls into the lowest decile as moments when funds face significant challenges, which in turn provide valuable learning opportunities for the managers. They argue that during these critical periods, fund managers learn more about the industry and sharpen their skills, ultimately leading to better performance.

Supporting the importance of managerial skill, research by Chevalier and Ellison (1999) indicates that managers who graduated from higher-SAT undergraduate institutions have higher risk-adjusted excess returns. Golec (1996) shows that younger managers with MBA degrees and longer tenure at their funds had better risk-adjusted performance.

Several studies have validated the association between age, managerial confidence, and performance. Bai et al. (2019) note that older managers make superior stock selections and demonstrate greater decision-making confidence. Ding and Wermers (2012) observe that experienced managers of large funds often exceed performance benchmarks, in contrast to their counterparts in smaller funds who frequently underperform due to managerial entrenchment.

This paper also relates to the literature on mutual fund investment horizons and the relationship between fund turnover and performance. Binsbergen et al. (2024) decompose mutual fund value added by the length of fund holdings using transaction-level data, showing that fund turnover correlates negatively with the horizon over which value is added and positively with price impact costs. Cremers and Pareek (2016) show that among high active share portfolios—whose holdings differ substantially from their benchmark—only those with patient investment strategies outperform on average by more than 2% per year. They also find that funds that trade frequently generally underperform, including those with high active share. Lan et al. (2023) show that long-horizon funds exhibit positive future long-term alphas by holding stocks with superior long-term fundamentals. They also show that stocks predominantly held by long-horizon funds outperform those largely held by short-horizon funds by more than 2% annually, adjusted for risk, over the following 5-year period.

Overall, these studies highlight various factors that can impact mutual fund managers' performance, including natural ability, learned components, age, confidence, investment strategies, fund size, and industry-level dynamics. Understanding these factors can help investors make more informed decisions about which mutual funds to invest in. This paper contributes to this line of literature by exploring the dynamic learning processes of fund managers and examining their impact on decision-making quality and performance.

The rest of the paper is organized as follows: Section 3.2 describes the data sources and the characteristics of the financial market data used. Section 3.3 presents the empirical methodology and the main findings. Finally, Section 3.4 concludes.

3.2 Data

The data in this paper is collected from multiple sources. The mutual funds quarterly holdings and obtained from Thomson Reuters. The stock return data is sourced from the Center for Research in Security Prices (CRSP), while details regarding mutual funds' monthly returns, total net assets (TNA), characteristics, and investment objectives are obtained from the CRSP Survivorship-Bias-Free Mutual Fund database.

Following Chen et al. (2010), I rely on CRSP's reported dummy variable *retail_fund* to identify retail mutual funds. Similar to Kacperczyk et al. (2006), and Huang et al. (2011), I filter actively managed U.S. equity mutual funds based on their investment objectives, asset composition, and fund name. B.2 explains the details of the sample selection.

Since some mutual funds have multiple share classes, the total net assets (TNA) in all share classes are combined for each fund. Net returns and expense ratios of the funds are calculated as TNA-weighted averages across all share classes. Fund age is defined as the age of the share class with the longest history. I subset holdings data for the funds with AUM under 80 million dollar and above 1 million dollar which represents the first quartile of the funds.

All stock related data, like stock returns, trading volume and market capitalization, are obtained from CRSP. Only stocks with share code 10 or 11 are included in the sample. The analyst coverage data are from the I/B/E/S database provided by Thomson Reuters.

Table 3.1 shows the summary statistics of the sample. There are 5,693 and 10,027 different funds and fund managers in the dataset, respectively. Some funds have more than one portfolio manager, and I consider all of them as separate managers who hold the fund's portfolio in order to measure the stock-specific experience. On average, fund managers have 4.71 quarters of stock-specific experience, with a minimum of 1 quarter and a maximum of 53 quarters.

Following Carhart (1997b), I use the four-factor model to assess the performance of individual stocks within fund managers' portfolios. To ensure the reliability and accuracy of a stock's abnormal return (alpha) estimation, I use a 60-month rolling regression to estimate monthly alphas. The monthly alphas are then averaged quarterly. I denote the abnormal return of each stock i by $\alpha_{i,t+1}$ throughout the study.

The weighted abnormal return for each stock i is $w_{i,t}\alpha_{i,t+1}$, where $w_{i,t}$ is the stock's weight in a manager's portfolio. TNA represents total net asset value in millions. Turnover refers to the turnover of the managers' portfolios. Flow is the fund's flow, calculated to reflect the net movement of assets into or out of the fund, excluding performance-driven changes, and is specified as follows:

$$Flow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1} \cdot (1 + R_{j,t}) - MGN_{j,t}}{TNA_{j,t-1}}$$

In this formula, $TNA_{j,t}$ denotes the total net assets of fund j at time t, $R_{j,t}$ represents the return of the fund j at time t, and $MGN_{j,t}$ stands for the change in total net assets attributable to merger events.

Stock-specific turnover refers to the turnover of each individual stock within a manager's portfolio, which is explained in section 3.3.2. Stock size decile refers to the decile to which each stock belongs based on its market cap at each point in time. The number of analysts refers to the number of analysts who cover the stock for up to one year ahead at any given time. Industry experience and Industry dummy are two measures of a manager's experience level in each industry, as explained in section 3.3.3.

3.3 Identification strategy and results

3.3.1 Main results

The proxy for measuring a fund manager's experience with a specific stock is defined as the total number of quarters the stock has been in the manager's portfolio from the start of her career up to any given quarter. This is mathematically represented by the cumulative count of quarters for each stock held by the manager:

$$\text{Experience}_{i,j,t} = \sum_{t'=1}^{t} I_{i,j,t'} \tag{3.1}$$

Here $\textit{Experience}_{i,j,t}$ is the experience of manager j on stock i at quarter t, which is measured as the number of quarters stock i has been held by fund manager j up to quarter t. $I_{i,j,t'}$ is an indicator function that equals 1 if stock i is held by manager j in her portfolio in quarter t', and 0 otherwise.

The other important variable in my study is weighted alpha, denoted as $w_{i,j,t}\alpha_{i,t+1}$. This variable is computed by leveraging the stake of stock i within manager j's portfolio at time t ($w_{i,j,t}$). Weighted alpha is the value added by stock i (in dollars) to manager j's portfolio, in proportion to the portfolio's total value. The value added by stock i ($\textit{Value added}_{i,j,t+1}$) is equal to $p_{i,t}q_{i,j,t}\alpha_{i,t+1}$, where $p_{i,t}$ is the price of stock i at quarter t and $q_{i,j,t}$ is the quantity of stock i held in the portfolio of manager j at quarter t. Normalizing the dollar value added by the total value of the portfolio at quarter t yields:

$$\frac{\text{Value added}_{i,j,t+1}}{\text{Total portfolio value in quarter } t} = \frac{p_{i,t} q_{i,j,t} \alpha_{i,t+1}}{\sum_{k \in Portfolio_{jt}} p_{k,t} q_{k,t,j}} = w_{i,j,t} \alpha_{i,t+1} \tag{3.2}$$

Therefore, the concept of weighted alpha quantifies the value stock i adds to manager j's portfolio proportional to the total value of the portfolio, as shown in Equation (3.2). This metric measures the proportional impact of each stock on the fund's total performance. Using stocks' alpha together with weighted alpha not only highlights the absolute performance of individual stocks within managers' portfolios but also underscores the relative performance and the strategic allocation impact of the fund on its portfolio's overall value, providing a better understanding of investment efficacy.

To test the relationship between managers' stock-specific experience and stock performance, I use the following regression models. Collectively, these models test the relationships between managers' experience, stock allocation strategies, and subsequent stock performance, providing a multifaceted view of how expertise in fund management might influence portfolio returns.

The first model investigates the direct correlation between a stock's abnormal return, which is currently managed by a manager, next quarter ($\alpha_{i,t+1}$) and the manager's experience in the current quarter:

$$\alpha_{i,t+1} = \theta_1 \cdot \text{Experience}_{i,j,t} + \theta_2 \cdot \text{Controls} + \text{FEs} + \epsilon_{i,j,t} \tag{3.3}$$

This model evaluates how stock i's future abnormal return is correlated with the experience of the managers who currently hold the stock. A positive θ_1 shows a positive correlation between the managers' experience level with a specific stock in their portfolio and the subsequent abnormal return of the stock.

The second regression model tests the correlation between the stock's weighted abnormal return next quarter ($w_{i,j,t}\alpha_{i,t+1}$) and the manager's current experience:

$$w_{i,j,t}\alpha_{i,t+1} = \theta_1 \cdot \text{Experience}_{i,j,t} + \theta_2 \cdot \text{Controls} + \text{FEs} + \epsilon_{i,j,t} \tag{3.4}$$

The coefficient θ_1 measures the extent to which the managers' experience level is related to the proportional value that the stock adds to the manager's portfolio.

The third regression model shows how the stock's weight in the fund's portfolio is related to the interaction between the stock's alpha and the fund managers' experience:

$$w_{i,j,t} = \theta_1 \cdot \alpha_{i,t+1} \times \text{Experience}_{i,j,t} + \theta_2 \cdot \text{Experience}_{i,j,t} + \theta_3 \cdot \alpha_{i,t+1} + \theta_4 \cdot \text{Controls} + \text{FEs} + \epsilon_{i,j,t} \tag{3.5}$$

In this regression, the focus is on understanding whether the proportion of investment in stock i ($w_{i,j,t}$) is guided by the combination of stock performance ($\alpha_{i,t+1}$) and managerial experience.

The idea is that a manager's experience could modify the relationship between a stock's future performance and its current weight in her portfolio. For example, if a stock's ex-post abnormal return is positive next quarter and a manager has an accurate prediction, then it might be optimal for the manager to put more weight on the stock. A positive coefficient θ_1 in equation (3.5) shows that when the actual abnormal return of a stock is higher next quarter, managers will put higher weight on the stock. Additionally, the more experienced a manager is, the more weight she will assign to the stock, which is a sign of a more accurate prediction of the future stock's return by the experienced managers.

Controls in regressions (3.3), (3.4), and (3.5) include a fund's age, turnover, size, flow, and expense ratio. These control variables are described in B.3, with a detailed literature review provided to justify their inclusion and to elucidate their expected impact based on previous research findings. To account for unobservable variables that could influence the relationships under study, fixed effects of stock, fund, manager, quarter, and stock × quarter (when it does not eliminate the variation in stocks' abnormal return) are incorporated. The latter fixed effect allows for the control of any unobservables which could affect the performance of any given stock held by different funds at any given quarter, ensuring that the analysis is robust to omitted variable bias. The control variables and fixed effects remain consistent across all regression models presented in this paper.

Table 3.2 presents key findings. The first column displays the correlation between experience and the next quarter's alpha. Since the data only includes portfolio holdings, this column demonstrates that, on average, when a more experienced fund manager holds a specific stock, the stock will have a higher alpha in the next period. Each additional quarter of experience with a specific stock corresponds to a 0.9 basis point higher abnormal return on a monthly basis, which translates to a 2.7 basis point higher alpha quarterly. This highlights the significance of experience in forecasting the future performance of a stock.

The second column indicates that each additional quarter of experience a fund manager holds a stock translates into a 2.06 percent increment in the weighted alpha ($w_t\alpha_{t+1}$) or the proportional value the stock adds to her portfolio will increase by 2.06%. Also when interpreting this finding under the assumption that the weight of the stock in the portfolio (w_t) is constant at 1%, the increment attributable to each quarter of additional experience amounts to a 2.06 basis point higher next quarter stock's alpha (α_{t+1}). This quantification provides a measure of how incremental experience contributes to enhancing the stock-specific performance within a fund, reinforcing the premise that deeper familiarity, experience, and understanding of a stock by fund managers can improve portfolio returns.

The last column of Table 3.2 shows that as experience increases, the fund will allocate a greater weight to the stock when its next-period alpha is higher ex-post. This means that fund managers with higher experience have a better ability to predict alpha ex-ante compared to those with lower experience, leading them to reasonably assign a higher weight to the stock.

Table 3.3 highlights a fund managers' experience effect conditional on different stock sizes and analyst coverage on different stocks. More specifically, this table shows the results of the following regressions:

$$\begin{aligned} w_{i,j,t}\alpha_{i,t+1} = {} & \theta_1 \cdot \text{Experience}_{i,j,t} \times \text{Size}_{i,t-1} \\ & + \theta_2 \cdot \text{Experience}_{i,j,t} + \theta_3 \cdot \text{Size}_{i,t-1} + \theta_4 \cdot \text{Controls} + \text{FEs} + \epsilon_{i,j,t} \end{aligned} \tag{3.6}$$

$$\begin{aligned} w_{i,j,t}\alpha_{i,t+1} = {} & \theta_1 \cdot \text{Experience}_{i,j,t} \times \text{Analyst Coverage}_{i,t-1} \\ & + \theta_2 \cdot \text{Experience}_{i,j,t} + \theta_3 \cdot \text{Analyst Coverage}_{i,t-1} + \theta_4 \cdot \text{Controls} + \text{FEs} + \epsilon_{i,j,t} \end{aligned} \tag{3.7}$$

Table 3.3 shows the results of regression equations (3.6) and (3.7), for both weighted alphas and alphas as outcome variables. In these regressions, $Size_{i,t-1}$ represents the decile of the market value of stock i in quarter $t-1$,[1] and $Analyst\ Coverage_{i,t-1}$ is the total number of analysts covering stock i in quarter $t-1$. Controls and fixed effects are the same as those used in the main regressions.[2]

The result of regression (3.6) is reported in the first two columns of Table 3.3. The

[1] the stocks with largest market value are in decile 10.

[2] Controls include the fund's age, turnover, size, flow, and expense ratio. The fixed effects are stock, fund, manager, quarter, and stock × quarter.

result indicates that the incremental advantage derived from fund managers' experience with a stock diminishes as the size of the stock increases. This suggests that while experience contributes positively to the performance of investments in smaller stocks, its impact is less pronounced for larger stocks. This phenomenon could be attributed to the fact that larger stocks, typically belonging to well-established companies, are more closely followed by analysts and investors, with information about them more readily available and reflected in their prices. Consequently, the unique insights or additional value that experienced fund managers might bring through their familiarity with these stocks could be less significant compared to their contributions to smaller, potentially less well-known stocks.

The findings in the last two columns of Table 3.3, which are associated with regression (3.7), highlight how the marginal benefit of fund managers' experience with a stock is influenced by the extent of analyst coverage it receives. Specifically, as the number of analyst reports on a stock rises, the unique advantage offered by a fund manager's experience begins to wane.

The underlying rationale is that analyst reports increase the availability and accessibility of detailed analysis on the stock's prospects, performance, and risks, making these insights available to all market participants, including those fund managers with less direct experience with the stock. As a result, in environments where stocks are widely covered by analysts, the differential impact of experience on forecasting stock performance and making informed portfolio decisions diminishes. In essence, the abundance of analyst coverage can serve as a leveling factor, making experience less of a distinct advantage in predicting future stock performance. This observation suggests that in highly scrutinized markets, the breadth and depth of publicly available analyses may partially substitute for personal experience accumulated by fund managers.

One potential concern about the results is that the experience measure could be mechanically higher for stocks included in a manager's benchmark for a longer period. This does not necessarily reflect the manager's actual experience with the stock. Therefore, one could argue that the outperformance of stocks with a longer history in a given benchmark might be driving the results.

To address this concern, I conduct a placebo test using index funds. The idea is that the index funds cover all the benchmarks a fund manager could follow, and if I show that there is no correlation between these index funds' stock-specific experience (which is stocks' history with different benchmarks) and the outperformance of the stock, then I can rule out the possibility I discussed in the previous paragraph. To achieve this, I run three regression equations (3.3), (3.4), and (3.5), specifically for index funds. The experience metric for the index funds would be the cumulative quarters a stock belongs to the benchmark the index fund follows.

The findings in Table 3.4 show that the effect of experience is not consistent for index funds. There is no significant difference in performance between an index fund and a particular stock, even if the stock has been in the fund's passive portfolio for an extended period. These results support the main findings by ruling out the previously mentioned potential mechanism.

3.3.2 Stock-specific turnover

The results so far indicate that fund managers with extensive experience in particular stocks tend to outperform and achieve higher alpha from investments in those stocks. This advantage likely arises because sustained engagement with specific stocks enhances a fund manager's focus and understanding of the stocks' fundamental performance metrics. Next, I examine the effect of a fund manager's trading activity intensity, as proxied by stock-specific turnover in a particular stock, on their performance. The question I address in this subsection is whether more frequent trading improves a manager's learning across different stocks and helps them perform better.

To investigate the effect of trading frequency on performance, I define the turnover of stock i in manager j's portfolio during period t as:

$$\text{Stock Turnover}_{i,j,t} = \frac{p_{i,t}|q_{i,j,t} - q_{i,j,t-1}|}{TNA_{j,t}} \tag{3.8}$$

Here, $q_{i,j,t}$ represents the number of shares of stock i held by manager j at time t, and $p_{i,t}$ is the price of stock i at the same time. This measure of turnover helps quantify the extent of trading activity undertaken by the manager in managing her stock holdings.

To explore the relationship between more frequent trading by experienced fund managers and their outperformance, I use the following regression models:

$$\begin{aligned} \alpha_{i,t+1} = {} & \theta_1 \cdot \text{Experience}_{i,j,t} \times \text{Stock Turnover}_{i,j,t} \\ & + \theta_2 \cdot \text{Experience}_{i,j,t} + \theta_3 \cdot \text{Stock Turnover}_{i,j,t} + \theta_4 \cdot \text{Controls} + \text{FEs} + \epsilon_{i,j,t} \end{aligned} \tag{3.9}$$

$$\begin{aligned} w_{i,j,t}\alpha_{i,t+1} = {} & \theta_1 \cdot \text{Experience}_{i,j,t} \times \text{Stock Turnover}_{i,j,t} \\ & + \theta_2 \cdot \text{Experience}_{i,j,t} + \theta_3 \cdot \text{Stock Turnover}_{i,j,t} + \theta_4 \cdot \text{Controls} + \text{FEs} + \epsilon_{i,j,t} \end{aligned} \tag{3.10}$$

The coefficients of interest in regressions (3.9) and (3.10) are θ_1 and θ_3. A positive estimate of θ_3 indicates that, when the experience level is zero, more frequent trading by managers translates into higher stock-specific performance. Conversely, a negative estimate of θ_1 suggests that more frequent trading by experienced managers diminishes the benefits of stock-specific experience.

The regression results, as shown in Table 3.5, indicate that intensified engagement with specific stocks (higher stock turnover) enhances fund managers' performance in terms of abnormal returns, but it will diminish marginal effect of stock-specific experience. A one-unit increase in stock turnover for a manager with one quarter of experience with a stock translates into a 4.3 basis point increase in abnormal return. The results also show that this effect does not exist for weighted alpha. Furthermore, including or excluding portfolio turnover as a control, which could be correlated with stock-specific turnover, does not change the coefficients significantly. The rationale behind these results is that experience helps managers outperform on a specific stock due to the learning advantage it provides regarding the stock's fundamentals which usually not changing at high-frequency. Therefore, experience may assist a manager with making low-frequency predictions about a stock's future performance rather than relying on high-frequency predictions. Additionally, Column 5 of Table 3.5 shows that there is no significant correlation between stock turnover and experience, while stock-specific experience is negatively correlated with portfolio turnover.

3.3.3 Learning about an industry

This subsection examines the potential advantages a mutual fund manager can gain by specializing in a specific industry. It specifically focuses on whether a fund manager's extensive experience within a given industry correlates with superior performance, as evidenced by an enhanced ability to generate alpha on the industry's stocks held within the manager's portfolio.

Similar to the stock-specific experience effect, a fund manager with a strategic focus and prolonged investment in a specific sector is likely to possess a refined ability to process relevant information more efficiently than managers who are less focused on that sector. This expertise enables better identification and exploitation of profitable opportunities within the sector, potentially leading to higher returns from related stocks.

To test this hypothesis, it is essential to precisely measure 'industry experience' for each fund manager. I propose a metric to quantify a fund manager's industry experience by calculating the time-weighted average duration of their investments in a particular industry. Assuming fund manager j begins operations at time $t = 0$, her experience in industry I at time T is defined by the following formula:

$$\text{Industry Experience}_{I,j,T} = \frac{1}{T}\sum_{\tau=0}^{T} w_{I,j,\tau} \cdot \tau \tag{3.11}$$

Here, $w_{I,j,\tau}$ represents the weight of manager j's investments in industry I at time τ. This formula provides a dynamic measure of the fund manager's accumulated industry experience, reflecting the intensity and duration of their focus within the industry.

To empirically validate the hypothesis that a fund manager's industry-specific experience enhances managerial skill within the industry, I use two regression models. The first model assess the relationship between the manager's experience in a specific industry and the subsequent abnormal returns of stocks within that industry. The regression model is structured as follows:

$$\alpha_{i,j,t+1} = \theta \cdot \text{Industry Experience}_{I(i),j,t} + \gamma \cdot \text{Controls} + \text{FEs} + \epsilon_{i,j,t} \tag{3.12}$$

Here, $\alpha_{i,j,t+1}$ represents the abnormal return of stock i, which is part of industry $I(i)$ and managed by fund manager j, for the period following time t. This model evaluates how past experience within a specific sector correlates with the future performance of stocks within that sector that are part of the manager's current investments.

The second regression model is formulated to assess the effect of industry specific experience on stocks' weighted-alpha:

$$w_{i,j,t}\alpha_{i,j,t+1} = \theta \cdot \text{Industry Experience}_{I(i),j,t} + \gamma \cdot \text{Controls} + \text{FEs} + \epsilon_{i,j,t} \tag{3.13}$$

$w_{i,j,t}$ is the weight manager j allocates to stock i which includes in industry $I(i)$ at quarter t.

The use of *Industry Experience*$_{I(i),j,t}$ as an explanatory variable in this regression framework evaluates the effect of accumulated sector-specific knowledge on the economic gains achieved within the portfolio, thereby providing a measure of how strategic industry focus influences fund performance.

Table 3.6, columns 1 and 3, presents the results of regressions (3.12) and (3.13). The findings indicate that each additional unit of industry-specific experience for a manager corresponds to an average of 1.9 basis point higher abnormal return in the next quarter for the stocks held in the manager's current portfolio. Additionally, this experience translates to a 3.37% increase in proportional value added by the stock.

To further assess the impact of industry-specific experience on fund performance, I propose an additional empirical test. Suppose a fund manager adds a new stock to her portfolio. The idea is to test whether the manager's experience with the stock's industry can explain the stock's abnormal return in the next quarter. Therefore, the objective is to compare the performance of fund managers with varying degrees of industry-specific experience to which the newly added stock belongs. My analysis focuses on the quarters during which a fund adds a new stock from a specific industry.

To do this analysis, I create a dummy variable that distinguishes between fund managers with no industry experience regarding the new stock (dummy variable set to 0) and those with some level of experience (dummy variable assigned a value based on the quintile index of the fund manager's industry experience). This differentiation allows me to not only compare the performance across managers with varying degrees of familiarity with the industry but also to examine how fund managers with no prior experience perform relative to those with some experience.

The following regression model is then designed to evaluate the relationship:

$$\alpha_{i,j,t+1} = \theta \cdot \text{Industry Dummy}_{I(i),j,t} + \gamma \cdot \text{Controls} + \text{FEs} + \epsilon_{i,j,t} \tag{3.14}$$

$$w_{i,j,t}\alpha_{i,j,t+1} = \theta \cdot \text{Industry Dummy}_{I(i),j,t} + \gamma \cdot \text{Controls} + \text{FEs} + \epsilon_{i,j,t} \tag{3.15}$$

Table 3.6 columns 2 and 4 show the results of regressions (3.14) and (3.15). The results indicate that a one-unit increase in the industry dummy (a one-unit jump in industry experience quintile) corresponds to a 2.24 basis point increase in abnormal returns and a 6.21% higher proportional added value from a new stock to the portfolio within the industry. Therefore, when experienced managers within an industry add a new stock from that industry to their portfolio, they outperform their peers.

The findings consistently suggest that funds with more extensive industry experience tend to outperform those with shorter or no experience, supporting the hypothesis that industry-specific expertise contributes to higher alpha generation and overall value addition to the portfolio.

3.4 Conclusion

This study explores the role of experience and industry-specific expertise in mutual fund managers' portfolio decisions and the associated performance outcomes. The study analyzes the ability of funds with greater experience to generate alpha and allocate a larger share of their portfolio to stocks with higher next-period alphas. The empirical findings emphasize the significance of experience in predicting stock performance and the allocation of resources within a portfolio.

The paper also investigates the advantages of concentrating on a specific industry for a fund. The results suggest that funds with more industry experience have superior performance compared to those with less or no experience in a given sector, supporting the hypothesis that industry-specific expertise can lead to higher alpha generation and value addition to the portfolio.

Additionally, the study examines the impact of fund managers' turnover on a given stock and whether it leads to the generation of additional value. The findings indicate that increased engagement with a particular stock, through higher stock-specific turnover, enables fund managers to gain deeper knowledge and insights into that stock, ultimately enhancing their investment outcomes. However, the effect of stock turnover on performance is not as robust as the direct impact of experience.

3.5 Tables

Table 3.1: Summary statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Experience	1,447,822	4.71	5.1	1	1	6	53
Abnormal return	1,371,816	0.001	0.06	-2	-0.03	0.03	1
Weighted abnormal return	1,371,816	0.00001	0.002	-0.6	-0.0003	0.0003	0.6
TNA (in million)	1,447,822	34	22	1	15	51	80
Flow	1,444,646	0.05	2	-3	-0.01	0.02	225
Turnover	1,447,822	1	2	0	0.4	1	48
Stock specific turnover	1,447,822	0.006	0.5	0	0	0.005	319
Expense Ratio (in percent)	1,447,822	1	0.5	0.01	1	2	28
Fund age	1,447,822	8	6	0.003	3	11	36
Number of analysts	1,407,632	16	10	1	8	22	66
Stock size decile	1,407,632	6	3	1	3	8	10
Industry Experience	1,407,632	1	2	0	0.2	1	23
Industry Dummy	370,078	3	1	0	1	4	5

Table 3.2: Fund managers stock-specific experience, funds performance and portfolio allocation

Dependent Variables:	α_{t+1}	$w_t\alpha_{t+1}$	w_t
Model:	(1)	(2)	(3)
Variables			
Experience	0.900***	2.06***	0.028***
	(4.72)	(6.83)	(13.45)
Experience × α_{t+1}			0.30***
			(4.39)
α_{t+1}			0.088
			(0.99)
log(Age)	-1.46	6.58**	-0.040***
	(-1.29)	(2.36)	(-4.51)
log(TNA_{t-1})	-0.233	-5.03***	-0.024***
	(-0.419)	(-3.82)	(-6.00)
ER	-0.024	0.118	0.002***
	(-1.16)	(1.61)	(9.06)
Flow	-0.581**	-1.70***	-0.005**
	(-2.56)	(-3.13)	(-2.04)
Turnover	-0.319	1.08	0.027***
	(-0.87)	(1.38)	(9.07)
Fixed-effects			
Stock	Yes	Yes	Yes
Quarter	Yes	Yes	Yes
Fund	Yes	Yes	Yes
Manager	Yes	Yes	Yes
Stock×Quarter	NO	Yes	Yes
Fit statistics			
Observations	1,328,056	1,328,056	1,328,056
R^2	0.08	0.53	0.83
Within R^2	0.004	0.003	0.006

Notes: This table shows the results of regressions (3.3), (3.4), and (3.5). The abnormal returns and weights are reported in basis points and percentages, respectively. The Stock × Quarter interaction is excluded from the regression represented in the first column, as including it would eliminate the variation in stock abnormal returns. The control variables used are the logarithm of the fund's age, the logarithm of the fund's total net asset value in the previous quarter, the fund's expense ratio (ER) in percentage, fund flows, and portfolio turnovers. Standard errors are clustered at stock level. In the parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 3.3: Stock-specific experience effect conditional on stock size and analyst coverage

Dependent Variables:	α_{t+1}	$w_t\alpha_{t+1}$	α_{t+1}	$w_t\alpha_{t+1}$
Model:	(1)	(2)	(3)	(4)
Variables				
Experience	1.58***	0.899**	0.968*	0.911***
	(2.69)	(2.08)	(1.87)	(6.26)
Experience × Size_{t-1}	-0.287***	-0.15***		
	(-3.30)	(-2.61)		
Experience × Analyst_{t-1}			-0.084***	-0.043**
			(-2.84)	(-2.04)
Size_{t-1}	-69.4***	-4.17		
	(-21.1)	(-0.62)		
Analyst_{t-1}			-5.79***	-0.950
			(-8.79)	(-1.19)
log(Age)	2.29	15.3*	4.58*	15.3**
	(0.89)	(1.96)	(1.79)	(1.97)
$\log(\text{TNA}_{t-1})$	-0.843	-11.2***	-4.26***	-11.3***
	(-0.64)	(-3.21)	(-3.18)	(-3.22)
ER	0.007	0.343*	0.028	0.342*
	(0.17)	(1.74)	(0.59)	(1.74)
Flow	-2.14***	-3.44***	-2.28***	-3.45***
	(-2.83)	(-2.71)	(-2.98)	(-2.72)
Turnover	-2.14***	-3.53*	-1.99***	-3.56*
	(-2.87)	(-1.79)	(-2.72)	(-1.80)
Fixed-effects				
Stock	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes
Fund	Yes	Yes	Yes	Yes
Manager	Yes	Yes	Yes	Yes
Stock×Quarter	NO	Yes	NO	Yes
Fit statistics				
Observations	1,304,473	1,304,473	1,304,473	1,304,473
R^2	0.09	0.53	0.08	0.53
Within R^2	0.007	0.003	0.002	0.003

Notes: This table shows the results of the regressions (3.6) and (3.7). The abnormal returns and weights are reported in basis points and percentages, respectively. The Stock × Quarter interaction is excluded from the regressions represented in the column (1) and column (3), as including it would eliminate the variation in stock abnormal returns. The control variables used are the logarithm of the fund's age, the logarithm of the fund's total net asset value in the previous quarter, the fund's expense ratio (ER) in percentage, fund flows, and portfolio turnovers. Standard errors are clustered at stock level. In the parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 3.4: Placebo test

Dependent Variables:	α_{t+1}	$w_t\alpha_{t+1}$	w_t
Model:	(1)	(2)	(3)
Variables			
Experience	-0.104	-0.248	0.0002
	(-0.48)	(-0.95)	(0.81)
Experience $\times$ α_{t+1}			0.004*
			(1.73)
α_{t+1}			-11.3
			(-0.005)
log(Age)	-4.34*	4.59	0.044***
	(-1.65)	(0.98)	(9.63)
log(TNA$_{t-1}$)	0.048	-7.48***	-0.003
	(0.04)	(-3.13)	(-1.45)
ER	-6.653	-14.497	0.156***
	(-0.79)	(-0.95)	(8.03)
Flow	0.035	-4.17**	-0.001
	(0.043)	(-2.03)	(-0.15)
Turnover	-0.557	-0.948	0.0006
	(-1.25)	(-1.25)	(0.33)
Fixed-effects			
Stock	Yes	Yes	Yes
Quarter	Yes	Yes	Yes
Fund	Yes	Yes	Yes
Manager	Yes	Yes	Yes
Stock$\times$Quarter	No	Yes	Yes
Fit statistics			
Observations	1,169,377	1,169,377	1,169,377
R^2	0.07	0.56	0.87
Within R^2	0.00003	0.00001	0.0002

Notes: The table shows the placebo test results. More specifically, it shows the results of the regressions (3.3), (3.4), and (3.5) for index funds. The abnormal returns and weights are reported in basis points and percentages, respectively. The Stock $\times$ Quarter interaction is excluded from the regression represented in the first column, as including it would eliminate the variation in stock abnormal returns. The control variables used are the logarithm of the fund's age, the logarithm of the fund's total net asset value in the previous quarter, the fund's expense ratio (ER) in percentage, fund flows, and portfolio turnovers. Standard errors are clustered at stock level. In the parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 3.5: Stock-specific experience effect and stock-specific turnover

Dependent Variables: Model:	α_{t+1} (1)	$w_t\alpha_{t+1}$ (2)	α_{t+1} (3)	$w_t\alpha_{t+1}$ (4)	Experience (5)
Variables					
Experience	0.746***	1.50**	0.753***	1.49**	
	(3.74)	(2.47)	(3.77)	(2.45)	
Experience×Stock Turnover	-3.17**	-95.7	-3.14**	-95.7	
	(-2.13)	(-1.22)	(-2.14)	(-1.22)	
Stock Turnover	7.43***	346.0	7.37***	345.9	0.0006
	(4.04)	(1.35)	(4.08)	(1.35)	(0.170)
log(Age)	4.37*	15.0*	4.31*	14.9*	0.855***
	(1.69)	(1.94)	(1.67)	(1.93)	(25.4)
log(TNA$_{t-1}$)	-3.44***	-10.0***	-3.59***	-10.2***	-0.078***
	(-2.58)	(-2.76)	(-2.69)	(-2.82)	(-5.61)
ER	2.62	34.5*	2.75	34.7*	0.469***
	(0.555)	(1.75)	(0.583)	(1.76)	(11.4)
Flow	-2.17***	-4.17***	-2.10***	-4.06***	-0.007
	(-2.84)	(-3.07)	(-2.75)	(-2.99)	(-1.11)
Turnover			-2.07***	-2.82	-0.059***
			(-2.78)	(-1.40)	(-5.99)
Fixed-effects					
Stock	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes
Fund	Yes	Yes	Yes	Yes	Yes
Manager	Yes	Yes	Yes	Yes	Yes
Stock × Quarter	NO	Yes	NO	Yes	NO
Fit statistics					
Observations	1,328,056	1,328,056	1,328,056	1,328,056	1,402,261
R^2	0.08	0.55	0.0.08	0.55	0.55
Within R^2	0.004	0.006	0.004	0.006	0.028

Notes: This table shows the results of the regressions (3.9) and (3.10). The abnormal returns and weights are reported in basis points and percentages, respectively. The Stock × Quarter interaction is excluded from the regressions represented in the column (1), column (3), and column (5) as including it would eliminate the variation in stock abnormal returns. The control variables used are the logarithm of the fund's age, the logarithm of the fund's total net asset value in the previous quarter, the fund's expense ratio (ER) in percentage, fund flows, and portfolio turnovers. Standard errors are clustered at stock level. In the parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

Table 3.6: Industry-specific experience and funds performance

Dependent Variables:	α_{t+1}		$w_t\alpha_{t+1}$	
Model:	(1)	(2)	(3)	(4)
Variables				
Industry Experience$_{I(i),j,t-1}$	1.911***		3.354***	
	(6.23)		(7.31)	
Industry Dummy		2.249**		6.21***
		(2.56)		(3.22)
log(Age)	3.77	6.78	16.4**	-4.38
	(1.46)	(1.07)	(2.13)	(-0.302)
log(TNA$_{t-1}$)	-3.83***	-6.92**	-11.2***	-14.5**
	(-2.87)	(-2.49)	(-3.21)	(-2.19)
ER	0.015	0.209**	0.289	0.573
	(0.325)	(1.98)	(1.48)	(1.56)
Flow	-2.17***	-5.03	-3.37***	-1.82
	(-2.82)	(-1.47)	(-2.64)	(-0.256)
Turnover	-2.25***	-2.63	-3.20	-13.4
	(-3.00)	(-1.08)	(-1.60)	(-1.26)
Fixed-effects				
Stock	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes
Fund	Yes	Yes	Yes	Yes
Manager	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,087,498	206,473	1,327,547	206,473
R^2	0.08	0.17	0.53	0.74
Within R^2	0.003	0.003	0.009	0.004

Notes: This table presents the results of industry-specific experience regressions. Columns (1) and (3) show the results of regressions (3.12) and (3.13), respectively. Columns (2) and (4) display the results of regressions (3.14) and (3.15), respectively. The abnormal returns and weights are reported in basis points and percentages, respectively. The control variables used are the logarithm of the fund's age, the logarithm of the fund's total net asset value in the previous quarter, the fund's expense ratio (ER) in percentage, fund flows, and portfolio turnovers. Standard errors are clustered at stock level. In the parentheses, t-statistics are reported. *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% level, respectively.

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A Appendix to Do CEOs Manipulate News? Evidence from Fixed-term Employment Contracts

A.1 Definitions

Table A1: Description of Variables used in this Study. This table defines the main variables used in this study.

Variable	Definition and description
Pre_{jit}	A dummy equals to one when t for firm i is j quarters before it's renewal date.
$Post_{jit}$	A dummy equals to one when t for firm i is j quarters after it's renewal date.
$\hat{\text{Renewal}}$ Date_i	The predicted renewal date based on the contract length
$\hat{Pre}_{jit}$	A dummy equals to one when t for firm i is j quarters before $\hat{\text{Renewal}}$ Date_i.
$\hat{Post}_{jit}$	A dummy equals to one when t for firm i is j quarters after $\hat{\text{Renewal}}$ Date_i.
$\overline{Pre}_{ji}$	Predicted value derived from the regression of Pre_{jit} on $\hat{Pre}_{jit}$.
$\overline{Post}_{ji}$	Predicted value derived from the regression of $Post_{jit}$ on $\hat{Post}_{jit}$.
News Items_{it}	The number of discretionary news items at time t for firm i
Sentiment_{it}	The difference between the number of positive and negative discretionary news items for firm i at time t
Performance_i	Average monthly CAPM alphas of the firm from the day a CEO starts her job to two quarters before her contract's renewal date

Chairman	A dummy equals one when a CEO is the chairman of the board two quarters before and after her contract renewal date and zero otherwise.
AGM	Annual general meeting
Board	Board meetings
EA	Earning announcement
GVKEY	a unique number which is assigned to each company in the Compustat Capital IQ database that remain constant, regardless of the name changes or other instances, is never reused.

A.2 Contract terms

Figure A1: An example of a CEO contract

a. Employment. The Employer hereby employs the Employee, and the Employee hereby accepts employment by the Employer, as the President and Chief Executive Officer of the Employer. The Employee also agrees to serve as President and Chief Executive Officer of the Bank and a Director of the Employer and the Bank if elected to such positions, and the Employer agrees to include the Employee on management's slate of directors for the Bank and the Employer.

(a) Employment

2. Base Compensation. The Employer agrees to pay the Employee so long as he is employed pursuant to this Agreement a base salary at the total rate of Three Hundred Thirty Thousand Dollars ($330,000) per annum commencing with the Commencement Date (as defined below) or at such higher rate as the Board may thereafter establish (the "Base Salary"). The Base Salary shall be payable on the same schedule as salaries of other executive officers of the Employer are paid. Once increased, the Employee's Base Salary may not thereafter be decreased. The Employer will pay the Employee the Base Salary for so long as the Employer is an employer of the Employee hereunder. The Commencement Date shall be January 1, 2005.

(b) Compensation

3. Term. The Employee's employment by the Employer pursuant to this Agreement is for the period commencing on the Commencement Date and ending thirty-six (36) months thereafter or on such earlier date as is determined in accordance with Sections 10 and 12 of this Agreement or such later date as provided herein. On the first anniversary of the Commencement Date and on each successive anniversary of such date thereafter the term of this Agreement shall be extended for one additional year, unless this Agreement is sooner terminated as provided in Sections 10 and 12 unless either the Board or the Employee advises the other, in writing no less than ninety (90) days prior to any anniversary of the Commencement Date that this Agreement will no longer be extended; provided, however, that the term of this Agreement shall end on the sixty-fifth (65) birthday of the Employee. Notwithstanding the foregoing, in the event of a Change of Control, the date the Change of Control occurs shall become the Commencement Date for all purposes thereafter, and each Change of Control thereafter shall result in a new Commencement Date on the date of the latest Change of Control.

(c) Potential termination date

d. Termination by the Employer Without Just Cause or by the Employee for Good Reason.

(i) Payment of Base Salary. The Board may, during the term of this Agreement, by written notice to the Employee, immediately terminate his employment at any time for a reason other than Just Cause or the Employee may terminate this Agreement for Good Reason by written notice to the Employer delineating in detail such Good Reason and by providing reasonable opportunity for the Employer to cure or correct any such Good Reason. In the event of such a termination, the Employee shall be entitled to receive, as a severance benefit, an amount equal to the aggregate of the Base Salary plus any appropriate cash bonus on an annual basis at the rate then in effect times two, following such termination of this Agreement; provided, however, if termination is made in connection with a Change in Control of the Employer, then the provisions of Section 12 shall apply. For purposes of this subparagraph "Good Reason" shall mean (A) the requirement that the Employee move his personal residence out of the geographic area of the Bank and/or a further distance from said area than is his present residence, as the case may be; (B) the assignment to the Employee of duties and responsibilities substantially inconsistent with those normally associated with his position described in Section 1 hereof; (C) a material reduction in the Employee's responsibilities or authority (including reporting responsibilities) in connection with his employment with the Employer; (D) a reduction of the Employee's Base Salary or a material reduction of his benefits provided hereunder taken as a whole; or (E) the Employer shall materially breach this Agreement and upon written notice by the Employee to the Employer of said breach, the Employer shall not cure said breach within thirty (30) days after such notice from the Employee..

(d) Termination cost

Note: This figure shows some parts of a contract between 1st Constitution Bancorp and Robert F.Mangano as a CEO. Panel A shows the employment and the role of the CEO. Panel B shows the base compensation and its details. Panel C shows some dates that are mentioned as potential dates for renewing or terminating the contract. Panel D shows the termination cost for the board.

B Appendix to Dynamic Learning in Mutual Fund Management: The Impact of Stock-Specific Experience

B.1 Theoretical model

The model I propose here extends the static model developed by Kacperczyk et al. (2016) into a dynamic framework. It assumes a continuum of investors, each denoted by a unique index j ranging from 0 to 1. These investors experience a two-period lifespan, throughout which they want to maximize their mean-variance utility derived from their final wealth. All investors share a common cognitive attention limit, represented by the capacity K. This cognitive capacity denotes the attentional constraint impacting their ability to effectively handle asset selections.

Consider a market consisting of n uncorrelated risky assets and one risk-free asset (with a zero riskless rate), the payoff of asset i at time $t = 2$ is denoted as D_i. Each investor enters the market with a prior belief about asset i's distribution, modeled as a normal distribution $N(\mu_i, \sigma_i)$.

At $t = 0$ each investor conducts an initial research on the assets without any trades at this time. More specifically, Each investor j allocates a specific amount of research $k_{i|j}$ to asset i, subject to the constraint that the total research across all assets does not exceed their attention capacity K:

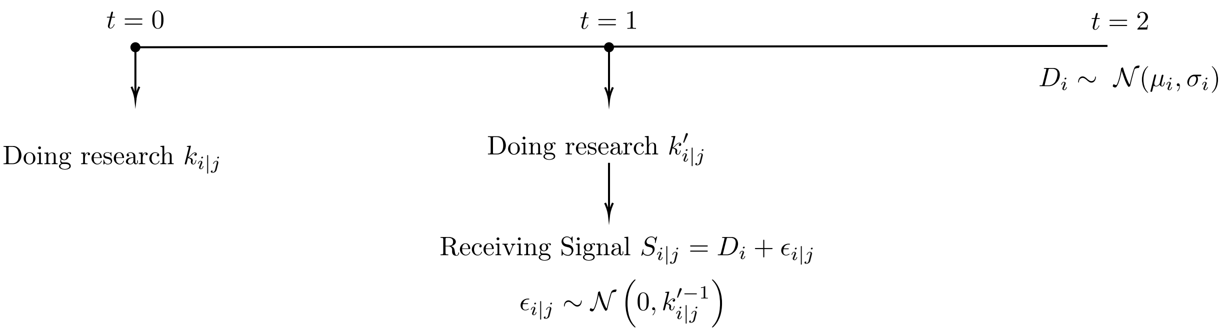
$$\sum_{i=1}^{n} k_{i|j} \leq K. \tag{B.1}$$

The research effort $k_{i|j}$ is aimed at either reducing the cost of further research or increasing the marginal benefit of conducting additional research on asset i in the future. This preparation sets the stage for the next period's activities.

At $t = 1$, the framework for how much additional research $k'_{i|j}$ each investor can conduct is adjusted by the function $f(k_{i|j})$, which is concave and satisfies the condition $f(x) \geq 1$ for all x and $f(0) = 1$. This function modulates the research effort based on the initial investment in research $k_{i|j}$, such that more initial research enhances the effectiveness of subsequent research. The attention constraint for investor j at $t = 1$ can be expressed as:

$$\sum_{i=1}^{n} \frac{k'_{i|j}}{f(k_{i|j})} \leq K. \tag{B.2}$$

This equation implies that the effective cost of continuing to research an asset at $t = 1$ is inversely related to the function $f(k_{i|j})$, which scales with the amount of prior research $k_{i|j}$ dedicated to that asset. A higher $k_{i|j}$ not only increases $f(k_{i|j})$ but also allows for a proportionally larger amount of $k'_{i|j}$, enhancing the depth and potentially the quality of the information gathered in the ongoing analysis of asset i. This dynamic interplay between periods shapes how investors allocate their limited attention across various assets, aiming to optimize the trade-offs between research costs and benefits.



At $t = 1$, when investors conduct further research on different assets, they receive a signal about each asset based on the attention they allocate to it. The signal on asset i received by investor j at time 1 is given by $S_{i|j} = D_i + \epsilon_{i|j}$, where the error term $\epsilon_{i|j}$ follows $\mathcal{N}(0, {k'_{i|j}}^{-1})$, The variance of the error term inversely relates to the amount of research ${k'_{i|j}}^{-1}$ conducted at $t = 1$, indicating that more research reduces uncertainty about the asset's payoff. Therefore, investors observe their own signals and the asset price at time 1, and, after learning about each asset's payoff using their signal and the price, they determine their demand.

Note that the price of each asset reflects an aggregation of signals received by investors, and due to the law of large numbers, the aggregate signal will possess perfect information about the asset's payoff. However, by assuming that the supply of asset i at time 1, denoted by $\tilde{x}_i$, follows a random normal distribution with mean 0 and variance σ_x, I prohibit the prices to be fully revealing for the investors.

Each investor has a mean-variance utility over their final wealth. Therefore, investor j's utility at time 0 can be expressed as:

$$U_j = \mathbb{E}_{0|j}\left[\mathbb{E}_{1|j}\left[w_2^j\right] - \frac{\rho}{2}\mathrm{Var}_{1|j}\left[w_2^j\right]\right] \tag{B.3}$$

Where $\mathbb{E}_{0|j}[.]$ and $\mathbb{E}_{1|j}[.]$ represent the conditional expectations held by investor j based on the information available to her at times 0 and 1, respectively.

The problem of investor j at time 1, after learning about assets' payoffs by observing their signals and prices will be:

$$\max_{\{q_{i|j}\}_{i=1}^{n}} \mathbb{E}_{1|j}\left[w_2^j\right] - \frac{\rho}{2}\text{Var}_{1|j}\left[w_2^j\right] \tag{B.4}$$

$$w_2^j = w_1^j + \sum_{i=1}^{n} q_{i|j}(D_i - P_i) \tag{B.5}$$

Where investor j seeks to choose q_j in order to maximize her utility on her final wealth. Therefore, we have:

$$q_{i|j} = \frac{\mathbb{E}_{1|j}[D_i|S_{i|j}, P_i] - P_i}{\rho\text{Var}_{1|j}[D_i|S_{i|j}, P_i]} \tag{B.6}$$

Where:

$$\hat{\sigma}_{i|j} \equiv \text{Var}_{1|j}[D_i|S_{i|j}, P_i] = \left(\sigma^{-1} + \sigma_{p_i}^{-1} + k'_{i|j}\right)^{-1} \tag{B.7}$$

$$\hat{\mu}_{i|j} \equiv \mathbb{E}_{1|j}[D_i|S_{i|j}, P_i] = \hat{\sigma}_{i|j}\left(\sigma^{-1}\mu + \sigma_{p_i}^{-1}P_i + k'_{i|j}S_{i|j}\right) \tag{B.8}$$

By imposing the market clearing condition for each asset, we can compute the price function. The market clearing condition for asset i is given by $\int q_{i|j}dj = \tilde{x}_i$. Consequently, we get the following results:

Corollary 1. *The price function at time 1 is:*

$$P_i = \frac{\sigma_i^{-1}\mu_i}{\sigma_i^{-1} + \overline{K}'_i} + \frac{\overline{K}'_i}{\sigma_i^{-1} + \overline{K}'_i}D_i - \frac{\rho}{\sigma_i^{-1} + \overline{K}'_i}\tilde{x}_i \tag{B.9}$$

Where $\overline{K}'_i = \int k'_{i|j}dj$ represents the aggregate attention investors allocate to stock i.

Proof. I propose that the price of the i^{th} asset at time 1 follows a linear form, given by:

$$P_i = a_i + b_iD_i + c_i\tilde{x}_i \tag{B.10}$$

The objective is to demonstrate that the price function adheres to this linear form and to compute the coefficients a_i, b_i, and c_i. Observe that if we define $\eta_{p_i} \equiv \dfrac{P_i - a_i}{b_i}$, then

η_{p_i} will be equal to $D_i + \frac{c_i}{b_i}\tilde{x}_i$, which is a non-biased signal of D_i. In my analysis, I will use η_{p_i} instead of P_i to compute investors' posterior beliefs about assets' payoffs. It is important to note that $\eta_{p_i} \sim \mathcal{N}(D_i, \sigma_{p_i})$, where I will determine the value of σ_{p_i} later in this section.

Given investor j's demand function, which incorporates updated expressions for variance $\hat{\sigma}_{i|j}$ and expected value of asset i, we have:

$$q_{i|j} = \frac{\hat{\sigma}_{i|j}\left(\sigma^{-1}\mu + \sigma_{p_i}^{-1}P_i + k'_{i|j}S_{i|j}\right) - P_i}{\rho\left(\sigma^{-1} + \sigma_{p_i}^{-1} + k'_{i|j}\right)} \tag{B.11}$$

By substituting $S_{i|j} = D_i + \epsilon_{i|j}$ into the equation and integrating over all investors j, the market clearing condition can be expressed as:

$$\int q_{i|j}\, dj = \tilde{x}_i \tag{B.12}$$

This integral simplifies the demand across all investors to equal the supply of asset i. Expanding the integral, I apply the linearity of integration to each term:

$$\int \frac{\hat{\sigma}_{i|j}\left(\sigma^{-1}\mu + \sigma_{p_i}^{-1}P_i + k'_{i|j}(D_i + \epsilon_{i|j})\right) - P_i}{\rho\left(\sigma^{-1} + \sigma_{p_i}^{-1} + k'_{i|j}\right)} dj = \tilde{x}_i \tag{B.13}$$

This integral can be decomposed further into parts that are analytically tractable, noting that $\epsilon_{i|j}$ is a noise term with mean zero and that $\hat{\sigma}_{i|j}$ might depend on $k'_{i|j}$. Simplifying and solving this equation will provide the equilibrium asset price P_i as a function of the aggregated demands, known parameters, and the realization of D_i.

□

Corollary 2. *Using Collary 1, it is clear that* $\sigma_{p_i} = \frac{\sigma_x}{K_i'^2}$.

Taking one step back to consider investors' problem at time 1 but just before receiving their signals and when deciding on their attention capacity allocation, their problem can be formulated as follows:

$$\max_{\{k'_{i|j}\}_{i=1}^n} \mathbb{E}_b\left[\mathbb{E}_{1|j}\left[w_2^j\right] - \frac{\rho}{2}\mathrm{Var}_{1|j}\left[w_2^j\right]\right] \tag{B.14}$$

$$w_2^j = w_1^j + \sum_{i=1}^n q_{i|j}(D_i - P_i) \tag{B.15}$$

Here, $\mathbb{E}_b$ represents the expectation at time 1, before observing any signals or prices.

By plugging (B.6) into (B.15) and then plugging the result into (B.14), we can rewrite the expected utility function (B.14) as follows:

$$\mathbb{E}_b\left[\mathbb{E}_{1|j}\left[w_2^j\right]-\frac{\rho}{2}\text{Var}_{1|j}\left[w_2^j\right]\right]=w_1^j+\frac{1}{2}\sum_{i=1}^{n}\mathbb{E}_b\left[\frac{1}{\hat{\sigma}_{i|j}}(\hat{\mu}_{i|j}-P_i)^2\right] \tag{B.16}$$

Since both $\hat{\mu}_{i|j}$ and P_i are normally distributed, $\frac{1}{\hat{\sigma}_{i|j}}(\hat{\mu}_{i|j}-P_i)^2$ can be considered as a non-central χ^2 distribution from the perspective of time 1, before observing signals and prices. If I define $m_{i|j}=\frac{1}{\sqrt{\hat{\sigma}_{i|j}}}(\hat{\mu}_{i|j}-P_i)$, then (B.16) will be equal to $tr(\text{Var}(m_{i|j}))+$
$\mathbb{E}[m_{i|j}]^2$. Following Kacperczyk et al. (2016), the maximization problem for investor j can be formulated as:

$$\max_{\{k'_{i|j}\}_{i=1}^n}\sum_{i=1}^{n}\lambda_i k'_{i|j}+\text{constant} \tag{B.17}$$

$$\text{s.t.}\quad\sum_{i=1}^{n}f(k_{i|j})k'_{i|j}\leq K \tag{B.18}$$

$$\text{Where }\lambda_i=\Psi_i\left[1+\left(\rho^2\sigma_x+\overline{K}'_i\right)\Psi_i\right] \tag{B.19}$$

$$\Psi_i^{-1}\equiv\int\hat{\sigma}_{i|j}^{-1}dj=\sigma^{-1}+\sigma_{p_i}^{-1}+\overline{K}'_i \tag{B.20}$$

As I'm looking for a symmetric equilibrium, I'll drop the subscript j for simplicity.

The objective and the constraint are linear in terms of $\{k'_i\}$s. Therefore, investor j will allocate her attention to the assets with the maximum $\frac{\lambda_i}{f(k_i)}$. There could be more than one asset that shares the maximum amount of $\frac{\lambda_i}{f(k_i)}$. Without loss of generality, assume that assets $1,2,\ldots,l$ share the maximum, and therefore:

$$\frac{\lambda_1}{f(k_1)}=\frac{\lambda_2}{f(k_2)}=\ldots=\frac{\lambda_l}{f(k_l)} \tag{B.21}$$

Investors will be indifferent about assets $1,2,\ldots,l$ and will assign zero attention to assets $l+1,l+2,\ldots,n$ at $t=0$, because otherwise they would waste their time 0 attention capacity for no gain in expected utility.

Therefore, investor j' maximum utility will be equal to:

$$\frac{\lambda_1}{f(k_1)}K+Constant \tag{B.22}$$

Now consider the problem faced by investor j at time $t = 0$. The investor aims to select values for $k_1, k_2, \ldots, k_n$ as her initial research on assets that maximize the expression $\frac{\lambda_1}{f(k_1)}$, while adhering to the constraint outlined in equation (B.21). Solving this problem leads to the following theorem:

Theorem 3. *Each investor will select only one asset for intense research at the initial stages ($t = 0$ and $t = 1$), which results in enhanced performance on this singularly chosen asset. This theoretical insight supports the hypothesis that targeted research enhances utility through focused learning, resulting in superior asset knowledge and subsequent investment returns.*

Proof. It is clear from the formulation that at the optimal solution, $k_m = 0$ holds true for all $m \in \{l+1, l+2, \ldots, n\}$. Proceeding with the analysis, I differentiate equation (B.22) with respect to k_1 to obtain the following derivative:

$$\frac{\partial}{\partial k_1}\frac{\lambda_1}{f(k_1)} = -\frac{\left(\rho^2\sigma\sigma_x^2 + \overline{K_1'}^2\sigma + 2\overline{K_1'}\sigma\sigma_x + \sigma_x\right)\left(\frac{d}{dk_1}f(k_1)\right)\sigma\sigma_x}{\left(\overline{K_1'}^2\sigma + \overline{K_1'}\sigma\sigma_x + \sigma_x\right)^2 f(k_1)^2} \tag{B.23}$$

Given that $f(k_1)$ is decreasing in k_1, I conclude that $\frac{\partial}{\partial k_1}\frac{\lambda_1}{f(k_1)}$ is positive. Therefore, there's a symmetric equilibrium in which investors assign all their attention capacity into just one stock at time 0. □

Theorem 3 demonstrates that investors and fund managers, constrained by limited attention capacities, tend to concentrate their focus on a single asset. This specialization enables them to deepen their knowledge about that specific stock over time. As a result, their experience with and understanding of the asset improve, leading to enhanced performance due to more accurate information about the asset.

B.2 Sample selection

I follow previous studies on mutual funds (e.g., Kacperczyk et al. (2008); Dou et al. (2022)) to filter the set of active equity mutual funds. In particular, I do the following steps to select equity mutual funds:

1. I first select funds with the following Lipper objective codes: CA, CG, CS, EI, FS, G, GI, H, ID, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, MR, NR, S, SCCE, SCGE, SCVE, SG, SP, TK, TL, UT

2. If the Lipper objective code is unavailable, I select funds with the following Strategic Insight objectives: AGG, ENV, FIN, GMC, GRI, GRO, HLT, ING, NTR, SCG, SEC, TEC, UTI, GLD, RLE

3. If none of the above is available, I select funds with the following Wiesenberger codes: G, G-I, G-S, GCI, IEQ, ENR, FIN, GRI, HLT, LTG, MCG, SCG, TCH, UTL, GPM

4. Finally, since objective classes do not always correctly identify equity mutual funds, I include fund observations with at least 80 percent invested in common stocks.

Next, following previous studies (e.g., Busse and Tong (2012), Ferson and Lin (2014)) I do the following steps to filter out index funds:

1. I identify a fund as an index fund if its "index fund flag" in the CRSP data is B, D, or E.

2. I also consider a fund as an index fund if its ETF flag is "F" or "N".

3. Next, I also identify a fund as an index fund if its name includes any of the following strings: Index, Ind, Idx, Indx, Mkt, Market, Composite, S&P, SP, Russell, Nasdaq, DJ, Dow, Jones, Wilshire, NYSE, iShares, SPDR, HOLDRs, ETF, Exchange-Traded Fund, PowerShares, StreetTRACKS, 100, 400, 500, 600, 1000, 1500, 2000, 3000, 5000, INDEX Passive

In the next step, I select retail mutual funds by using the retail fund flag and institutional fund flag in the CRSP database. These two indexes are not mutually exclusive, so I only select funds that are identified as being retail funds and notinstitutional. Following Kacperczyk et al. (2005), I drop fund observations with less than

\$1 million TNA in the previous quarter. I also drop newly born funds that were established less than 1 year ago. This consists of a small fraction of observations. Finally, fund flows and returns are winsorized at 0.5 and 99.5 percent to correct for data errors.

B.3 Supporting literature for control variables

This appendix presents a comprehensive literature review on each of the control variables employed in this study, elucidating their relevance and impact on fund performance.

1. **Smart Money Effect**: Gruber (1996) introduced the concept of "smart money," referring to the net new money flows in mutual funds associated with higher returns. Sapp and Tiwari (2004) connected the smart money effect to momentum strategy, as investors tend to chase recent winners. Berk and Green (2004) developed a model based on rational expectations of investors to explain this phenomenon.

2. **Expense Ratio**: The expense ratio represents the cost of managing a fund and has been shown to have a negative impact on fund performance (Babalos et al. (2009), Carhart (1997b), Elton et al. (1996), Ferreira et al. (2013), Grinblatt and Titman (1994), Gruber (1996)). Wermers (2000) demonstrated that expenses and transaction costs significantly reduced net returns.

3. **Fund Size**: The size of a mutual fund can affect performance through economies and diseconomies of scale. Several studies have identified an "inverted U-shaped" relationship between size and performance (Ciccotello and Grant (1996), Indro et al. (1999), Latzko (1999)). Negative effects of size on performance have been reported by Chen et al. (2004), Ferreira et al. (2013), Pollet and Wilson (2008), and Yan (2008).

4. **Portfolio Turnover Ratio**: The portfolio turnover ratio measures the extent of active trading in equity mutual funds, reflecting the impact of such trading strategies on performance. Carhart (1997b) and Wermers (2000) found a negative effect of portfolio turnover ratio on mutual fund performance, with Yin-Ching and Mao-Wei (2003) supporting these findings using a stochastic dominance approach.

5. **Age of the Fund**: The age of a mutual fund refers to its years in existence, with older funds potentially benefiting from a "learning by doing" effect. Chen et al. (2004) found no relationship between a fund's age and performance in the United States, while Otten and Bams (2002) reported a positive relationship in five European countries.

This literature review provides a solid foundation for understanding the control variables employed in this study, which are essential for assessing their impact on fund performance.