Essays in Corporate Finances and Firm Dynamics

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Abstract

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This dissertation examines how the changes in the structure of corporate boards of publicly traded firms can have an impact on both the corporate finance decisions of the firm as well as have broader market-wide implications due to the subsequent changes in relative firm dynamics that may result from the changes at the board level. Central to this study is the role of the outside board of director. This outside director has at least two channels of effect on the firm. Each of the chapters closely examines one of these effects. The first chapter explores how outside directors can aid firms in "competitively positioning" the firm in both a product-market and technological-market space. The increasing prevalence of shared directors among firms has led to more boards being connected through a board network. Contrary to the long standing belief that closeness on a board network aids in imitation across firms, I document the presence of "strategic differentiation" between the firms. I provide causal evidence that changes in the distance between two boards, or changes in the board network distance, is inversely related to the similarities in revenue distribution from industries. Moreover, this board network distance also has explanatory power over how firm decide their long-term technological direction(measured by the distribution of technology classes of the patents granted and also by the change in the number of relative patent-citations between the two firms). In other words, closeness between firms on a board network leads to "strategic differentiation" in both the product-market and technological-market space.

However, contrary to classical explanations of collusion between firms, I find that there is no evidence that the prevalence of industry connections between boards, has led to changes in average industry prices. I attribute this to the possibility that board networks aid firms in avoiding wasteful duplication of products and technologies. The second chapter take a more micro view of the heterogenous nature of the outside director. Media press releases of firms often extol the unique qualifications and experiences of the outside directors that they hire, yet their contributions to the firm are often difficult to measure. This chapter argues that "industry expertise" is a highly sought after and measurable quality of the outside director. To quantify the effects of the outside director's industry expertise on the firm, I introduce a novel new methodology for constructing this industry expertise measure from the director's resume. The simplicity of the measure also allows it to incorporate the entirety of the director's historical resume, including employment at private firms. With this measure, I find that boards actively seek out outside directors that contribute unique industry expertise thereby expanding the firm's expertise areas. This has a profound effect as I show that firms that hire directors that are more different than their expertise areas are then more likely to invest and R&D. This acceleration of spending also results in more product differentiation from the firm's primary competitors.

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DEDICATION

to my dear wife, kids, and parents

Chapter 1

TIES THAT DIFFERENTIATE

Public companies are among the most innovative firms in the economy and account for a large fraction of R&D as well as patenting, see Autor et al. (2016). But what determines the direction or similarity of their innovative activity? We analyze this question through the lens of what we call competitive positioning, defined as the similarity of firms along the two dimensions of product market space as well as technology space. While recent empirical evidence by Bloom, Schankerman and Van Reenen (2013*a*) has shown that competitive positioning influences the degree of R&D spillovers across firms, much of the current literature takes the competitive position of firms as given. We therefore empirically explore how governance arrangements impact public firms endogenous competitive positioning and innovation.

The governance arrangement we have in mind are board networks, which are groups of public firms that are directly or indirectly linked through their independent directors. In the wake of financial accounting scandals in the early 2000s as well as associated changes in financial regulation, such as the Sarbanes-Oxley Act, there has been a recent push for independent directors on corporate boards. As has been documented by Fich and Shivdasani (2007); Harford (2003), this has led to an increasing number of directors sitting on multiple boards, and correspondingly, an explosion of interlocking directorates, which means that two firms are linked by sharing the same director, see Davis, Yoo and Baker (2003). Our work is in the spirit of recent empirical studies that have analyzed the consequences of these growing board networks. For example, studies such as Fracassi and Tate (2012) and Fracassi (2017) have shown how board networks influence monitoring activities as well as corporate financial policies. However, to our knowledge, ours is the first study to analyze the impact of board networks on competitive positioning and the direction of innovation. Specifically, our question is whether more closely connected companies imitate each other's competitive positions or rather seek to differentiate from each other. Our goal is to estimate the impact of distance in the board network on competitive positioning across companies.

A key empirical challenge for our analysis is the fact that firms endogenously determine the composition of their boards and will therefore have an influence on the board network distance, see Weisbach (1988). To address this endogeneity issue, we follow an approach similar to Fracassi (2017), by exploiting the exogenous variation of unexpected director deaths as an instrument for changes in the board network distance between two companies. We then analyze the impact of increasing board network distance on competitive positioning along its two dimensions of product market and technology space. For this purpose, we bring together measures for competitive positioning from different sources. First, we provide two alternative measures of product market positioning, one based on similarity of revenue distributions along industries in Compustat and one based on product description similarity in regulatory filings from Hoberg and Phillips (2016). Second, we measure technology space positioning by the similarity of technology classes in patent applications from the USPTO as well as patent citation flows from Kogan et al. (2017).

Prior work on board networks has established that more closely connected firms are more similar along corporate financial policies, Fracassi (2017), Chen, Dyball and Wright (2009), and Haunschild (1993); and corporate governance choices, Nguyen (2012) and Bouwman (2011). In contrast, we find that more closely connected companies tend to be more differentiated instead of less differentiated with respect to their competitive positioning. In particular, we estimate that an exogenous increase in board network distance causes product market similarity to increase not to decrease. In other words, increases in board network distance between two companies imply less product differentiation. We document this pattern by estimating an increase in similarity of both, the industry composition of revenues as well as the product descriptions in regulatory statements. Increases in differentiation are not just limited to the product market space, but also apply to the technology space. In particular, an exogenous increase in network distance also implies an increase in the similarity of technology-class patent applications as well as an increases in patent citation flows. In other words, firms that are further away in the board network tend to be more likely to patent in similar technologies and are also more likely to cite each others patents. Taken together, all these results suggest that more closely linked companies are more differentiated, while distant companies imitate each other more.

We then offer a deeper exploration of propagation through the board network, by focusing on indirectly affected firms. These are companies that are connected through the board network but are not directly affected by an unexpected director death. Since the board network distance between such indirectly connected company increases in response to an unexpected director death by a third party company, this allows us to analyze spillover effects of increased network distance. We find that board network spillover effects are similar to our baseline effects, in that more distant companies tend to become more similar in their competitive positioning.

There are at least two explanations for our findings that increased board network distance implies more similar competitive positioning. On the one hand, board networks might enable companies to transmit information about their product and technology choices, so that potential competitors can optimally product differentiate. We call this the information transmission model. On the other hand, board networks might be tools of tacit collusion, enabling more closely connected companies to credibly commit to not directly compete with each other. To directly investigate the tacit collusion mechanism, by analyzing industry prices, this mechanism has a clear prediction that more collusion should imply higher prices. Using our director death IV, we then analyze how exogenous changes in average board network distance within industries impact prices and do not find much support for the tacit collusion model.

Our work is related to at least three different literatures. First, we build on recent advances in understanding the interaction of innovation and competition. Firms compete with each other in the product market space, giving rise to business stealing effects while they benefit from technology spillovers. This separation of product market and technology space effects goes back at least to studies on R&D cooperation and competition, such as papers by Katz and Ordover (1990), but has also been prominently featured in Bloom, Schankerman and Van Reenen (2013*a*), which is closely related. More broadly, our work is related to the analysis of interactions between innovation and competition, such as the effects of patent protection on innovation (Hall and Ziedonis (2001), Galasso and Schankerman (2017)) and the impact of competition on innovation (Aghion et al. (2005), Bloom, Draca and Van Reenen (2016), Autor et al. (2016), Kueng, Li and Yang (2016)).

A second related literature focuses on governance arrangements and innovation, which broadly analyses the impact of institutional context on firm innovation. Studies in this literature have focused on a number of different institutional factors influencing innovation, such as ownership patterns (Aghion, Van Reenen and Zingales (2013), Tribo, Berrone and Surroca (2007), Antón et al. (2017)), corporate governance and investor protection (Becker-Blease (2011), Xiao (2010)) and the market for corporate control (Sapra, Subramanian and Subramanian (2014)).

Third, we also contribute to the growing literature on the importance of information transmission via board networks. Recent studies highlight the importance of these networks for corporate policies (Fracassi (2017)), acquisitions (Field and Mkrtchyan (2017)) as well as the influence of board member heterogeneity for investment and innovation, Fan (2017).

1.1 Measurements

We begin first by characterizing how the board networks are measured, including direct interlocks between firms as well as spillover effects of these interlocks due to changes in network distances. Next, we will introduce our measurements of outcomes. We will discuss how we measure two firms competitive positioning as well as innovative direction.

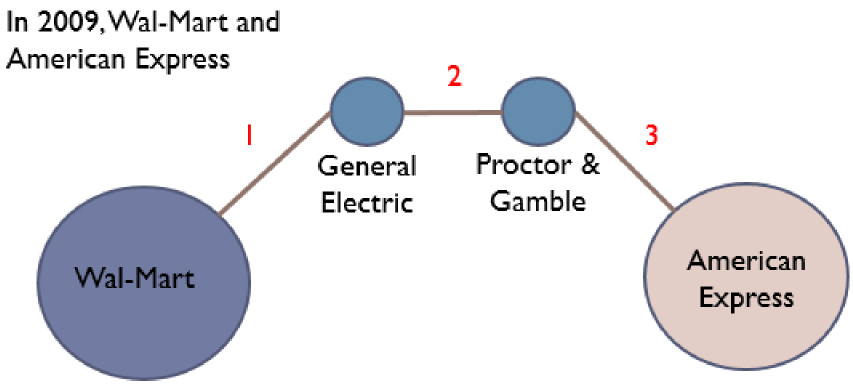

Figure 1.1: Example: Local board network spanned by shared directors.

1.1.1 Measurement of Board Networks

Two firms are defined to have a connection in a given year through a board network if these two firms share a director on their board. In other words, a director simultaneously sits on the board of both firms. The two firms are said to be linked, connected or interlocked and the distance between these two firms is defined to be one.

Figure 1. provides an example of how a director can interlock two firms. In 2009, Wal-Mart and General Electric Co. were connected by Doctor Jim Cash Jr. Mr. Cash was a long tenured Wal-Mart independent director, joining Wal-Mart in 1996 before joining General Electrics board in 2006. By joining General Electrics board while simultaneously sitting on Wal-Marts board, Mr. Cash interlocks the two firms. Similarly, a different director simultaneously sits on the boards of General Electric and Proctor Gamble while another director sits on the board of Proctor & Gamble and American Express.

Related to the definition of connection is the definition of network distance. While connections describe whether a link between two firms exist of not, the network distance describes the minimum path between two firms, as measured by how many directors need to be involved in connecting the two firms. Previously for Wal-Mart and General Electric,

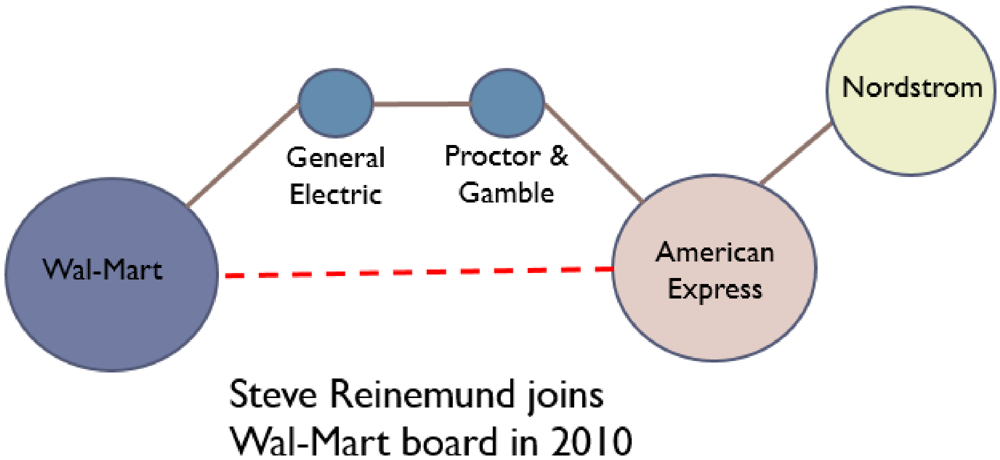

Figure 1.2: Example: Change in Network Distance.

a single director connects both firms directly, therefore the network distance is one. The same is true when we consider the firms General Electric and Proctor & Gamble as well as Proctor & Gamble and American Express. However, for firms not directly connected such as Wal-Mart and American Express, for information to travel between both boards, it needs to travel through three different directors, therefore the two firms have a network distance of three.

Direct connections between firms provide an obvious opportunity for two firms to exchange information. However, as new connections are formed or severed, this has potential consequences to surrounding firms as well. Consider again Wal-Mart and American Express in 2009 in Figure 12. Three directors separate the two boards. However, American Express is also interlocked with Nordstrom at the same time. Thus, Wal-Mart and Nordstrom are separated by 4 directors so the network distance is 4. For information to travel to travel from Nordstrom to Wal-Mart and vice-versa in 2009, four directors need to be involved. A connection between Wal-Mart and American Express in 2010 not only directly interlocks Wal-Mart and American Express, but also indirectly influences the relationship between Wal-Mart and

Nordstrom. Specifically, the network distance between Nordstrom and Wal-Mart now decreases from four to two. Therefore, the direct connection between Wal-Mart and American Express that forms in 2010 not only has a direct impact on the dynamics between these two firms, but this connection also has a spillover effect on surrounding firms by possible decreasing their network distance. This spillover effect will be explicitly considered in our empirical analysis.

1.1.2 Measurement of Outcomes

Product Market Rivalry

To measure the relative competitiveness between firms that sell into multiple product lines or segments requires a more general measure of competition when revenue comes from multiple sources. Our measurement for segment sales competition is adapted from Jaffe (1986) that allows for both spatial and product dimensions.

Each year, firms report product line sales figures in their annual report to the SEC. Suppose two firms i and j, each sell into n product market segments. Each product market segment that each firm participates in generates revenue for the firms. Let these revenues for the firms be $R_{i_t,n}$ and $R_{j_t,n}$ at time t, for segment n, for firms i and j, respectively. For two firms that produce primarily in the same market segment, a majority of sales agents will overlap and thus competition will be relatively more intense than a pair of firms that do not overlap in segment sales. More generally though, firms will distribute their sales force across multiple market segments that they participate in. The more similar these distributions are for any two firms, the more intense the competition is likely to be between them.

Formally, let firms is sales share at time t in n segments be a 1xN vector, $F_{i,t} = \{F_{1,t}, F_{2,t}, F_{3,t}, F_{n,t}\}$. Similarly, firm js sales share at time t in n segments also be an 1xN vector, $F_{j,t} = \{F_{1,t}, F_{2,t}, F_{3,t}, F_{n,t}\}$.Then, the Product Market Competition Score between firms i and j is:

$$PMR_{ij,t} = \frac{F_i F_j'}{(F_i F_i')^{\frac{1}{2}} (F_j F_j')^{\frac{1}{2}}} \tag{1.1}$$

In the extreme case in which both firms sell exactly the same amount into the same segments, then the vectors , $F_{i,t}$ and $F_{j,t}$ will be identical, thereby reducing the product market competition score to one. The product market competition score is between 0 and 1. Larger scores indicate greater competitive intensity between the two firms while a smaller score close to 0 indicates less competition. The score also has the attractive properties of being invariant to the number of segments.

Product Differentiation

One possible concern with our sales segment similarity measure may be that abated competition may not be observed if product market segments are too broadly defined. Therefore, as a complement to the product market competition score, we also utilize a measure that captures product similarity more directly. The Hoberg-Philips Text-Based product description similarity score provides this measurement. Annual 10-K reports to the SEC contain managerial description of the product that are produced by the firm. Similar to the annual reports that contain segment sales data, these managerial descriptions are also by law required to be accurate. The basic premise of the Hoberg-Philips product similarity score is that if two managerial descriptions contain similar verbiage, the products are more likely to be similar as well. Practically, the product similarity score is created by constructing a word matrix of the product description using a web-crawling algorithm to read in the product descriptions for each firm. Common words are excluded. The remaining words for each firm are used to create a similarity score for each firm pair. Scores for each firm pair that are close to one indicate similar products. Firm-pairs that report scores that are close to zero indicate products that are very different.

The main attractive feature of the Hoberg-Philips Product Similarity Score is that it complements the sales-based product market competition score with data from a different source. Moreover, since the similarity score is calculated each year, panel analysis allows us to compare the average change in product differentiation for any two firms over time.

Patenting Similarity

To measure change in the technology space we utilize an adapted technological similarity score by Jaffe (1986). We adapt an innovation measure that captures the Technological Similarity Score between two firms based on the types of patents that the firms produce. The USPTO has 408 technology classes for patents. The firms distribution of patents into these technology classes describes the average technological positioning of firms in a technology space. Changes in the distribution of patents in technology classes over time, can be map into changes in technological similarities between two firms.

The construction of technological similarity of patenting is similar to our measure of product market rivalry. Suppose two firms i and j, patent into k technology classes. Each technology class that each firm patents into, requires innovation inputs[1]. Let these innovation inputs for the firms be $Z_{it,k}$ and $Z_{jt,k}$ at time t, for tech class k, and for firms i and j, respectively. Firms that patent in the same technology class, will overlap more in innovation inputs, thus the two firms will be close in some technology space. More generally though, firms will distribute their patents across multiple technology classes, the more similar these distributions are for any two firms, the more similar their technology are between them, and the closer they are in some technology space.

Formally, let firms is sales share at time t in n segments be a 1xK vector, $T_{i,t} = \{T_{1,t}, T_{2,t}, T_{3,t}, , T_{k,t}\}$. Similarly, firm js sales share at time t in k segments also be an 1xK vector, $T_{j,t} = \{T_{1,t}, T_{2,t}, T_{3,t}, , T_{k,t}\}$. Then, the Technology Similarity Score between firms i and j is:

[1]Innovation inputs can be R&D expenditures or in the case of Jaffe (1986), scientist for each technology class.

$$TSIM_{ij,t} = \frac{F_i F_j'}{(F_i F_i')^{\frac{1}{2}} (F_j F_j')^{\frac{1}{2}}} \tag{1.2}$$

Similar to the product market competition score for two firms, this technology score is also invariant to the number of classes. The score value is between 0 and 1. Patenting data and patenting distribution across time allow us to track how technological positioning my alter following interlocking events. The data section provides a more detailed treatment on how we go about calculating this statistic empirically.

Patent-related information flows and Patent Citations.

The technological similarity score describes the average positioning of innovations by firms but it is silent on the direction of information flows. However, future innovations often build on past innovations. The implied information flow from knowledge about past innovations to new innovations is captured in patent citations. (Trajtenberg (1990)).

To measure information flows on innovation, we consider how patent citation numbers change over time. Since firm A and B operate in a similar technological space, they improve on each others existing patents, by applying for new patents. However, to demonstrate that their new improvements sufficiently warrant a new patent, a patent examiner will consider other patents to look closely at. These other patents are frequently revealed ahead of time or cited by the inventor to ensure the patent examiner closely considers those patents or these other patents may be found by the examiner herself as part of the examination process. As part of this application process, it is also generally in the best interest of the inventor to reveal all similar patents to the examiner to avoid patent infringement litigation.

1.2 Methodology

1.2.1 Endogeneity Problem and Instrumental Variable Strategy

The main challenge in any corporate board study is the fact that corporate board structure is endogenously determined Adams, Hermalin and Weisbach (2010); Hermalin and Weisbach (2003), Hermalin and Weisbach (1988*a*). These papers describe a tension between CEO power and board composition. Hermalin and Weisbach (1988*b*) find that the boards of directors are endogenously chosen but board independence (number of outside directors) declines with the tenure of the CEO. Others describe the number of outside directors increasing with poor firm performance. When a director from another firm joins a new firm as an outside director, the impact that the director has on the firm (influence effect) may be difficult to disentangle from the fact that the firm may have anticipated a shift in policy and thus sought out directors who were familiar with these policies (familiarity effect). Within the framework of this paper, the endogeneity issue raised prevents us from making a causal statement regarding the impact of a new director connection (board interlock) and subsequent changes in firm behaviors.

To address this endogeneity issue, we turn to unexpected *director deaths* as a source external variation in network connectivity. Nearly all larger public firms have corporate bylaws in place that stipulate how directors are replaced. In general, for planned vacancies, the nomination committee puts forth nominees to be voted upon at the companys next annual shareholder meeting. The outgoing director stays on during this transition process to ensure a smooth transition. However, for unplanned vacancies such as a director death, the board seat generally remains vacant until the next shareholder meeting.

In the sample, 303 such events occur between firm-pairs. When such death events occur, it creates a disconnection between two firms that were previously connected. Likewise, the disconnection is unexpected and thus is uncorrelated with any concurrent change in relative firm performance. In Section IV, the data section also verifies empirically that the director death events are not correlated with concurrent changes in the relative firm-performance. This satisfies the exogeneity requirement. Since firm-firm disconnections also cause an increase in network distance between the two previously connected firms, our instrumental variable *director deaths* serves as a good explanatory variable for change in network distance. We limit these director deaths to only firm-pairs that share the same director at some $t-1$ and observe relative changes in outcome at time t.

For each of our four outcome measurements, we estimate a 2SLS first-difference model, estimating the endogenous variable: changes to network distance in the first-step using our instrument *same director deaths*.

$$\begin{aligned}
&\Delta NetDist_{ij,t} \\
&\quad = \alpha_1 * DirDeath_{ij,t} + \alpha_2 * Connection_{ij,t-1} + \alpha_3 * \Delta Controls_{ij,t-1} \\
&\quad + \alpha_4 * Geo_{ij} + \alpha_5 Year_{ij,t} + error
\end{aligned} \tag{1.3}$$

In the second step, we use the estimated change in network distance to explain changes in relative firm-firm outcome.

$$\begin{aligned}
&\Delta FirmBehavior_{ij,t} \\
&\quad = \beta_1 * \Delta NetDist_{ij,t} + \beta_2 * Connection_{ij,t-1} + \beta_3 * \Delta Controls_{ij,t-1} \\
&\quad + \beta_4 * Geo_{ij} + \beta_5 Year_{ij,t} + error
\end{aligned} \tag{1.4}$$

We apply appropriate controls for each of the four outcome measurements. The controls are chosen to control for relative differences in firm characteristics, firm performance, or year effects that may also explain the outcome changes. Firm characteristic controls include firm size as measured by lagged assets or market value, number of market segments as a measurement of firm complexity, and total number of directors for both firms. Firm performance controls include measures of profit-margin, ROA, ROI and research intensity proxied by R&D expenditure weighted by total revenue.

Throughout our analysis we also control for the geographical position of firms. We believe this to be especially relevant for our analysis of the technology space, as firms that are geographically proximate might benefit from knowledge spillovers due to the fact that they are part of the same industry cluster. To be able to capture the broadest set of spillovers, our geographic unit is going to be US States.

1.2.2 Network Spillover Analysis

We define spillover effects as the impact of changes in network distance for companies that we not directly linked through a director. To fix ideas, consider a two-path network (Figure 2) in which companies A and D are connected through two paths: first, the path A-B-C-D, in which A and D are linked through 3 directors and second, the path A-E-F-G-D which has a path length of 4. Suppose the link between B and C is now exogenously disconnected. Then the shortest path distance increases from 3 to 4 links.

Although A and D are never share a director and are therefore not directly connected, the shortest path length between these two companies increases, which is what we call a spillover effect.

We are interested in potential spillover effects of exogenous changes in network distance for at least two reasons. First, the spillover itself is an object of interest, as it captures the indirect propagation of information through the board network. Second, we believe that an investigation of these spillover effects may shed light on whether the information transmission or tacit collusion mechanism is important for board networks. To understand our basic idea, lets return for a moment to the example of the chain A-B-C-D with the link between B and C exogenously disconnect. In an information-transmission model, the disconnection between B and C will imply a longer path between A and D and therefore a lower degree of information transmission. In contrast, in a model of tacit collusion, the disconnection of B and C might imply more competition between B and C directly, but does not necessarily have any implications for A and D[2].

In terms of our econometric specification, we are interested in the changes in the shortest path between two companies that are implied by disconnected intermediate links, as in figure 2, so our first stage in this case becomes:

[2] For example, this will be the case if consumer demand for the products offered by the firms in the figure exhibit the independence of irrelevant alternatives (IIA) property.

$$
\begin{aligned}
&\Delta NetDist_{kl \neq ij,t} \\
&\qquad = \alpha_1 * DirDeath_{ij,t} + \alpha_2 * Connection_{kl \neq ij,t-1} + \alpha_3 * \Delta Controls_{kl \neq ij,t-1} \\
&\qquad + \alpha_4 * Geo_{kl \neq ij} + \alpha_5 Year_{ij,t} + error
\end{aligned}
\tag{1.5}
$$

with $kl \neq ij$ denoting that the network distance pair under consideration is different from the direct pair affected by the director death. In the example in figure 2, this change for the indirectly affected pair A and D is 1 (from a distance of 3 to a distance of 4 links).

Correspondingly, we will then analyze the impact of this change in the shortest path on firm behavior of the indirectly affect firm pair:

$$
\begin{aligned}
&\Delta FirmBehavior_{kl \neq ij,t} \\
&\qquad = \beta_1 * \Delta NetDist_{kl \neq ij,t} + \beta_2 * Connection_{kl \neq ij,t-1} + \beta_3 * \Delta Controls_{kl \neq ij,t-1} \\
&\qquad + \beta_4 * Geo_{kl \neq ij} + \beta_5 Year_{ij,t} + error
\end{aligned}
\tag{1.6}
$$

1.2.3 Price Impact Analysis

Although suggestive, the evidence on spillovers by itself does not conclusively differentiate between the information transmission and tacit collusion model. One might argue, that increased competition between two formerly directly connected companies might be indicative of the breakdown of a tacit collusion agreement among a group of companies. For instance, in figure 2, A, B, C and D might be part of an implicit collusion agreement, which breaks down with the disconnection of B and C, which therefore induces all involved parties to compete more strongly with each other.

We call the idea that companies utilize board networks to implicitly collude board network collusion. We measure the potential of such board network collusion, using the shortest paths within the board network between all company pairs in an industry. Therefore, the closer connected company pairs within an industry are via board networks, the more likely they will collude. We combine this measurement with our instrumental variable of unexpected director deaths. In particular, we look at all pairs of companies within an industry that are directly and indirectly connected through board directors and calculate the change in shortest paths implied by exogenous director deaths. For our first stage, our dependent variable is therefore the average change in board network distance between all pairs in an industry, while the instrument is the number of director deaths that directly or indirectly affect the board network distances of company pairs in the industry.

$$\overline{\Delta Distance_{s,t}} = \alpha_1 * \sum_{ij \in \Omega_s} DirDeath_{ij,t} + \alpha_2 * \Delta Controls_{ij,t-1} + error \tag{1.7}$$

Where Ω_s is the set of companies in industry s. For our second stage, we analyze the impact of this exogenous change in average board network distance on average prices in the industry. Price data has the distinct advantage that the predictions of tacit collusion for prices are clear: when companies collude, price should be higher than when companies do not collude.

$$\Delta Price_{s,t} = \beta_1 * \overline{\widehat{\Delta Distance}_{s,t}} + \beta_2 * \Delta Controls_{ij,t-1} + error \tag{1.8}$$

If collusion is indeed an explanation of the patterns for the impact of increased distance on competitive positioning and innovation, one would expect the coefficient on the average change in industry distance to be negative, as increased distance would imply less collusion and therefore lower prices.

1.3 Data

This section details the datasets used in this paper. Our paper uses a variety of datasets and this section briefly provides insight into how our data was obtained, why we chose a dataset, as well as provide some summary statistics that describe the overall data.

Observations are based on annual firm-to-firm pairs between 2003-2013. These firms are based on the S&P 1500 index which provide a broad sample of firms, smaller (S&P 600

Small-Cap), medium sized (S&P 400 Mid-Cap), and larger (S&P 500)[3].

Board network connectivity and director characteristics are obtained from BoardEx. This data set contains corporate board data as well as director characteristics data obtained from public firms annual proxy statements to shareholders. Matching BoardEx data to our Compustat list of S&P 1500 firms requires first matching based on security CUSIP[4]. Most of the firm-years are matched using this method. For firms not matched by CUSIP, we match first by ticker symbol if the firms are still active and then manually ensured a correct match. For firms that are inactive, we match by firm name directly if available. Using this procedure, we match about 93% of S&P 1500 firms from 2003 and after[5].

For each year of firm that we match to BoardEx board data, we observe the boards director composition, including the name of the director, the position of the director, the length of time the director has been on the board, and the total number of board seats on the board. Each BoardEx firm has a unique identifier for the firm as well as the director. Using overlaps of the same director across multiple firms, we can map out the system of board networks that connect firms together. Since we observe the tenure of the director on each board, this allows us to determine the year two firms are connected through a director and whether the connection originates from one firm to the other firm or if the director is new to both firms. The median firm in our sample has 10 directors and these directors are connected to 7 other firms each year. The median director is also quite experienced at 7.3 years on the firm.

Data on director deaths also comes from BoardEx. Since we consider the effect of an

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[3]Index constituents are obtained from Compustats Historical Index Constituent List. Since index membership may change throughout the year, we classify a firm as belonging to the S&P 1500 index if it is part of the index for the majority of the year or six months.

[4]BoardEx uses a unique board identifier *boardid* and director identifier *directorid*, while Compustat uses the unique firm identifier, *gvkey*.

[5]Since BoardEx data is obtained from annual proxy reports to shareholders, report dates can and generally do occur mid-year. We apply the standard practice of converting the dates into calendar years. For report dates that occur in July, we classify information regarding the firms board to that same year. For report dates that occur in June or before, we classify that as the firms board data for the previous year. This is also our standard procedure for converting Compustat fiscal year data into calendar year data.

exogenous change in network distance due to a director death, we match director deaths that occur at time $t-1$ and consider the change in network distance for the firm pairs between time $t-1$ to t. Director deaths occur in any firms in the sample roughly 2% of the time, however for a director death to have an exogenous effect on the network distance between any two firms, we require that the director be a board member of both firms at the time of his unexpected death[6]. We observe 302 such events in our sample.

Formally, two firms are interlocked in a given year if they share at least one director in that year. We define this as a link or connection between the two firms. Two firms become connected if they did not share a director in the previous year but do share one in the current year. Similarly, a disconnection occurs when two firms were connected through at least one director in the previous period but are no longer connected through *any* director in the current period.

In the sample, a very small number of firms are connected at any given time. For firms with matched BoardEx boards, only about 0.3% of the possible firm-pair years represent connected pairs, highlighting the rarity and importance of network connections. In terms of firm pairs, about 0.4% of firm-pairs are connected at any given time.

While connections between firms are rare, firms can be indirectly connected through a network of interconnected firms. To get a better sense of what it means to be indirectly connected, it is informative to provide some summary statistics for the average shortest path. Table 1. summarizes the shortest network distance between two firms in the sample. For any two firms in any year, the median distance between them is 5. This is slightly larger than the Small-World Phenomenon as described by Davis, Yoo and Baker (2003)[7]. Our sample consists of small, medium, and large firms. Larger S&P 500 firms tend to be more

[6]For a more concrete interpretation of the director death on the exogenous change in network distance, we also require that the director death occurs between two firms such that at the time of the directors death, all connection links are severed, that is, there is no other board member that still connects both firms.

[7]Using a sample of Fortune 500 firms and select banking/financial firms, Davis finds that the shortest distance between two firms stayed roughly the same at 3.46 between the years 1982, 1990, and 1992.

connected, the average number of interlocks for an S&P 500 firm is about 12.6 (Table 2) and the median average shortest path between any two S&P 500 firms is 4, the same as Davis, Yoo and Baker (2003) with a more comparable set of firms. As a whole though, our full S&P 1500 sample in contrast to Davis, Yoo and Baker (2003), contains a broader range of firm sizes, including smaller (S&P 600) firms that tend to be less connected than other firms, averaging only about 4.75 interlocks.

Table 1.1: Summary of Network Link Distributions of S&P 1500 Firms

This table provides a summary the *minimum* network distance between S&P 1500 firm pairs in the sample from 2003-2013. Network distance refers to the number of different corporate boards that separate two firms. A network distance of 1 means that two firms are directly connected through a shared director (that presides on both firms simultaneously). A network distance of 2 refers to the fact that two firms are indirectly connected through an intermediary firm where each of the two firms share a different director with the intermediary firm. The average network distance between all firm pairs in the sample is 4.68 while the median is 5.

Network Distance	**Frequency**	**Cumulative Distribution**
1	70,464	0.47
2	430,666	3.36
3	1,997,192	16.74
4	4,406,086	46.25
5	4,404,214	75.75
6	2,417,036	91.95
7	886,818	97.89
8	246,872	99.54
9	56,416	99.92
10	10,578	99.99
11	1,556	100
12	186	100
13	16	100
4.682	14,928,100	100

Table 1.2: Average Network Distance by S&P Classification

This table provides a summary the *minimum* network distance between S&P 1500 firm pairs in the sample from 2003-2013. Network distance refers to the number of different corporate boards that separate two firms. A network distance of 1 means that two firms are directly connected through a shared director (that presides on both firms simultaneously). A network distance of 2 refers to the fact that two firms are indirectly connected through an intermediary firm where each of the two firms share a different director with the intermediary firm. The average network distance between all firm pairs in the sample is 4.68 while the median is 5.

SP Classification	Frequency	Average Network Distance	Std.	10%	90%
SP 1,500 Annually	13,225	4.569	0.97	3.744	5.685
SP 500 to SP 500	4,999	3.761	0.601	3.145	4.525
SP 500 to SP 1,500	5,027	4.21	0.629	3.639	4.967
SP 400 to SP 1,500	3,699	4.641	0.923	4.007	5.606
SP 600 to SP 1,500	4,499	4.911	1.166	4.097	6.0737

Table 1.3: Average Number of Firm Interlocks by S&P Classification

This table displays the average number of firm interlocks sorted by S&P classification. Two firms have interlocked boards when they share at least one director who serves on both boards simultaneously. S&P 500 firms on average have 12.62 interlocks or the directors on the board sit on 12.6 other unique boards.

SP Classification	Average Number of Interlocks	Std.
S&P 600	4.752	4.157
S&P 400	7.024	4.692
S&P 500	12.624	6.774
Total	8.496	6.481

Table 1.4: Summary of Dependent Variables of Board Network Study

This table summarizes the dependent variables of our main regressions. Product Market similarity score refers to the similarity of revenue shares between firms. Hoberg-Philips Product Differentiation Score is based on the Hoberg-Philips Text-based Network Industry Classifications from firm 10-K product descriptions. The technology similarity score is based on the similarity of technology classes of patents by firms. Patent-Citation is based on the number of patents that are cited by each firm. Both the technology similarity score and the patent-citation score use a rolling three-year calculation of patents.

	Variables	**Observations**	**Mean**	**Std.**
Level				
	Product Market Similarity Score	20,654,328	0.00762	0.0812
	Hoberg-Philips Product Differentiation Score	24,730,502	0.00168	0.0122
	Technology Similarity Score	2,770,780	0.0157	0.0752
	Patent-Citation	317,915	41.383	669.893
Logs				
	Product Market Similarity Score	20,654,328	0.00552	0.0574
	Hoberg-Philips Product Differentiation Score	24,730,502	0.00161	0.0114
	Technology Similarity Score	2,770,780	0.0135	0.0586
	Patent-Citation	317,915	0.867	1.379

Not all firm pairs can be reached through board networks though. About a third of firm boards cannot be reached by other firm boards even though board data exists for both firms. These represent firms that are disconnected from board networks, driven by the fact that their boards are either not interlocked with any other firm or are interlocked only locally with other firms. In our sample, the vast majority of firm-pairs (80%) that are not connectible through the S&P 1500 board network includes one of the firms from the firm-pair as a member of the S&P 600 index[8].

Two different sources of data are used to calculate and determine the relative product market space positioning of each firm-pair. First, we use Compustat Historical Product Segment data to determine the product market segment similarity score between two firms. Firms in our sample self-report selling into an average of about 3 product segments[9]. When categorized by SICs, the effective number of segments is smaller due to overlapping segments. Smaller firms sell in to less number of product segments as compared to larger S&P 500 and S&P 400 firms, on average.

The product similarity data is based on Hoberg and Phillips (2010, 2016)[10]. The data is based on web crawling and text parsing algorithms that process the text in the business descriptions of 10-K annual filings on the SEC Edgar website from 1996 to 2011. Since the product descriptions are legally required to be accurate, they should sufficiently represent the managers insight to their own firms product lines. One of the key benefits of a statistic like the Hoberg-Philips similarity score is that it can be calculated regardless of whether each firm pair produces in the same primary SIC.

Our measurements of technological space similarity come from two main sources. Patent

[8]In tabulated results not shown here, 1115 unique firms of the 2618 index constituents make up one of the unconnected firm pairs. This proportion might seem large but in fact it is the S&P 600 index members that typically transition in/out of the S&P1500 index most often. In practice, movements in and out of S&P500 and S&P400 firms results in the inclusion of the firm into S&P400 or S&P600 index, respectively, more often than not.

[9]Firms define their own product segment market categories but categorical groupings by sic may overlap resulting in a smaller effect product segment market average.

[10]Additional resources can be found at: `http://hobergphillips.usc.edu/idata/Readme_tnic3.txt`

class and patent-citation data is obtained from USPTO (NBER U.S. Patent Citations Data File) and Kogan et al. (2017). These datasets contain the patent number, patent application date, CRSP permno, technology class that is associated with the patent, and citations that the patent includes from 2000-2010. However, a few changes are made in constructing the score variable that are noteworthy. First, we consider patent applications as opposed to patent grants as patent granting procedures may include timing lags that firms are not able to control for. Second, since firms may submit patent applications for many patents one year but not patent for the next few years, we consider a patent-application window of three years[11]. This is to capture the uncertainty of R&D effort on patent application outcomes. Therefore, for each firm-pair-year, we use the past 3-years patent activity as the basis for constructing our score measure. One additional issue with using patent data is the inherent annual heterogeneous component. Economic conditions and patenting environments may change year-to-year, thereby changing the incentives of firms to pursue R&D. Lerner and Seru (2017) proposes an adjusted citation measure where the total number of citations received by a firm are adjusted by the average number of citations received by patent cohorts in the same year. We implement this as our main variable for capturing patent citations although an unadjusted version of the patent-citation measure shows nearly identical results.

1.4 Results

This section documents our main results. Throughout this section, where appropriate, we display our first stage results next to the second stage main results to maximize transparency. This is helpful, since data coverage varies either for different types of dependent variables, such as product market rivalry as opposed to patenting, as well as different empirical approaches.

[11] We also considered patent-application windows of two or four years but results were qualitatively similar.

1.4.1 Main Results

Our results begins with Table 5, the main model specification as estimated using pooled OLS regression. The first two columns display the results of changes in the product market space. Column (1) displays results for our the product market rivalry measure, which captures the similarity of sales distributions across Compustat segments. Column (2) of table 5 displays our results for the Hoberg-Phillips product similarity measures that are derived from regulatory statements. In each, changes in board network distance are positively related to increased competition in the product market space. Similar results are in columns (3) and (4) for technological space orientation. Increases to board network distance are positively related to more similar long-term strategic product placement. Column (3) shows that network distance is positively related to technological patenting class overlap. Column (4) shows that relative patent-citations also increase with network distance.

Table 6 begins our main results of the impact of exogenous disconnections in the product market space. Column (1) is the first stage regression of the instrumental variable regression. The dependent variable is the change in network distance. Here, shared director deaths lead exogenously to increases in network distance. Columns (2), (3), and (4) are instrumental variable regressions with the product rivalry measure as the dependent variable. Column (4), our main specification with time, location, and industry fixed effects, captures the similarity of sales distributions across Compustat segments. As can be seen, exogenous increases in board network distance increase sales similarity. In other words, more distant firms will tend to become more similar in terms of their competitive positioning and will therefore more directly compete with each other. To get an idea of the involved magnitudes, we note that the standard deviation of network distance in the S&P 1500 sample is 0.97 according to table 2. We combine this with the estimated coefficient from table 5, to obtain the impact of one standard deviation change in network distance on product market rivalry, which is 2.281 ($= 2.352 * 0.97$). This compares with an average log product market rivalry score of 63.31, which shows that there is a economically significant effect of exogenous disconnections on product market similarity (3.6% per change in standard deviation).

These results on the impact of network distance on product market rivalry can be understood in terms of information-sharing models of oligopolistic competition. Under the assumption that firms that are more closely connected through the board network are more likely to share information on private information such as costs and demand, these models predict that firms that share more information are also more differentiated in terms of outcomes such as market shares, see Amir, Jin and Troege (2010). The intuition behind the incentive of firms to share internal cost or demand information is that information sharing leads to strategic commitment effects. In the case that a firms cost is lower and product demand is higher than that of other firms, information sharing leads to a gain of market share and higher profits. In the opposite case of high costs and low idiosyncratic demand, information sharing leads to lower market shares and profits. Since firm profits are convex in market shares, the gains from information sharing will outweigh the costs and therefore information disclosure is beneficial, under both Cournot and Bertrand competition.

But the effects of network distance on product market competition are not limited to the effect on market shares. Column 4 of table 7 displays our results for the Hoberg-Phillips product similarity measures that are derived from regulatory statements. We find a highly significant impact of exogenous changes in network distance on product differentiation. As before, firms that see an increase in distance will tend to increase their similarity, now in terms of product descriptions. To gauge the quantitative impact, we again calculate the effect of a one standard deviation change in network distance, which is 2.212 ($= 2.280 * 0.97$), which compares to a sample mean of 62.218 for the log Hoberg-Phillips product similarity measure. Hence, as in the case of segment sales, board network connections have a economically significant impact on product market positioning (3.5% per change in standard deviation). An attractive feature of these additional results is that they are completely independently constructed from the Compustat segments data, which was used for the product market rivalry similarity measures and therefore provide additional independent evidence on the competitive positioning effects of board network distance.

Table 1.5: Pooled OLS Results

Variables	(1) **ΔProduct Market Revenue**	(2) **ΔHP Product Score**	(3) **ΔTechnology Score**	(4) **ΔPatent Citations**
ΔNetwork Distance	0.023	0.021	0.050	0.205
	(47.26)***	(105.95)***	(17.80)***	(4.56)***
Connected	-0.504	-0.429	-0.758	-2.036
	(55.08)***	(71.53)***	(21.81)***	(7.29)***
Δ# Connections	26.384	23.562	31.870	21.242
	(239.95)***	(277.95)***	(224.43)***	(15.71)***
Δ# Directors	0.323	0.301	1.448	2.850
	(53.59)***	(117.06)***	(35.66)***	(5.50)***
Δ# Ind. Segments	0.624	0.609	1.652	2.426
	(68.69)***	(134.12)***	(39.54)***	(4.61)***
ΔRel. ROA	-0.173	-0.061		
	(16.73)***	(16.84)***		
ΔRel. Profit Margin	0.340	0.206		
	(30.81)***	(55.75)***		
ΔRel. Market Value	1.348	1.207		
	(86.87)***	(102.56)***		
ΔRel. ROI			0.242	-1.529
			(9.78)***	(3.15)**
ΔRel. Assets			0.381	-0.672
			(9.37)***	(0.67)
ΔRel. R&D/Rev.			0.003	-0.540
			(2.84)***	(23.25)***
Fixed Effects Year	Yes	Yes	Yes	Yes
Geography	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Observations	9,843,372	10,767,090	822,854	154,872

t-statistics are in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.6: Main Results - Product Market Revenue and Network Distance

	(1)	(2)	(3)	(4)
ΔProduct Market Revenue	**IV: First Stage Regression**	**IV: FE, Min. Controls**	**IV: No FE, Controls**	**IV: FE, Controls**
Same Director Death	1.902			
	(10.01)***			
ΔNetwork Distance		21.147	2.361	2.352
		(15.10)***	(8.45)***	(8.01)***
Connected	-0.275	76.498	0.131	0.133
	(80.76)***	(155.16)***	(1.68)	(1.68)
Δ# of Connections	-3.529		34.832	34.654
	(83.58)***		(30.32)***	(26.45)***
Δ# of Directors	-0.611		1.451	1.745
	(157.25)***		(8.36)***	(8.46)***
Δ# Industry Segments	0.194		0.278	0.170
	(37.05)***		(1.99)*	(1.21)
ΔRelative ROA	0.117		-0.487	-0.445
	(14.32)***		(2.14)*	(2.04)*
ΔRelative Profit Margin	0.070		0.095	0.176
	(10.52)***		(0.51)	(0.95)
ΔRelative Market Value	0.541		0.119	0.082
	(95.52)***		(0.62)	(0.41)
Fixed Effects				
Year	Yes	Yes	No	Yes
Geography	Yes	Yes	No	Yes
Industry	Yes	Yes	No	Yes
Observations	9,843,372	9,843,372	9,843,372	9,843,372

t-statistics are in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.7: Main Results - Product Market Descriptions and Network Distance

	(1)	(2)	(3)	(4)
ΔHP Product Score	**IV: First Stage Regression**	**IV: FE, Min. Controls**	**IV: No FE, Controls**	**IV: FE, Controls**
Same Director Death	1.857			
	(9.81)***			
ΔNetwork Distance		19.033	2.288	2.280
		(15.12)***	(8.94)***	(8.46)***
Connected	-0.269	68.504	0.175	0.178
	(84.36)***	(159.49)***	(2.48)**	(2.46)**
Δ# of Connections	-3.460		31.570	31.422
	(88.08)***		(33.84)***	(28.81)***
Δ# of Directors	-0.611		1.402	1.681
	(166.69)***		(8.73)***	(8.90)***
Δ# Industry Segments	0.196		0.267	0.163
	(38.60)***		(2.01)*	(1.22)
ΔRelative ROA	0.116		-0.351	-0.323
	(15.24)***		(1.71)	(1.63)
ΔRelative Profit Margin	0.076		-0.052	0.034
	(12.75)***		(0.32)	(0.21)
ΔRelative Market Value	0.531		0.034	0.003
	(101.92)***		(0.22)	(0.02)
Fixed Effects				
Year	Yes	Yes	No	Yes
Geography	Yes	Yes	No	Yes
Industry	Yes	Yes	No	Yes
Observations	10,767,090	10,767,090	10,767,090	10,767,090

t-statistics are in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.8: Main Results - Technology Space and Network Distance

ΔTechnology Score	(1) **IV: First Stage Regression**	(2) **IV: FE, Min. Controls**	(3) **IV: No FE, Controls**	(4) **IV: FE, Controls**
Same Director Death	1.54			
	(2.59)**			
ΔNetwork Distance		3.460	3.144	3.112
		(3.49)***	(3.42)***	(3.46)***
Connected	-0.335	0.272	0.273	0.267
	(32.39)***	(0.81)	-0.89	(0.90)
Δ# of Connections	-0.611		34.118	33.755
	(10.28)***		(39.46)***	(34.55)***
Δ# of Directors	-0.337		2.642	2.478
	(18.82)***		(5.25)***	(5.19)***
Δ# Industry Segments	0.577		-0.071	-0.120
	(31.52)***		(0.12)	(0.20)
ΔRelative ROI	0.096		-0.348	-0.052
	(7.50)***		(1.11)	(0.20)
ΔRelative R&D/Revenue	0.126		-0.023	-0.005
	(6.76)***		(0.08)	(0.02)
ΔRelative Total Assets	0.011		-0.031	-0.029
	(19.20)***		(2.47)**	(2.43)*
Fixed Effects				
Year	Yes	Yes	No	Yes
Geography	Yes	Yes	No	Yes
Industry	Yes	Yes	No	Yes
Observations	822,854	822,854	822,854	822,854

t-statistics are in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.9: Main Results - Patent-Citations and Network Distance

	(1)	(2)	(3)	(4)
ΔRelative Patent-Citations	**IV: First Stage Regression**	**IV: FE, Min. Controls**	**IV: No FE, Controls**	**IV: FE, Controls**
Same Director Death	1.623			
	(2.12)*			
ΔNetwork Distance		0.066	0.062	0.077
		(2.20)*	(2.14)*	(1.99)*
Connected	-0.267	-0.001	-0.004	-0.000
	(20.67)***	(0.12)	-0.37	(0.04)
Δ# of Connections	-1.867		0.238	0.352
	(16.89)***		(4.81)***	(4.28)***
Δ# of Directors	0.037		0.013	0.026
	(1.07)		(0.86)	(1.69)
Δ# Industry Segments	0.517		0.008	-0.014
	(19.44)***		(0.34)	(0.59)
ΔRelative ROI	0.141		-0.040	-0.026
	(5.09)***		(2.73)**	(2.01)*
ΔRelative R&D/Revenue	0.437		-0.025	-0.039
	(7.48)***		(1.16)	(1.67)
ΔRelative Total Assets	0.009		-0.006	-0.006
	(6.59)***		(5.53)***	(5.11)***
Fixed Effects				
Year	Yes	Yes	No	Yes
Geography	Yes	Yes	No	Yes
Industry	Yes	Yes	No	Yes
Observations	154,872	154,872	154,872	154,872

t-statistics are in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The same argument holds for our analysis of patenting and patent citation patterns, which is collected in table 8 and table 9. While the results, based on the Hoberg-Phillips measures suggest that board network distance influences firms product differentiation choices, we consider direct evidence from patenting to be even more convincing. The reason is that the Hoberg-Phillips are mostly self-reported, even if firms cannot contain false statements due to the regulatory audience. In contrast,patenting data is from the USPTO, which spends considerable resources to determine the technological similarity of patents and whether patent claims about novelty are indeed justified. As column 4 of table 8 shows, we find that an exogenous increase in board network distance leads to significantly higher technological similarity in terms of patenting.

Quantitatively, our technology similarity score effects implies that a one standard deviation increase in distance leads to an increase of 3.012 ($= 3.112 * 0.97$), which compares to an average log technology similarity of 69.289 for S&P 1500 firms. This again suggests that increases in board network distance have a meaningful effect on the similarity of technological investments and patenting choices. We also note at this point, that due to the lumpiness in the patenting data, these results should not be interpreted as year-to-year changes, but that they reflect the changes from one patent to the next, which might typically be more than one year apart.

In addition to the technological similarity of patent applications, we also consider patent citations as direct measure of knowledge flows. These citation flows have the advantage that they directly refer to patents held by other firms, although the incidence of these flows is relatively rare. As column 4 of table 9 shows, an exogenous increase in network distance has a significant impact on patent citation flows. In other words, more distant firms tend to cite each other patent more and not less often. While surprising on its own, this pattern is consistent with our competitive positioning results in terms of product market and technology space. Even more surprising is that while the effect is statistically significant, the implied effects are also economically large.

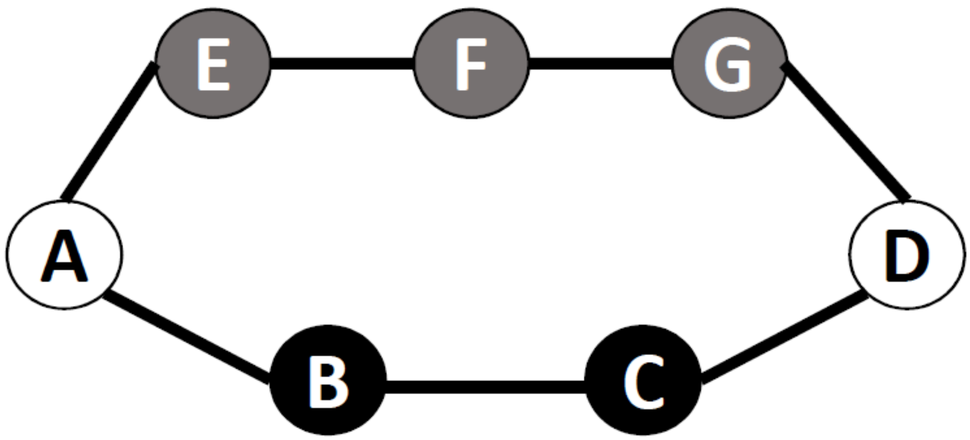


Figure 1.3: Network Spillover Effect

1.4.2 Network Spillover Effects

In this section we present our results regarding the analysis of spillovers in the board network. These spillovers capture the effects of exogenous increases in network distance for third party firms that are not part of the pair that was directly affected by the director death. As previously mentioned, we believe that these results support the identification of our effects, as these spillovers are by definition unlikely to be influenced by any type of policy action of the directly affected firms.

Figure 1.3 demonstrates an example of network spillover effects. Consider two firms that are indirectly connected, A and D. Firm A is interlocked with firm B and firm E while firm D is interlocked with firm C and firm G. Since firm B and firm C are not interlocked, the network distance between firms A and D is 4, requiring the two firms indirectly connect through firms E, F, and G. A new connection between firms B and C, now shortens the distance between firm A and D from 4 to 3.

Table 10 summarizes the spillover effects in the product market space. As the coefficient estimates show, indirectly affected firms exhibit smaller network distance effects, which are around one third to half the size of our baseline estimates.

This suggests that the informativeness of information flows through the board network strongly declines. However, we also note that a typical S&P 1500 firm is connected to a variety of firms, so that changes in other firms network positions might easily sum up to push the focal firm strongly into one position or another.

Table 11 reports the results of our network spillover analysis for the technology space variables. As before, column (2) shows that director deaths have strong spillover effects on not directly affected firms in the board network. The robustness of these results is even more remarkable, once one takes into account that all our specifications do control for the geographical position of firms, which by itself control for possible knowledge spillovers due to physical proximity. However, we also note that although the results remain highly statistically significant, the size of the effect shrinks considerably. In contrast the effects on patent citation flows do become insignificant, mostly driven by sample attrition in the reduced subset of firms indirectly affected by director deaths.

Table 1.10: Network Spillover Effects - Product Market Space

Network distance is based on the geodesic between firm pairs. Spillover firms are defined as firm pairs that have network path/geodesic changes due to disconnections of other firm pairs along their geodesic path. The director death instrumental variable is an indicator that is one if changes in the network path is the result of a director death. Product market segment scores are based on the similarity of revenue shares based on segment market sales from Compustat Historical Segments. The segments are categorized by 4-digit sic codes. The Hoberg-Phillips product differentiation score is based on the similarity of product descriptions from firm's annual 10-Ks statements.

	(1)	(2)	(3)	(4)
Variables	**ΔNetwork Distance**	**ΔProduct Market Segment Score**	**ΔNetwork Distance**	**ΔHP Product Differentiation Score**
Director Death (IV)	0.0866***		0.0799***	
	(0.00464)		(0.0440)	
ΔNetwork Distance		0.00187**		0.00113***
		(0.000877)		(0.000396)
ΔIndustry Segments	0.0651***	0.00226***	0.0646***	0.0220***
	(0.00809)	(0.000494)	(0.00782)	(0.000386)
ΔNumber of Directors	0.00671	0.0104***	0.0211***	0.00898***
	(0.00585)	(0.000245)	(0.00553)	(0.000170)
ΔRelative ROA	0.0374**	-0.00417***	0.0196	-0.00183***
	(0.0133)	(0.000375)	(0.0122)	(0.000171)
ΔRelative Profit Margin	-0.0378***	0.00942***	-0.0217*	0.00687***
	(0.0106)	(0.000436)	(0.00939)	(0.000233)
ΔRelative Market Value	0.0750***	0.0451***	0.0705***	0.0401***
	(0.00271)	(0.000287)	(0.00259)	(0.000231)
Time Fixed Effects	Yes	Yes	Yes	Yes
Geography Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,460,548	1,460,548	1,592,188	1,592,188

t-statistics are in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.11: Network Spillover Effects - Technology Space

The technology score is based on the similarity of the patents by the firm pairs. The similarity score is based on the similarity in technology classes of the patents as assigned by the USPTO. Patent citations are based on the the annual frequency that the firms are cited against each other. Patent citations can be self-reported at the time of the patenting or assigned by the patent inspector. The observation counts differ from each other due to the fact that the technology score is based on all patents by a firm. The patent citation count occurs only when one of the firms lists the other firm on the patent application.

	(1)	(2)	(3)	(4)
Variables	**ΔNetwork Distance**	**ΔTechnological Score**	**ΔNetwork Distance**	**ΔPatent Citations**
Director Death (IV)	0.242***		0.144***	
	(0.0143)		(0.0399)	
ΔNetwork Distance		0.00164**		0.396
		(0.000521)		(0.226)
ΔIndustry Segments	0.123***	0.00898***	0.131***	-0.0301
	(0.0177)	(0.000871)	(0.0339)	(0.0592)
ΔNumber of Directors	0.0287	0.00755***	0.0198	0.122***
	(0.0157)	(0.000818)	(0.0432)	(0.0514)
ΔRelative ROI	-0.0193	-0.00238***	0.0195	-0.0434
	(0.0140)	(0.00582)	(0.0366)	(0.0412)
ΔRelative Assets	0.108***	0.0523***	-0.197***	0.197
	(0.00606)	(0.000377)	(0.0465)	(0.0825)
ΔR&D/Revenue			0.449***	-0.220
			(0.0706)	(0.146)
Time Fixed Effects	Yes	Yes	Yes	Yes
Geography Fixed Effects	Yes	Yes	Yes	Yes
Observations	234,144	234,144	27,654	27,654

t-statistics are in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.12: Board Network Changes on Average Industry Price

ΔNetwork Distance is measured by the change in the average geodesic between firms in the same NAICS industry. For changes in network distances between same-industry firm pairs that become disconnected through the S&P1500 network, Network Distance2 is a subjective value for un-connectible firm pairs of 9 (geodesic of 10 is the 99th percentile sample distance). The director death instrumental variable includes all within-industry pairs of firms that are affected by a director death and deaths that cause network paths to increase from a spillover effect. Prices are based on NAICS annual prices and logged. Standard errors are clustered at the industry level.

	(1)	(2)
	Adjusted Geodesic	
Variable	Δ Average Network Distance	Δ Price
Director Death (IV)	0.00260**	
	(0.000994)	
ΔAverage Network Distance		-10.134
		(40.473)
Constant	-0.459***	1.0299
	(0.0626)	(18.246)
Time Fixed Effects	Yes	Yes
Observations	847	847

1.4.3 *Impact of Average Network Distance on Prices*

Here we document the results of our analysis of the impact of exogenous changes in average network distance on prices, to evaluate whether collusion might part of our results. To calculate the average network distances, we need to confront the issue that a significant fraction of firms within a NAICS industry do not seem to be connected. To make our calculations, we therefore choose a higher value of the distance for all unconnected firms, which corresponds to the 99th percentile of network distances.

As table 12 shows, our first stage is highly significant as director deaths lead to strong increase in the average board network distance of firms in the sample SIC industry. However, as the second column of table 8 shows, there is no significant impact of increase board network distance on average prices in SIC industries.

1.5 Robustness

In this section we explore two extensions of our baseline analysis. First, we explore the impact of exogenous changes in board network distance on longer-term dynamic patterns of product market and technology positioning. Second, we analyze to what extend our baseline results of product market positioning are driven by changes in market shares within a fixed set of industries as opposed to industry entry.

1.5.1 *Cumulative Impact*

Our baseline results suggest that firms significantly adjust their competitive positioning in response to exogenous changes in board network distance. There are at least two reasons why a longer term analysis of the impact of board network distance changes are interesting. First, the changes in competitive positioning we documented in our main results may not be sustained. For instance, firms might not be able to re-establish severed connections to other firms through the board network in the short run, but might be able to do so in the long run. Second, there might be considerable mean reversion in competitive positioning

Table 1.13: Cumulative Effects of Disconnections - Product Market Space

This table displays the cumulative effect on product markets from time t to t+2 following a disconnection between two S&P 1500 firms at time t.

	(1)	(2)	(3)
Variables	**ΔNetwork Distance**	**ΔProduct Market Segment Score**	**ΔHP Product Differentiation Score**
Director Death (IV)	0.586***		
	(0.193)		
ΔNetwork Distance at time *t*		0.00707*	0.00497*
		(0.00290)	(0.00233)
Cumulative ΔInd. Segments	-0.284**	0.00424**	-0.00269**
	(0.0575)	(0.00143)	(0.000859)
Cumulative ΔNum. of Directors	-0.164**	0.0178	0.0107***
	(0.134)	(0.00591)	(0.00334)
Cumulative ΔRel. ROA	0.718	0.00138	-0.00536
	(0.433)	(0.00692)	(0.00394)
Cumulative ΔRel. Profit Margin	-0.778*	0.0151	0.00991*
	(0.186)	(0.00792)	(0.00446)
Cumulative ΔRel. Mkt. Value	-0.105*	0.0116	0.00660
	(0.0519)	(0.00726)	(0.00423)
Time Fixed Effects	Yes	Yes	Yes
Geography Fixed Effects	Yes	Yes	Yes
Observations	8,578	8,578	8,578

t-statistics are in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.14: Cumulative Effects of Disconnections - Technology Space

This table displays the cumulative effect on product markets from time t-1 to t+2 following a disconnection between two S&P 1500 firms at time t.

	(1)	(2)	(3)	
Variables	**ΔNetwork Distance**	**ΔTechnological Score**	**ΔNetwork Distance**	**ΔPatent Citation**
Director Death (IV)	0.529**		0.527**	
	(0.191)		(0.191)	
ΔNetwork Distance at time t		0.00716**		0.0409*
		(0.00303)		(0.0179)
Cumulative ΔInd. Segments	-0.289***	0.00292*	-0.293***	-0.0553***
	(0.0576)	(0.00136)	(0.0576)	(0.00981)
Cumulative ΔNum. of Directors	-0.192	0.00866**	-0.193	0.0101
	(0.136)	(0.00287)	(0.137)	(0.0125)
Cumulative ΔRel. ROI	-0.0578	0.00738	-0.0471	0.110***
	(0.0186)	(0.00417)	(0.121)	(0.0281)
Cumulative ΔRel. Assets	0.0456	0.0141**	0.267*	0.0509*
	(0.0396)	(0.00513)	(0.131)	(0.0225)
Cumulative ΔRel. R&D/Revenue			-0.0154	0.0225**
			(0.182)	(0.0824)
Time Fixed Effects	Yes	Yes	Yes	Yes
Geography Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,578	8,578	8,578	8,578

t-statistics are in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

choices. Even if C-level executives might decide to optimally reposition a firm, there might be considerable internal resistance to changes, so that attempts at competitive repositioning are undone in the long run.

To provide a longer term analysis, we look at cumulative effects over a 3-year horizon, that will allow enough time for board member replacements and internal resistance efforts to take hold. Table 9 documents the cumulative results for competitive positioning along the product market space, while table 10 reports cumulative results for the technology space. Both of these tables offer a consistent view that competitive repositioning effects in response to exogenous changes in board network distance are sustained in the long run. The estimated coefficients all increase in size, relative to our baseline results, emphasizing the fact that mean reversion is not an issue.

1.5.2 Intensive vs. Extensive Margin

An open question in our baseline analysis is whether the changes in competitive positioning, are driven by entry and exit into product market segments (henceforth extensive margin effects) or whether they are driven by changes in market share, conditional on a given set of segments (henceforth intensive margin effects). It is important to note that this question mostly affects our product market rivalry measure that is based on Compustat segments, rather than the Hoberg-Phillips product description data.

To shed light on the question of whether extensive margin effects matter, we rerun our product market rivalry results, using two different strategies. First, we fix the set of initial industry codes and only consider similarity measures for the S&P 1500 firms that are calculated using revenue distributions on this fixed set of initial industries. Second, we focus on a subset of firms that never change their industry segments in our sample.

The results of both exercises are summarized in table 11. As the table shows, the impact of exogenous changes in network distance is almost identical for data on intensive margin changes only. In other words, most of our results can be understood as reflecting relative market positioning changes for a given set of industries, rather than reflecting entry

Table 1.15: Intensive Margin Changes- Product Market Space

This table compares the intensive margin effects (model 1 columns 1-2), firms that do not change segments (model 2 columns 3-4), and the main results of the product market segment analysis (model 3 columns 5-6) for S&P 1500 firms from 2003-2013. The intensive margin effects are found by holding holding product market segments constant. The firm's first product market segments are used and held throughout their sample. Changes in the similarity score between two firms must only be a result of similarities in revenue share and not segment participation. Columns 3-4 is a subsample of firms that maintain the same product market segments throughout the sample. Similarly, changes in the similarity score are only a result of changes in the revenue shares between firms within the same segments. Sample sizes differ due to firms changing product market segments and no longer selling in their "starting" product market segments.

	Intensive Margin		**Same Segment Firms**	
Variable	ΔNetwork Distance	ΔProduct Market Segment Score	Δ Network Distance	ΔProduct Market Segment Score
Director Death (IV)	2.177***		2.332***	
	(0.213)		(0.0274)	
ΔNetwork Distance		0.00403***		0.00380***
		(0.00112)		(0.000940)
Connected	0.307***	-0.00664***	0.319***	-0.00677***
	(0.00435)	(0.00064)	(0.00560)	(0.000610)
ΔNum. of Connections	0.137***	0.261***	0.0619*	0.265***
	(0.0244)	(0.0207)	(0.0309)	(0.0199)
ΔIndustry Segments	-0.0349***	0.00613***	-0.0738***	0.00640***
	(0.00527)	(0.000821)	(0.00664)	(0.000784)
ΔNumber of Directors	0.847***	0.00259***	0.0514***	0.00312***
	(0.00383)	(0.000305)	(0.00516)	(0.000306)
ΔRelative ROA	-0.0913***	0.00457	-0.0241*	-0.000822*
	(0.00852)	(0.000398)	(0.0114)	(0.000373)
ΔRelative Profit Margin	0.0685***	0.00192***	0.0280**	0.00247***
	(0.00680)	(0.000463)	(0.00911)	(0.000463)
ΔRelative Market Value	-0.0275***	0.0150***	-0.0351***	0.0143***
	(0.00341)	(0.00340)	(0.00426)	(0.00322)
Time Fixed Effects	Yes	Yes	Yes	Yes
Geography Fixed Effects	Yes	Yes	Yes	Yes
Observations	9,038,690	9,038,690	5,028,544	5,028,544

and exit into an out of industry categories. However, we also note that the estimated changes in product market similarity on the intensive margin are also somewhat smaller than the full effects, implying that entry and exit into industry segments does reinforce the documented intensive margin effects.

1.6 Conclusion

In this study we explored how board networks shape competitive positioning among public firms, along both the product market and technology space. Our results suggest that board networks have an important role in terms of information transmission, especially among large public firms that are active in multiple markets and technology segments. We see at least three promising avenues for future research.

First, there is need for a deeper understanding for how exactly information is transmitted within the board network. Does it matter how powerful board members are and how they are related to the CEO? Does information transmission happen within officially documented meetings or through informal social gatherings?

Second, how does the impact of board networks on competitive positioning compare with other types of social networks? It is true that the weak ties of professional networks such as through corporate boards is stronger than the effect of strong ties, as is the case for job references, see Granovetter (1973).

Third, our results suggest that a deeper theoretical analysis of the interaction of board networks and endogenous product differentiation and innovation choices of firms would be promising. Such an analysis would be at the intersection of the literature on R&D cooperation on the one hand and the literature on information transmission in oligopolistic markets on the other hand.

Chapter 2

STRENGTH IN DIVERSITY: HOW BOARD HETEROGENEITY INFLUENCES INVESTMENT, R&D, AND PRODUCT DIFFERENTIATION

In a press release on February 1st, 2016, 3M President, chairman, and CEO, Inge Thulin announced the election of Gregory R. Page to the board of 3M:

> "We are extremely pleased to welcome Mr. Page ... to our board," said Thulin. "We look forward to the valuable insight Mr. Page brings to 3Ms Board from his extensive experience leading Cargills global business. (He was)...an outstanding leader, with tremendous business experience in leading complex global organizations." [1]

There is significant anecdotal evidence to suggest that directors with diverse industry expertise are highly sought after by corporate boards today for their advising and related industry expertise. The quote by 3M's president and CEO Inge Thulin of nominee Gregory Page, highlights an example of the demand for these types of directors whose diverse expertise extend beyond the same industry expertise as the board[2]. Yet, the corporate governance literature has largely ignored the advising impact of these broader industry experts[3]. This paper fills this gap in the literature by proposing a methodology that will allow analysis of all types of industry expertise areas of a director for the first time. I find that directors have

[1] `http://investors.3m.com/news/press-release-details/2016/3M-Elects-Two-New-Members-to-Board-of-Directors/default.aspx`

[2] Figure 1. is an example of a director nomination announcement.

[3] The literature on advising has generally focused on prior director acquisition experience, Field and Mkrtchyan (2017) and McDonald, Westphal and Graebner (2008); prior financial expertise, Minton, Taillard and Williamson (2014),Agrawal and Chadha (2005), Cohen et al. (2014); and same industry expertise, Masulis et al. (2012) and Faleye, Hoitash and Hoitash (2017).

Figure 2.1: Director Nomination Announcement: Microsoft 10/06/2017

Microsoft proposes election of new board members

news.microsoft.com |

REDMOND, Wash. — Oct. 16, 2017 — Microsoft Corp. on Monday released its annual proxy statement and announced two nominations to its board of directors. The nominees are Penny S. Pritzker, founder and chairman of PSP Capital and former U.S. Secretary of Commerce, and Arne Sorenson, president and chief executive officer of Marriott International. Both are accomplished leaders and will bring significant global experience to Microsoft. They will be presented for election at the company's annual shareholders meeting on Nov. 29, 2017.

"Penny and Arne are both strong leaders with impressive accomplishments and contributions that span business and public service," said John Thompson, independent Microsoft board chairman. "They will serve as valuable additions to the board."

Pritzker, 58, is the founder and chairman of PSP Capital and its affiliate, Pritzker Realty Group. From June 2013 through January 2017, she served as U.S. Secretary of Commerce. She is an entrepreneur, civic leader and philanthropist and has nearly 30 years of experience as a business executive across numerous industries, building dozens of successful companies. Pritzker is a member of the board of trustees of the Carnegie Endowment for International Peace, a member of the Aspen Strategy Group and the Aspen Economic Strategy Group, and a co-chair of the Cyber Readiness Institute. She and her husband, Dr. Bryan Traubert, co-founded the Pritzker Traubert Foundation, a private philanthropic foundation that works to foster increased economic opportunity for Chicago's families.

Sorenson, 58, has served as president and chief executive officer of Marriott International since 2012 and was elected to Marriott's board of directors in 2011. In addition, he is the chairman of Marriott's Global Diversity and Inclusion Council and co-founded Marriott's Global Sustainability Council in 2007. In Sorenson's career at Marriott International, he has also served as chief operating officer, executive vice president, and chief financial officer and president of continental European lodging. Sorenson serves on the board of Brand USA. He is a member of the Luther College Board of Regents and is a member of the board of trustees for The Brookings Institution.

Other board members include John W. Thompson, Microsoft independent chairman; William H. Gates, Microsoft founder and technology advisor; Reid Hoffman, partner at Greylock Partners; Hugh Johnston, vice chairman and chief financial officer of PepsiCo; Teri L. List-Stoll, executive vice president and chief financial officer of Gap Inc.; Satya Nadella, chief executive officer of Microsoft; Charles H. Noski, former vice chairman of Bank of America Corp.; Dr. Helmut Panke, former chairman of the board of management at BMW AG; Sandra E. Peterson, group worldwide chair for Johnson & Johnson; Charles W. Scharf, chief executive officer of The Bank of New York Mellon Corp.; John W. Stanton, chairman of Trilogy Equity Partners; and Padmasree Warrior, CEO and chief development officer of NIO USA Inc.

Microsoft (Nasdaq "MSFT" @microsoft) is the leading platform and productivity company for the mobile-first, cloud-first world, and its mission is to empower every person and every organization on the planet to achieve more.

many more areas of industry expertise than the literature has considered. I find that both shareholders and boards value this diversity of expertise on a board (Board Heterogeneity). First, I present evidence that this diversity of expertise is valued by shareholders by showing positive abnormal returns following the nomination announcement of one of these diverse directors. Next, I provide evidence that the demand for diverse industry expertise directors is driven by advising needs; needs such as the firm's growing business complexity, growth opportunities, and scope of business and not by monitoring concerns. Finally, and most importantly, I find that increased board heterogeneity has a causal impact on the long-term strategic implications for the firm's investment and R&D strategy and as a result benefits through product differentiation.

Using a sample of S&P 1500 firms from 2003-2013, I construct measures of the director's expertise using the director's prior employment history. This builds on the methodology of Masulis et al. (2012), Faleye, Hoitash and Hoitash (2017), Cohen et al. (2014) where industry expertise is linked to the the previous employer's sic. These authors used a firm's two-digit sic code to categorize firms into industries. Directors who were previously employed in these industries then had the unique industry expertise from working in that specific field. While prior authors considered only if there was an industry expertise overlap between the director and the firm[4], I extend this methodology in several important ways. First, I capture the full range of industry expertise of a director each year. This allows me to make comparisons based on the degree of similarity between directors and the director's industry expertise to the board level. Second, this paper uses both public and non-public[5] prior employment data. Prior studies, including the authors above, restrict their sample only to those firms

[4]For example, Masulis et al. (2012) measures the proportion of independent directors on a board with same industry expertise while Faleye, Hoitash and Hoitash (2017) measures the relative number of industry experts to independent directors, the total number industry experts on a board, and a dummy for if an industry expert director is on the board.

[5]Non-public firms are firms that do not issue securities. Included are private firms, non-profits, and some governmental agencies. These non-public firms represent approximately two-thirds of all publicly held firm positions by directors. For the S&P 1,500 directors in the sample, roughly 45% of all positions held by the outside directors were non-public positions.

with available sic codes in BoardEx. Crucially, I show that using only public data creates a downward bias on the level of industry expertise held by outside directors.

Directors with industry expertise different from the board, can provide the firm with a new perspective on ongoing business opportunities. Using a matched sample of outside director appointments, I show that shareholders value this diversity of expertise using an event study approach. I find that there is nearly a 0.3% cumulative abnormal return premium when the announcement of a more diverse director is made over a director that has more similar industry expertise with the board members. This is on top of 0.9% premium that others like Nguyen and Nielsen (2010) have found for independent directors. Next, using the same matched sample, I find that the cross-sectional variations in the outside director's similarity to the board can be partially explained by variations in the firm complexity, growth opportunities, and scope of business needs. This result complements a large set of literature that examines the interaction between the firm's advising needs and the firm's business environment[6].

Next, I find causal evidence that board heterogeneity increases net investment and R&D intensity and that this strategic change by the firm is productive as it supports the firm's ability to product differentiate. Not only is the impact on net investment and R&D intensity statistically significant, but it is economically significant as well. I estimate that a one standard deviation increase in board heterogeneity on average increases net investment and R&D intensities by 8.4% and 13.4%, respectively.

Since board composition is endogenous, Adams, Hermalin and Weisbach (2010), I exploit the exogenous variation of board heterogeneity due to director deaths. This instrumental variable approach builds on the approach of many authors in corporate finance including recent papers like Fracassi (2017), Fan (2017), Drobetz et al. (2017), and Nguyen and Nielsen (2010). Outside directors as innovation drivers have been studied in a very narrow sense. Ellis, Fee and Thomas (2017) find that business segment net investments increase following

[6]See Coles, Daniel and Naveen (2012) and Boone et al. (2007) as examples.

the introduction of outside directors that have industry expertise in that segment, though they restrict their study to only conglomerates. While they find that outside directors with industry expertise can exacerbate the internal politics problem in conglomerates and are lured by "familiarity bias" to misappropriate internal capital allocations, I find that this result may be different when viewed from the perspective of product differentiation. Consistent with literature from strategic management, the results that I find are consistent with the resource-based view of the director. My results complement those of Dalziel, Gentry and Bowerman (2011) and I too find that outside directors allow firms gain better product positioning in the market, however, this paper attributes the outside director's broad industry expertise while Dalziel, Gentry and Bowerman (2011) considers the directors' human and relational capital as the reason.

The results of this paper also complement that of Fan (2017) who find that board interlocks through director network connections have a significant long-term impact on innovation direction and product market direction. My paper complements that work by introducing a specific channel to which outside directors can impact innovation direction and product market direction, broad industry expertise.

One of the major reasons why this paper finds results different from prior work is specifically that this paper is the first to document that outside directors have significantly broader industry expertise that was not previously considered[7]. This is in sharp contrast to the literature's general portrayal of the homogeneous outside director. Papers like Masulis et al. (2012) and Faleye, Hoitash and Hoitash (2017) consider only one dimensional differences in outside directors such as same industry expertise overlap with the board. Other papers consider only independence, Faleye (2014) and Fahlenbrach, Low and Stulz (2015).

This paper also makes several other important contributions to the literature. First, this paper contributes to the more recent focus on the director's monitoring and advising trade-off. The results of this paper imply that the monitoring and advising trade-off as sug-

[7]The average director in the sample has industry expertise in more than two industries.

gested by Kim, Mauldin and Patro (2014) this does not have to necessarily be the case. I find that the director/board traits that have been shown to weaken monitoring and governance in the literature, also tend to attract outside directors that are more similar to the board, the opposite of the multi-industry talented directors.

This paper is also related to the resource-based and strategic change literature. I find that multi-industry expert directors are an important information resource that is leveraged by firms. Bharadwaj (2000) and Tanriverdi (2005) have argued that firms who operate in complex information gathering environments often seek IT resources to facilitate synergies across the firm's multiple information gathering resources. The results in this paper support this claim. I find evidence that cross-sectional variations in director-board similarities can be explained by variations in firm complexity. Moreover, the increase in board heterogeneity as a result of hiring more diverse directors, results in increase net investment and R&D intensity. Similarly, recent works like Oehmichen, Schrapp and Wolff (2017) show that industry expertise can allow firms to make strategic changes including changes in the firm's financial resource allocation profile.

Finally, this paper is also related to the recent works on product market competition and innovation. This literature describes the interaction between competition and innovation. Recent works like Aghion, Van Reenen and Zingales (2013) and Fan (2017) have turned to governance mechanisms to explain the relationship between competition and innovation. While Aghion, Van Reenen and Zingales (2013) considers institutional ownership and Fan (2017) considers board interlocks, this paper introduces board heterogeneity as a possible incentive to innovate at the firm level.

The remainder of the paper is as followed: Section 2 describes the data used in the paper. Section 3 describes the methodology behind creating the expertise measures and introduces the models that will be used to estimate the demand for board heterogeneity as well as how board heterogeneity impacts corporate polices in the future. Section 4 presents the results of the model. Section 5 concludes this paper by providing some robustness checks. To ensure that the results are not driven entirely by conglomerate firms, a robustness check examines a subsample of only single-segment firms. Next, a deeper analysis of board heterogeneity is done by examining a subsample of firms that only expand their expertise level over time.

2.1 Data

S&P 1,500 firms from 2003-2013 are obtained from the Compustat Constituents list. This set of firms offers a balance between a wide distribution of firm sizes and access to a relatively reliable corporate board data set. Choosing the sample period after 2002 excludes the transitional period of the SarbanesOxley Act of 2002 [8]. Since firms had be compliant in most of the governance areas by 2002, using data post 2003 avoids possible board composition contamination issues that might arise during the 2001-2002 transitional periods as boards scrambled to be in compliance of the new guidelines.

Corporate board membership data is obtained from the BoardEx Organizational Summary. The match rate for BoardEx after 2003 is also markedly better than that from 2000-2002[9]. A match of 2,147 out of 2,307 possible S&P 1,500 firms between 2003-2013 is made. This consists of a baseline sample of 21,467 unique directors, 149,254 director-board-years, and 15,573 firm-years. Since BoardEx collects most director data from annual proxy statements, firms that de-list due to merger/acquisitions may not issue proxy statements in their last year. Ultimately, 15,573 out of 16,481 possible S&P 1,500 firms-years are matched.

Employment data on directors is obtained from the BoardEx Individual Profile Employment database. It consists of both publicly-traded and non-traded "private" firms[10]. Approximately 8,752 publicly-traded and 18,929 non-traded firms are represented in the

[8]Section101 (d) of the Sarbanes-Oxley Act - Public Company Oversight Board and 301(2) - Audit Committee Selection and Oversight had SEC deadlines of April 26, 2003, which would be considered 2002 in our sample.

[9]The match rate for 2003 was 91%, while only 78% for 2002 and 72% for 2001.

[10]Private firms are more accurately described as non-security issuing firms. Many of the "private" firms used in the sample are in fact government entities or private universities. Table 1. is a list of the top 20 private institutions that employed directors in the sample. On this list are 4 private universities, 2 lobbyists, 6 US government entities, and 7 private firms.

Table 2.1: Director Employment History

This table contains current and prior employment data for S&P 1,500 directors between 2003-2013 that is obtained from the BoardEx Individual Profile Employment database. For non-board positions, industry expertise is obtained if the director worked in some officer capacity at the firm. Trade associations where the director may be a passive employee are not used. Non-Public firms refer to firms that do not issue securities. These firms include government entities, private universities, public universities, private firms, and nonprofit entities such as lobbying groups. The top 20 public and non-public firms that hire directors in our S&P 1500 sample of directors is shown below.

Public Firms	**# Employed**	**Non-Public Firms**	**# Employed**
I.B.M. Corp.	224	N.Y.S.E Inc	147
J.P. Morgan Chase	197	Harvard Business School	144
General Electric Co.	164	McKinsey&Co Inc.	128
AT&T Corp.	163	US Chamber of Commerce	128
Proctor&Gamble Co.	139	Arthur Andersen LLP	127
Bank of America Corp.	136	PriceWaterhouseCoopers	118
CitiGroup Inc.	127	National Institutes of Health	105
HP Inc.	121	Harvard University	99
Ford Motor Co.	115	Stanford University	93
Honeywell International	107	Ernst&Young LLP	90
Merrill Lynch&Co.	103	KPMG LLP	84
Motorola Inc.	102	M.I.T.	74
Goldman Sachs&Co.	101	Deloitte LLP	72
Morgan Stanley	92	Federal Reserve: N.Y.	72
Pepsico Inc.	88	U.S. Dept. of Energy	69
Microsoft Corp.	87	U.S. Senate	66
Xerox Corp.	77	U.S. S.E.C.	60
Coca-Cola Co.	74	Federal Reserve: Cleveland	60
Pfizer Inc.	72	Donaldson Lufkin&Jenrette	58
Johnson & Johnson	71	Kohlberg Kravis Roberts&Co.	54
8,752 Total Public Firms	62,212	18,929 Total Private Firms	50,700

sample. Additionally, these S&P 1,500 directors were(are) employed at 62,212 publicly-held and 50,700 non-publicly-held firm positions, respectively. This means that the average S&P 1,500 director with 12 prior firm positions, work at nearly 5 non-public firms.

Historical board committee data is collected from the BoardEx Board and Committee Detail dataset. For each SP&P 1,500 director, the director's entire SP&P 1,500 board appointments and committee memberships is obtained. This is then matched to the director's biographical data; including age, gender, education, death, and social activities that are obtained from the BoardEx Individual Profiles dataset.

Table 2. summarizes the biographical details of incoming directors or directors that will join a board in the following period. Column 1 is the mean value for all incoming directors who join a board between 2004-2013, measured during the prior year. This includes all outside directors and inside promotions to the board. Since director characteristics are for the year prior to appointment, this table captures the potential characteristics of the director than might affect the hiring of the director. Column 2 and 3 are subsamples based on whether the director is an outside or insider, respectively. New incoming outside directors tend to be older and male. About a third of them have MBA degrees and a majority of them are financial experts[11]. The average incoming outside director also has been employed at more firms than the average inside director and based on my measurements, is an industry expert in almost three industries.

The S&P 1,500 firms are matched to CRSP returns. Industry returns are based on the Fama-French 12-Industry classification. I calculate daily returns and annual returns for each firm.

I create a matched incoming director-target board sample from 2004-2013 based on observed board membership data. Director and board characteristics are collected for the year prior to the connection. For the director, this data includes employment data, prior

[11]Based on Fracassi and Tate (2012), a director is a financial expert if she has an MBA or related finance degree, prior audit committee experience, works in the financial sector, or have a certification in an auditing capacity (CPA)

Table 2.2: Incoming Directors Characteristics of S&P 1500 Firms

This table provides a summary of all incoming outside and incoming inside directors that join boards from 2004-2013. The summary statistics are based on the prior year before they join the board. Biographical data for directors (*age*, *female*) is obtained from the BoardEx Individual Profiles Details database and ISS RiskMetrics database. Education data comes from the BoardEx Individual Education database. A *Finance Degree* includes all undergraduate and graduate degrees related to finance that are not *MBA degrees*(These include degrees in accounting, economics, and financial engineering). The *Leadership* dummy implies that the director has managerial training either from an executive MBA program, certified managerial degrees, or other leadership type training. A director is a *Financial Expert* if the director has prior audit committee experience, was a certified accountant, has an MBA degree, or a graduate level degree in economics or finance. *Firm affiliation* was the total number of firms that a director was affiliated with. This is different from *Employed* positions as it also includes trade/craft affiliations. *FF12 Industry* is the number of different Fama-French 12-Industries the director is an expert in as an executive or higher capacity.

Variable	**All Directors**	**Outside Directors**	**Inside Directors**
Age	54.96	55.44	50.75
Female	0.170	0.181	0.076
MBA Degree	0.333	0.336	0.31
Finance Degree	0.113	0.112	0.12
Leadership	0.051	0.051	0.054
Financial Expert	0.625	0.59	0.51
Firm Affiliation	11.90	12.09	7.22
Employed	7.98	8.51	5.34
FF12 Industry	2.69	2.79	1.77
Similarity Score	0.48	0.49	0.45
Number of Observations	9,768	8,791	977

Table 2.3: Firm Characteristics of Incoming Directors of S&P 1500 Firms

This table describes the characteristics of firms that appoint directors from 2004-2013. This is a matched sample to the directors of Table II. and is based on prior connection year firm characteristics. S&*P* 1,500 firms are matched to BoardEx, Compustat, and CRSP data. *Num. Directors* refers to the number of board members annually. *Num. Independents* is the board-reported number of independent directors. *Ind. Adj. Return* is the prior two-year Fama-French 12-Industry adjusted return for the firms each year. *ROA* is the operating income before depreciation divided by book assets. *Tobin's Q* is the market value of assets divided by the book value of assets. The *Net Investment Intensity* and *R&D Intensity* is the annual net investment and R&D expenditures scaled by annual revenues each year. Annual similarity scores are based on $t-1$ similarity score between the incoming director industry expertise vector and the board expertise vector. The 25th, 50th, 75th quartiles are 0.378, 0.471, and 0.577 respectively.

Variable Name	**Mean**	**Director-Board Similarity Score**			
		1st Quartile	2nd	3rd	4th
Num. Directors	9.808	9.989	9.886	9.996	9.452
Num. Independents	7.887	8.069	7.979	8.0877	7.517
Ind.Adj. Return	-0.120	-0.111	-0.127	-0.124	-0.121
ROA	0.0380	0.0368	0.0420	0.0392	-0.0357
Tobin's Q	4.140	3.837	4.0301	4.170	4.455
Assets	36,883	36,380	39,736	31,064	37,219
Net Investment	3,558	3,568	3,649	3,855	3,264
Net Investment Intensity	0.420	0.420	0.426	0.421	0.415
R&D Expenditures	343	283	349	365	375
R&D Intensity	0.0802	0.0683	0.069	0.0899	0.0897
Number of Observations	9,768	2,711	1,734	2,327	2,996

board data, and biographical data. From the firm, I collect prior performance measures (ROA, industry-adjusted returns, Tobin's Q), board characteristics data (board size, % independent...etc), and firm characteristics data (assets, revenue, net investment, R&D expenditures..etc). This dataset contains 9,768 directors, of which 852 are new CEOs and 8,118 are considered independent by the board. Excluding the CEOs, the remaining directors are matched to 7,024 announcement dates from the BoardEx Board and Director Announcement data set.

To measure the effect of industry expertise on major corporate policies, I obtain net investment and R&D expenditures from Compustat. These are scaled by annual revenues to determine the net investment and R&D intensities. Table 3. summarizes these S&P 1,500 firms. Other performance measures of the board, ROA and Tobin's Q are also measured from Compustat data. ROA is the operating income before depreciation divided by book assets and Tobin's Q is the market value of assets divided by the book value of assets.

Two measures of product market competition are used. First, the product market segment similarity score measures the ex-post revenue similarities of the products sold by two firms across product market segments. Data on market segment revenues comes from the Compustat Historical Segments dataset. Since Compustat records these revenues based on sic classifications, the segments are converted into Fama-French 12-Industries. Not all firms report segment sales and converting 4-digit sic codes to the Fama-French 12-Industry classification reduces the segment sales of some firms to one. About 45% of firms in the sample only report segment one segment[12].

The second product differentiation measure is based on the Hoberg-Phillips Text-based Network Industry Classifications (TNIC) data set. The Hoberg-Phillips TNIC data, Hoberg and Phillips (2016), estimates the degree of similarity of the products produced between firms by measuring the degree of similarity of the product descriptions from the firm's annual 10-K filings[13]. Both measures of product differentiation are measured at the firm-pair level.

[12] The construction of the product market segment similarity score is documented in the Appendix.

[13] `http://hobergphillips.usc.edu/industryclass.htm`

2.2 Measurements

This section describes how the industry expertise vectors are constructed and how the similarity scores/board heterogeneity measures are calculated.

2.2.1 Board Heterogeneity

Board heterogeneity is the defined as the degree of difference in industry expertises of a board. This can be measured by the distribution of industry expertises of the directors or by changes in industry expertises at the board level over time. I present several ways to measure board heterogeneity in this paper. The measure presented in this section emphasizes the diversity of industry expertise between the director and the board. This measurement focuses on how different the average director is from the board in terms of industry expertise overlap.

A second measurement for board heterogeneity is presented in the Appendix. This second measure focuses on the annual changes in board-level industry expertise. I constrain the board to either having industry expertise or not. In that sense, board heterogeneity arises over time when a new incoming director brings in new industry expertise to the board that the board did not previously have.

2.2.2 Director Industry Expertise Vectors

A director has industry expertise in an industry if at the present time or any time in the past, has worked at some officer-level capacity in the industry. The industry is defined by the Fama-French 12-Industry classification (FF12).

Both public and non-traded firms are matched to their FF12 classification equivalents by sic codes where possible[14]. If sic codes are unavailable, industry descriptions in the sample are matched to the closest FF12 equivalent by hand. Non-public (private) firms are matched

[14] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html

to the FF12 classification if at least three other directors have previously worked at the firm. Roughly 3,200 non-public firms remain unmatched using this procedure. These remaining unmatched firms are generally much smaller firms with very little industry impact.

Aggregating at the FF12 level facilitates the categorization of non-public firms that do not have available sic data. These firms without sic data are categorized by hand based on their best fit into the FF12[15]. Recall from the data section that roughly 45% of all director prior employers were of these non-public firms. Therefore, this necessary simplification allows me the ability to utilize this entire dataset.

A director's industry expertise at time t, is a 1x12 vector. Each element in the vector is either a 0 (if the director has no current or prior executive-level experience in the industry) or 1 (if the director has current or prior experience in the industry). Directors are assumed to not lose expertise over time. Once a director gains industry expertise by having experience in the relevant industry, the director is considered to be an expert in the sample.

Table 4 and 5 is an example of how a director's resume is decomposed into an industry expertise vector. Table 4. is the resume of Steve Jobs. Each prior employer of Jobs is classified by sic code (column 6) and translated into the appropriate FF12 equivalent (column 7)[16]. Jobs' industry expertise is primarily in the Information Technology Hardware and Media-Entertainment sectors but he gains industry expertise in the General Retailers industry when he becomes a director at The Gap Inc in 1999.

Table 5. translates Jobs' resume into annual industry expertise vectors. In 2000, Jobs' industry expertise vector now shows that he is an industry expert in FF9 as a director at The Gap Inc. Going forward, Jobs will always be an industry expert in this industry. The industry expertise vector of Jobs is quite typical of outside directors in the sample. The average director has industry expertise in nearly three industries in the sample (Table 2).

[15]The uncentered correlation proximity method that I use to calculate the similarity score is not affected by the categorization size. This is discussed in the appendix.

[16]In this example, Jobs' prior position as a non-executive employee at Atari gave him industry expertise in FF12. In constructing the industry expertise vectors for this paper though, industry expertise is reserved for executive or director level positions only

Table 2.4: Industry Expertise Example: Steve Jobs Resume

This table provides a summary of Steve Job's employment that is obtained from BoardEx Employment Data. *Industry* and *FF12* classification variables are based on the Fama and French 12-Industry classification of industry. The list is organized by the employer and includes the entire duration of the tenure. Only the last role is displayed in the sample.

Employer	**Date Start**	**Date End**	**Role**	**Industry**	**SIC**	**FF12**
HP Inc.	1968	1970	Employee	Information Technology Hardware	3570	6
Atari	1974	1976	Employee	Media&Entertainment	7994	12
Apple Inc.	1976	1985	Co-Founder	Information Technology Hardware	3571	6
NeXt Computer	1985	1997	Co-Founder	Software&Computer Services	3571	6
Apple Inc.	Aug-97	Jan-00	Interim CEO	Information Technology Hardware	3571	6
Apple Inc.	Jan-00	Aug-11	CEO, Executive Officer, Co-Founder	Information Technology Hardware	3571	6
Apple Inc.	Aug-11	Oct-11	Chairman	Information Technology Hardware	3571	6
Gap Inc.	Sep-99	Jan-02	Director-SD	General Retailers	5651	9
Pixar Inc.	Mar-91	May-06	Chairman/CEO, Co-Founder	Media&Entertainment	7812	12
Walt Disney	May-06	Oct-11	Director-SD	Media&Entertainment	4841	12

Table 2.5: Industry Expertise Example: Steve Jobs Industry Expertise Vectors

This table provides a summarizes how to de-construct Steve Job's prior employment data from Panel A in a 1x12 industry expertise vector. For example, in 1995, Steve Jobs has industry expertise in Fama-French 12-Industry category 6 (Business Equipment - Computers, Software, and Electronic Equipment) and Fama-French 12-Industry category 12 (Other -Entertainment).

Year	**Director**	**Fama-French 12-Industry Categories**											
1995	Steve Jobs	0	0	0	0	0	1	0	0	0	0	0	1
2000	Steve Jobs	0	0	0	0	0	1	0	0	1	0	0	1
2005	Steve Jobs	0	0	0	0	0	1	0	0	1	0	0	1

Fama-French 12-Industry Categories

FF-01	Consumer Non-Durables
FF-02	Consumer Durables
FF-03	Manufacturing
FF-04	Energy, Oil, Gas, Coal Extraction
FF-05	Chemicals
FF-06	Business Equipment
FF-07	Telecom Transmission
FF-08	Utilities
FF-09	Wholesale/Retail
FF-10	Healthcare and Equipment
FF-11	Money and Finance
FF-12	Media & Entertainment and Misc.

2.2.3 Board Expertise

Board industry expertise can be aggregated from the industry expertise of board members. Motivation for this aggregation of expertise at the board level can bee seen from survey evidence[17]. Results from annual surveys of corporate directors suggests that boards often decide on nominees based on board expertise deficiencies[18].

Table 6. is an example of how the board industry expertise vector is aggregated from the twelve incumbent board members of Walt Disney in 2005. Each incumbent director has an annual 1x12 industry expertise vector based on current and prior work experience. For each of the FF12 Industries except non-durable goods production (industry two), the board has at least one board member that has industry expertise. Thus, in 11 of the 12 categories, the board has industry expertise. Therefore the annual board industry expertise vector is a 1x12 industry expertise vector with 1's in every column except FF12 category 2. Table 7. describes the number of firms per year with the corresponding number of areas of industry expertise. More detail on how board expertise is constructed is in the Appendix.

2.2.4 Board Heterogeneity Measure

Board heterogeneity is a measurement of the diversity of industry expertise of the board members on a board. This diversity can be the result of board members having different industry expertise combinations or directors who are specialists and contributes a unique industry expertise not shared by other directors.

For some director D_1 that presides on board B_k at time t, the degree of industry expertise similarity between the director and the board is given by the an uncentered correlation in equation 1. This director-board similarity score measure captures to what degree the director's industry expertises overlap with the board's expertises.

[17] PWC's Annual Corporate Director's Survey 2017: `http://www.pwc.com/us/en/governance-insights-center/annual-corporate-directors-survey/assets/pwc-2017-annual-corporate--directors--survey.pdf`

[18] PWC's Corporate Director's Survey 2017 found that digital/IT and cybersecurity expertise were two of the most cited industry expertises that boards were actively seeking to fill.

Table 2.6: Board Industry Expertise: Board of Walt Disney Holdings Co. 2005

This table lists the board of The Walt Disney Holdings Co in 2005. There are ten independent directors out of the twelve. Each director's resume is used to create the annual industry expertise vector based on Fama-French 12-Industry classifications. The board's expertise (Walt Disney) is determined by whether a member director has expertise. If the a director has expertise in one of the Fama-French 12-Industries, it is assumed that the board also has expertise in that industry, For 2005, the board has expertise in all industries except industry two. Since no board member has industry expertise in Fama-French 12-Industry category 2(Consumer Durables – Cars, TV's, Furniture, Household Appliances), the board has no industry expertise in category 2 as well.

Fred Langhammer*	Estee Lauder Chairman	1	0	0	0	0	0	0	0	1	0	1	1
Aylwin Lewis*	Sears Holding CEO	1	0	0	1	0	0	0	0	1	0	0	1
Judy Estrin*	Packet Design Inc CEO	0	0	0	0	0	1	0	0	0	0	1	1
Gary Wilson*	Northwest Airlines Chairman	0	0	0	0	0	1	0	0	0	0	1	1
George Mitchell Jr*	Former US Senator	1	0	0	0	0	1	0	1	1	0	1	1
Father Leo O'Donovan*	Fmr. Pres. of Georgetown Univ.	0	0	0	0	0	0	0	0	0	0	0	1
John Chen*	Sybase Inc Chairman/President	0	0	0	0	0	1	0	0	0	0	1	1
Bob Iger**	Disney President/CEO	0	0	1	0	0	0	0	0	0	0	1	1
John Bryson*	Edison International Chairman	1	0	1	0	0	0	0	1	0	0	1	1
Robert Matschullat*	Clorox Company Chairman	1	0	0	0	1	0	1	0	0	1	1	1
Lisa Pitney*	California Chamber of Commerce	0	0	0	0	0	0	0	0	0	0	0	1
Monica Lozano*	La Opinion Magazine CEO	0	0	0	0	0	0	0	0	0	1	1	1
WALT DISNEY	Board Expertise	1	0	1	1	1	1	1	1	1	1	1	1

* Independent Director, ** President/CEO

Table 2.7: Number of Total Industry Expertises on a Board

This table provides a summary of the total number of industries that a firm has expertise in. Expertise are based on Fama-French 12-Industry classification. The board has expertise in an industry if a board member has expertise in that industry. For example, a value of five indicates that the firm has expertise in five of the twelve FF12 industries. Column 2 is the entire sample 2003-2013. Columns 3-5 are for years 2003, 2008, and 2013, respectively. A Wilcoxon Rank-Signed test rejects the null that the number of total FF12 industries on average for each firm is constant throughout the sample.

Number of Total FF12 Industries	**2003-2013**	**2003**	**2008**	**2013**
1	15	2	2	0
2	223	26	24	18
3	702	73	59	50
4	1,214	127	118	89
5	1,549	151	134	141
6	2,046	211	178	159
7	2,247	194	218	205
8	2,284	177	205	235
9	2,242	163	211	218
10	1,723	138	163	178
11	1,004	82	78	107
12	324	24	30	34
Mean	7.31***	7.03	7.29	7.56
Standard Deviation	2.35	2.39	2.34	2.30
Median	7.00	7.00	7.00	8.00
7.31	15,573	1,368	1,420	1,434

*** A Wilcoxon Signed Rank test t for the mean = -6.440; p-value=0.00

$$S_{k,i,t} = \frac{B_{k,t}D'_{1,t}}{(B_{k,t}B'_{k,t})^{\frac{1}{2}}(D_{1,t}D'_{1,t})^{\frac{1}{2}}} \tag{2.1}$$

To consider board heterogeneity differences over time, first I construct an average director-board similarity score as in equation 2 by averaging across the directors on the board. This equation is interpreted as the similarity between the average director and board. For values of $\overline{S_{k,t}}$ that are large,it is implied that there is a great deal of substitutability between directors on the board based on industry expertise. In other words, if a director were to resign, there would be sufficient overlap in industry expertise provided by other directors that the board level expertise would not change much.

$$\overline{S_{k,t}} = \Sigma_i^j S_{k,i,t} \tag{2.2}$$

A change in the average director-board similarity score shows how board heterogeneity changes over time:

$$\Delta\overline{S_{k,t,t-1}} = \overline{S_{k,t}} - \overline{S_{k,t-1}} \tag{2.3}$$

Hence, there is difference between a board comprised primarily by specialists verses a board comprised by generalists. A board with primarily specialists would lose board expertise if a director were to resign. This would not necessarily be true for a board filled with generalist. Consider Walt Disney's board in 2005 (Table 6.). The average director-board similarity score in 2005 of Walt Disney was 0.63. While smaller than the median director-board similarity score for S&P 1,500 firms in 2005 (0.667), Table 5. shows that there is still quite a dispersion of industry expertise in directors. This implies that the majority of the directors on the board are generalists with a broad range of industry expertises.

To test whether or not shareholders value directors with more heterogeneous industry expertise and whether boards demand these directors, a matched sample of incoming directors and the board is created. Here, the director-board similarity score is measured at time $t-1$ for directors that join a board at time t. Given industry expertise vectors at time $t-1$, the director-board similarity score for incoming directors is given by equation 4 below.

$$S_{k,i,t-1} = \frac{B_{k,t-1}F'_{1,t-1}}{(B_{k,t-1}B'_{k,t-1})^{\frac{1}{2}}(F_{1,t-1}F'_{1,t-1})^{\frac{1}{2}}} \tag{2.4}$$

If boards tend to hire directors that already have overlapping industry expertise with the board, the $t-1$ director-board similarity scores between the incoming director and the board would be very large and close to one and when compared to the next period's t score, the two similarity scores would be very similar. In contrast, if the director and the board are very different at $t-1$, the similarity score would be very small and the difference in the similarity score over time will be large.

One potential issue with equation 4 is that firms with larger board sizes can possibly have more board expertise simply by having more directors. This may unintentionally cause the director-board similarity scores to be higher if the boards have more expertise. Therefore, I also construct a similarity score measure that is weighted by the board size where Z_k is the size of board k.

$$S_{k,i,t-1,weighted} = \frac{\frac{B_{k,t-1}F'_{1,t-1}}{(B_{k,t-1}B'_{k,t-1})^{\frac{1}{2}}(F_{1,t-1}F'_{1,t-1})^{\frac{1}{2}}}}{Z_k} \tag{2.5}$$

To see how board heterogeneity can change when a director joins or resigns from a board, consider the example of Jobs joining the board of Disney in 2006. The similarity score between Jobs' industry expertise and that of the board of Disney is 0.52. While there is overlap in industry expertise between Jobs' and the board, there is still considerable diversity in expertises. Therefore, upon joining the board, the average director-board similarity score drops slightly from 0.63 to 0.61. Likewise, when Jobs' dies in 2012, the average director-board increases from 0.65 to 0.67. This measurement of board heterogeneity emphasizes the differences in the distribution of industry expertises between the directors and the board.

2.3 Methodology

2.3.1 Demand for Board Heterogeneity

Figure 4. plots the annual average number of industry expertises of a firm between 2003-2013. There has been a gradual and consistent increase in the number of industry expertises at the board level (7.03 in 2003 to 7.56 in 2013). A Wilcoxon test shows that this change is significant.

Figure 5. normalizes the total number of industry expertises per board by the board size to control for the number of directors. The results remain the same and a Wilcoxon test shows that this change is also significant. Firms are gaining industry expertises over time and these are unique Fama-French 12-Industry expertises.

Since board industry expertises are a result of director industry expertises increasing over time, a natural question to ask is whether all directors are becoming equally diverse in industry expertise or if directors are individually becoming more different and contributing different types of industry expertises to the firm. If the former were true, then the annual director's similarity in industry expertise would remain constant. However, Figure 2. implies that this is not the case. The average director similarity score has been decreasing as well, indicating that each director that joins a board over time is slightly more different than the board in terms of industry expertise. In other words, the reason why boards gaining more diverse industry expertise must be coming from the fact that directors are becoming more diverse in industry expertise as well.

Next, I consider source of this demand for board heterogeneity in two ways. First, the systemic increase in diverse directors must be valued by shareholders. While directors are still by majority nominated by the board, shareholders have gained significant influence over

Figure 2.2: Average Director-Board Similarity Score 2003-2013

This figure displays the annual average same-board director-director similarity score from 2003-2013. For each director on a board each year, a director-director similarity score is calculated by finding the similarity between their industry expertise vectors. The director-director similarity scores are averaged at the board level. The board-level average director-director similarity score is then averaged annually.

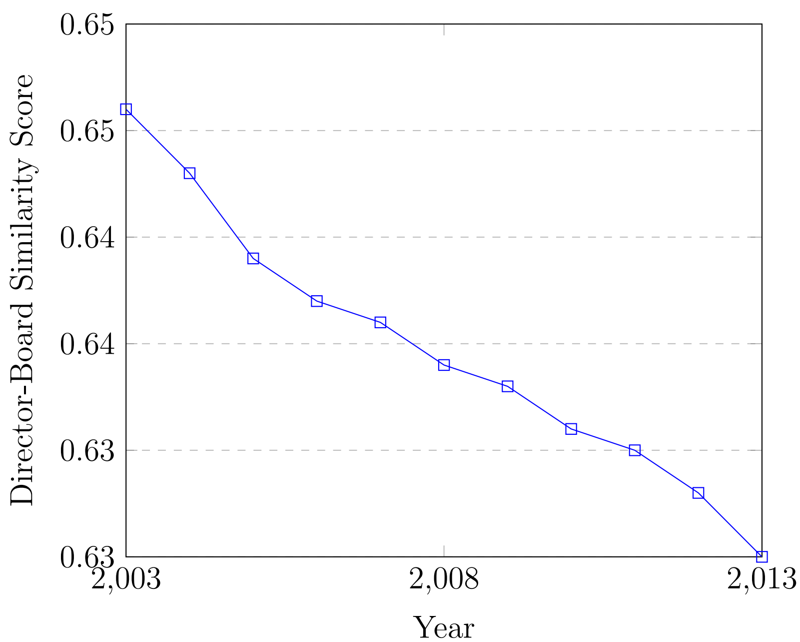


Figure 2.3: Annual Average Director Numbers of Industry Expertise

This figure plots the annual average number of industry expertises for each director from 2003-2013. Industry expertise categorization is based on the Fama-French 12-Industry classification. The average number of industry expertises for all directors is 2.26 while the number is higher for incoming outside directors at 2.79.

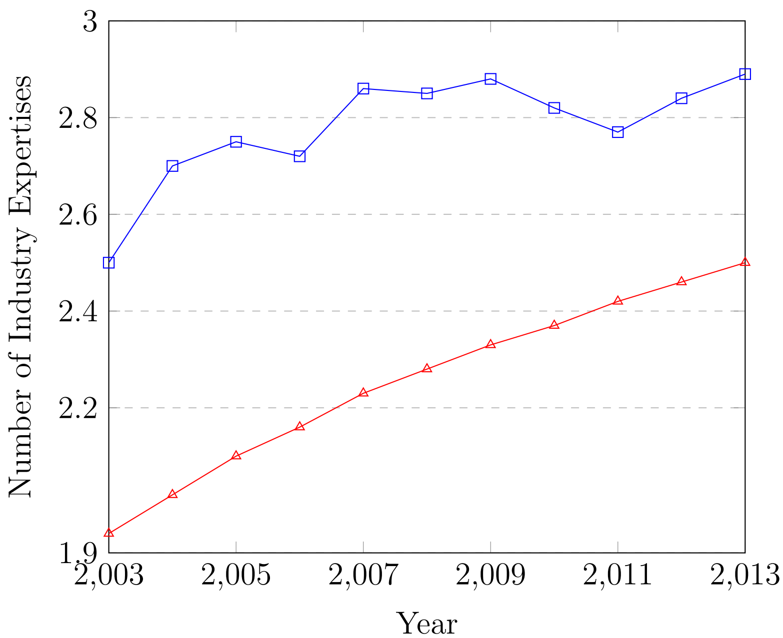


Figure 2.4: Average Total Number of Industries per Firm

The annual average number of industry expertises for each S&P 1500 firm between 2003-2013 is plotted below. Industry expertise classifications are based on the Fama-French 12-Industry.

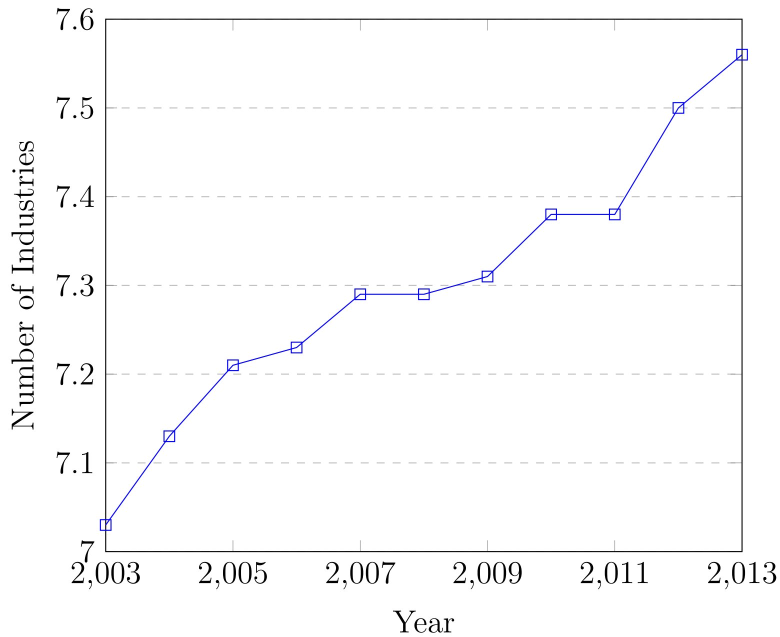
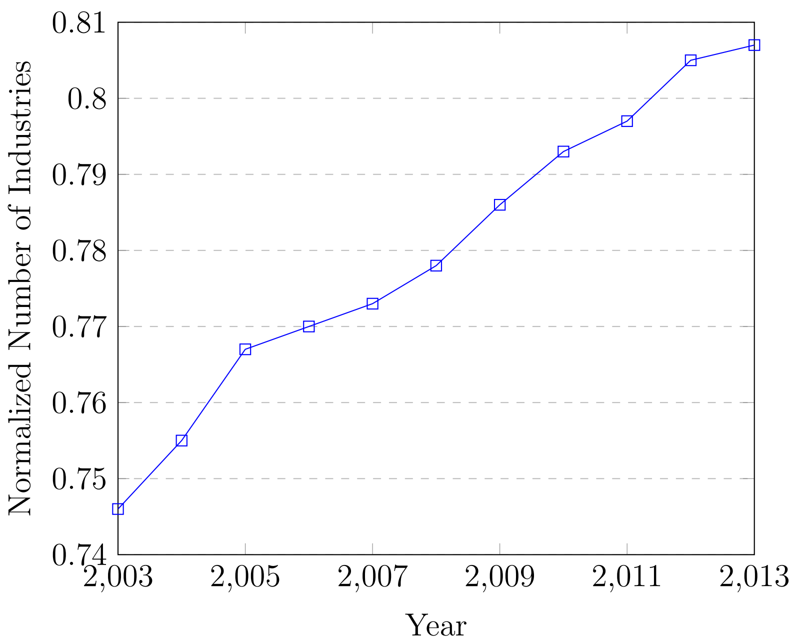


Figure 2.5: Normalized Industries: Total Industries/Number Directors

The average number of industries each year per S&P 1500 firm between 2003-2013 is weighted by the firm's number of directors.



nominations through new measures by the SEC[19] and through the activities of activist shareholders[20]. Therefore, I consider a event study approach to analyzing abnormal returns around the announcement of these directors. Second, since there is an observed equilibrium rise in diverse directors, I construct a model to examine some of the demand determinants of these diverse industry expertise directors.

To study the rise in board heterogeneity, I construct a matched sample of directors who join S&P 1,500 boards. First, I consider directors at time $t-1$ who will join a firm the following year at time t. I consider only directors who do not become CEOs of the target firm. Since some directors are hired as part of the CEO-succession plan, I exclude incoming directors that become CEO within 3 years of joining the board. A much smaller sample of directors are promoted to the board from within. These are current executives who join the board as insiders.

To evaluate the value of board heterogeneity by shareholders, a standard event study is conducted on the announcement returns of directors who are hired to the board. For each incoming outside director, a measurement window of [-210,40] is used to generate the predicted return by the firm. An event window of [-4,+1][21] is used to measure the abnormal returns. There are 7,024 matched new director announcement dates in BoardEx. Each incoming director's announcement date is matched for other announcements of resignations, internal promotions, earnings, mergers/acquisitions, and committee membership details. Directors were excluded if other announcements were made 30 days prior to the new director announcement date. The remaining director announcement dates were then filtered for other types

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[19]Since Aug 25, 2010, new measures adopted by the SEC require proxy materials to include director nominations of long-term shareholders.

[20]According to FactSet's SharkRepellent, there has been a four-fold increase in the number of attempted proxy campaigns between 2010-2013 (253). While many of them do not reach a proxy vote, many still are resolved through a proxy settlement.

[21]The choice of the [-4,+1] event window is based on Masulis et al. (2012) whose announcement return methodology is closest to mine. Nguyen and Nielsen (2010) uses an event window of [-1,+2] but that announcement is in regards to a director death.

of company news events[22]. Of the 7,024 directors with announcement dates, 1,301 director announcements fit the criteria as independent events.

Next, I consider the demand for board heterogeneity from the board. There is a growing body of literature that suggests a significant trade-off between the monitoring and advising performances of outside directors[23]. Therefore, to determine how board heterogeneity plays a role in shaping corporate policies, I first consider how the weakened monitoring of the board may impact on the type of director that is elected. The issue at hand is that the similarity score gives no indication of whether the director hired is for monitoring or advising purposes. If poor governance gives rise to outside directors with lower similarity scores, this may provide evidence of this monitoring/advising trade-off.

From the corporate finance literature, I include controls for the determinant of the demand for directors and categorize them as monitoring or advising. First, I control for whether or not a social networking connection exists between the board and the incoming director based on Fracassi and Tate (2012)'s social-networking links. This work follows from a long line of anecdotal and survey evidence that suggests that directors are chosen primarily by other director recommendations[24]. Survey evidence suggests that while most nomination committees are ultimately responsible for finding the new director, the pool of potential directors still often results from word-of-mouth recommendations between the directors on the board.

I build on Fracassi and Tate (2012)'s social connection methodology by searching for existing relationships between the incoming director and the entire board at $t-1$[25]. These

[22] News searches were made for firm related news during the event window. Firms that had news pertaining to litigation or litigation updates, FDA announcements, new product lines, missed earnings, or shareholder meetings overlapping were also excluded from the sample.

[23] See Brown, Dai and Zur (2016) and Kim, Mauldin and Patro (2014) as examples.

[24] see PwC's Annual Corporate Directors Survey 2016 and Annual GSB Stanford: Board of Directors Evaluation and Effectiveness Survey: `https://www.pwc.com/us/en/corporate-governance/annual-corporate-directors-survey/assets/pwc-2016-annual-corporate--directors--survey.pdf` and `https://www.gsb.stanford.edu/sites/gsb/files/publication-pdf/cgri-survey-board-directors-evaluation-effectiveness-2016.pdf`, respectively.

[25] Fracassi and Tate (2012) examines social links between the CEO and incoming director. Fracassi (2017)

social connections are based on prior education ties, prior employment overlaps, current employment overlap, and other outside activity overlaps[26]. If social connections exist between the incoming director and a member on the board, the similarity between the two may be driven entirely by prior correspondence and not due to any demand for industry expertises of the director by the board.

From Hermalin and Weisbach (2003), I control for CEO power in the firm. CEOs with more bargaining power in the firm may be able to surround themselves with directors that they can control. By exerting influence over the board, the CEO may be more likely to appoint directors who are more similar to the firm due to prior connections with the CEO as opposed to directors with desirable industry expertises. Therefore, I include proxies for CEO power by controlling for CEO tenure and dual CEO-chairman roles[27].

Three firm performance measures are used, Tobin's Q, ROA, and the firm's prior two year industry-adjusted return. Firm complexity is measured by the number of product market segments participated by a firm and by the firm's current board size. The literature has explored the economic determinants of board structure[28]. Since boards with more industry expertise may be a direct result of the firm's complexity, I also control for the total number of industry expertises on a board based on the incumbent director's expertises.

Finally, I include several director and board characteristics. These characteristics include the director's age, gender, and the percentage of independent board members on the board. I also control for the total number of industry expertise categories of the director.

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examines social links between firm pairs.

[26]A social connection exists if *any* of the four connections are made. I consider both a weak connection and a strong connection. A strong connection exists if 1) prior education cohorts graduate within a year of year other and 2) outside social activities memberships are of as an officer or above.

[27]There is a large literature that looks at the effects of CEO power. SeeGraham, Kim and Leary (2017), Li, Lu and Phillips (2016), and Shivdasani and Yermack (1999) to name a few.

[28]Using a random sample of firms, Markarian and Parbonetti (2007) find that director allocations to firms based on director classifications are not random. Externally complicated firms are more likely to employ "community influentials" as opposed to "insiders." Similarly, Coles, Daniel and Naveen (2008) finds that board size is directly related to firm complexity and scope of business needs where firms that have greater advising requirements typically have larger boards.

Directors with more overall industry expertise across all categories may mechanically have a larger similarity score with high expertise boards.

The monitoring, advising, and director characteristics can be broadly categorized into director characteristics, firm characteristics, and board characteristics. Formally, I estimate the demand for diverse industry expertise directors by the equation 6 below:

$$SimScore_{i,k,t-1} = \beta_0 + \beta_1 Dir_{i,t-1} + \beta_2 Firm_{k,t-1} + \beta_3 Board_{k,t-1} \tag{2.6}$$

I consider multiple specifications for the model in equation 6. All specifications are based on outside directors who join the board as non-CEOs. Table 8, Columns 1 and 2 consider Tobin's Q as the performance measure of the firm. Column 1 measures firm complexity and scope of business by the board's total number of industry expertises. A firm that is more complex with greater advising needs is assumed to have a more diverse set of industry expertise already on the board. Column 2 measures firm complexity based on the number of industry segments and the board size.

Columns 3 and 4 measures the board demand for heterogeneous directors by considering the performance measures of ROA and the prior industry-adjusted excess return. Column 1 to 4 follows Fracassi and Tate (2012)'s specification for establishing a social connection between the incoming director and the board. A "weak" connection is a more conservative approach in establishing a link between board members. This means that a connection is more conservatively likely to exist. The differences between a "weak" connection and a "strong" connection include requiring a maximum one year degree award date separation for an education connection or officer status in other social activities for a strong connection to exist.

Table 2.8: The Demand for Board Heterogeneity: Incoming Directors

This table describes model 5. The dependent variable is the similarity score between the incoming director and the board's industry expertise based on equation 1. All incoming directors are outside directors who do not become CEOs of the target firm. *CEO Tenure* is log of the CEO's tenure in years. *CEO-Chair Dual Title* is a dummy variable that is 1 if the current CEO is also the chairman and 0 if not. *Weak Connection* and *Strong Connection* are dummy variables that are 1 if social networking ties exist between the incoming director and the board members. *Weak Connection* are connections that are based are a weaker set of criteria to establish a connection, namely degree attainment at same school within four years and any position in other outside activities (See the methodology section for a more detail summary). *% Independent* is the percentage of incumbent board members who are classified as independent. *CEO < 1 Year* is a dummy variable that is 1 if the current CEO has been in the role for less than one year. *Board Size* is the log of the number of directors on the board. *# of Segments* is the number of Fama-French 12-Industry segments that the firm derives revenue from.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
BOARD					
CEO Tenure	-0.00398	0.00367	0.00379	0.00352	-0.00443
	(-1.69)	(1.72)	(1.85)	(1.69)	(-1.87)
CEO-Chair Title	0.00507	-0.00748*	-0.00678*	-0.00786*	0.00464
	(1.24)	(-2.04)	(-1.98)	(-2.22)	(1.13)
Weak Connection	0.0454***	0.0271***	0.0275***	0.0275***	
	(11.87)	(7.95)	(8.32)	(8.27)	
Strong Connection					0.0330***
					(9.34)
% Independent	0.0181	-0.0808***	-0.0893***	-0.0880***	0.0197
	(0.93)	(-4.38)	(-5.03)	(-4.91)	(1.02)
CEO <1 Year	-0.00249	0.00317	0.00243	0.00234	-0.00238
	(-0.41)	(0.57)	(0.45)	(0.43)	(-0.39)
Board Size		-0.0473***	-0.0518***	-0.0516***	
		(-6.23)	(-7.31)	(-7.22)	

Table 2.9: The Demand for Board Heterogeneity: Incoming Directors Cont.

Total Industry Expertise is the total number of industry expertise of the board based on equation 15. The performance measures *Tobin's Q*, *ROA*, and *Industry Excess Return* are operating income before depreciation divided by book assets, the market value of assets divided by the book value of assets, and the CRSP two-year prior industry-adjusted return, respectively. *Overlapping Industry Expertise* is a dummy variable that is 1 if the incoming director is an industry expert of the primary FF12 industry of the firm. For director characteristics.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
FIRM					
# of Segments		-0.00434***	-0.00433***	-0.00439***	
		(-3.63)	(-3.76)	(-3.80)	
Total Industry Expertise	-0.0824***				-0.0846***
	(-11.93)				(-12.17)
Tobin's Q	0.00103***	0.000797**			0.00109***
	(2.72)	(2.83)			(2.88)
ROA			-0.251		
			(0.185)		
Industry Excess Return				0.00210	
				(1.08)	
Overlapping Expertise	0.0909***	0.107***	0.107***	0.107***	0.0912***
	(25.45)	(32.85)	(33.85)	(33.70)	(25.46)

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.10: The Demand for Board Heterogeneity: Incoming Directors Cont.

Total Board Membership is the total number of other current board positions that the director is active in. This includes all listed and unlisted firms. *SP1500 Committee EXP* is a dummy variable that is 1 if the director has prior committee experience (nomination, executive, audit, corporate governance) at a S&P 1,500 firm. *Chairman* is a dummy that is 1 if the director's role is a chairman when hired. *Age* is the log of the director's age in years. *Female* is a dummy variable that is 1 if the director is a female. Finally, *MBA Degree* is a dummy that is 1 if the director holds an MBA degree the year before joining the board.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
DIRECTOR					
Total Board Membership	0.0290***	0.0140***	0.0133***	0.0134***	0.0286***
	(13.44)	(7.15)	(7.03)	(7.05)	(13.20)
SP1500 Committee EXP	0.0632***	0.00558	0.00515	0.00520	0.0649***
	(14.19)	(1.37)	(1.30)	(1.30)	(14.57)
Chairman	0.109	-0.0143	-0.00607	-0.00435	0.0103
	(0.25)	(-0.40)	(-0.19)	(-0.13)	(0.25)
Age	0.0289**	0.0194	0.0166	0.0171	0.0250
	(2.19)	(1.58)	(1.41)	(1.45)	(1.89)
Female	0.0129**	0.00148	0.000539	-0.00296	0.117**
	(2.90)	(0.37)	(0.14)	(-0.08)	(2.64)
MBA Degree	0.0146***	0.000568	0.0000	-0.0000367	0.0158***
	(3.93)	(0.17)	(-0.00)	(-0.01)	(4.24)
Constant	0.414***	0.379***	0.409***	0.407***	0.429***
	(7.26)	(7.02)	(8.04)	(7.96)	(7.49)
FIXED EFFECTS					
Fama-French 12-Industry	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
Observations	6,548	6,548	6,997	6,935	6,548

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.3.2 Net Investment and R&D Intensity

To consider the impact of board heterogeneity on strategic corporate policies, I consider net investment and R&D intensity. The literature surrounding the determinants of innovation and the impact of outside directors as advisors has been a source of great discussion. Survey evidence like the ones previously discussed, point to directors playing a central role in deciding major firm strategies and initiatives, yet the literature remains divided in how to approach measuring the impact of the director on major strategic policies. Ellis, Fee and Thomas (2017) comes closest to my approach by constructing a narrative in which conglomerates hire outside directors with specific expertise in the their sectors. These outside directors increase net investment but at the aggregate, the investments are wasteful due to inefficiencies of internal capital allocation. This story is at odds with the resource-dependency literature of Tanriverdi (2005) and Fan (2017) who finds evidence of major innovation directional changes following board interlocks. Moreover researchers like Aghion, Van Reenen and Zingales (2013) argue that governance features like block ownership, can play an important in focusing long-term R&D projects. This suggests that the net investment and R&D expenditures that occur due to outside director advising must be deliberate. If outside directors are demanded and valued for their advising capabilities and their benefits are in bringing in expertise that the board does not have, then these outside directors with the most unique perspective, should be the ones that generate the highest intensities of net investment and R&D.

I measure the effect of an increase in board heterogeneity on net investment intensity and R&D intensity. However, since board composition is endogenous, firms with long-term projects in place may seek out industry experts to see them through. Under this explanation, outside directors play a much smaller role, one that only provides oversight to projects. Thus, I use director deaths as an instrumental variable in determining the causal impact of board heterogeneity changes on net investment and R&D intensity changes.

Equation 5. measures the demand for board heterogeneity by decomposing the demand into monitoring and advising parts. Even after controlling for monitoring, I find that the demand for diverse industry expert directors can be explained by the demand for them as advisors. To access the effect of board heterogeneity on net investment and R&D intensity, I estimate the following IV regression for firm k for net investments:

$$\Delta SimScore_{k,t,t+1} = \beta_0 + \beta_1 Death_{k,t,t+1} + \beta_2 Controls_{k,t,t+1} + \epsilon_{t,t+1} \tag{2.7}$$

$$\Delta NetInvest_{k,t+1,t+2} = \gamma_0 + \gamma_1 \Delta Sim\hat{Score}_{k,t,t+1} + \gamma_2 Controls_{k,t,t+1} + \omega_{t,t+1} \tag{2.8}$$

and for Δ R&D:

$$\Delta SimScore_{k,t,t+1} = \beta_0 + \beta_1 Death_{k,t,t+1} + \beta_2 Controls_{k,t,t+1} + \epsilon_{t,t+1} \tag{2.9}$$

$$\Delta R\&D_{k,t+1,t+2} = \gamma_0 + \gamma_1 \Delta Sim\hat{Score}_{k,t,t+1} + \gamma_2 Controls_{k,t,t+1} + \omega_{t,t+1} \tag{2.10}$$

Director deaths are aggregated at the firm level annually. There were four cases where a firm experienced more than one director death annually. Therefore, the director death variable, *Death*, takes on the value of 0, 1, or 2. I also include other controls. At the firm level, I control for the change in assets between time t and $t+1$. Prior performance is based on the prior two-year industry adjusted excess returns for the firm. At the board level, I control for the total number of directors on the board, the number of independent directors, and the average age of board members. These board level controls are to control for the other board dynamics that may change following the death of a board member. Note in this framework, the change in the similarity score already controls for the change in the areas of industry expertise of the remaining board members. To ensure that industry and year effects are not driving the results, I also include Fama-French 12-Industry and year fixed effects.

Director deaths are a suitable instrumental variable because when a director death occurs, a vacancy on the board is created. Public corporate boards, especially the larger firms in our sample, are governed by corporate bylaws enacted by and ratified by the board[29].

[29]See Microsoft Bylaws as an example:
https://www.sec.gov/Archives/edgar/data/789019/000119312508201369/dex32.htm

These bylaws stipulate the minimum and maximum number of directors for the board, the types of board committees and committee membership procedures, and most importantly, the nomination process for directors. Nearly all of the S&P 1,500 firms in the sample nominate new directors at annual shareholder meetings, with proxy materials distributed in advance. Under normal circumstances, succession planning begins when a director informs the board that he/she is planning on resigning. Most boards do not have director succession plans in place. The director normally stays on until the next annual shareholder meeting when another director can be nominated. In the event of immediate resignations, vacant seats are left open until the next annual meeting.

Director deaths are unexpected and the vacancy implies that the board loses any industry expertise that the director had. There are potentially two effects on the board. The level of board industry expertise can be affected if the director has exclusive industry expertise that no other board member has. The second effect on the board can come from the overall mix of the director's industry expertise. A loss of a director with very diverse industry expertise can affect the firm in a very different way than a specialist director can.

Table 11. summarizes the director deaths in the sample. In total, 312 director deaths are observed in the sample. Compared to the 9,881 directors that exit in the sample[30], directors who die tend to be slightly older, more tenured in the firm, more likely to be an independent director, and in a firm with slightly less board heterogeneity when compared to the sample average. Overall, the director death seem to be a reasonable representation of the the group of directors that exit a board. The smaller board heterogeneity score is precisely the reason why director deaths cause board heterogeneity to fall (director-board similarity scores to rise).

[30] A director exit occurs when a director leaves the board of the firm at least 2 year before the last board date in the sample.

Table 2.11: Comparisons of Director: Entrants, Exits, and Deaths

This table provides a summary of directors that join boards, resign, or vacate due to death. *Entering directors* are directors that join a board for the first time. *Exiting directors* are directors that are no longer in the firm the following year and the firm continues to be listed for at least two years. *Director Death* refers to directors who die while still director serving the board.

Variable	**Entering Director**	**Exiting Director**	**Director Death**
Time in Board	0.572	10.536	13.754
Time in Company	1.643	11.778	14.433
Age	56.005	63.73	70.129
CEO	0.0884	0.0805	0.0609
Chairman	0.0176	0.102	0.167
Executive	0.111	0.0921	0.0192
Independent Director	0.829	0.736	0.817
Dir-Firm Sim Score	0.59	0.586	0.597
Excess Return	-0.00808	-0.103	-0.0938
Assets	39,890.68	42,583.09	18,096.66
R&D	350.591	351.818	208.5912
Net Investment	3,789.092	3,791.411	2,176.21
Number of Observations	9,941	9,881	312

2.3.3 Product Differentiation

Next, I turn to whether the change in net investment and R&D intensities following increases in board heterogeneity is beneficial to the firm. Ellis, Fee and Thomas (2017) argues that within a conglomerate framework, familiarity bias leads to internal capital mis-allocation. They argue that this leads to unproductive investments into pet projects which ultimately is detrimental to the firm's performance. However, performance measures are noisy and subject to demand shocks. Moreover, R&D is inherently risky and may yield no result, thus I approach this question from the lens of product differentiation instead.

I use two measures of product differentiation. The first measure of product differentiation uses the similarity of ex-post revenue shares[31]. This measure captures the effectiveness of the increase in net investment and R&D intensities in generating revenue streams in other business segments. If outside directors with more diverse industry expertise provide advice and new perspectives that open up new product lines or expand outside the firm's core business, evidence of this may be found in where the firm is generating revenue from. If outside directors help deploy internal resources efficiently, then their industry expertises might allow them the ability to see different opportunities which the firm should be able to, on average, better position themselves in the product market space. I estimate this using equations 8 and 9 below.

$$\Delta SimScore_{k,t,t+1} = \beta_0 + \beta_1 Death_{k,t,t+1} + \beta_2 Controls_{k,t,t+1} + \epsilon_{t,t+1} \tag{2.11}$$

$$\Delta PMSS_{k,t+1,t+2} = \gamma_0 + \gamma_1 \Delta Sim\hat{Score}_{k,t,t+1} + \gamma_2 Controls_{k,t,t+1} + \omega_{t,t+1} \tag{2.12}$$

The same empirical strategy is employed. Using director deaths as an instrumental variable, I attempt to establish a causal link between increases in board heterogeneity and product differentiation in the firm's product market space.

[31] see Appendix for a more detailed discussion on how this measure is constructed

While the first measure of product differentiation in a sense, measures the successes of a firm's ability to transition the business, the second measure is an ex-ante product differentiation measure. The Hoberg-Phillips (HP) Text-based Network Industry Classifications data set is based on regulatory statements. Each year, firms self-report 10-K product descriptions that have to be lawfully accurate. Unlike the similarity scores calculated by ex-post revenue streams, these product descriptions are ex-ante and forward-looking. If outside directors help efficiently redeploy internal resources, the new product direction will be evident by the key word descriptors that they provide on their regulatory statements. Thus, to measure this, I estimate equations 10 and 11.

$$\Delta SimScore_{k,t,t+1} = \beta_0 + \beta_1 Death_{k,t,t+1} + \beta_2 Controls_{k,t,t+1} + \epsilon_{t,t+1} \tag{2.13}$$

$$\Delta HP_{k,t+1,t+2} = \gamma_0 + \gamma_1 \Delta Sim\hat{S}core_{k,t,t+1} + \gamma_2 Controls_{k,t,t+1} + \omega_{t,t+1} \tag{2.14}$$

2.4 Results

Three main empirical facts motivate this paper. First, outside directors have diverse industry expertises. According to Table 2., the average outside director has industry expertise in almost three Fama-French 12-Industry classification industries. Figure 3. plots the time-series change in average industry expertises of outside directors. Part of this discrepancy could be due in part to most literatures ignoring the employment of directors at non-public firms. Outside directors on average have been employed at 8.5 prior firms. Based on the BoardEx employment sample, more than 50% of the employer firms are private firms. For studies that have focused on only public firm data, this implies that the literature has vastly underestimated and undervalued the different industry expertises of outside directors.

Second, there has been a sustained decline in the average similarity between directors on a board over time. Figure 2 and Table 12. both show a gradual but consistent decline

Table 2.12: Director-Board Similarity Score

This table provides a summary of the total number of industries that a firm has expertise in. Expertise are based on Fama-French 12-Industry classification. The board has expertise in an industry if a board member has expertise in that industry. For example, a value of five indicates that the firm has expertise in five of the twelve FF12 industries. Column 2 is the entire sample 2003-2013. Columns 3-5 are for years 2003, 2008, and 2013, respectively. A Wilcoxon Rank-Signed test rejects the null that the number of total FF12 industries on average for each firm is constant throughout the sample.

Year	Director-Board Similarity Score	Obs.	Std.	Median
2003	0.675	1,368	0.0967	0.669
2004	0.671	1,398	0.0956	0.665
2005	0.667	1,396	0.0942	0.657
2006	0.665	1,400	0.0948	0.654
2007	0.661	1,388	0.0930	0.654
2008	0.660	1,419	0.0954	0.651
2009	0.659	1,447	0.0960	0.648
2010	0.656	1,419	0.0973	0.643
2011	0.652	1,445	0.0969	0.639
2012	0.651	1,450	0.100	0.640
2013	0.645	1,434	0.0995	0.634
Mean	0.660***	15,564	0.0967	0.650

***A Wilcoxon Signed Rank test t for the mean = -8.440

p-value=0.00

in this similarity score over time. This decline is statistically significant[32]. There are two possible explanations to this and both offer support that the current homogeneous outside director interpretation is incorrect. One possible explanation is that directors are increasingly becoming specialists and boards are hiring specialists that do not overlap in terms of industry expertise each other. While can be a possibility, this is unlikely due to the fact that the average outside director has industry expertise in almost three industries. The other explanation is that while there is industry overlap, directors are gaining considerable non-overlapping industry expertise as well. This seems to be more likely the case. Figure 3 shows that the annual average director industry expertise is rising both for all incoming directors and outside directors, though at the level, the outside directors have more industry expertises by a significant margin. In other words, outside directors have broader ranges of industry expertise and it is the mix of industry expertises that are of value to shareholders and the board as it allows the director to provide a unique perspective on the business environment from the lens of multiple industries. Both of these explanations are in contrast to the current literature's treatment of outside directors as ones with same industry expertise (Masulis et al. (2012) and Faleye, Hoitash and Hoitash (2017)) or explicit experience as financial experts or acquisitions (Minton, Taillard and Williamson (2014) and Field and Mkrtchyan (2017)). This is something that I will examine closely in the following sections.

Finally, board industry expertise has increased substantially over the sample. Figure 4-5. and Table 7. provide this empirical fact. Table 7. shows that the mean annual average number of total industry expertise on a board has increased from 7.03 in 2003 to 7.56 in 2013. This is also statistically significant[33]. There are two noteworthy points here. First, the average S&P 1,500 firm has a large number of different industry expertise areas. Few papers have even looked at how board expertises can affect the firm. These papers have considered only related industry expertise, Dass et al. (2014), or political expertise, Agrawal

[32] A Wilcoxon signed rank test rejects the null that the average similarity score of directors on a board has been constant over the sample period

[33] A Wilcoxon signed rank test here also rejects the null that the average number of total industry expertises on the board has remained constant.

and Knoeber (2001). To my knowledge, no author has examined just how many numbers of industry expertise a board is associated with. Second, the number of industries that a board gains expertise in, is rising over time. This means that boards are either leveraging outside directors to increase expertise not found on the board or incumbent directors are seeking board seats in other industries and bringing expertise back to the firm. According to Figure 4-5., both are possibly true.

In all, these three facts point to a need for a more thorough analysis of the impact of diverse industry expertise on boards. To see how this board heterogeneity affects the firm, I first consider whether or not shareholders value this additional expertise by examining announcement returns of nominations of directors with different industry expertise. Next, I consider some of the demand determinants of board heterogeneity from the firm's perspective.

Finally, I consider the impact of board heterogeneity on the long-term strategic direction of firms. This emphasizes the advising effectiveness of these directors in how they are able to shape the long-term direction of the firm.

2.4.1 Shareholder Gains from Announcement Returns

I find that shareholders value outside directors with more different industry expertise backgrounds as the board. Table 13. summarizes the key results. There is a statistically significant 0.28% announcement return premium for outside directors using a [-4,+1] event window. The sign of this abnormal return complements studies like Nguyen and Nielsen (2010) who find a -0.85% abnormal return from an outside director's death. The differences in the size of the abnormal return can be possibly attributed to the different sample periods used. Nguyen and Nielsen (2010) uses 1994-2007, a period when outside directors increased substantially due to compliance with Sarbones-Oxley [34].

While the 0.28% abnormal return is statistically significant, when broken down by //

[34] In my sample 2002-2013, outside directors account for over 80% of all board members and that number has held fairly steady for a number of years. However, the outside director percentage rose dramatically from under 50% in 1996 to over 70% in 2005 according to Duchin, Matsusaka and Ozbas (2010)

Table 2.13: Shareholder Gains from Announcement Returns

This table displays the results of the event study of announcements of incoming directors. Cumulative abnormal returns are calculated based on an estimation window of [-210,-40] and event window of [-4,+1]. The market return is based on the Value-Weighted CRSP return. Incoming directors are from S&P 1500 firms from 2003-2013. An initial sample of 8,995 directors are matched with announcement dates from BoardEx. Directors announcements are excluded if they coincide with earnings announcements, executive/board turnovers, mergers/acquisitions, and other events such as litigations, product recalls, FDA product statements..etc.

	Obs.	**Mean**	**t-Statistic**	**%>0**
All Directors	1301	0.00282**	3.03	51%
Directors(outsiders)<Median	550	0.00447**	2.78	59%
Directors(outsiders)>Median	751	0.00100	1.56	51%
Directors(insiders) <Median	81	-0.00276	-0.71	50%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

***A Wilcoxon Signed Rank test t for the mean = -8.440

p-value=0.00

similarity of outside director to the board at $t-1$, outside director with less similar industry expertises are much more valued by shareholders. I find evidence of a +0.45% announcement return premium of less similar outside directors. The same is not observed for outside directors who more similar to the board they are about to join. For inside directors or directors who are to be promoted from within the firm, the results are even of the opposite sign, though insignificant. For each of these categories, I compare the new director-board similarity score to the median similarity score value for the year.

Taken together, the results suggest that shareholders do value outside director appointments to the board, but not because they are simply outsiders, rather the shareholder's positive view is driven by the outside directors potential industry expertise contribution to the board.

2.4.2 Demand for Board Heterogeneity

Next, the results of the demand determinants of board heterogeneity are presented in Table 8-10. Here, I examine the ex-ante characteristics of new director-board connections the following year. I find evidence that more complicated firms are associated with the hiring of directors that are bring in unique outside industry expertise. In columns 2-4, firm complexity is measured by the number of Fama-French segments and larger board sizes. I find firms that participate in more product market segments are related to the hiring of more different outside directors. These outside directors have more different industry expertise than the board's level of expertise. These results are consistent with the findings of Markarian and Parbonetti (2007) and Ellis, Fee and Thomas (2017) that find that firm complexity is tied with outside director expertise. The result is also evident when I consider board size as well. Larger boards tend to hire more heterogeneous outsiders. Again, columns 2-4 show a strong negative relationship between board size and similarity of the director with the board. Theory has suggested that smaller boards may reduce agency costs and asymmetry of information among board members but our results are consistent with the broader empirical findings of Coles, Daniel and Naveen (2008), Boone et al. (2007), and Linck, Netter and Yang (2008) who find that larger board are favored by firms that have organizational complexity and a greater dependence on external resources.

Not all firms report segment sales in to different FF12 industries and not all complex firms sell into different industry segments to begin with. In the sample, roughly 30% of all firm years of the S&P 1,500 firms did not report segmented FF12 sales. To ensure that the results are not driven by conglomerate firms, I use the board's *Total Industry Expertise* as a proxy for firm complexity. In column 1, the results show that there is a statistically significantly negative relationship between the total number of board expertises and the hiring of similar directors. Taken with the evidence from the number of segments, the results suggest that firm complexity and directors with different industry expertises are strongly related. Complex firms have a tendency to hire more different directors and this results is generalized to all firm types, not just conglomerates. From an advising perspective, the results are consistent with Faleye, Hoitash and Hoitash (2017) in that outside directors with industry expertise can help a firm with complex business needs such as advising firms on industry risks and regulations which can therefore contribute to firm value in the future.

Next, columns 2-4 compares different firm performance measures of the firm at $t-1$. Prior ROA and industry-adjusted returns do not seem to motivate the hiring of directors with different expertises where as a lower Tobin's Q does (column 2). One possible explanation for this is that ROA is an accounting-based performance measure. When ROA is high, the results can be due to successes of previous managerial actions, Hutchinson and Gul (2004). The same logic can be applied to the industry-adjusted returns that are insignificant. These measures are backwards looking and only reflect short-term successes based on decisions made in the past. Tobin's Q though, can reflect the firm's growth opportunities, Bozec, Dia and Bozec (2010). The positive relationship between Tobin's Q and director similarity score suggests that when firms are undervalued, the board seeks advice from outside help. In our sample of S&P 1,500 firms, the lowest Tobin's Q value is still greater than 1. The results could suggest that the firms with Q values at the lower end, may benefit the most from investments because they are undervalued. To make the most of their investments, they turn to outside advisors. Taken into context with the results from ROA and industry-adjusted returns, this set of results suggests that the advising sought after by boards from directors of different industry expertises is advice that can aid the firm in long-term strategic planning. This is explored in the next section.

Finally, the results of the demand for board heterogeneity also suggests that firms associated with weaker corporate governance (poor monitoring), hire outside directors that are more similar to the board. A director that has a pre-existing relationship based on the Fracassi and Tate (2012)'s social connections[35], results in a director hiring that decreases board heterogeneity. In other words, the new incoming director is more likely to overlap in industry expertises with the board. This result is unsurprising in the sense that survey evidence has always pointed to the fact that the pool of potential outside directors has predominately come from word of mouth[36]. Since social connections also include prior and current employment relationships, it is unsurprising that existing social connections leads to increased board similarity.

While CEO power (CEO tenure and CEO-Chair dual title), has been well established in the literature as source of weakened corporate governance[37], our results do not show that. One possible explanation is that while CEO power may result in hiring directors as poor monitors, this does not seem to impact the industry expertise similarity of the director.

Boards with a greater percentage of independent directors are also more likely to hire outside directors with different industry expertise. This result is consistent with the monitoring mechanism literature that boards with more outsiders increases firm transparency and reduces agency costs[38]. This result is also consistent with the advising literature in that

[35] A social connection exists if there is a education connection, prior employment connection, current employment connection, or connection from other social activities.

[36] See the annual corporate directors survey by pWc and annual board of directors evaluation and effectiveness survey by TMG

[37] See seminal works by Westphal and Zajac (1996), Daily and Dalton (1997), Hermalin and Weisbach (1988*a*) and more recent works by Albuquerque and Miao (2013) and Graham, Kim and Leary (2017).

[38] See Byrd and Hickman (1992), Brickley, Coles and Terry (1994), Westphal and Zajac (1996), and Borokhovich, Parrino and Trapani (1996) as well as more recent work by Henry (2010) who suggests that

boards with a larger proportion of independent directors also tend to have more advisory needs. Much like firms with more product market segment participation, boards with higher director independence percentages may be a proxy for firm complexity.

The results presented here also provide an attractive empirical baseline in which outside directors provide advising benefits to the firm while at the same time preserving monitoring incentives. Recent studies in corporate governance[39] have suggested that there are persistent monitoring trade-off costs of hiring outside directors. The results here are very much consistent with those papers. For example, Fich and Shivdasani (2006) attributes director busyness (too many concurrent outside directorship positions) as a potential reason why outsiders may be poor monitors. My results point to the same conclusion. Directors with more outside directorship positions (identified as poor monitors that lead to worse governance outcomes), also on average diminish board heterogeneity when they join the board. These outside directors consequently do not benefit the firm from an advisory capacity nor are proper monitors in preserving shareholder rights.

2.4.3 Impact of Board Heterogeneity on Firm Strategic Policies: Net Investment and R&D Intensity

The prior section highlighted the growth of board heterogeneity since 2003 and that this increase in the demand for board heterogeneity may possibly be driven by each board's desire to acquire different industry expertise through it's outside directors. One noteworthy result was that of all performance measures of the firm, only Tobin's Q, a possible measurement of the firm's long-term growth opportunities, had any explanatory power on the firm's demand for heterogeneous directors. Here, I discuss the results of how changes in board heterogeneity may be the cause for long-run changes in two strategic corporate measures.

This section presents evidence that this increase in board heterogeneity has real effects on firms. Specifically, firms that increase board heterogeneity see positive increases to net

agency costs are lower the higher the number of independent directors on the board.

[39] See Crifo and Roudaut (2017) and older papers such as Brick and Chidambaran (2005).

investment rates and R&D rates.

Identification is done with director deaths as the exogenous variation of board heterogeneity. There are 312 observed director deaths in the sample. Of the 15,573 firm-years, three firms had two director deaths in the same year[40]. Table 10. compares entering, exiting, and director deaths. Directors who pass away while in office tend to be older, tenured longer, independent directors, in smaller firms, and less R&D firms but the average director-board similarity scores are quite similar.

Table 14. presents the net investment intensity results. Column 1 and 3 are the first-stage regressions of the board heterogeneity based on director-board similarity score and the weighted director-board similarity score, respectively. Director deaths are exogenous events and unanticipated. Moreover, columns 1 and 3 indicate that director deaths significantly explain positive variations in board heterogeneity. When directors die, average board heterogeneity decreases (average directors become more similar) in part because the directors who die tend to be outside directors.

Columns 2 and 4 are the main 2SLS regression results. There is causal evidence that suggests that increases in board heterogeneity positively impacts net investment intensity. Not only is this statistically significant, but it is economically significant as well. A one standard deviation decrease of the similarity score equates to an increase of net investment intensity by roughly 8.4%. For a sense of scale, the death of Jobs' in 2012 increased the average director-board similarity score from 0.65 to 0.67. On average, the results presented here translate to roughly a 3% decrease in net investment intensity.

This is in line with results from Ellis, Fee and Thomas (2017) that find that outside advisors can positively impact net investment. However, the results here are more broadly applicable. Ellis, Fee and Thomas (2017)'s results apply only to conglomerates while here, all firms are considered. Of my sample of S&P 1,500 firms, nearly 40% of firms only report to one segment. Since Ellis, Fee and Thomas (2017) focus only on whether or not an outside

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[40]Brookline Bancorp Inc. 2008, South Jersey Industries Inc. 2009, and HMS Holdings Corp. 2009

Table 2.14: Board Heterogeneity and Net Investment Intensity

Director Deaths is the total possible annual director deaths in a firm from 2003-2013. *Ind. Adj. Return* is the Fama-French 12-Industry adjusted prior two-year return. *Number of Directors* and *Number of Independents* are the number of directors and independent directors on the board. *Total Assets* is the natural log of prior year's total assets. Columns 1 and 3 are the first stage regression of the 2SLS. Board heterogeneity is measured based on the change in similarity score of directors and board industry expertise in column 1 while weighted by board size in column 3. Columns 2 and 4 are the 2SLS regressions. The dependent variable of columns 2 and 4 are the change in net investment intensity.

	Δ Dir.-Firm First-Stage	**ΔNet Invest. Intensity**	**Δ Dir.-Firm First-Stage***	**ΔNet Invest. Intensity***
Director Deaths	0.00570***		0.000700***	
	(8.31)		(9.59)	
Δ Director-Firm		-1.318***		
		(-5.73)		
Δ Director-Firm				-30.526***
(weighted)				(-5.44)
Avg. Age of Directors	-0.00862***	0.444***		
	(-30.93)	(215.37)		
Number of Directors	0.0169***	0.0321***	0.000348***	0.755***
	(18.83)	(7.53)	(3.77)	(141.98)
Number of Independents	0.000833	0.00544***	0.000342***	-0.0772***
	(0.98)	(3.73)	(3.43)	(-14.67)
Ind. Adj. Return	-0.00147***	-0.0180***	-0.000133***	-0.0115***
	(-9.02)	(-3.87)	(-6.44)	(-8.65)
Total Assets	-0.000973***	-0.00299**	-0.000121***	-0.00902***
	(-12.76)	(-10.43)	(-14.80)	(-10.80)
Fixed Effects				
Fama-French Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	12,517	12,517	12,517	12,517

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.15: Board Heterogeneity and R&D Intensity

Director Deaths is the total possible annual director deaths in a firm from 2003-2013. *Ind. Adj. Return* is the Fama-French 12-Industry adjusted prior two-year return. *Number of Directors* and *Number of Independents* are the number of directors and independent directors on the board. *Total Assets* is the natural log of prior year's total assets. Columns 1 and 3 are the first stage regression of the 2SLS. Board heterogeneity is measured based on the change in similarity score of directors and board industry expertise in column 1 while weighted by board size in column 3. Columns 2 and 4 are the 2SLS regressions. The dependent variable of columns 2 and 4 are the change in R&D intensity.

	Δ Dir.-Firm First-Stage	**ΔR&D Intensity**	**Δ Dir.-Firm First-Stage***	**ΔR&D Intensity***
Director Deaths	0.00722***		0.000781***	
	(6.11)		(5.52)	
Δ Director-Firm		-2.0859***		
		(-5.60)		
Δ Director-Firm				-11.241***
(weighted)				(-6.02)
Avg. Age of Directors	-0.00992***	0.547***		
	(-27.41)	(143.68)		
Number of Directors	0.0195***	0.0464***	0.000450**	0.0330***
	(14.62)	(5.68)	(3.01)	(7.76)
Number of Independents	0.00261*	0.0159***	0.000488**	0.00576***
	(2.08)	(4.51)	(3.15)	(3.99)
Ind. Adj. Return	-0.000575***	0.000767	-0.000052*	-0.00156***
	(-2.80)	(0.99)	(-1.94)	(-3.62)
Total Assets	-0.00158***	-0.00437***	-0.000169***	-0.00317***
	(-17.03)	(-6.72)	(-15.30)	(-10.55)
Fixed Effects				
Fama-French Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	7,102	7,102	7,102	7,102

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

director has segment industry expertise, their measured impact of the outside director might be understated as it ignores all other industry expertise of the directors.

Table 15. shows similar results with respect to R&D intensity. I find that R&D intensity increases when boards become more heterogeneous. Likewise, a one standard deviation increase in board heterogeneity would equate to an average in crease of R&D intensity of 13.4%. In other word, the death of Jobs' would cause R&D intensity at Disney to decrease by approximately 4.5%.

This is consistent with Masulis et al. (2012) as well asFaleye, Hoitash and Hoitash (2017) who find that outside directors with prior industry experience are associated with greater innovation (patenting outcomes). The results are also consistent with Fan (2017) whose findings suggests that innovation direction and optimal technological space locations by firms are largely influenced by outside directors that join boards. Taken together, the results suggests that outside directors are understated advisors. These results are also consistent with the findings from the previous section that outside advisors with more different industry expertise are demanded by boards that have growth opportunities or are becoming increasingly more complex. Moreover, the contributions made by these outside directors have long-run strategic implications on firm direction as opposed to temporary short-term impacts on ROA or period-period returns.

2.4.4 Impact of Board Heterogeneity on Product Markets

In the prior section, I established causal evidence that board heterogeneity positively impacts net investment and R&D intensity. Since in a large part, board heterogeneity is the result of outside directors joining boards with more different industry expertise, it is the advising that these outside directors bring to the boards that affects the firm's long-term strategic decisions.

However, increased net investment and R&D expenditures may not be productive. Ellis, Fee and Thomas (2017) find empirical evidence that a "familiarity bias" exists whereby outside directors contribute to the internal politics of conglomerate firms by engaging in inefficient allocations of firm resources to segments that the directors are experts in. This paper addresses a similar but broader question of whether outside directors provide a net benefit to the firm or not. I address this question though product market space placement as it is less subject to the uncertainties of other performance measures.

Table 16 and 17. provide causal evidence again that shows that product differentiation increases when board heterogeneity increases. This is an important conclusion as it shows that firms actively seek out advisors with unique expertises and these expertises are leveraged by firms to increase investments and R&D, and finally these investments and R&D expenditures benefit the firm by allowing them to separate from their competitors. I show that this result holds when using two sources of product differentiation measures. The product market similarity score provides ex-post evidence of product differentiation by measuring revenues from segment sales. The second Hoberg-Phillips product differentiation score provides ex-ante evidence of product differentiation. Unlike the product market similarity score that utilizes revenues, the Hoberg-Phillips score captures the firm's intent in the product description. Therefore, the HP score captures product differentiation and the long-term direction of the firm.

2.5 Robustness

2.5.1 Segment Analysis

One possible channel in which increasing board heterogeneity can contribute to increased net investment and R&D intensity is that outside directors are hired by firms to advise the specific segments in which they are experts of and that this effect dominates in this sample. This is the explanation put forth by Ellis, Fee and Thomas (2017). To ensure that the results are not due to this conglomerate effect, I perform some subsample analysis based on the firm's product segments.

I divide the sample into single segment firms and firms that report two or more segments of sales. Table 18-19. displays the first set of results of the subsample analysis on the

Table 2.16: Board Heterogeneity and Average Product Market Similarity

Director Deaths is the total possible annual director deaths in a firm from 2003-2013. *Ind. Adj. Return* is the Fama-French 12-Industry adjusted prior two-year return. *Number of Directors* and *Number of Independents* are the number of directors and independent directors on the board. *Total Assets* is the natural log of prior year's total assets. Columns 1 and 3 are the first stage regression of the 2SLS. Board heterogeneity is measured based on the change in similarity score of directors and board industry expertise in column 1 while weighted by board size in column 3. Columns 2 and 4 are the 2SLS regressions. The dependent variable of columns 2 and 4 are the change in the Average Product Market Similarity Score.

	ΔDir.-Firm First-Stage	**ΔProduct Mkt Segment Score**	**ΔDir.-Firm First-Stage***	**ΔProduct Mkt Segment Score***
Director Deaths	0.00799***		0.000839***	
	(9.36)		(8.69)	
Δ Director-Firm		0.206**		
		(3.25)		
Δ Director-Firm				1.961**
(weighted)				(3.22)
Avg. Age of Directors	-0.00975***	-0.00975***		
	(-29.66)	(-29.66)		
Number of Directors	0.0178***	0.0178***	0.000193	0.000406
	(16.56)	(16.56)	(1.79)	(0.82)
Number of Independents	0.00317**	0.00317**	0.000599***	-0.00191**
	(3.18)	(3.18)	(5.13)	(-3.15)
Ind. Adj. Return	-0.00122***	-0.00122***	-0.000135***	0.000630***
	(-6.70)	(6.70)	(-5.76)	(5.24)
Total Assets	-0.00116***	-0.00116***	-0.000134***	0.000099
	(-14.38)	(-14.38)	(-14.47)	(0.91)
Fixed Effects				
Fama-French Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	9,062	9,062	9,062	9,062

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.17: Board Heterogeneity and Average Product Differentiation

Director Deaths is the total possible annual director deaths in a firm from 2003-2013. *Ind. Adj. Return* is the Fama-French 12-Industry adjusted prior two-year return. *Number of Directors* and *Number of Independents* are the number of directors and independent directors on the board. *Total Assets* is the natural log of prior year's total assets. Columns 1 and 3 are the first stage regression of the 2SLS. Board heterogeneity is measured based on the change in similarity score of directors and board industry expertise in column 1 while weighted by board size in column 3. Columns 2 and 4 are the 2SLS regressions. The dependent variable of columns 2 and 4 are the change in the Average Product Differentiation Score. The Product Differentiation Score is based on the Hoberg-Phillips Product Differentiation score from firm's annual 10-Ks.

	ΔDir.-Firm First-Stage	**ΔProduct Differentiation**	**ΔDir.-Firm First-Stage***	**ΔProduct Differentiation***
Director Deaths	0.00602***		0.000697***	
	(7.08)		(7.70)	
Δ Director-Firm		0.203***		
		(4.65)		
Δ Director-Firm				1.754***
(weighted)				(4.86)
Avg. Age of Directors	-0.00915***	0.00202***		
	(-29.39)	(4.95)		
Number of Directors	0.0169***	-0.00255**	0.000228*	0.000745**
	(16.47)	(-3.16)	(2.22)	(2.93)
Number of Independents	0.00263**	-0.00158***	0.000581***	-0.00210***
	(2.75)	(-6.01)	(5.24)	(-6.76)
Ind. Adj. Return	-0.00119***	0.000515***	0.000133***	0.000507***
	(-6.65)	(7.38)	(-5.82)	(7.36)
Total Assets	-0.00114***	0.000283***	-0.000143***	0.000301***
	(-14.85)	(5.00)	(-16.46)	(5.15)
Fixed Effects				
Fama-French Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	9,846	9,846	9,846	9,846

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

demand determinant model. Column 1 is the results of estimating equation 6 but restricting the sample only to single segment firms. Column 2 is restricting the same model but to only firms with more than two segments. I find similar qualitative results between the two samples. In most cases, the coefficient magnitudes for multi-segment firms is slightly larger than that of the single-segment firm. However, I find no evidence to suggest that the demand determinants of board heterogeneity is exclusive to only single-segment firms.

Next, I consider net investment intensity and R&D intensity. Again, the subsample analysis in Tables 20-21 show roughly the same results as Table 14-15. Director deaths seem to be strong predictors of increases in board *similarity* from columns 1 and 3. This increase in board similarity then causes net investments and R&D to slow. Again, this effect is slightly more pronounced in conglomerate firms but still very much present in single segment firms.

For product differentiation, Table 22. performs the same analysis as Table 17. Since the product market similarity score is based on the similarities of segment sales shares, I use only the Hoberg-Phillips product differentiation score in this robustness test. For multi-segment conglomerate firms, product differentiation can mean emphasizing different product lines. However, for single segment firms, it is not clear what the change in product market similarity score implies especially if both firms are single-segment firms. Since the product market segment average product differentiation measure does not give a clear interpretation under this scenario, I only report the results based on the Hoberg-Phillips product differentiation score. The same results are largely the same. Table 13. Panel C displays these results. I find that board heterogeneity leads to product differentiation, regardless of the number of product market segments the firm participates in.

In all, I do not find evidence that the conglomerate effect is impacting the results of the paper. I do find that board heterogeneity has the same qualitative impact (though smaller quantitative impact) on the firm's net investment and R&D intensity as well as increasing product differentiation.

Table 2.18: Robustness: Segment Analysis- Demand for Heterogeneous Directors

The dependent variable is the $t-1$ director-board similarity score. Column 1 restricts the sample only to firms that report one segment of sales. Column 2 restricts the sample to only firms that report more than one segment of sales. *Social Networking Connection* is based on the weaker criteria of creating a potential link between the director and the board.

	Single Segment Director-Board Score	**2 or more Segments Director-Board Score**
CEO Tenure	-0.00621	-0.00267
	(-1.46)	(-0.94)
CEO-Chair Dual Title	0.00101	0.000955
	(1.42)	(0.19)
Social Networking Connection	0.0413***	0.0468***
	(5.92)	(10.25)
% Independent	0.00308	0.0248
	(0.09)	(1.05)
CEO <1 Year	-0.00682	-0.000231
	(-0.62)	(-0.03)
Total Industry Expertise	-0.0977***	-0.0745***
	(-8.64)	(-8.36)
Tobin's Q	0.000413**	0.00121**
	(2.63)	(2.57)
Overlapping Expertise	0.0902***	0.0929***
	(13.65)	(21.71)
Total Board Membership	0.0290***	0.0319***
	(13.44)	(12.43)
SP1500 Committee EXP	0.063***	0.0622***
	(7.58)	(11.80)

Table 2.19: Robustness: Segment Analysis- Demand for Heterogeneous Directors Continued

	Single Segment	**2 or more Segments**
	Director-Board Score	**Director-Board Score**
Chairman	-0.0459	0.0363
	(-0.63)	(0.73)
Age	0.00974	0.0391*
	(0.44)	(2.38)
Female	0.0100	0.000539
	(1.21)	(0.14)
MBA Degree	0.0149*	0.0145**
	(2.21)	(3.27)
Constant	0.527***	0.0.355***
	(5.49)	(5.00)
Fama-French 12-Industry	YES	YES
Year	YES	YES
Observations	6,548	6,997

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.20: Robustness: Segment Analysis- Net Investment Intensity

This table displays the robustness analysis of the effect of the number of segments on the results of Table 14. Columns 1 and 3 are the first-stage regressions of the 2SLS. Columns 3 and 4 are the 2SLS regressions themselves. The dependent variable for columns 3 and 4 is the change in net investment intensity between time $t + 2$ and $t + 1$.

	Single Segment		**2 or more Segments**	
	First-Stage	**ΔNet Invest. Intensity**	**First-Stage**	**ΔNet Invest. Intensity**
Director Deaths	0.00971***		0.00447***	
	(7.67)		(5.54)	
Δ Director-Firm		-1.0672***		-1.396***
		(-5.05)		(-3.98)
Avg. Age of Directors	-0.00881***	0.447***	-0.00890***	0.441***
	(-14.64)	(215.47)	(-29.19)	(135.28)
Number of Directors	0.0178***	0.0391***	0.0172***	0.0309***
	(10.21)	(8.43)	(16.32)	(4.74)
Number of Independents	-0.00313*	-0.0996***	0.00240***	0.0116***
	(-1.94)	(-3.88)	(2.40)	(5.96)
Ind. Adj. Return	-0.00232***	-0.0310***	-0.00113***	-0.00109*
	(-6.64)	(-4.18)	(-6.25)	(-1.96)
Total Assets	-0.000162	-0.00178***	-0.00125***	-0.00338***
	(-0.82)	(-6.64)	(-16.24)	(-6.80)
Fixed Effects				
Fama-French Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	3,555	3,555	8,962	8,962

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.21: Robustness: Segment Analysis- R&D Intensity

This table displays the robustness analysis of the effect of the number of segments on the results of Table 15. Columns 1 and 3 are the first-stage regressions of the 2SLS. Columns 3 and 4 are the 2SLS regressions themselves. The dependent variable for columns 3 and 4 is the change in R&D intensity between time $t+2$ and $t+1$.

	Single Segment		**2 or more Segments**	
	First-Stage	**ΔR&D Intensity**	**First-Stage**	**ΔR&D Intensity**
Director Deaths	0.00568*		0.00807***	
	(2.03)		(6.82)	
Δ Director-Firm		-3.771*		-1.620**
		(-1.95)		(-6.03)
Avg. Age of Directors	-0.00882***	0.537***	-0.0105***	0.549***
	(-13.11)	(30.85)	(-23.99)	(187.99)
Number of Directors	0.0203***	0.0894*	0.0187***	0.0308***
	(8.93)	(2.17)	(11.21)	(5.12)
Number of Independents	-0.000975	0.000827	0.00495**	0.0218***
	(-0.47)	(0.09)	(3.11)	(6.48)
Ind. Adj. Return	-0.00194***	0.00107	0.000010	-0.000325*
	(-5.45)	(0.25)	(0.04)	(-0.65)
Total Assets	-0.00140***	-0.00652*	-0.00169***	-0.00350***
	(-7.14)	(-2.23)	(-15.67)	(-6.94)
Fixed Effects				
Fama-French Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	2,275	2,275	4,827	4,827

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.22: Robustness: Segment Analysis- Average Product Differentiation (Hoberg-Phillips Score)

This table displays the robustness analysis of the effect of the number of segments on the results of Table 17. Columns 1 and 3 are the first-stage regressions of the 2SLS. Columns 3 and 4 are the 2SLS regressions themselves. The dependent variable for columns 3 and 4 is the change in the Hoberg-Phillips Product Differentiation score between time $t+2$ and $t+1$. The product differentiation scores are aggregated at each firm's Fama-French 12-Industry level.

	Single Segment		**2 or more Segments**	
	First-Stage	**ΔProduct Differentiation**	**First-Stage**	**ΔProduct Differentiation**
Director Deaths	0.00837***		0.00487***	
	(4.55)		(5.12)	
Δ Director-Firm		0.101*		0.262***
		(2.10)		(3.91)
Avg. Age of Directors	-0.00904***	0.000599	-0.00807***	0.00273***
	(-16.63)	(1.34)	(-26.44)	(4.23)
Number of Directors	0.0170***	-0.00136	0.0150***	-0.00335**
	(9.37)	(-1.56)	(12.92)	(-2.68)
Number of Independents	0.00257	-0.000384	0.00324**	-0.00212***
	(1.51)	(-1.23)	(2.92)	(-5.43)
Ind. Adj. Return	-0.00131***	0.000256**	-0.00141***	0.000618***
	(-3.64)	(3.11)	(-6.85)	(5.87)
Total Assets	-0.00108***	0.000258***	-0.00138***	0.000310***
	(-7.26)	(3.45)	(-16.08)	(3.88)
Fixed Effects				
Fama-French Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	2,902	2,902	6,944	6,944

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.5.2 *Alternative Board Heterogeneity Specifications*

The board heterogeneity measure used through out this paper (equation 1), emphasizes the similarity between the director's industry expertise and the board's industry expertise. However, an alternative way to consider board heterogeneity would be to consider how the board's industry expertise level varies over time. Board heterogeneity measured in this way, emphasizes less on the degree of industry expertise dispersion across the directors on the board, rather it focuses on the board entirely. It is important to note that board heterogeneity when specified this way, only changes when the board loses or gains an industry expertise and that industry expertise cannot be replicated by another board member. This formulation also discounts the effect of industry expertise stacking across its board members.

Since annual board industry expertises are a 1x12 vector, a similarity score can be calculated by comparing how the vector elements change over time. The same uncentered correlation measure is used to calculate the similarity score across time. Thus, board heterogeneity is alternatively calculated below:

$$B_{k,t-1,t} = \frac{B_{k,t}B'_{k,t-1}}{(B_{k,t}B'_{k,t-1})^{\frac{1}{2}}(B_{k,t}B'_{k,t-1})^{\frac{1}{2}}} \tag{2.15}$$

Here, a large similarity score implies that the industry expertise has remained very close to the same. For example, suppose an elected director to the board contributes all the same industry expertise that the board already has, the board similarity score would remain the same. This si not true under the previous measure of board heterogeneity. However, if the newly elected director brings to the board, an industry expertise that is entirely unique, then board similarity over time would decrease.

Table 23. displays the results of this alternative specification. Results remain qualitatively the same under the new specification for board heterogeneity for both net investment intensity and R&D intensity. Director deaths remain a significant instrumental variable as

Table 2.23: Alternative Board Heterogeneity: Board Industry Expertise Similarity for Net Investment Intensity and R&D Intensity

This table displays uses an alternative specification for board heterogeneity. Board heterogeneity is based on year-to-year changes of board-level industry expertise differences.

	ΔBoard Expertise First-Stage	**ΔNet Invest. Intensity**	**ΔBoard Expertise First-Stage**	**ΔR&D Intensity**
Director Deaths	0.0198***		0.0163***	
	(13.34)		(6.21)	
ΔBoard Expertise		-0.315***		-0.895***
		(-6.82)		(-5.62)
Avg. Age of Directors	0.00380***	-0.456***	0.00186*	0.570**
	(5.58)	(1033.67)	(2.01)	(520.60)
Num. Directors	0.00181	0.00970***	-0.00191	0.00158
	(0.85)	(7.85)	(-0.60)	(0.40)
Num. Independents	-0.000785***	0.00160	-0.00491	0.00656
	(-3.88)	(1.26)	(-1.55)	(1.72)
Ind. Adj. Return	0.00156***	0.000688*	0.00167**	0.00367***
	(3.89)	(2.36)	(3.21)	(4.03)
Total Assets	0.000267	-0.00156***	0.000713**	-0.000238
	(1.50)	(-8.04)	(3.08)	(-0.80)
Fixed Effects				
Fama-French Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	10,920	10,920	6,195	6,195

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.24: Alternative Board Heterogeneity: Board Industry Expertise Similarity for Product Differentiation

This table displays uses an alternative specification for board heterogeneity. Board heterogeneity is based on year-to-year changes of board-level industry expertise differences.

	ΔBoard Expertise First-Stage	**ΔProduct Segment Score**	**ΔBoard Expertise First-Stage**	**ΔProduct Differentiation Score**
Director Deaths	0.0214***		0.0233***	
	(11.88)		(13.65)	
ΔBoard Similarity		0.0764**		0.0516***
		(3.29)		(5.71)
Avg. Age of Directors	0.00172***	-0.000482**	0.00344***	-0.000033
	(4.18)	(-2.49)	(4.85)	(-0.43)
Number of Directors	0.0000962	0.00108	0.00215	0.000792***
	(0.49)	(1.89)	(0.97)	(3.60)
Number of Independents	-0.00726**	-0.000186	-0.00896***	-0.000550**
	(-3.48)	(0.34)	(-4.33)	(-2.65)
Ind. Adj. Return	0.00172***	0.000225*	0.00185***	0.000163***
	(4.18)	(2.20)	(4.52)	(4.16)
Total Assets	0.000550**	-0.000212**	0.000647***	0.0000009
	(3.13)	(-2.93)	(3.60)	(0.40)
Fixed Effects				
Fama-French Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	9,054	9,054	9,822	9,822

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

shown in columns 3 and 4. Columns 2 and 4 show that when directors die, exogenously increasing board similarity, this increase board similarity decreases the net investment intensity and R&D intensity.

The results here indicate that gaining specific industry expertises matter at the board level. As firms gain expertise in other areas it previously did not have by electing directors with those expertise, it increases the intensities of net investment and R&D.

Next, in Tables 24, the results for the product differentiation are shown. The results are again consistent with the prior specifications for board heterogeneity. Similarly, the lack of advancement in board industry expertise causes product differentiation fo stagnant. This is true when measured by the product market similarity score and by the similarities in 10-K statements.

2.6 Conclusion

This paper begins by introducing three empirical facts that the corporate finance literature has largely ignored. First, outside directors have significant diverse industry expertise. This fact is inconsistent with the recent trend in the literature to focus very narrowly on specific director characteristics such as prior acquisition experience or same-industry expertise while assuming the director is homogeneous in all other facets. Second, board heterogeneity (average difference in the director's industry expertises) has increased over time. Directors are increasingly becoming more different from each other in terms of industry expertise. Third, board-level industry expertise has risen sharply over time. Whether the directors hired have more diverse expertise or firms have become more complex, the number of industry expertises that a corporate board has access to has grown steadily over time.

I introduce a simple methodology to construct director industry expertise vectors from prior employment data. This simple decomposition method then allows board expertise to be aggregated from the director expertise vectors. Using an uncentered correlation proximity measure based on Jaffe (1986), I can construct similarity score measures that compare how similar directors on a board are to each other and how similar a board is to itself over time.

I find that over the sample period 2003-2013, directors on the same board are becoming increasingly different in industry expertise offerings and the the same is also true at the board level.

I find that board heterogeneity is valued both by shareholders and the board. An event study using a matched sample of director-board connections describes an announcement return premium associated with the nomination of diverse industry expertise outside directors. This is only true and significant for outside directors with more diverse industry expertise than the board the director is joining and not true for more similar directors and inside executives who are promoted to the board.

I also find that at the board level, the demand for heterogeneous directors can be traced to both the increases in complexity of firms over time and the scope of the firm's business needs. Growth opportunities may also play an important role as well. Evidence points to a positive relationship between undervalued firms (low Tobin's Q) and the greater likelihood of hiring a different outside director, leading to more board heterogeneity

The increase in board heterogeneity over time has implications for the firm's major strategic policies and product market direction. Using unexpected director deaths as a source of exogenous variation in board heterogeneity, I show that increases in board heterogeneity increase net investment and R&D intensity. The results imply that a one standard deviation increase in board heterogeneity would on average increase net investment and R&D intensities by 8.4% and 13.4%, respectively. This result is consistent with many strands of literature that describe the outside director as an important advisor to the firm. I show that these increases in intensities are not a direct result of these outside directors inefficiently redirecting internal capital markets to their personal projects, rather the increases in board heterogeneity, net investment intensity, and R&D intensity result in firms product differentiating.

In all, the results of this paper show that the advise of outside directors play a very important role in the strategic planning by a firm. The results presented in this paper can explain why despite all the empirical research on the benefits of hiring homogeneous outside directors, the evidence from press releases point to boards choosing outside directors with increasingly more diverse industry expertise instead.

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Appendix A
APPENDIX

A.1 Industry Expertise Vectors and Similarity Scores

In this section, I develop some of the theoretical foundations for the expertise vectors and similarity scores that are constructed.

Given a director 1 employed at board k at time t, the director's industry expertise vector is given by:

$$D_{1,t} = \{\ D_{1,1,t}, D_{1,2,t}, D_{1,3,t}...D_{1,n,t}\} \tag{A.1}$$

Similarly, director 2's industry expertise at time t is also a 1xn vector where n is the number of industry expertise subdivisions.This paper uses the Fama-French 12-Industry classification, thus n is 12. Prior papers have used other classifications such as the two-digit sic code.

$$D_{2,t} = \{\ D_{2,1,t}, D_{2,2,t}, D_{2,3,t}...D_{2,n,t}\} \tag{A.2}$$

Industry expertise similarity between director 1 and director 2 at time t is based on well-known Jaffe (1988) proximity measure or uncentered correlation of the vectors $D_{1,t}$ and $D_{2,t}$.

$$DD_{1,2,t} = \frac{D_{1,t}D'_{2,t}}{(D_{1,t}D'_{1,t})^{\frac{1}{2}}(D_{2,t}D'_{2,t})^{\frac{1}{2}}} \tag{A.3}$$

The proximity measure is a relative distance measure. This method of calculating the similarity score between two vectors is invariant to number of subdivisions in the categorization. To see this, if a broader categorization of industry is used it can causes more overlaps between industry expertises. Based on equation 14, the numerator might increase. However, a broader categorization also increases the denominator. Therefore, since the number of overlaps of subdivisions are normalized by the number of subdivisions, this proximity measure is invariant to the scale of industry classification[1].

The similarity measure has several attractive attributes. The similarity measure is 0 if two directors share no industry expertise and their industry expertises are orthogonal. The similarity measure is 1 if the directors exactly overlap in industry expertises. For similarity scores between 0 and 1, the similarity measure captures the degree of overlap of industry expertise; a higher similarity score indicates a greater degree of industry expertise overlap.

Director expertise vectors can be aggregated to the board-level expertise. Since director industry expertises are simply dummy variables, this paper considers a simple approach to board expertise, namely a board has expertise in an industry if one of the board members has expertise in that industry. Therefore, board expertise is also a 1x12 vector as in equation 4 with each element a 1 if a director on the board has expertise in that industry and 0 if no director has expertise[2].

$$B_{k,t} = \{\ B_{1,t}, B_{2,t}, B_{3,t}...B_{12,t}\} \tag{A.4}$$

where

$$B_{1,t} = \begin{cases} 1 & \text{if } \Sigma_i D_{i,1,t} > 0 \\ 0 & \text{if } \Sigma_i D_{i,1,t} = 0 \end{cases}$$

For some director D_1 that presides on board B_k at time t, the degree of industry expertise similarity between the director and the board is given by the same uncentered correlation equation 5. This director-board similarity score measure captures to what degree the director's industry expertises overlap with the board's expertises. In other words, this similarity

[1]See also Bloom, Schankerman and Van Reenen (2013*b*) Appendix C for a proof..

[2]In ongoing work, we allow board expertise to stack, where directors with overlapping expertises contribute to a larger expertise in an industry

score measures what a director can contribute that is unique to the board.

$$S_{k,i,t} = \frac{B_{k,t}D'_{1,t}}{(B_{k,t}B'_{k,t})^{\frac{1}{2}}(D_{1,t}D'_{1,t})^{\frac{1}{2}}} \tag{A.5}$$

An average director-board similarity score for a firm at time t can be calculated by averaging across all j incumbent directors of board k:

$$\overline{S_{k,t}} = \Sigma_i^j S_{k,i,t} \tag{A.6}$$

A change in the average director-board similarity score shows how board heterogeneity changes over time:

$$\Delta\overline{S_{k,t,t-1}} = \overline{S_{k,t}} - \overline{S_{k,t-1}} \tag{A.7}$$

For incoming director that will join a board at time t, similarity scores can also be found by comparing director and board industry expertise vectors at time $t-1$.

$$S_{k,i,t-1} = \frac{B_{k,t-1}F'_{1,t-1}}{(B_{k,t-1}B'_{k,t-1})^{\frac{1}{2}}(F_{1,t-1}F'_{1,t-1})^{\frac{1}{2}}} \tag{A.8}$$

A.2 Board Similarity Score

A second way that we can measure board heterogeneity focuses on the board's expertise. Board heterogeneity can also occur if boards desire to seek out directors to fill specific expertise needs.

Board expertise is a 1xn vector for n industries.

$$B_{k,t} = \{\ B_{1,t}, B_{2,t}, B_{3,t}...B_{n,t}\} \tag{A.9}$$

A board has industry expertise in an industry if at least one of its directors has expertise in that industry[3]. A board lacks expertise in an industry if no director on the board has expertise in that industry.

The similarity score of a board can be calculated across time, emphasizing the persistence (or lack of persistence) of board expertise on the board.

$$B_{k,t-1,t} = \frac{B_{k,t}B'_{k,t-1}}{(B_{k,t}B'_{k,t-1})^{\frac{1}{2}}(B_{k,t}B'_{k,t-1})^{\frac{1}{2}}} \tag{A.10}$$

A.3 Product Market Segment Scores

Product differentiation can be implied by how firms derive revenue from multiple product market segments. For two competing firms, each firm may decide to emphasize sales into different product segments to decrease competition. As firms increasingly sell into more different product lines, the products offered between the two firms will differ, but increasing product differentiation.

To measure product differentiation, first we measure the product market segment score based on the similarity of revenue shares across market segments between two firms. Two firms are highly competitive if they derive similar revenue in the same market segments. The product market segment score generalizes this by comparing the revenue shares across all segments the firms sell into.

The product segment score is an adaptation of the Jaffe (1986) proximity measure used by Bloom, Schankerman and Van Reenen (2013*a*) and Fan (2017). In the sample, I place no restriction product segments, thus generalizing the results of Ellis, Fee and Thomas (2017). In contrast to the Hoberg-Phillips score measure, this product measure accounts for ex-post product sales as opposed to the Hoberg-Phillips score that relies only on regulatory descriptions of products. As such, these two product measures provide two different perspectives on product market competition. Below we briefly describe the micro-foundations of the product

[3] In ongoing work, we allow board expertise to stack, where directors with overlapping expertises contribute to a larger expertise in an industry

market segment similarity score. Suppose firms compete in a unit product market space. Firms are positioned inside this unit space and the distance between any two firms measures the degree of competitiveness between the two firms based on the products that they sell. Consider two firms i and j that are inside the unit product market space.

The two firms i and j sell in to n product markets such that their revenue in each segment is $R_{it,n}$ and $R_{jt,n}$ at time t. In each product market segment that the firm earns revenue, the firm employs sales agents. The more overlapping sales agents two firms have in each segment, the more *competitive* the two firms are in that segment.

Firm i and firm j's sale shares at time t in n segments is a $1xN$ vector.

$$F_{i,t} = \{ \ F_{1,t}, F_{2,t}, F_{1,t}...F_{n,t}\} \tag{A.11}$$

$$F_{j,t} = \{ \ F_{1,t}, F_{2,t}, F_{1,t}...F_{n,t}\} \tag{A.12}$$

Firm i and firm j's proximity in a product market space can be approximated by the following uncentered correlation proximity measure:

$$PS_{i,j,t} = \frac{F_i F_j'}{(F_i F_i')^{\frac{1}{2}}(F_j F_j')^{\frac{1}{2}}} \tag{A.13}$$

Equation 19 calculates the product market similarity score between two firms, i and j at time t. If firms i and firm j derive revenue from very different product market segments, the product market similarity score will be small, indicating that the two firms are located far apart in the product market space. Similarity, if the product market similarity score is large, approaching one, firms i and firm j derive revenue from overlapping product market segments. This implies that the two firms are likely engaged in heavy competition.

The product market segment scores are based on the uncentered correlation proximity measure. By construction, this measure is robust to aggregation[4]. In Bloom, Schankerman and Van Reenen (2013*a*) and Fan (2017), the shares are based on 2-digit sic classifications.

[4]See Bloom, Schankerman and Van Reenen (2013*a*) for a detailed analysis.

Here, the industries are based on Fama and French 12-Industries. This is used to match the industry classification of the director industry expertises.

Changes in the product market segment scores imply pair-wise changes in product differentiation. To measure broader product differentiation implications, I aggregate all pair-wise product market segment scores at the Fama-French 12 Industry level. This measures the average product differentiation for a firm against it's Fama-French 12 industry competitors. For some firm i in industry FF12=z at time t, the average product similarity score is given by equation 25.

$$PS_{i,FF=z,t} = \Sigma_j F_{i,FF=z,t}/j \tag{A.14}$$

To measure the change in product differentiation over time, one can measure the change in the average distance from equation 26.

$$\Delta PS_{i,FF=z,t} = PS_{i,FF=z,t} - PS_{i,FF=z,t-1} \tag{A.15}$$