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Essays on Networks and Corporate Finance

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by

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Abstract

In my dissertation I explore how personal networks affect firms' financial decisions. In the first essay, I study how social connections among divisional managers affect the capital allocation to divisions in diversified conglomerates. In contrast to the previous studies, I focus on the horizontal connections or connections formed among managers of the same level of corporate hierarchy. I show that connections among divisional managers lead to higher sensitivity of segment capital spending to segment's growth opportunities, higher firm-level allocation efficiency and higher firm value. Additionally, firms tend to strategically assign better-connected managers to these segments, and connections help to reduce internal information asymmetry. The results are consistent with the idea that connections facilitate interdivisional cooperation and better alignment of divisional and firm's incentives.

In the second essay, I examine capital structure decisions of suppliers with social connections to major customers, which invest in relation-specific assets. Suppliers connected to major customers with relation-specific assets have higher debt ratios. The effect is more pronounced when intensity and duration of business relationship is high, and when information asymmetry between parties is high. In addition, building up debt helps suppliers to reduce underleverage and move faster toward target leverage ratios. Overall, the results are consistent with the view that connections help to strengthen implicit contracts through establishing trust between trading parties.

In the third essay, I study the effect of divisional manager-CEO social connections on the scale and success of corporate innovation activities. Divisional managers who previously worked or studied with CEO file a greater number of patents during their tenure at the segment. These patents receive more citations in future and represent a greater scientific and economic value. These findings can imply that socials connections help to mitigate adverse selection problems associated with R&D investments.

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CHAPTER 1: DIVISIONAL MANAGER CONNECTEDNESS AND CAPITAL ALLOCATION EFFICIENCY

1 Abstract

Social connections among divisional managers are associated with capital allocation improvements in S&P500 industrial conglomerates. Using plausibly exogenous changes in connections due to deaths and retirements of managers at the sample firms and at other local firms for identification, we show that connections among divisional managers lead to higher sensitivity of segment capital spending to segment's growth opportunities, higher firm-level allocation efficiency and higher firm value. Connections to peers benefit the firm in two possible ways. First, connections help to secure more funds to segments with better prospects, especially as firms tend to strategically assign better-connected managers to these segments. Second, connections help to reduce internal information asymmetry. Ultimately, the results of this study support the idea that connections help to mitigate misallocation of funds by facilitating interdivisional cooperation and better alignment of divisional and firm's incentives. The conclusions hold after accounting for the effects of manager's human capital, reverse causality, connections to CEO or connections to other executives of public and private companies.

2 Introduction

The growing body of research has been exploring the impact of social connections on capital allocation process in multidivisional firms. Social connections can create social and political forces that affect the way the capital is allocated across divisions (e.g. Xuan (2009), Gaspar and Massa (2011), Duchin and Sosyura (2013), Glaser, Lopez-De-Silanes, and Sautner (2013)). However, numerous papers focus on *vertical* connections or social connections that exist between higher- and lower-ranking managers in the corporate hierarchy, such as connections between divisional managers and CEO. The novelty of our paper is the focus on *horizontal* connections or connections among managers of the same level of hierarchy. Diversified conglomerates represent an ideal setting to study the effect of horizontal connections, because each divisional manager has likely an equal authority over investment decisions in his/her division.

In this paper, we examine the potential impact of horizontal (bilateral) connections among divisional managers on the capital allocation decisions inside the conglomerates. There can be both positive and negative causal relations between connections and firm value. We might observe the positive effect if horizontal connections provide incentives to engage in cooperative behavior through creating trust and mutual cooperation among divisional managers. The negative effect can emerge if connections facilitate the collusion of divisional managers in extracting the resources from the conglomerate. For example, connected managers can more easily over-report both their effort and the investment opportunities of their segments. Our results suggest that social connections among divisional managers have a strong positive effect both on the efficiency of capital allocation and on the firm value of conglomerates. We also explore the channels through which connections among divisional managers within firm positively affect the efficiency of capital allocation and firm value.

We build on the vast literature in sociology and economics showing that connections can create trust and promote cooperation between connected individuals (e.g. Coleman (1988), Nahapiet and Ghosal (1998), Woolcock (1998), Putnam (2000), Karlan, Mobius, Rosenblat, and Szeidl (2009)). The underlying idea of this stream of research is that social networks create trust, because connections serve as a social collateral (or "credit slip"), and the possibility of losing valuable ties (friendships) secures informal transactions just as physical collateral secures borrowing-lending transactions. As Coleman (1988) and Karlan, Mobius, Rosenblat, and Szeidl (2009) emphasize the importance of closed networks in facilitating cooperation, the tight networks of divisional managers with mutual direct connections to each other are likely to strengthen cooperation between them. In the context of internal capital markets, where capital markets are competitive (Williamson (1975)), divisional managers tend to be self-interested (Milgrom (1988)), and decisions over allocation of funds ex ante are not contractible and subject to informal judgment (Grossman and Hart (1986), Graham, Harvey and Puri (2015)), trust and mutual cooperation become important for efficient allocation of funds across divisions.[1] We propose that connections among divisional managers lead to better alignment of divisional and firm's incentives and goals through creating trust and mutual cooperation.

There are at least three mechanisms, which can explain the impact of connections on the capital allocation efficiency. The first mechanism, which we refer to as *efficient bargaining* hypothesis, is that horizontal connections correct inefficiencies in capital allocation through more efficient bargaining over distribution of investment funds across divisions. For example, the literature on internal capital markets has discussed inefficient capital allocation in a form of cross-subsidization, when strong divisions end up subsidizing weak ones (e.g. Scharfstein and Stein (2000)). This, in turn, creates incentives for the strong divisions to engage in "defensive" investment to protect their funds from poaching by other divisions. To avoid unproductive defensive investments, headquarters of conglomerates tend to underinvest in segments with high investment opportunities (Rajan, Servaes and Zingales (2000)). If horizontal connections among divisional managers create networks of "friends," then trust and higher likelihood of mutual cooperation will reduce the allocation inefficiencies. The weaker division is less likely to demand transfers, and the stronger division's manager is also less likely to engage in defensive investment, because she knows her division's surplus will not be poached by friends. Hence, connections will lead to more efficient allocation of funds.

The second mechanism, which we label as *information asymmetry* hypothesis, is that the horizontal connections help to reduce internal information asymmetry between headquarters and divisional managers.[2] When top managers are better informed about the segments' performance,

[1]The allocation of funds can not be contracted (Grossman and Hart (1986)), so the decisions over funds allocation is a result of bargaining between divisions and headquarters (Graham, Harvey and Puri (2015)).

[2]Information asymmetry between headquarters and divisions has been documented by financial literature as a known factor leading to inefficiency and financial losses. For example, Meyer, Milgrom and Roberts (1992) argue that information asymmetry between CEO and divisional managers and competition for internal resources may lead to managers' misreporting, when they emphasize their own division advantages and exaggerate the disadvantages of other divisions. This leads to distorted capital allocation (Harris and Raviv (1996)).

the financing they provide should more likely reflect segments' investment opportunities. If connections create networks of friends and facilitate better alignment of divisional and firm's goals, then better connected teams of divisional managers will report more accurately to headquarters.[3] The costs of misreporting include the damage to potentially valuable connections and friendships. In addition, the network itself can put a pressure on the person who would like to deviate from the "optimal information transfer" strategy by punishing negative behavior (e.g. Boot, Greenbaum and Thakor (1993), Brass and Labianca (2006)). Richer information provided to headquarters implies lower internal information asymmetry, improved allocation efficiency and higher firm value (Billett, Chen, Martin and Wang (2014)).

The third mechanism, which we denote *individual influence* hypothesis, is that relatively more connected divisional managers can command greater shares of capital spending allocations regardless of their segments' growth opportunities. Social science research has long associated overall within-group connectedness with concepts of individual influence and power (e.g. Mizruchi and Potts (1998), Nahapiet and Ghosal (1998)). The investment transfers toward the more connected – and more influential – divisional managers may be the consequence of headquarters' favoritism (say, in order to exploit private benefits due to being associated with influential divisional managers). Then, the extra investment allocations exacerbate the inefficiencies of internal capital markets, and should have negative effect on firm value (Scharfstein and Stein (2000), Rajan, Servaes and Zingales (2000)).

To study how connections among divisional managers affect the efficiency of capital allocation, we hand-collected data on 765 divisional managers from a random sample of 100 industrial S&P500 conglomerates from 2006 to 2013. We identify divisional managers using information from companies' annual reports, proxy statements, press releases and BoardEx. We define two divisional managers as being connected if they studied at the same academic institution or worked in the same organization at a same time in the past. Requiring time overlap in measuring con-

[3]It is possible that if connections facilitate better alignment of only divisional, but not the firm's goals, then better connected teams of divisional managers will communicate across divisions, but not toward headquarters. This would lead to the collusion against the headquarters, higher internal information asymmetry and lower firm value. However, we do not find any empirical evidence for such collusion.

nections allows us to better account for actual interaction between two people in the past. The majority of connections are employment-based, and such connections are more frequent than other connection types. Further, employment-based connections are likely to build up common experiences and shape long-term reputations in a corporate environment.

Our main results are as follows. After controlling for various segment and manager characteristics (including managers' ability and formal power) and firm fixed effects, we find that bilateral connections among divisional managers are a relevant factor for allocation of capital. Connections lead to economically sizeable improvements in segment allocation efficiency. When segment growth opportunities (measured by segment's Tobin's Q) move from 25th to 75th sample percentile, the segment capital spending remains virtually constant for unconnected segments. However, each additional social connection of a particular divisional manager is associated with 9.9% more capital allocated to the division, or $7.7 million in extra annual capital expenditure, on average. The increased sensitivity of capital spending leads to improvements in firm-level allocation efficiency, and, ultimately, to higher firm values. When the overall firm connectedness – measured by the weighted connections of all firm's segments – changes from 25th to 75th sample percentile, the firm's excess value over the hypothetical value of its stand-alone segments improves by 10.6%, on average.

However, empirical estimation of the effect of social connections on allocation efficiency and firm value poses an identification challenge, because social connections are endogenous. To address this challenge, we use two approaches. The first approach exploits the plausibly exogenous variation in social connections due to deaths and retirements of connected divisional managers unrelated to recent firm performance (Fracassi and Tate (2012)). For this subset of plausibly exogenous managers' turnovers, we use estimation in first differences to eliminate all unobserved firm-level, segment-level and manager characteristics that affect the allocation of funds to segments. We show that increase in the manager's social connections corresponds to an increase in the sensitivity of capital expenditures to opportunities, and vice versa.

In the second approach for identification we use two instrumental variables for social connections. The first instrument again relies on plausibly exogenous changes in social connections due to deaths and retirements of connected divisional managers. The second instrument uses the unexpected changes in social connections due to deaths and retirements of executives at *other* local firms. This instrument is motivated by the work of Karolyi (2018), who shows that deaths and retirements at other firms significantly increase the probability of turnover in the sample firm due to changes in supply-demand in the market for executives. Both instruments are likely to satisfy the exclusion restriction because they are plausibly independent from unobserved firm and personal characteristics.

In two stages least squares estimation we use instrumental variables in combination with firm fixed effects, allowing us to identify the causal effect of social connections only through within-firm changes in social connections due to plausibly exogenous departures of connected managers. After instrumenting social connections the significant positive effect of connections on allocation efficiency and firm value remains statistically significant at 5% level.

Our analysis provides support for two possible mechanisms that potentially can explain the positive effect of social connections on allocation efficiency and firm value. Specifically, consistent with the *efficient bargaining* hypothesis, we show that improvement in firm value is especially strong in at firms with diverse investment opportunities (as measured by Rajan, Servaes and Zingales (2000)'s Segment Diversity), suggesting that connections mitigate investment inefficiencies by reducing internal power struggles for resources. We provide further evidence that firms may pursue policies allowing strategic matching of well-connected managers into segments with the superior investment opportunities. Amid frequent rotation of managers across segments, we show that managers are less likely to leave the segment with high growth opportunities (measured by Tobin's Q) if they are highly connected.[4]

Consistent with the *information asymmetry* hypothesis, we provide evidence that social

[4]The frequent rotation of managers across firm segments (about 35% of the managers' sample turnovers represents within company re-assignments) suggests some conglomerates may have a rotation policy on a regular basis. In fact, Stein (2003) states that "..General Electric, which is widely viewed to be one of the most successful diversified conglomerates .. apparently follows a policy of rotating its senior managers across different divisions on a regular basis".

connections between divisional managers reduce internal information asymmetry in the company. We follow the approach of Ravina and Sapienza (2010) and Chen, Martin, Wang, Roychowdhury and Billett (2016) and measure internal information asymmetry between divisional managers and top corporate managers as the difference in their respective trading profits on their own company's stock. We find that firms with better connected teams of divisional managers demonstrate lower difference in trading profits between divisional and top managers, or lower internal information asymmetry.

We do not find support for the *individual influence* hypothesis. In multivariate tests social connections *per se* are not related to divisional capital allocation. We also find that firm-level connectedness benefits firm value, what contradicts with the predictions of this hypothesis.

Our results are robust to consideration of numerous alternative explanations and different definitions of connections. Specifically, we study the possibility that managers who receive more funds in the segments with ample growth opportunities end up developing more connections among their peers. In this case, the effect of connections on capital allocation sensitivity would be also positive, but the direction of the effect would be reverse. We are able to eliminate this reverse causality explanation by showing that our results remain unaffected when considering only connections formed five years before the manager starts his tenure in the current position as a divisional manager. Another possibility is that better connected managers could be connected to CEO, and connections to CEO, not to other divisional managers could drive our results. We show that our results do not change if we additionally control for CEO connections. Additionally, our conclusions do not change if we account for the connections of divisional managers to other executives of public and private companies.

To the best of our knowledge, this paper is the first to study the effects of horizontal connections among divisional managers on the efficiency of internal capital markets. Numerous papers focus on vertical connections between divisional managers and CEO (Xuan (2009), Gaspar and Massa (2011), Duchin and Sosyura (2013), Glaser, Lopez-De-Silanes, and Sautner (2013)). For example, Xuan (2009) questions if CEO allocates more capital to the division, which he previously operated, and finds the opposite - the CEO will strategically favor unconnected divisions, because CEO has lower information about businesses in these divisions. Duchin and Sosyura (2013) continue the "information asymmetry" story and find that connections to CEO can improve firm value if they mitigate information asymmetry intrinsic to conglomerates. The authors find support for the positive role of connections as a channel of information transfer documented in many studies (Cohen, Frazzini, and Malloy (2008, 2010), Engelberg, Gao, and Parsons (2012)). Gaspar and Massa (2011) find support for the role of CEO-manager connections as a trust-inducing mechanism and show that better connected managers are associated with improved allocation efficiency and increased firm value, when better connected managers preside over segments with high growth opportunities. We complement these findings by showing that allocation efficiency and firm value improve when managers have connections to their peers, not just connections to CEO.

Ultimately, our paper contributes to the large stream of literature dealing with the debate over the value-increasing ("bright side" view) vs. value-destroying ("dark side" view) effects of internal capital markets.[5] In addition, our paper is related to the studies about the factors that affect the efficiency of capital allocation. Wulf (2002, 2009) shows that firm-level incentive pay (i.e. equity) is one of the mechanisms to mitigate the inefficiencies of capital allocation. Our evidence complements these findings and is consistent with social connections providing non-monetary incentives in mitigating capital allocation inefficiencies.

[5]Integration of several businesses under one roof allows to solve underinvestment problem through ability to borrow more than single-segment firms (Lewellen (1971)) or, holding the amount of available funds constant, does a better job in financing most profitable projects ("bright side" view), because CEOs have incentive to engage in value-enhancing allocations (Gertner, Scharfstein and Stein (1994), Li and Li (1996), Stein (1997), Matsusaka and Nanda (2002), Maksimovic and Phillips (2002)). On the other hand, if divisional managers engage in rent-seeking behavior ("dark-side" view), they will try to use their bargaining power to get from CEO more compensation and resources in form of allocations to their divisions (Meyer, Milgrom and Roberts (1992), Rajan, Servaes and Zingales (2000), Scharfstein and Stein (2000), Wulf (2009)).

3 Sample and Data

3.1 Firms and Segments

We select all the companies that enter S&P500 for one or more years within our sample period of 2006-2013. We then exclude financial and utilities companies leaving 507 companies. We next require that conglomerates operate in industrial segments, that segments have non-missing SIC values, that firms have at least 2 business segments with non-missing values for segment assets and segment capital expenditures, and that the sum of segment sales does not deviate more than 5% from the total firm sales. These filters produce 237 firms. We then randomly select 100 firms out of those 237 firms with information for all divisional managers for these firms. If a firm doesn't provide information on all divisional managers, we replace the firm with another firm from our sample of multisegment firms. To avoid the reduction of the sample size due to missing financial data, we additionally hand-collect missing financial data (operating profit and segment assets) from 10-K annual reports for our sample of firms with information about divisional managers. We collect information on 765 divisional managers, but our final sample utilized in regressions consists of 2008 division-year-observations, which cover 620 divisional managers, 431 unique divisions and 100 companies.[6]

We report summary statistics on firms and segments in our sample in Panel A Table 1. An average conglomerate has book assets valued at $31.4 billion, has Tobin's Q of 1.56, operates in 4.12 business segments and has annual capital expenditures of 4.1% of book assets.

[6]In unreported analysis we compare our sample to all other industrial conglomerates in the S&P500 index (that are excluded by sample filters) across the following measures: firm size (natural logarithm of total assets), book-to-market, investment (firm capital expenditures scales by total assets), profitability (return on assets), firm cash flow (cash flow scaled by total assets). The comparison shows that there are no significant differences between our sample and other industrial conglomerates (which are included in S&P500) across these measures. One notable exception is the firm size – specifically, the average firm in our sample is larger than other conglomerates. This finding is not surprising, since larger firms provide more information both for segment financials and for divisional managers. Even though our sample constitutes roughly one third of all S&P500 industrial conglomerates, the firms in our sample represent 44% of book assets and 40% of market equity of all S&P500 industrial conglomerates.

3.2 Capital Allocation

We use three common measures of capital allocation between segments: (1) capital expenditures; (2) industry-adjusted capital expenditures and (3) industry-firm-adjusted capital expenditures. All variables are defined in the Appendix A. We obtain data on segments' capital expenditures and book assets from the Compustat segments database.

The first measure, segment capital expenditures (*CAPEX*), is defined as annual amount of divisional capital expenditures divided by book assets. Table 1 shows that the average segment capital expenditures is $286 million, what represents 5.1% of segment book assets.

The second measure that we use is industry-adjusted capital expenditures (*IA CAPEX*), which is defined as the difference between the segment capital expenditures (divided by book assets) and median capital expenditure ratio for the industry in which the division operates (as measured by median capital expenditures of single-segment firms with the same two-digit SIC code). The adjustment for industry median capital expenditures helps to control for scale and capital intensity of different industries, since some industries invest more than others.

The third measure that we use is the industry-firm-adjusted capital expenditures (*IFA CAPEX*) or "segment transfer" as in Rajan, Servaes and Zingales (2000), which is the industry-adjusted capital expenditures additionally adjusted for average firm capital expenditures. Firm-level adjustment allows to account of over- and under-investment on a firm level. As shown in Table 1 the values of industry-adjusted and industry-firm-adjusted measures are very small (the medians values are in fact close to zero), but display a considerable variance.

3.3 Divisional Managers

Our sample of divisional managers consists of 765 people. To identify the divisional manager responsible for the business segment, we follow the procedure of data collecting described in Duchin and Sosyura (2013). We read biographical histories of the firm's executives in the annual reports (both types of reports - "for investors" and 10-Ks) and proxy statements. In addition to these sources we use biographical information in BoardEx database and other publicly available sources of information: Bloomberg Executive directory, Reuters and companies press releases. Divisional managers typically hold the following titles: "Executive Vice President", "Senior Vice President", "Divisional President" or "Chief Executive Officer" (of the corresponding subsidiary). We select only the managers who are responsible for a particular business segment. We disregard managers who are responsible for a functional area across all or many segments (such as senior vice president of finance, senior vice president of marketing), because it is not possible to establish a clear match between these managers and particular business segments.

In matching managers to segments we consider only the highest-level executive responsible for a business segment in a given period of time. In some cases the segment names in Compustat and in annual reports disagree. For example, the segments reported by Compustat are sometimes more aggregated than divisions reported in the annual report. In this situation, we match the segment with the highest-level manager among all the managers responsible for the segment as reported by Compustat. In addition, we collect starting and ending dates of the managers' tenure in the position. If a segment changes its manager during the fiscal year we assign both old and new managers to the segment in this year. If several managers are assigned to a particular segment, in our empirical tests we use the maximum number of connections across all the divisional managers assigned to the particular segment.[7]

Panel B of Table 1 presents the summary statistics of the sample of divisional managers. The average tenure in the company is approximately 14 years, the average tenure at segment is 6 years, and the average age of the divisional manager is 53 years. The overwhelming majority of the managers are males. About half of the managers have tenure more than 10 years, and about one fifth of the managers have graduated from universities of Ivy League.

[7]Our results are robust if we use the average number of connections across all the divisional managers assigned to the particular segment.

3.4 Social Connections

We consider two managers to be socially connected if at one moment in their past they participated in the same organization. In our approach of measuring connections we require that participation in the same organization has *time overlaps*. This stricter approach in measuring connections allows us to better account for actual interaction between two people in the past. Arguably, just having the same organization in their CV's does not guarantee that two managers were at one place in any period of time in the past.

We obtain data on social connections from the BoardEx database. BoardEx provides information on pairwise connections, based on their educational, employment and non-professional background. For each pair of people we have dates of their overlap in the same organization, type of organization and the persons' roles in that organization during the connection period. We apply the following filters to compute the connections. First, we count only one earliest connection between two managers irrespective of when and where it was established, and drop all observations that represent duplicate connections between the same pair of managers but differ in dates of intersection (for example, "promotions" within the same organization), or in type of connected organization (university or employer). Second, we include only connections formed at least 2 years before the year of interest.[8] Third, we drop the connections made during employment in the current company in the executive roles. Using the connections remaining after these filters, we compute the number of pairwise connections the divisional manager has with other divisional managers of a company for a given year.

As shown in Panel B of Table 1, 55% of our sample divisional managers can be connected through working in a listed company, 9% had prior employment in a same private company, and 0.5% of the managers studied at the same university at the same time. In our subsequent analysis, we count only one connection per pair – that is, we consider two people connected once any type of a connection exists between them. Once we disregard the overlaps, 63% of our

[8]In robustness tests, we show that our results hold if we keep only connections established 5 years before the arrival of the manager at the segment of interest.

managers are connected. The majority of connections are employment-based connections rather than social connections coming from sharing the common educational or social backgrounds. Such employment-based connections are more frequent than other connection types. Further, employment-based connections are likely to build up common experiences and shape long-term reputations in a corporate environment.

In our empirical tests we use four measures of social connections. The first measure, *Segment Connections*, is the absolute number of social connections of a divisional manager in a given firm-year. The second measure, *Average Segment Connections*, is the sum of Segment Connections of divisional managers across all segments scaled by a number of business segments in the given firm-year. As all segments in a given firm-year are assigned the same value of Average Segment Connections, this measure helps to identify firms, in which the majority of managers are connected among each other. It is possible that even the segments with low Segment Connections can benefit from being in a high-connected company. The third measure, *Asset-weighted Segment Connections* is the asset-weighted value of Segment Connections in a given firm-year. The variable captures similar concept as Average Segment Connections, but takes the segment size into consideration. The fourth measure, *High- (Low-) Connected Firm* is an indicator that equals one, and zero otherwise, if the Average Segment Connections are above (below) the sample median. This variable will allow us to assess the economic significance of differences between well-connected and less-connected firms, as opposed to the impact of individual connections. Panel C shows that a mean [median] divisional manager possesses 1.37 [1.00] Segment Connections in a given firm-year. Managers in a given firm also have 1.36 [1.00] mean [median] Average Segment Connections in a given year. Smaller segments appear to be associated with better-connected managers, as the mean [median] Asset-weighted Segment Connections are 1.04 [0.71], i.e. less than the corresponding Average Segment Connections statistics. All connection variables in Panel C of Table 1 display considerable variance around their mean values.

3.5 Additional Variables

In our regressions we include the standard control variables used in the literature. Following Shin and Stulz (1998), we control for the *Tobin's Q* in the segment's two-digit SIC industry. Following the stream of research of determinants of the capital allocation inside the firm, we additionally control for *Segment Cash Flow* (defined as sum of operating profits and depreciation divided by segment assets), *Segment Size* (natural logarithm of segment assets), *Segment Relative Size* (ratio of segment assets to firm assets) and *CEO Ownership* (percent of the firm's outstanding stock hold by CEO) in the firm. We winsorize all continuous variables at 1% and 99% levels to mitigate the effect of outliers. In addition, to mitigate the effect multicollinearity between variables due to different units of measurement, we standardize all variables.

We control for manager ability and formal influence in order to isolate these two effects from the role of manager's connections. We utilize two proxies for manager ability developed by Duchin and Sosyura (2013). The first proxy is the *Relative ROA*, which reflects the manager's relative performance and is computed as the difference between the industry-adjusted ROA of the manager's division and the average industry-adjusted ROA of remaining divisions in a firm.[9] The second proxy for ability and skill is the dummy variable that indicates the attendance of the Ivy League university. We utilize the following proxies for divisional manager's formal influence within firm: board membership (*Board Member*), status as one of the firm's top-paid executives listed on Execucomp (*High Salary*), tenure at firm greater than 10 years (*Long Tenure*) and seniority status (*Senior Title*). Using similar proxies, McNeil and Smyth (2009) find that manager's formal influence distorts capital allocation efficiency, because more powerful managers obtain more capital. In addition, we add retirement age indicator (*Retirement Age*), which captures the possible changes in manager's investment behavior when he is close to the retirement (Jenter and Lewellen (2015)).

[9] Due to high correlation of this variable with Segment Cash Flow variable, we orthogonalize these variables.

4 Empirical Results

4.1 Social Connections and Segment-Level Efficiency of Capital Allocation

4.1.1 Baseline Results: Cross-Sectional Analysis

We begin our analysis by reporting the univariate results on the relation between the measures of segment capital expenditures and the investment opportunities of segments. We compare these relationships between high- and low-connected segments. Panel A of Table 2 shows tests of differences in three measures of capital expenditures comparing the segments above or below the sample median in investment opportunities. We show that in the subsample of high-connected managers, segments with high (above-median) investment opportunities receive consistently more capital than segments with low (below-median) investment opportunities. The differences between these two groups of segments are highly statistically significant for all three measures of capital allocation. In contrast, in segments led by low-connected managers we do not observe significant differences in capital allocation between segments with high and low investment opportunities. These findings are consistent with our *efficient bargaining* hypothesis that suggests horizontal connections are associated with capital optimally flowing primarily to segments with good growth opportunities.[10]

Interestingly, in Panel B, we observe that better connected managers indeed get more capital for the segments they operate irrespective to the investment opportunities of these segments. While this result could support our *individual influence* hypothesis stating that better connected managers could attract more investment funds regardless of segment investment opportunities, no definite inferences can be drawn from this relation. It is possible that connectedness of

[10] Panel A also shows that segments with high-connected managers tend to invest significantly more (regardless of growth opportunities) compared to the investment by segments with low-connected managers. In unreported analysis, we find that while firm values are negatively affected by high levels of capital (over)investment in firms with low connectedness among managers, high capital spending does not hurt corporate value in high-connected firms – again consistent with the efficient bargaining hypothesis. In addition, in subsequent analysis in this paper (starting with Table 3), we specifically control for segment- and firm-related determinants of capital spending, in addition to managerial connectedness.

divisional managers and the segment growth opportunities are related - in this case the capital expenditure differences may result from diverse growth opportunities and not from the effect of connections per se. Consequently, in order to fully capture the determinants of segment capital spending, we have to turn to multivariate analysis.

We first study the relation between social connections and the sensitivity of a firm capital expenditures to investment opportunities. Measuring the sensitivity of investment to segment investment opportunities (as measured by Tobin's Q) is a common approach in evaluating investment efficiency in literature (e.g., Shin and Stulz (1998), Billett and Mauer (2003), Ozbas and Scharfstein (2009)). We use the following baseline regression model:

$$I_{ivt} = \beta_1 \mathit{Connections}_{ivt} + \beta_2 \mathit{Tobin's\ Q}_{ivt} + \beta_3 \mathit{Connections}_{ivt} \times \mathit{Tobin's\ Q}_{ivt} + X_{ivt}\gamma + \lambda_v + \mu_t + \epsilon_{ivt} \quad (1)$$

For firm v the dependent variable I_{ivt} is one of the measures of segment i capital expenditures in the fiscal year t, $\mathit{Connections}_{ivt}$ is one of the measures of social connections of segment i formed in the past, $\mathit{Tobin's\ Q}_{ivt}$ denotes segment i Tobin's Q, measured at the beginning of the fiscal year t, X_{ivt} - vector of segment-level controls. We include in the regressions firm fixed effects λ_v to isolate within-firm variation and year fixed effects μ_t to account for common time trends in capital allocation. Our main variable of interest is the interaction term $\mathit{Connections}_{ivt} \times \mathit{Tobin's\ Q}_{ivt}$, which captures the effect of social connections on the sensitivity of capital allocation to investment opportunities. In all regressions we control for segment-level and manager-level factors (discussed above), which are known to affect the level of capital expenditures in segments. We cluster standard errors at the division level to account for the time-series correlation of capital allocations to a given division.

Panel A of Table 3 presents the results of panel regressions of the measures of capital expenditures on segment investment opportunities. We control for the year and firm fixed effects in all models, but in columns (4)-(6) and (10)-(12) we additionally include higher-dimensional industry-year fixed effects (based on Fama-French 49-industry classification) to control for timevariant industry-level factors. For example, the managerial teams may differ by the amount of industry specific expertise they possess, and they may share this knowledge through visiting professional conferences and meetings. The empirical results are consistent with our univariate results and show that across all three measures of capital allocation, the positive sensitivity of capital expenditures to investment opportunities increases with connections. The result is robust to the sets of fixed effects and to the measures of social connections we use (the continuous variable, columns (1) - (6), or the dummy variable, columns (7) - (12)). Looking at our main variable of interest, which is the interaction term between social connections and segment Tobin's Q, we see that the coefficient on interaction term is positive and significant at 5% or better for three measures of capital allocation. For example, as shown in Column (1) for CAPEX, the coefficient on *Connections* $\times$ *Tobin's Q* is positive (= 0.082) and statistically significant (t = 2.49). The effect is economically sizable: when segment growth opportunities (measured by segment's Tobin's Q) move from 25th to 75th sample percentile, each additional social connection of a particular divisional manager is associated with 9.9% more capital allocated to the division, or $7.7 million in extra annual capital expenditure, on average. These results indicate that investments become sensitive to segment opportunities, when these segments are led by better connected managers.[11]

Importantly, we also show that across all specifications, coefficient on Tobin's Q is close to zero and insignificant. This suggests that without connections, capital expenditures do not depend on the growth prospects of the divisions. As the coefficients on Tobin's Q are close to zero and not statistically significant, we then check if capital expenditures are sensitive to growth opportunities only in the presence of connections. The results in Panel B show that omitting Tobin's Q keeps the results unchanged, suggesting that connections indeed serve as a channel for allocation improvement.

Our findings that connections improve allocation efficiency provide support for the efficient bargaining hypothesis. However, Table 3 results do not provide support for the individual influ-

[11] In unreported analysis, we find that if segments with high investment opportunities are led by well-connected managers, then these segments are able to both retain a greater share of cash flows generated in the segment and capture greater positive share of cash flows generated by other segments.

ence hypothesis. The coefficients on social connections are positive and marginally significant only in two models (out of twelve) in both Panel A and Panel B, suggesting that better-connected divisional managers are not likely to command more capital, after specifically controlling for segment growth opportunities. This result contrasts to our univariate evidence and shows that social connections is not a significant determinant for capital allocations. This result is also consistent with Duchin and Sosyura (2013) that social connections among divisional managers is not a strong predictor of capital spendings.

Overall, the evidence in this section indicates that at the segment level, social connections are associated with improved capital allocation. This effect remains positive and significant after controlling for segment-level characteristics, proxies for managerial abilities and proxies for formal influence.

4.1.2 Baseline Results: Unobservable Factors

While we control for a number of segment-level variables and firm-level unobservable factors (through firm fixed effects) in the above regressions, there is still a possibility that other unobservable segment-level variables are driving our results. One example is that differences in managers' personal characteristics (such as ability or skill) can affect both social connections between divisional managers and capital expenditures. Hence, some divisional managers are able to obtain more capital than other managers because of their human capital, not because being highly connected allows them to extract benefits of networking through efficient bargaining. We need to separate the effect of social connections from the effect of manager's human capital on the capital expenditures. To address the problem of omitted unobservable variables, we perform the first-differences estimation for divisional managers' turnover events - this approach cancels the effects of all unobservable segment-level and manager characteristics as long as they remain constant over the year.

An important concern in this analysis is that turnovers of divisional managers can depend on other firm and segment factors. To mitigate this concern, we use a subset of plausibly exogenous turnovers of divisional managers driven by deaths and retirements of other divisional managers, unrelated to firm performance (similarly to, Fracassi and Tate (2012)). Specifically, we focus only on changes in social connections driven by departures of other divisional managers in a given firm due to retirements of other managers unrelated to firm performance. Importantly, retirement decisions of other divisional managers are also plausibly unrelated to a particular manager's ability and her personal characteristics, since the manager cannot control the retirement decisions of other divisional managers. Consequently, a retirement of a divisional manager with a network tie to a given manager is likely to create a shock to her connections and ability to cooperate with other divisional managers. Specifically, if connections of a divisional manager increase [decrease] exogenously, then we expect the sensitivity of capital spending to growth opportunities in her division to increase [decrease]. For example, if connections of a manager leading a high-Q division decrease, then we expect this manager (still operating a high-Q segment) no longer be able to extract higher allocations for her division, because the other divisional managers are no longer likely to cooperate.

To empirically estimate the effect of exogenous shocks to managers' networks, we filter divisional managers' retirements from all managers' departures. We keep the departures of divisional managers, in which he leaves at the age of 60 or above (this threshold is used in Parrino (1997); Huson, Parrino and Starks (2001)). This filter forms a sample of potential retirements. Next, we check each potential retirement using firms' press releases and media articles. If we find a press-release about the planned retirement in media, we classify the potential retirement as a retirement, otherwise - we exclude the retirement from the sample. If the divisional manager did not retire, usually information from BoardEx confirms that he accepted other position. Using this process, we find that about 52% of all departures of divisional managers are retirements.

We estimate the first-differences regression, in which the dependent variable is the annual change in the division's capital expenditures for division-year observations, where the network of the divisional manager has changed due to the retirement of other (connected) divisional manager, but the divisional manager has not changed. We run the following model:[12]

$$\Delta I_{ivt} = \beta_1 \Delta \mathit{Connections}_{ivt} + \beta_2 \Delta \mathit{Tobin's\ Q}_{ivt} + \beta_3 \Delta(\mathit{Connections}_{ivt} \times \mathit{Tobin's\ Q}_{ivt}) + \Delta X_{ivt}\gamma + \Delta\mu_t + \Delta\epsilon_{ivt} \tag{2}$$

The results in Table 4 show that there is a positive and statistically significant relationship between changes in divisional manager's social connections and changes in efficiency of capital allocation. Specifically, Panel A suggests that when divisional manager's social connections decrease [increase] (as a result of the exogenous change in her connections), the relation between segment capital expenditures and its growth opportunities becomes weaker [stronger]. In other words, the reduction in manager's connections is associated with reductions in capital allocation efficiency, and vice versa. In Panel B we take differences using restricted version of models in Table 3 (with the insignificant effect of the change in Tobin's Q omitted), and our results hold with similar magnitudes and strong significance levels.

Ultimately, our analysis presented in Table 4 captures the effect of a change in managerial connections, while canceling the effect of personal human capital as long as it remains constant over the year. Since the divisional manager has not changed, and the retirement decision of a divisional manager from her network is presumably not dependent on her human capital, these results indicate that social connections affect efficiency of capital allocation over and above the unobserved manager's characteristics.

As a robustness check, we take into account that CEO turnovers may affect the capital allocation to a particular manager, because the manager's connections to CEO could change as a result of CEO turnover ((Duchin and Sosyura (2013)). To address this concern we exclude years with CEO turnovers and keep only observations, when CEO remains the same from the previous year. All the results reported in Table 4 remain unchanged.

[12] This model directly follows from the model (1):
$\Delta I_{ivt} = I_{ivt} - I_{ivt-1} = \beta_1(\mathit{Connections}_{ivt} - \mathit{Connections}_{ivt-1}) + \beta_2(\mathit{Tobin's\ Q}_{ivt} - \mathit{Tobin's\ Q}_{ivt-1}) + \beta_3((\mathit{Connections}_{ivt} \times \mathit{Tobin's\ Q}_{ivt}) - (\mathit{Connections}_{ivt-1} \times \mathit{Tobin's\ Q}_{ivt-1})) + (X_{ivt} - X_{ivt-1})\gamma + \lambda_v - \lambda_v + \mu_t - \mu_{t-1} + \epsilon_{ivt} - \epsilon_{ivt-1} = \beta_1 \Delta \mathit{Connections}_{ivt} + \beta_2 \Delta \mathit{Tobin's\ Q}_{ivt} + \beta_3 \Delta(\mathit{Connections}_{ivt} \times \mathit{Tobin's\ Q}_{ivt}) + \Delta X_{ivt}\gamma + \Delta\mu_t + \Delta\epsilon_{ivt}$

4.2 Social Connections, Firm-Level Efficiency of Capital Allocation, and Firm Excess Value

4.2.1 Social Connections and Firm-Level Efficiency: Cross-Sectional Analysis

So far, we documented that there is a positive effect of social connections on the capital allocation efficiency at the segment level. In this section we study if such effects exist at firm level. To do this, we use the measure of firm-level capital allocation efficiency, *Relative Value Added by Allocation,* which is introduced by Rajan, Servaes and Zingales (2000) and represents the overall value impact of divisional capital allocations. Relative Value Added by Allocation is measured as the sum of the weighted Industry-Firm-Adjusted Capital Expenditure across all segments of a firm in a given year:

$$\textit{Relative Value Added by Allocation} = \frac{\sum_{j=1}^{N} BA_j(q_j - \bar{q})\left(\frac{I_j}{BA_j} - \frac{I_j^{ss}}{BA_j^{ss}} - \sum_{j=1}^{N} w_j\left(\frac{I_j}{BA_j} - \frac{I_j^{ss}}{BA_j^{ss}}\right)\right)}{BA}$$

where I denotes capital expenditures of segment j, BA denotes book assets, q denotes industry Tobin's Q, $\bar{q}$ denotes average industry Tobin's Q for the firm, ss denotes single-segment firms in the segment's two-digit industry, and w_j is the ratio of segment assets to firm assets.

Panel A of Table 5 reports the estimates obtained by regressing the allocation measure on firm-level connections measures. In our regressions we control for the same set of variables as in Rajan, Servaes and Zingales (2000): *Firm Sales* (firm sales scaled by total assets), *Segment Diversity* (standard deviation of asset-weighted segment Qs divided by equally weighted average segment Qs in a firm) and *Inverse of Average Q* (defined as inverse of equally weighted Q). The reported results show that overall higher firm connectedness (measured by average segment connections or by asset-weighted segment connections) is associated with improved allocation, as captured by Relative Value Added by Allocation.

Next, we estimate the direct effect of social connections on firm value. We use common approach in literature and compute *Excess Value* as in Berger and Ofek (1995). We define Excess

Value as the natural logarithm of the ratio of the conglomerate actual value to its imputed value. A conglomerate actual value is the market value of assets, which is equal to the market value of equity minus book assets and book value of debt. A conglomerate imputed value is the sum of imputed values of its segments, where each segment's imputed value is equal to segment's sales multiplied by the sales multiple (median market value of assets-to-sales ratio of all single-segment firms in a segment two-digit SIC industry). We use sales multiplier because according to Rajan, Servaes and Zingales (2000) it is less likely to have strategic reporting bias.

Panel A of Table 6 presents the results of regressions of excess value on firm connectedness measures and firm-level controls similar to those utilized by previous research: firm cash flow, firm sales, segment diversity and CEO ownership. For example, results from column (1) show that coefficient on Excess Value is 0.071 (t=3.82) suggesting that higher firm connectedness is associated with higher firm values. Economically, this effect of 0.071 translates into 10.6% increase in Excess Value when firm connectedness (measured by the average connections of all firm's segments) changes from 25th to 75th sample percentile.

4.2.2 Social Connections and Firm-Level Efficiency: Instrumental Variable Methodology

The effect of firm-connectedness on allocation efficiency and firm value is subject to potential endogeneity concerns. For example, in cross-section we may observe a positive correlation between team connectedness and firm performance simply because connectedness is an attribute of well-performers, but not because it is the cause of better performance. Also firm connectedness might be explained by the same factors that affect firm value, - for example, by firm strategy. In time-series, firms might build more connected teams exactly when firms' performance goes up. Hence, to proper estimate the effect of firm connectedness on firm-level allocation efficiency and firm value, we need to control for unobserved common factors that affect both firm connectedness and firm value.

To address the endogeneity of the firm connectedness, we use two instrumental variables for firm connectedness. The first instrumental variable *Lost Connections* relies on the plausibly exogenous variation in connections, created by deaths and exogenous retirements of divisional managers during the sample period (as described in Section 3.1.2).[13] We construct the instrument in the following way: for each firm we sum all connections of all retired managers (to other divisional managers) in a given fiscal year. This helps to account for multiple retirements during the fiscal year. If in some firm-year there are no events of retirement(s) of managers connected to other divisional managers, we set the value to zero. Next for each firm we find the cumulative number of these connections, accumulated up to a given year, starting from the fiscal year of retirement. This cumulative value of connections in the next fiscal year (after the retirement fiscal year) would represent the total number of connections lost (by divisional managers) because of the retirements.

In construction of the second instrumental variable *(Exogenous Job Openings)* we use executive deaths and retirements at other local firms. These deaths and retirements are likely to increase the likelihood of executive turnover at the sample firm (Karolyi (2018)), and result in executive's transfer to the firm with the vacant position. Hence, these deaths and retirements will create an exogenous shock to firm connectedness, and will result in change in connections due to managers' departures. We start with identifying the deaths and retirements at other companies using Execucomp data. Following Karolyi (2018), we focus on a subset of executive's departures with codes for the reason "Deceased", "Resigned" and "Retired". To truly filter all retirements, we require the executive to have age exceeding 60 years at the year of the departure (Parrino (1997); Huson, Parrino and Starks (2001)). We additionally restrict the departing executives' titles to titles corresponding to CEO, CFO, COO, Executive Vice President or Division/Group President positions to focus only on those vacant positions, which could potentially serve as divisional managers prospective jobs. Then for each state we count the number of the retirements and deaths in each 2-digit SIC industry. The rationale for the state and industry classifications is that previous studies have shown that the markets for executives are geographically segmented (Yonker (2017)) and executives have industry-specific expertise (Parrino (1997)). Our final variable

[13]Because there are only 3 deaths of connected managers during the sample period, we are unable to construct a separate instrument based on only deaths.

(*Exogenous Job Openings*) shows the number of job openings due to plausibly exogenous deaths and retirements of executives in all other firms in the state and industry corresponding to those of the sample conglomerate. Further, in the tests we take a 1-year lag of this variable to better account for the subsequent effect on connections.

Next, we test whether our instruments are correlated with firm connectedness. In regressions with instruments we add firm fixed effects - this allows us to identify effects of firm connectedness purely through within-firm (i.e time series) variation. The first stage regressions reported in Panel B of Table 5 show that both instruments (*Lost Connections* and *Exogenous Job Openings)* are negatively correlated with firm connectedness measures, suggesting that firm connectedness decreases in the year, following the year of retirement(s)/departure(s) of connected manager(s). This result also implies that on average the incoming replacing manager is less connected than the departing manager. Both instruments are statistically relevant, since they pass weak instruments test (Cragg-Donald Wald F statistic exceeds Stock and Yogo (2005) thresholds at 5%). In the second stage, in Panel B of Table 5, we use only the within-firm decreases in firm connectedness, which are predicted by our instruments, to identify the effect on allocation efficiency and excess value. The estimates show that after instrumenting *Firm Connectedness* - the significant positive effect of connections on Relative Value Added by Allocation remains statistically significant, so there seems to be exogenous variation in firm connectedness variables that *causes* the improvement of allocation efficiency.

In Panel B of Table 6, we perform the same two-stage instrumental variable analysis to analyze the effects of firm connectedness on excess value. Again, find the instrumented firm connectedness is a significantly positive determinant of excess value, suggesting that exogenous increase in connectedness leads to higher firm values.

Altogether, the results in Tables 3-6 suggest that better connected divisional managers are associated with greater segment-level investment efficiency. This leads to improved firm-level allocation efficiency (proxied by the Relative Value Added by Allocation) and to greater firm values. These findings are consistent with the *efficient bargaining* hypothesis that states connections facilitate cooperation among divisional managers, which should mitigate investment inefficiencies (such as cross-subsidization, underinvestment in high-Q segments) and allow for more efficient distribution of investment funds across divisions. In addition, improvements in allocation efficiency and greater firm values are also consistent with *information asymmetry* hypothesis that asserts connections reduce information asymmetry within the firm thanks to more accurate reporting by the divisions to the headquarters, allowing the headquarters to better identify growth opportunities of segments worth financing.

Our results allow us to reject the *individual influence* hypothesis. First, while we do not find that segments led by managers with greater number of social connections command greater shares of capital allocations. Second, we find that firm connectedness leads to improvements in firm-level allocation efficiency and excess value, what contradicts with the predictions of this hypothesis about distortions in capital allocation and reduction in firm value caused by managers' influence.

In the next section, we will analyze channels through which connections lead to improved allocation efficiency and higher firm values, consistent with both *efficient bargaining* and *information asymmetry* hypotheses.

4.3 Mechanisms of the Effect of Social Connections on Allocation Efficiency and Firm Value

4.3.1 Strategical Matching of Divisional Managers to Segments

Based on *efficient bargaining* hypothesis, we should expect that improvements in capital allocation and firm value to occur primarily when well-connected managers control high-Q segments. If connections facilitate cooperation and trust among divisions, then high-Q segment led by a well-connected manager is unlikely to be engaged in spending misallocation documented by Rajan, Servaes and Zingales (2000) due to defensive investment (to protect its funds from poaching requests by other divisions) and/or subsequent underinvestment induced by headquarters. Instead, such segment can properly (over)invest to take advantage of its superior growth opportunities, leading to greater firm-level efficiency and higher firm values. While the headquarters may be "passive beneficiaries" of the more efficient bargaining process, they still have their active role through affecting the assignments of managers into divisions and putting better connected managers into high-Q divisions. Consequently, we now analyze whether companies strategically match high-connected managers to high-Q segments to reduce inefficiencies caused by misallocation of funds primarily in high-Q divisions. We explore this question by studying the turnovers of divisional managers across firm segments. To identify turnovers more accurately, for each manager we hand-collected information about the start and the end dates of operating the segment.[14]

We begin by studying the divisional managers' appointments. If the location of the divisional manager at the high-Q segment is beneficial for the company, then we would expect that companies assign the better-connected managers to high-Q segments. To test this channel, we regress the beginning of the (previous) year Tobin's Q of the division on the social connections of the incoming divisional manager and his other characteristics. Column (1) of Table 7 shows that companies assign better connected managers to divisions with historically superior growth opportunities. Additionally, in columns (2) and (3) we test the idea if better connected managers are assigned to historically capital rich divisions. We regress beginning of the year capital expenditures measures on characteristics of the incoming manager. We do not find that divisional managers are appointed at historically capital rich divisions.

Overall, our tests show that companies tend to strategically assign better connected managers to higher-Q segments. It is also possible that the departures of divisional managers convey some information about the segments. For example, well-connected managers may have longer tenures at the high-Q segments. To capture this effect, we investigate how the manager departure from the the segment is related to the matching of his characteristics to the segment Tobin's Q.

[14]Every manager goes through formal promotions (such as promoting from Vice President to Executive Vice President) while still being the highest person responsible for the segment. To accurately identify tenure dates we used many resources: 10-Ks, companies press releases, BoardEx, Bloomberg executives database and the managers' Linkedin profiles.

Specifically, we estimate the hazard rate (or approximately) probability that a current divisional manager leaves the segment over the next year using the Cox (1972) proportional hazards model. The Cox model evaluates the probability of the divisional manager's exit from the segment as a function of her tenure at segment and control variables. For this test, we hand-collect the start and end dates of the manager tenure at the segment from BoardEx, annual reports, proxy statements, managers' LinkedIn profiles and companies' press-releases. Since manager's connections and segment investment opportunities vary from year to year, we allow the explanatory variables to vary with time (Cameron and Trivedi (2005)). It allows us to compare the probabilities of exits between high-connected managers that are properly matched to segments with those (high-connected managers) who are not properly matched to segments at each exit event. We estimate the following model:

$$\begin{aligned}\lambda(t|Z,\beta) = \lambda_0(t)\ \mathit{exp}(\beta_1 \mathit{Connections}(t) + \beta_2 \mathit{Mismatch}(t) + \\ \beta_3(\mathit{Connections}(t) \times \mathit{Mismatch}(t)) + X(t)\gamma)\end{aligned} \tag{3}$$

The dependent variable is a hazard rate of a divisional manager exit from a segment (company) within a sample period. We consider the managers' exits as right censored observations, when the divisional manager drops out the sample at the end of the sample period, but we can confirm that he continues to operate the segment in next fiscal year. The unit of observation is the combination of segment and manager in a given year. Following Jenter and Kanaan (2015) we keep only divisional managers with tenure at the segment at least 2 years. *Connections* is measured by firm-adjusted social connections to capture the relative connectedness of a particular divisional manager within a firm.[15] *Mismatch* measures the quality of matching between the managers and segments, and is equal to an absolute value of a difference between two ranks: connections rank of a divisional manager and the Tobin's Q rank of the segment (which this

[15]Firm-adjusted Social connections is computed as the absolute number of connections of a divisional manager (with other divisional managers) minus the average number of connections between divisional managers within a firm in a given year.

manager operates) within a firm in a given year.[16] Our main variable of interest is *Connections* $\times$ *Mismatch*, the interaction term of the social connections with a quality of matching between the connections of its manager and investment opportunities of the segment. We measure all explanatory variables at the beginning of the fiscal year, in which the manager leaves the segment. As in Jenter and Kanaan (2015) we control for potential retirements by including the dummy variable for managers' age greater than 60. Since the Cox model accounts for the effect of tenure on the probability of the manager turnover, we exclude the company tenure variable (*Long Tenure*) from the regressions.

Table 8 presents the results of the estimation. Column (1) shows that relatively better connected managers are less likely to leave the segment, however the greater initial mismatch between connections and segment Q increases the hazard rate of the turnover for these managers. The coefficient on *Connections*$\times$*Mismatch* is positive and significant at 1% level. If high-connected managers are properly matched to segments, then they are more likely to stay longer with the company. Our data shows that this is indeed the case: we estimate the hazard rate that a divisional manager will leave the company conditional she is leaving the segment. In column (2) the coefficient on *Connections* $\times$ *Mismatch* remains positive and significant for managers' exits from the company conditional on the exits from the segments.

To ensure that results are not driven by the specific choice of the Cox hazards model (which is apparently more suitable), we estimate the probability of the manager's exit using a parametric logit model. We additionally include in the logit regressions divisional manager's tenure at segment, computed in months and measured at the time of exit. Columns (3) and (4) present the results. The coefficients on *Connections* $\times$ *Mismatch* remain positive and highly significant (at 5% or better level). Specifically, we again observe that better connected managers are more likely to leave the segment (or company conditional on segment exit) if there they are previously assigned to a segment with a worse growth opportunities.. Based on logit regressions,

[16]We dropped the observations, where there is no variation either in segment connections or in Tobin's Q or both. We also corrected this variable by assigning zero values for cases when the difference appeared mechanically - the highest rank in connections was not equal to the highest rank in segment Q due to repeated values in connections or Q.

we estimate the conditional probabilities of managers' turnovers. The average implied probability of the divisional manager turnover increases from 12.46% to 15.27% if *Connections* drops from 90th to the 10th percentile and *Mismatch* increases from the 10th to the 90th percentile, what roughly corresponds to about 20% increase in implied probability of the divisional manager turnover for a median firm (with covariates taken at the median values).

Taken together, our results provide additional support to the *efficient bargaining* hypothesis and suggest that headquarters tend to understand the benefits of matching better connected managers to high-Q segments by strategically allocating the managers to improve capital allocation efficiency and firm value.

4.3.2 Social Connections and Segment Diversity

Rajan, Servaes and Zingales (2000) show that high segment diversity – i.e. variation in segment Qs within the same firm-year - is associated with reduction of firm excess value (we document the same relation in Panel A of Table 6). The reason is that capital allocation inefficiencies – such as the incentives to poach high-growth divisions, leading to desire to pursue defensive spending by such divisions, and limiting investment by headquarters into high-growth divisions (to prevent defensive spending) – should be greater precisely in firms that have both types – high-growth and low-growth – segments. Our *efficient bargaining* hypothesis states that managerial connections promote trust and cooperation among divisions, decreasing the likelihood of poaching and defensive spending. Consequently, the greatest benefits of firm connectedness should be observed in firms with sizable segment diversity.

To test whether connections help to reduce the negative effect of diversity in segments' Q, we examine whether firm connectedness mitigates the (known) negative impact of segment diversity on excess value. In Table 9 we report mean excess values for high- and low- connected firms. We also split the sample based on value of segment diversity. The results are consistent with our expectations. In the subsample of firms with high diversity (segment diversity is above the sample median), we observe a significant difference in excess values between high- and low-connected firms, with difference significant at 1% (t = 4.25). In contrast, in the low-diversity subsample (segment diversity is below the sample median), the differences in value are not significant. These results provide support to our *efficient bargaining* hypothesis and imply that horizontal connections may be beneficial for firm values in firms with diverse segment investment opportunities, because they help to correct misallocation of funds by mitigating power struggles for funds (Rajan, Servaes and Zingales (2000)).

4.3.3 Social Connections and Information Asymmetry

In this section we provide evidence for support of the *information asymmetry* hypothesis. This hypothesis suggests that connections reduce internal information asymmetry between divisions and headquarters through truthful reporting by divisional managers about the investment opportunities of their segments. We expect that when headquarters' managers are better informed about the segments' performance, the financing they provide will more likely reflect segments' investment opportunities, which will lead to improved allocation efficiency.

One reason for existence of information asymmetry between headquarters and divisional managers in conglomerates is that divisional managers may capture private benefits by distorting information about their divisions (e.g. Meyer, Milgrom and Roberts (1992)).[17] However, such behavior leads to inefficiencies in capital allocation (Harris and Raviv (1996), Ozbas (2005), Wulf (2009)), which destroys firm value and thus has negative consequences for other divisions. If connections among divisional managers facilitate cooperation and friendly relations, then better connected teams of managers should be associated with less incentives to misreport to headquarters. Individual managers might be less likely to pursue activities benefiting them at the expense of their colleagues. Instead, there should be greater alignment between divisional policies and overall firm's goal to maximize value. Deviation from the policy to jointly pursue firm goals may be costly - in firms with well-connected teams, untruthful reporting can damage valuable

[17] Consistent with the important role of information asymmetry in capital allocation decisions, Graham, Harvey and Puri (2015) in the recent survey note that CEO needs the most informational input from divisional managers in the capital allocation and investment decisions.

connections, ruin friendships and reputations (Brass and Labianca (2006)).

In testing the *information asymmetry* hypothesis, the main challenge is to measure *internal* information asymmetry, which is difference between the amounts of information that the headquarters and the divisional managers possess. We construct our measure of internal information asymmetry following Ravina and Sapienza (2010) and Chen, Martin, Wang, Roychowdhury and Billett (2016) and measure internal information asymmetry by comparing private information sets of divisional managers with those of top executives, which is reflected in the difference in the profitability of their insider trades. If divisional managers have some private information about their divisions, and they do not share this information with others, then ex post of profitability of their trades in their own firm stock will reveal this information. Hence the difference in the profitability of insider trades between divisional managers and top executives will indicate the relative information advantage of divisional managers over that of corporate headquarters.

For calculating the measure of internal information asymmetry we use data from the Thomson Reuters insider filings database. The process of calculation is as follows: we first sort insider trades into "routine" trades and information-based "opportunistic" trades as in Cohen, Malloy and Pomorski (2012). We label the trade as "routine" if an insider makes open-market trades in the same calendar month over a period of a least three consecutive years. If for that insider the trades do not fit into an obvious calendar pattern, they are labeled as "opportunistic". We compute the trading profit as an average cumulative market-adjusted abnormal return over the six-month period following insider trades made during current fiscal year. We then calculate internal information asymmetry as the difference in trading profits between the divisional managers and top-5 corporate managers for opportunistic trades.[18] To estimate the effect of social connections on internal information asymmetry, we regress this measure on our firm connectedness measures and additional controls based on Ravina and Sapienza (2010) - firm size and book-to-market ratio. As shown in Panel A of Table 10 the coefficients on all of our firm connectedness measures are negative and significant at 5% level, suggesting that firm connectedness reduces internal

[18]The group of top-5 corporate managers consists of: CEO, Chairman, Vice Chairman, CFO and COO.

information asymmetry.

In Panel B of Table 10 we address endogeneity of firm connectedness using two instruments we discussed in Section 3.2.2. Using two-stage least squares approach we can identify the effect of firm connectedness on internal information asymmetry only through within-firm changes in firm connectedness due to plausibly exogenous departures of connected managers. Columns (1) and (3) report the first-stage regressions, in which we regress firm connectedness on two instruments, and include the set of controls from Panel A, firm and year fixed effects. Both instruments have a significant negative impact on firm connectedness. Columns (2) and (4) report the results of the second-stage regressions, in which we regress internal information asymmetry on predicted firm connectedness. As in OLS regressions, we again find a positive significant effect of firm connectedness on internal information asymmetry. The corresponding coefficients on firm connectedness measures are -0.067 (t = -2.26) and -0.099 (t = -1.98). We also checked that both instruments pass the weak instruments test and satisfy the exogeneity assumption, because we cannot reject the overidentifying restrictions of both models.

Ultimately, our results provide support for the *information asymmetry* hypothesis that social connections contribute to lower internal information asymmetry.

4.4 Alternative Explanations and Robustness Checks

The main results in our paper suggest that better connected managers are associated with more efficient capital spending in their divisions. Our previous analysis rules out some confounding factors, but there are still at least two potential threats to identification. First, is it possible that managers of divisions that receive more capital end up developing more connections with other divisional managers? Second, could our results be driven by connections to CEO or better overall external connectedness of divisional managers? In this section we address these identification challenges.

Our results indicate that well-connected divisional managers, which operate high-Q divisions, obtain more capital for their divisions. One standard identification concern for papers measuring the effect of connections on capital allocation is the concern that the observed correlation results from the positive effect of capital allocation on connections (Duchin and Sosyura (2013)). To address this concern, we keep only connections that were established earlier than 5 years before the arrival of the manager at the segment of interest. This filter results in dropping only 20% of connections, suggesting that the majority of connections were formed long before the arrival of the manager at the segment of interest.[19]

Table 11 Panel A repeats the analysis of segment capital expenditures performed in Panel A Table 3, with the additional restriction that each of the connections measures is based only on connections formed earlier than 5 years before the arrival of the manager at the segment of interest. After applying this filter, we find that our results for all three capital expenditures measures are nearly unchanged compared to those presented in Table 3. That is, in columns (1)-(3) the coefficients on the interaction term between social connections measures and segment investment opportunities are still significantly positive, while social connections per se are not significantly related to capital spending. In Panel B we get the same results, when we repeat the analysis for the restricted model (which omits Tobin's Q). Hence, these findings suggest that our results are unlikely to be driven by reverse causality.

We next check the robustness of our results by excluding observations, in which the same division is overseen by multiple managers. There are about 14% of such observations, suggesting that these cases are relatively rare. Our main results (reported in columns (4)-(6)) remain unchanged if we remove these observations.

Existing research has documented that better connected to CEO managers receive more capital allocations (e.g. Xuan (2009), Duchin and Sosyura (2013)). If well-connected divisional managers are managers who are simply connected to more people - including CEO of their own company, then our results could be driven by the effect of connections to CEO, rather than connections to other divisional managers. To address this possibility we add to our baseline regressions the indicator variable *Connected to CEO*, which identifies managers connected to

[19] In our sample approximately 80% of connections were formed 5 years or earlier before the arrival at segment and 62% of connections were formed 10 years or earlier before the arrival at segment.

CEO. As shown in columns (7)-(9) of Table 11, the coefficient on *Connected to CEO* is positive and significant consistent with the role of connections to CEO in capital allocation documented in previous studies. Importantly, after controlling for connections to CEO we obtain results that are very similar to the regressions in Table 3.

Finally, there is concern that connections to other divisional managers is a proxy for overall connectedness of divisional manager. To address this concern, we compute two measures of centrality of divisional managers, which measure the degree of connectedness to other (outside) executives. We use BoardEx data to calculate centrality measures. Specifically, in creating the centrality measures we build the network using employment connections between individuals formed in listed and private firms located in the North American region. Employment connections are considered the most reliable, and not affected by self-reporting bias (El-Khatib, Fogel and Jandik (2015)). We compute two types of network centrality - *Degree* and *Eigenvector*. *Degree Centrality* measures the total number of social connections a given manager has to all other executives within the whole BoardEx network. *Eigenvector Centrality* also tracks the number of total social connections, but gives greater weight to links with better-connected individuals. As common in literature, our centrality measures are expressed in percentiles (1st percentile – least central, 100th percentile – most central), which capture the relative position of the manager in the entire network of BoardEx executives.[20]

As shown in columns (10)-(12) of Table 11, adding *Degree Centrality* does not change the results. Notably, the coefficient on *Degree Centrality* is not significant, suggesting that overall connectedness of divisional managers does not matter for capital allocation. We repeat analysis using *Eigemvector Centrality* instead (unreported), and our baseline results again do not change, while observing insignificant effect of *Eigemvector Centrality* on capital spending. Ultimately, because high-centrality individuals should be considered influential and/or powerful based on

[20]The mean (median) *Degree Centrality* is 81 (83), and the mean (median) *Eigenvector Centrality* is 78 (82). Divisional managers in our sample on average are more central compared to the sample of CEOs of S&P1500 in El-Khatib, Fogel and Jandik (2015). This is not surprising since our sample consists of the largest and most significant companies of S&P500, hence on average divisional managers in our sample are more connected than CEOs in S&P1500.

social science research (see e.g., Mizruchi and Potts (1998), Hanneman and Riddle (2005), Jackson (2010), Banerjee, Chandrasekhar, Duflo and Jackson (2012)), these results provide additional evidence for rejecting *individual influence* hypothesis.

5 Conclusion

Our paper contributes to the debate whether social connections are associated with allocation efficiency and firm value improvements. We use the hand-collected dataset of 765 divisional managers, matching them to segments of S&P500 conglomerate firms. We find that social connections among divisional managers lead to higher sensitivity of segment capital spending to segment's growth opportunities. We find the positive causal effects of social connections on firm-level capital allocation efficiency and firm value.

Our analysis provides support for two possible mechanisms that potentially can explain these results. Specifically, consistent with the *efficient bargaining* hypothesis, we show that the improvements in firm value tend to occur in firms with high dispersion of segment growth opportunities, where high-Q divisions are more likely to invest at lower sub-optimal levels (Rajan, Servaes and Zingales (2000)). Since social links likely promote cooperation and trust, well-connected managers may be able to secure enough investment funds into their high-growth segments, without inducing power struggles among divisional managers (which could lead to profit grabbing demands by low-Q divisions, and to defensive spending by high-Q segments). We provide further evidence that companies are likely to strategically match well-connected managers into segments with better investment opportunities, and that well-connected managers are less likely to leave their firm or a high-Q segment, once they get matched to it. However, we do not find support for the *individual influence* hypothesis stating that well-connected managers should be able to secure additional investment funds based on their greater influence and/or power.

We also find support for the *information asymmetry* hypothesis, as we document that firms with well-connected divisional managers are associated with less internal information asymmetry between divisions and headquarters – which likely allows headquarters to better assess true growth opportunities of firm's segments and thus finance divisions more efficiently. Our findings are consistent with the results in Billett, Chen, Martin and Wang (2014) that lower internal information asymmetry should enhance firm value.

Overall, our findings suggest that social connections among divisional managers play an important role in capital allocation process. They are associated with improved allocation efficiency and greater firm values.

6 References

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7 Tables

Table 1: Summary Statistics

The table reports summary statistics for a random sample of 100 S&P industrial conglomerates between 2006 and 2013, which operate in at least two business segments, have non-missing operating profit and segment assets and disclose identity of divisional managers. Panel A shows the financial characteristics of firms and segments. Panels B and C provide information about 620 divisional managers: personal characteristics related to the managers' employment in the company and their social connections. The accounting information is from merged Compustat and Compustat Historical Segments, identities of divisional managers' are collected from 10-K annual reports and data on divisional managers' personal characteristics and connections is from BoardEx. Appendix A provides definitions of these variables.

Panel A: Firms and Segments

Variable	Mean	25th perc.	Median	75th perc.	St. dev.
Company level					
Tobin's Q	1.560	1.217	1.494	1.826	0.444
Cash flow/Assets	0.104	0.075	0.104	0.138	0.064
Market value, $millions	48570	9596	23611	45165	102000
Book assets, $millions	31450	5796	14867	30941	85118
Number of business segments	4.120	3.000	4.000	5.000	1.398
Capital expenditure/Assets	0.041	0.020	0.028	0.046	0.043
Sales, $millions	23110	5628	11590	30908	26965
Segment level					
Return on assets (ROA)	0.180	0.084	0.149	0.254	0.232
Cash flow	0.227	0.122	0.192	0.305	0.168
Industry Tobin's Q	1.505	1.259	1.492	1.709	0.358
Capital expenditure, $millions	286	30	78	203	966
Capital expenditure/Assets	0.051	0.017	0.034	0.063	0.056
Sales, $millions	6008	1440	3027	6241	10572
Book assets, $millions	6692	1141	2429	5895	30892
Industry-Adjusted Capital Expenditure	0.018	-0.011	0.006	0.031	0.051
Industry-Firm-Adjusted Capital Expenditure	0.006	-0.010	0.001	0.018	0.041

Panel B: Divisional Managers

Variable	
Continuous variables	Mean
Tenure at the company (years)	14.42
Tenure at the segment (years)	6.19
Age	52.76
Indicator variables	% from total N
General:	
Male	92.42%
Senior	59.52%
Tenure >10 years	56.13%
Retirement Age	15.65%
Board Member	16.77%
High Salary	60.48%
Graduated from Ivy League	18.71%
Connections:	
Total connected managers	62.74%
Employment: Worked for the same listed company at the same time in past	54.68%
Employment: Worked for the same private company at the same time in past	9.03%
Education: Studied at the same university at the same time in past	0.48%

Panel C: Connections

Variable	Mean	25th perc	Median	75th perc.	St.dev.
Segment level (firm-year-segment)					
Segment connections	1.367	0.000	1.000	2.000	1.566
Firm level (firm-year)					
Average Segment Connections	1.363	0.000	1.000	2.000	1.440
Asset-Weighted Segment Connections	1.035	0.000	0.709	1.539	1.101

Table 2: Comparison of Capital Expenditure across Segments - Univariate Evidence

The table reports differences-in-means estimates across our three capital expenditures measures depending on segment connections and investment prospects of segments. Panel A compares *High Q* segments (that have Tobin's Q above the sample median) with *Low Q* segments (that have Tobin's Q below the sample median). *High (Low) Segment Connections* - indicator variable equals one for segments with connections above (below) sample median. Panel B compares capital expenditures between the segments with connections above and below the sample median. *Capital Expenditure (CAPEX)* – annual capital expenditure of the division (capxs) divided by the division's lagged one year book assets (ias). *Industry-Adjusted Capital Expenditure (IA CAPEX)* – annual capital expenditure of the division adjusted for the industry-specific variation in capital expenditures, as measured by the median capital expenditure of single-segment firms in the division's industry (two-digit SIC code). *Industry-Firm-Adjusted Capital Expenditure (FIA CAPEX)* – industry-adjusted capital expenditure further adjusted for the firm's asset-weighted average of industry-adjusted capital expenditures across all divisions. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Capital Expenditures and Segment-Level Efficiency of Allocation

High Segment Connections

	High Q	Low Q	Difference	t-statistic	
CAPEX	0.0636	0.0517	0.0119	2.76	**
Industry-adjusted CAPEX	0.0370	0.0184	0.0186	4.36	***
Industry-firm-adjusted CAPEX	0.0154	0.0041	0.0114	3.12	***

Low Segment Connections

	High Q	Low Q	Difference	t-statistic
CAPEX	0.0457	0.0501	-0.0044	-1.43
Industry-adjusted CAPEX	0.0139	0.0115	0.0023	0.90
Industry-firm-adjusted CAPEX	0.0044	0.0053	-0.0008	-0.42

Panel B: Capital Expenditures and Segment-Level Connections

	High Segment Connections	Low Segment Connections	Difference	t-statistic	
CAPEX	0.0571	0.0482	0.0090	3.45	***
Industry-adjusted CAPEX	0.0268	0.0126	0.0143	6.04	***
Industry-firm-adjusted CAPEX	0.0092	0.0049	0.0043	2.24	**

Table 3: Social Connections among Divisional Managers and Capital Allocation

The table presents the results of segment-level regressions of three capital expenditures measures on social connections measures, segment and manager controls. Columns (1) - (6) use *Segment Connections* as a measure of social connections, which is computed an absolute number of social connections of a divisional manager in a given firm-year. Columns (7) - (12) use *High Segment Connections*, which is an indicator that equals one if *Segment Connections* is above the sample median. Panel A shows the results of the full model, whereas Panel B shows the results of the restricted model, where *Tobin's Q* is omitted. All continuous variables are winsorized at 1% and 99% levels. All variables except for dummies are standardized. Other variables are defined in Appendix A. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the segment level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Full Model

Measure of Social Connections	Segment Connections						High Segment Connections (Dummy)					
Dependent Variable	CAPEX	IA CAPEX	IFA CAPEX	CAPEX	IA CAPEX	IFA CAPEX	CAPEX	IA CAPEX	IFA CAPEX	CAPEX	IA CAPEX	IFA CAPEX
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Social Connections	0.058*	0.037	0.021	0.068*	0.063	0.048	0.090	0.063	0.019	0.079	0.086	0.035
	(1.75)	(0.95)	(0.53)	(1.74)	(1.50)	(0.95)	(1.15)	(0.69)	(0.19)	(1.02)	(1.01)	(0.34)
Tobin's Q	0.032	0.015	0.019	0.032	0.025	0.034	-0.041	-0.069	-0.069	-0.047	-0.076	-0.071
	(0.75)	(0.30)	(0.32)	(0.67)	(0.44)	(0.52)	(-0.89)	(-1.27)	(-1.11)	(-1.03)	(-1.46)	(-1.16)
Social Con. x Tobin's Q	0.082**	0.094**	0.090**	0.083**	0.103**	0.101**	0.196***	0.226***	0.238**	0.214***	0.271***	0.285***
	(2.49)	(2.54)	(2.12)	(2.21)	(2.47)	(2.07)	(2.77)	(2.81)	(2.59)	(2.60)	(2.93)	(2.59)
Segment Cash Flow	0.237***	0.153***	0.118**	0.256***	0.143**	0.121*	0.236***	0.151***	0.116**	0.252***	0.138**	0.116*
	(5.41)	(3.40)	(2.34)	(4.69)	(2.51)	(1.87)	(5.41)	(3.39)	(2.32)	(4.66)	(2.45)	(1.82)
Segment Size	-0.202*	-0.190*	-0.183	-0.188	-0.160	-0.181	-0.202*	-0.189*	-0.183	-0.188	-0.159	-0.180
	(-1.87)	(-1.71)	(-1.43)	(-1.48)	(-1.23)	(-1.19)	(-1.87)	(-1.70)	(-1.43)	(-1.47)	(-1.22)	(-1.18)
Segment Relative Size	0.150**	0.086	0.073	0.140*	0.065	0.068	0.151**	0.086	0.075	0.142*	0.067	0.070
	(2.09)	(1.33)	(0.93)	(1.76)	(0.90)	(0.76)	(2.11)	(1.33)	(0.95)	(1.79)	(0.92)	(0.79)
CEO Ownership	0.321*	0.282	0.079	0.218*	0.251*	0.011	0.326*	0.288	0.085	0.220*	0.254*	0.010
	(1.92)	(1.44)	(0.61)	(1.95)	(1.68)	(0.09)	(1.94)	(1.46)	(0.66)	(1.94)	(1.68)	(0.08)

Panel A: Full Model

Measure of Social Connections	Segment Connections						High Segment Connections (Dummy)					
Dependent Variable	CAPEX	IA CAPEX	IFA CAPEX	CAPEX	IA CAPEX	IFA CAPEX	CAPEX	IA CAPEX	IFA CAPEX	CAPEX	IA CAPEX	IFA CAPEX
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Segment Relative ROA	0.116***	0.128***	0.161***	0.120***	0.129***	0.161***	0.116***	0.127***	0.159***	0.119***	0.128***	0.159***
	(3.37)	(3.61)	(4.11)	(3.46)	(3.60)	(3.91)	(3.38)	(3.62)	(4.11)	(3.47)	(3.62)	(3.94)
Board Member	0.066	0.104	0.095	0.068	0.130	0.118	0.066	0.105	0.098	0.068	0.129	0.120
	(0.91)	(1.21)	(0.95)	(0.88)	(1.45)	(1.10)	(0.92)	(1.24)	(0.99)	(0.90)	(1.48)	(1.13)
High Salary	0.024	0.041	0.069	0.038	0.067	0.074	0.020	0.038	0.066	0.036	0.066	0.072
	(0.54)	(0.82)	(1.32)	(0.84)	(1.36)	(1.25)	(0.46)	(0.76)	(1.27)	(0.79)	(1.33)	(1.21)
Retirement Age	0.073	0.001	-0.005	0.111	0.015	-0.002	0.075	0.004	0.001	0.118	0.022	0.009
	(0.94)	(0.01)	(-0.05)	(1.35)	(0.16)	(-0.02)	(0.96)	(0.04)	(0.01)	(1.44)	(0.24)	(0.08)
Long Tenure	-0.129**	0.000	0.001	-0.132**	0.001	-0.000	-0.121**	0.008	0.011	-0.118*	0.014	0.016
	(-2.19)	(0.00)	(0.01)	(-2.08)	(0.01)	(-0.00)	(-2.03)	(0.12)	(0.15)	(-1.87)	(0.21)	(0.21)
Senior Title	0.053	0.087	0.170	0.062	0.074	0.146	0.049	0.084	0.167	0.051	0.063	0.134
	(0.63)	(0.90)	(1.58)	(0.67)	(0.69)	(1.17)	(0.59)	(0.88)	(1.58)	(0.57)	(0.60)	(1.09)
Ivy League	-0.089	-0.101	-0.120	-0.113	-0.125	-0.129	-0.094	-0.106	-0.125	-0.119	-0.131	-0.137
	(-1.14)	(-1.25)	(-1.22)	(-1.42)	(-1.50)	(-1.29)	(-1.20)	(-1.30)	(-1.27)	(-1.48)	(-1.57)	(-1.35)
Year fixed effects	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	No	No	No
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
N	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008
R^2	0.49	0.37	0.17	0.55	0.44	0.20	0.49	0.37	0.17	0.55	0.44	0.21

Panel B: Restricted Model

Social Connections	0.058*	0.037	0.021	0.068*	0.063	0.048	0.087	0.059	0.014	0.074	0.079	0.028
	(1.75)	(0.95)	(0.53)	(1.74)	(1.50)	(0.94)	(1.11)	(0.63)	(0.14)	(0.96)	(0.93)	(0.27)
Social Con. x Tobin's Q	0.080**	0.094**	0.089**	0.082**	0.103**	0.101**	0.169***	0.181**	0.193**	0.184**	0.222**	0.239**
	(2.48)	(2.56)	(2.13)	(2.24)	(2.50)	(2.09)	(2.63)	(2.43)	(2.25)	(2.29)	(2.41)	(2.19)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	No	No	No
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
N	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008
R^2	0.49	0.37	0.17	0.55	0.44	0.20	0.49	0.37	0.17	0.55	0.44	0.20

Table 4: Exogenous Shocks to Social Connections: Death and Retirement Events

The table presents the results of regressions in first-differences, in which the dependent variable is the annual change in capital expenditures measures. The sample consists of segment-year observations, in which the network of the divisional manager has changed due to deaths and retirements of other (connected) divisional manager(s), but the divisional manager has not changed. Panel A shows the results of the full model, whereas Panel B shows the results of the restricted model, where *Tobin's Q* is omitted. *Social Connections* is measured by Segment Connections, which is an absolute number of social connections of a divisional manager (to other divisional managers) in a given firm-year. Explanatory variables are computed as annual changes. All regressions include firm and calendar-year fixed effects. All variables are defined in Appendix A. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the segment level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Full Model

Dependent Variable	ΔCAPEX	ΔIA CAPEX	ΔIFA CAPEX
Model	(1)	(2)	(3)
ΔSocial Connections	0.062	0.048	0.031
	(0.98)	(0.71)	(0.22)
ΔTobin's Q	0.068	-0.049	-0.115
	(0.55)	(-0.39)	(-0.37)
Δ(Social Connections x Tobin's Q)	0.144***	0.170***	0.256***
	(2.69)	(2.90)	(2.67)
ΔSegment Cash Flow	0.076	-0.026	-0.107
	(0.66)	(-0.24)	(-0.58)
ΔSegment Size	-2.694***	-3.289***	-5.972*
	(-3.02)	(-3.57)	(-1.93)
ΔSegment Relative Size	0.170	0.491	1.035
	(0.35)	(0.94)	(0.82)
ΔCEO Ownership	16.019***	16.035***	16.830**
	(3.13)	(3.48)	(2.57)
ΔRelative ROA	0.233**	0.138	0.175
	(2.13)	(1.28)	(1.14)
ΔBoard Member	0.161	0.056	-0.089
	(0.60)	(0.22)	(-0.23)
ΔHigh Salary	0.171	0.263**	0.709*
	(1.55)	(2.11)	(1.82)
ΔRetirement Age	1.163***	1.324***	2.080***
	(3.98)	(4.39)	(5.38)
ΔLong Tenure	5.348***	4.891***	6.358***
	(6.25)	(7.11)	(4.90)
ΔSenior Title	0.709	1.169*	2.527

Panel A: Full Model

Dependent Variable	ΔCAPEX	ΔIA CAPEX	ΔIFA CAPEX
Model	(1)	(2)	(3)
	(1.15)	(1.68)	(1.33)
ΔIvy League		omitted	
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
N	142	142	142
R^2	0.83	0.82	0.58

Panel B: Restricted Model

ΔSocial Connections	0.054	0.054	0.044
	(0.84)	(0.77)	(0.35)
Δ(Social Connections x Tobin's Q)	0.138**	0.174***	0.267***
	(2.52)	(3.02)	(2.80)
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
N	142	142	142
R^2	0.83	0.82	0.58

Table 5: Firm-Level Social Connections and Allocation Efficiency

The dependent variable in Panel A and in Panel B (in columns (2) and (4)) is *Relative Value Added by Allocation,* measured as the sum of the weighted Industry-Firm-Adjusted Capital Expenditure across all segments of a firm in a given year (Rajan, Servaes and Zingales (2000)). The dependent variable in Panel B (in columns (1) and (3)) is one of the measures of firm connectedness. *Average Segment Connection*s is the sum of Segment Connections of divisional managers across all segments scaled by a number of business segments in the given firm-year. *Asset-Weighted Segment Connections* is the asset-weighted value of Segment Connections in a given firm-year. *Lost Connections* is the cumulative number of connections lost (by divisional managers) due to deaths and retirements of connected managers in the previous fiscal year. *Exogenous Job Openings* is the total number of deaths and retirements of executives in all other firms in the state and industry corresponding to those of the sample conglomerate measured at the previous fiscal year. *Firm Sales* is the natural logarithm of the firm's sales. *Segment Diversity* is the standard deviation of asset-weighted segment Qs divided by equally weighted average segment Qs in a firm. *Inverse of Average Q* is the inverse of equally weighted industry Tobin's Q over segments of the firm. All variables are winsorized at 1% and 99% levels. t-statistics, reported in parentheses, are based on robust to heteroscedasticity standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: OLS Regressions

Dependent Variable	Relative Value Added by Allocation (x 100)	
Measure of Firm Connectedness	Average Segment Connections	Asset-Weighted Segment Connections
Model	(1)	(2)
Firm Connectedness	0.023***	0.027***
	(3.22)	(2.95)
Firm Sales	0.007	0.006
	(0.85)	(0.82)
Segment Diversity	-0.015	-0.038
	(-0.17)	(-0.42)
Inverse of Average Q	-0.028	-0.022
	(-0.36)	(-0.29)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
N	616	616
R^2	0.07	0.07

Panel B: IV-2SLS Regressions

Dependent Variable	Relative Value Added by Allocation (x 100)			
Measure of Firm Connectedness	Average Segment Connections		Asset-Weighted Segment Connections	
	First Stage	Second Stage	First Stage	Second Stage
Model	(1)	(2)	(3)	(4)
Firm Connectedness		0.080**		0.092**
		(2.03)		(1.99)
Lost Connections	-0.136***		-0.120***	
	(-6.81)		(-6.76)	
Exogenous Job Openings	-0.073**		-0.049*	
	(-2.38)		(-1.80)	
Firm Sales	0.093	-0.005	0.057	-0.002
	(0.54)	(-0.10)	(0.37)	(-0.04)
Segment Diversity	-0.055	0.079	0.296	0.046
	(-0.11)	(0.56)	(0.68)	(0.33)
Inverse of Average Q	0.398	-0.045	0.234	-0.035
	(0.99)	(-0.40)	(0.66)	(-0.31)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Wald F statistic	26.09		24.49	
Hansen J statistic (p-value)	0.24 (0.63)		0.41 (0.52)	
N	541	541	541	541
R^2	0.82	0.36	0.76	0.36

Table 6: Firm Connectedness and Firm Value

The dependent variable in Panel A and in Panel B (in columns (2) and (4)) is *Excess Value*, measured as the natural logarithm of the ratio of the conglomerate actual value to its imputed value (Berger and Ofek (1995)). A conglomerate actual value is the market value of assets, which is equal to the market value of equity minus book assets and book value of debt. A conglomerate imputed value is the sum of the imputed values of its segments, where each segment's imputed value is equal to segment's sales multiplied by the sales multiple (median market value of assets-to-sales ratio of all single-segment firms in a segment two-digit SIC industry). The dependent variable in Panel B (in columns (1) and (3)) is one of the measures of firm connectedness. *Average Segment Connections* is the sum of Segment Connections of divisional managers across all segments scaled by a number of business segments in the given firm-year. *Asset-Weighted Segment Connections* is the asset-weighted value of Segment Connections in a given firm-year. *Lost Connections* is the cumulative number of connections lost (by divisional managers) due to deaths and retirements of connected managers in the previous fiscal year. *Exogenous Job Openings* is the total number of deaths and retirements of executives in all other firms in the state and industry corresponding to those of the sample conglomerate measured at the previous fiscal year. *Firm Cash Flow* is the sum of firm's income before extraordinary items and depreciation scaled by firm's book assets. *Firm Sales* is the natural logarithm of the firm's sales. *Segment Diversity* is the standard deviation of asset-weighted segment Qs divided by equally weighted average segment Qs in a firm. *CEO Ownership* is the percent of the firm's outstanding stock hold by CEO. All variables are winsorized at 1% and 99% levels. t-statistics, reported in parentheses, are based on robust to heteroscedasticity standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: OLS Regressions

Dependent Variable	Excess Value	
Measure of Firm Connectedness	Average Segment Connections	Asset-Weighted Segment Connections
Model	(1)	(2)
Firm Connectedness	0.071***	0.091***
	(3.82)	(3.60)
Firm Cash Flow	3.341***	3.441***
	(6.30)	(6.48)
Firm Sales	-0.139***	-0.141***
	(-6.58)	(-6.78)
Segment Diversity	-0.347*	-0.418**
	(-1.89)	(-2.28)
CEO Ownership	2.345**	2.299*
	(2.00)	(1.96)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
N	644	644
R^2	0.19	0.18

Panel B: IV-2SLS Regressions

Dependent Variable	Excess Value			
Measure of Firm Connectedness	Average Segment Connections		Asset-Weighted Segment Connections	
	First Stage	Second Stage	First Stage	Second Stage
Model	(1)	(2)	(3)	(4)
Firm Connectedness		0.136**		0.167**
		(2.47)		(2.53)
Lost Connections	-0.137***		-0.117***	
	(-4.93)		(-4.54)	
Exogenous Job Openings	-0.073**		-0.046*	
	(-2.58)		(-1.92)	
Firm Cash Flow	-0.687	0.702**	-0.881**	0.758**
	(-1.35)	(1.99)	(-2.02)	(2.13)
Firm Sales	0.100	-0.184*	0.104	-0.188*
	(0.60)	(-1.72)	(0.73)	(-1.78)
Segment Diversity	-0.160	-0.183	0.139	-0.230
	(-0.50)	(-0.71)	(0.46)	(-0.91)
CEO Ownership	2.200	-9.058**	0.315	-8.812*
	(0.93)	(-2.00)	(0.13)	(-1.91)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Wald F statistic	30.53		28.21	
Hansen J statistic (p-value)	0.55 (0.46)		0.32 (0.57)	
N	555	555	555	555
R^2	0.82	0.86	0.77	0.86

Table 7: Social Connections, Capital Allocation and Managers' Turnovers

The table presents the results of segment-level regressions in which the dependent variable is one of the characteristics of a division, to which a particular manager is assigned at the time of turnover. *Social Connections* is measured by Segment Connections, which is computed an absolute number of social connections of a divisional manager in a given firm-year. The sample includes firm-segment-year observations in which the divisional manager has changed from the previous year. The control variables are characteristics of the incoming manager. All regressions include firm and calendar-year fixed effects. All variables are defined in Appendix A. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the segment level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable	Tobin's Q_{t-1yr}	$CAPEX_{t-1yr}$	IA $CAPEX_{t-1yr}$
Model	(1)	(2)	(3)
Social Connections	0.253**	0.172	0.303
	(1.97)	(1.09)	(1.40)
Segment Relative ROA	0.155**	0.051	0.107
	(2.55)	(0.69)	(1.10)
Board Member	0.152	0.323**	0.381*
	(0.63)	(2.05)	(1.95)
High Salary	-0.387**	-0.067	0.137
	(-2.35)	(-0.44)	(0.76)
Retirement Age	0.730***	-0.196	-0.453
	(2.73)	(-0.72)	(-1.57)
Long Tenure	0.022	-0.166	-0.258*
	(0.18)	(-1.55)	(-1.74)
Senior Title	0.161	0.165	0.249
	(0.71)	(0.50)	(0.63)
Ivy League	-0.575***	-0.064	-0.293
	(-2.78)	(-0.51)	(-1.47)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
N	153	145	145
R^2	0.87	0.84	0.72

Table 8: Social Connections, Mismatch and Subsequent Segment Departure

The table presents the coefficients of Cox proportional hazards and logit regressions, which predict that a divisional manager exits the segment (or company conditional on leaving the segment) over the next year. *Social Connections* is measured by the absolute number of connections of a divisional manager (with other divisional managers) minus the average number of connections between divisional managers within a firm in a given year. *Mismatch* is the absolute value of difference between two ranks: raw connections rank of a divisional manager and segment rank on Tobin's Q. All explanatory variables are measured at the beginning of the fiscal year, in which the manager leaves the segment. *Retirement Age* is an indicator that equals 1 if a divisional manager's age is above 60 years old in a given year. *Tenure at Segment* is the tenure of a divisional manager at the segment (in months) measured at the time of exit. z-statistics, reported in parentheses, are based on standard errors that allow for clustering at the firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Cox Hazards Regressions		Logit Regressions	
Dependent Variable	Segment Exit	Company Exit Conditional on Segment Exit	Segment Exit	Company Exit Conditional on Segment Exit
Model	(1)	(2)	(3)	(4)
Social Connections$_{t\text{-}1yr}$	-0.122*	-0.108	-0.197**	-0.170*
	(-1.72)	(-1.25)	(-2.27)	(-1.72)
Mismatch$_{t\text{-}1yr}$	0.189***	0.159**	0.020	-0.034
	(2.81)	(2.10)	(0.23)	(-0.34)
Social Con.$_{t\text{-}1yr}$ x Mismatch$_{t\text{-}1yr}$	0.122***	0.130**	0.149***	0.147**
	(2.87)	(2.49)	(2.91)	(2.32)
Retirement Age$_{t\text{-}1yr}$	0.853***	0.880***	1.470***	1.384***
	(5.32)	(4.67)	(4.53)	(4.42)
Tenure at Segment			-0.018***	-0.015***
			(-5.81)	(-4.36)
N	692	692	692	692

Table 9: Excess Value and Segment Diversity

The table reports differences-in-means estimates for *Excess Value*, measured as the natural logarithm of the ratio of the conglomerate actual value to its imputed value (Berger and Ofek (1995)). A conglomerate actual value is the market value of assets, which is equal to the market value of equity minus book assets and book value of debt. A conglomerate imputed value is the sum of the imputed values of its segments, where each segment's imputed value is equal to segment's sales multiplied by the sales multiple (median market value of assets-to-sales ratio of all single-segment firms in a segment two-digit SIC industry). *High- (Low-) Connected Firm* is an indicator that equals one (and zero otherwise) if the Average Segment Connections is above (below) the sample median, where *Average Segment Connections* is a sum of a number of social connections of divisional managers across all segments scaled by a number of business segments in the given firm-year. *High (Low) Diversity* is an indicator that equals one (and zero otherwise) if the Segment Diversity is above (below) the sample median, where *Segment Diversity* is the standard deviation of asset-weighted segment Qs divided by equally weighted average segment Qs in a firm. *** denotes statistical significance at the 1% level.

Firm Value and Segment Diversity

	High-Connected Firm	Low-Connected Firm	Difference	t-statistic	
High Diversity (> Median):					
Excess Value	0.128	-0.182	0.311	4.25	***
Low Diversity (< Median):					
Excess Value	-0.065	-0.137	0.073	0.93	

Table 10: Social Connections and Information Asymmetry

The dependent variable in Panel A and in Panel B (in columns (2) and (4)) is *Internal Information Asymmetry*, measured as the difference in trading profits between divisional managers and top-5 corporate managers (Chen, Martin, Wang, Roychowdhury and Billett (2016)). The trading profit is average cumulative market-adjusted abnormal return over the period of six months from the transaction date for open market insider ("opportunistic") trades in a given firm during the current fiscal year. The dependent variable in Panel B (in columns (1) and (3)) is one of the measures of firm connectedness. *Average Segment Connection*s is the sum of Segment Connections of divisional managers across all segments scaled by a number of business segments in the given firm-year. *Asset-Weighted Segment Connections* is the asset-weighted value of Segment Connections in a given firm-year. *Lost Connections* is the cumulative number of connections lost (by divisional managers) due to deaths and retirements of connected managers in the previous fiscal year. *Exogenous Job Openings* is the total number of deaths and retirements of executives in all other firms in the state and industry corresponding to those of the sample conglomerate measured at the previous fiscal year. *Firm Size* is the natural logarithm of the market value of the firm's equity. *Book-to-Market* is book value of common equity divided by the market value of the firm's equity. t-statistics, reported in parentheses, are based on robust to heteroscedasticity standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: OLS Regressions

Dependent Variable	Difference in Trading Profits between Divisional Managers and Top-5 Executives	
Measure of Firm Connectedness	Average Segment Connections	Asset-Weighted Segment Connections
Model	(1)	(2)
Firm Connectedness	-0.014**	-0.016**
	(-2.15)	(-2.08)
Firm size	0.004	0.004
	(1.49)	(1.45)
Book-to-Market	0.077*	0.082*
	(1.75)	(1.84)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
N	307	307
R^2	0.09	0.08

Panel B: IV-2SLS Regressions

Dependent Variable	Difference in Trading Profits between Divisional Managers and Top-5 Executives			
Measure of Firm Connectedness	Average Segment Connections		Asset-Weighted Segment Connections	
	First Stage	Second Stage	First Stage	Second Stage
Model	(1)	(2)	(3)	(4)
Firm Connectedness		-0.067**		-0.099**
		(-2.26)		(-1.98)
Lost Connections	-0.115***		-0.076**	
	(-3.32)		(-2.35)	
Exogenous Job Openings	-0.095**		-0.069*	
	(-2.08)		(-1.73)	
Firm Size	-0.012	0.002	-0.035	-0.001
	(-0.21)	(0.23)	(-0.74)	(-0.13)
Book-to-Market	0.208	0.103	0.088	0.098
	(0.40)	(1.37)	(0.17)	(1.33)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Wald F statistic	15.32		10.19	
Hansen J statistic (p-value)	0.003 (0.95)		0.001 (0.99)	
N	270	270	270	270
R^2	0.85	0.40	0.77	0.40

Table 11: Reverse Causality and Robustness Checks

The table presents the coefficients on main variables of interest from segment-level regressions from Table 3 Panel B. All regressions include the same set of control variables as in Table 3. All variables are defined in Appendix A.. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the segment level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Full Model

Specification	Keeping only Connections Formed Before Current Position			Excluding Divisions Overseen by Multiple Managers			Controlling for Connections to CEO			Controlling for External Manager Connectedness		
Dependent Variable	CAPEX	IA CAPEX	IFA CAPEX	CAPEX	IA CAPEX	IFA CAPEX	CAPEX	IA CAPEX	IFA CAPEX	CAPEX	IA CAPEX	IFA CAPEX
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Social Connections	0.042	0.022	0.033	0.061*	0.039	0.040	0.051	0.027	0.012	0.056*	0.042	0.024
	(1.28)	(0.56)	(0.73)	(1.77)	(1.02)	(0.91)	(1.56)	(0.72)	(0.31)	(1.67)	(1.06)	(0.58)
Tobin's Q	0.031	0.014	0.017	0.035	0.021	0.032	0.033	0.016	0.020	0.032	0.020	0.022
	(0.71)	(0.27)	(0.28)	(0.75)	(0.38)	(0.49)	(0.77)	(0.32)	(0.34)	(0.75)	(0.38)	(0.36)
Social Con. x Tobin's Q	0.081**	0.088**	0.075*	0.079**	0.088**	0.079*	0.082**	0.094**	0.090**	0.082**	0.094**	0.091**
	(2.40)	(2.30)	(1.69)	(2.25)	(2.23)	(1.72)	(2.49)	(2.55)	(2.13)	(2.47)	(2.50)	(2.12)
Connected to CEO							0.089*	0.124**	0.115*			
							(1.69)	(2.04)	(1.67)			
Degree Centrality										0.019	-0.008	0.019
										(0.72)	(-0.27)	(0.55)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2008	2008	2008	1729	1729	1729	2008	2008	2008	1981	1981	1981
R^2	0.49	0.37	0.17	0.49	0.37	0.19	0.49	0.37	0.17	0.49	0.37	0.17

Panel B: Restricted Model

Specification	Keeping only Connections Formed Before Current Position			Excluding Divisions Overseen by Multiple Managers			Controlling for Connections to CEO			Controlling for External Manager Connectedness		
Dependent Variable	CAPEX	IA CAPEX	IFA CAPEX	CAPEX	IA CAPEX	IFA CAPEX	CAPEX	IA CAPEX	IFA CAPEX	CAPEX	IA CAPEX	IFA CAPEX
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Social Connections	0.042	0.022	0.033	0.061*	0.039	0.040	0.051	0.027	0.012	0.056*	0.041	0.023
	(1.30)	(0.56)	(0.73)	(1.77)	(1.02)	(0.92)	(1.57)	(0.72)	(0.31)	(1.66)	(1.06)	(0.58)
Social Con. x Tobin's Q	0.080**	0.088**	0.074*	0.077**	0.087**	0.078*	0.080**	0.094**	0.089**	0.081**	0.093**	0.090**
	(2.40)	(2.30)	(1.69)	(2.26)	(2.25)	(1.73)	(2.49)	(2.56)	(2.14)	(2.47)	(2.51)	(2.13)
Connected to CEO							0.088*	0.123**	0.114*			
							(1.66)	(2.03)	(1.66)			
Degree Centrality										0.021	-0.007	0.020
										(0.79)	(-0.23)	(0.59)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2008	2008	2008	1729	1729	1729	2008	2008	2008	1981	1981	1981
R^2	0.49	0.37	0.16	0.49	0.37	0.19	0.49	0.37	0.17	0.48	0.37	0.17

8 Appendix A. Variables Definitions

A. Segment and Firm Financial Variables

- Capital Expenditure (CAPEX)– Annual capital expenditure of the division (capxs) divided by the division's lagged book assets (ias).
- Industry-Adjusted Capital Expenditure (IA CAPEX)– Annual capital expenditure of the division adjusted for the industry-specific variation in capital expenditures, as measured by the median capital expenditure of single-segment firms in the division's industry (two-digit SIC code), formally presented by the equation below. Here I denotes capital expenditures of segment j, BA denotes book assets, ss denotes single-segment firms in the segment's two-digit industry:

$$\textit{Industry-Adjusted Capital Expenditure} = \frac{I_j}{BA_j} - \frac{I_j^{ss}}{BA_j^{ss}}$$

- Industry-Firm-Adjusted Capital Expenditure (IFA CAPEX)– Industry-adjusted capital expenditure further adjusted for the firm's asset-weighted average of industry-adjusted capital expenditures across all divisions, formally presented by the equation below. Here I denotes capital expenditures of segment j, BA denotes book assets, ss denotes single-segment firms in the segment's two-digit industry, and w_j is the ratio of segment assets to firm assets:

$$\textit{Industry-Firm-Adjusted Capital Expenditure} = \frac{I_j}{BA_j} - \frac{I_j^{ss}}{BA_j^{ss}} - \sum_{j=1}^{N} w_j \left(\frac{I_j}{BA_j} - \frac{I_j^{ss}}{BA_j^{ss}} \right)$$

- Tobin's Q (industry) – the median Tobin's Q across all single-segment firms in the segment's two-digit SIC code industry, where the Tobin's Q for single-segment firms is equal to market value of assets (book assets (at) + market value of common equity (csho*prcc) − common equity (ceq) − deferred taxes (txdb)) / (0.9*book value of assets (at) + 0.1*market value of assets).
- High Q (Low Q) segment – division with Tobin's Q above (below) the sample median.
- Segment Size – the natural logarithm of the segment's lagged book assets (ias).
- Segment Relative Size - ratio of lagged segment assets (ias) to lagged firm assets (at).
- Segment Cash Flow – annual operating profit (ops) plus depreciation (dps) divided by lagged book assets (ias).

- Relative ROA – the difference between the industry-adjusted ROA of the division and the average industry-adjusted ROA of other divisions in the firm. Industry-adjusted ROA of a division is the difference between the ROA of the division and the median ROA of single-segment firms in the division's industry (two-digit SIC code).

- Firm Sales – the natural logarithm of the firm's sales (sale).

- Firm Cash Flow – sum of firm's income before extraordinary items (ib) and depreciation (dp) scaled by firm's book assets (at).

- Firm Size - the natural logarithm of the market value of the firm's equity.

- Book-to-Market - book value of common equity divided by the market value of the firm's equity.

- Inverse of Average Q – inverse of equally weighted industry Tobin's Q over segments of the firm.

- CEO Ownership – percent of the firm's outstanding stock hold by CEO.

- Excess Value – the natural logarithm of the ratio of the conglomerate actual value to its imputed value. A conglomerate actual value is the market value of assets, which is equal to the market value of equity minus book assets and book value of debt. A conglomerate imputed value is the sum of the imputed values of its segments, where each segment's imputed value is equal to segment's sales multiplied by the sales multiple (median market value of assets-to-sales ratio of all single-segment firms in a segment two-digit SIC industry).(Berger and Ofek (1995))

- Relative Value Added by Allocation – the sum of the weighted Industry-Firm-Adjusted Capital Expenditure across all segments of a firm in a given year (Rajan, Servaes and Zingales (2000)).

- Segment Diversity – standard deviation of asset-weighted segment Qs divided by equally weighted average segment Qs in a firm (Rajan, Servaes and Zingales (2000)). Here q denotes industry Tobin's Q of segment j, and w_j is the ratio of segment assets to firm assets:

$$\textit{Segment Diversity} = \frac{\sqrt{\sum_{j=1}^{N} \frac{(w_j q_j - \bar{wq})^2}{n-1}}}{\frac{\sum_{j=1}^{N} q_j}{n}}$$

- Internal Information Asymmetry (IIA) – difference in trading profits between divisional managers and top corporate managers (Chen, Martin, Wang, Roychowdhury and Billett (2016)). The trading profit of divisional managers is average cumulative market-adjusted abnormal return over the period of six months from the transaction date for the division managers' open market insider trades in a given firm during the current fiscal year. The trading profit of top corporate managers is average cumulative market-adjusted abnormal return over the period of six months from the transaction date for the top corporate managers managers' open market insider trades in a given firm during the current fiscal year. The group of top corporate managers includes top-5 executives: CEO, Chairman, Vice Chairman, CFO, COO. We consider only "opportunistic" trades. In calculating the abnormal return for open market sale transactions, we take the opposite sign.

B. Manager Variables

- Board Member – an indicator that equals 1 if a divisional manager is a member of the board of directors in a company in a given year.
- High Salary – an indicator that equals 1 if a divisional manager is reported by ExecuComp among firm's five executives with a highest salary.
- Retirement Age - an indicator that equals 1 if a divisional manager's age is above 60 years old in a given year.
- Long Tenure – an indicator that equals 1 if the tenure of a divisional manager in the company is more than 10 years.
- Senior Title – an indicator that equals 1 if a manager's role description on BoardEx includes "senior" or "executive".
- Ivy League – an indicator that equals 1 if a divisional manager graduated from an Ivy league school.
- Tenure at Segment – total tenure of a manager at the segment (in months).

C. Connections Variables

- Social Connections – an absolute number of social connections of a divisional manager in a given firm-year.
- Average Segment Connections – a sum of Segment Connections of divisional managers across all segments scaled by a number of business segments in the given firm-year.
- High (Low) Segment Connections – an indicator that equals 1 if segment connections are above (below) the sample median.
- Asset-weighted Segment Connections – asset-weighted value of Segment Connections in a given firm-year.
- High- (Low-) Connected Firm – an indicator that equals one (and zero otherwise) if the Average Segment Connections are above (below) the sample median.

- Mismatch – an absolute value of difference between two ranks: rank of social connections of a divisional manager and segment's (which this manager operates) rank on Tobin's Q.
- Connected to CEO - an indicator that equals 1 if a divisional manager has at least one social connection (through prior employment or education) to CEO in a company in a given year.
- Degree Centrality – degree centrality for a divisional manager in a given year, measured in percentiles (1 to 100), and based on employment network formed in quoted and private companies in North America.
- Eigenvector Centrality – eigenvector centrality for a divisional manager in a given year, measured in percentiles (1 to 100), and based on employment network formed in quoted and private companies in North America.

CHAPTER 2: THE EFFECT OF SOCIAL CONNECTIONS ON CAPITAL STRUCTURE IN SUPPLIER-CUSTOMER RELATIONSHIPS

1 Abstract

Using a matched supplier-customer sample of U.S. firms, we examine capital structure decisions of suppliers with social connections to major customers, which invest in relation-specific assets. Suppliers connected to major customers with relation-specific assets have higher debt ratios. To establish causality, we use top executives' turnovers at the customer firms as exogenous shocks to supplier connections. We document that following the turnover supplier firms significantly reduce debt ratios. We propose two explanations for this result. Consistent with the role of connections in bonding trading parties' commitment, connections to major customers help to increase customer purchases and support longer business relationships. Consistent with the role of connections in mitigating information asymmetry, connected suppliers choose higher debt only when information asymmetry is high. In addition, building up debt helps suppliers to reduce underleverage and move faster toward target leverage ratios. Overall, our results are consistent with the view that connections help to strengthen implicit contracts through establishing trust between trading parties.

2 Introduction

There is a large stream of literature that studies the choice of capital structure in the presence of relation-specific investments (e.g. Titman (1984), Maksimovic and Titman (1991), Kale and Shahrur (2007), Banerjee, Dasgupta and Kim (2008), Hennessy and Livdan (2009), Chu (2012)). Theoretical arguments imply that suppliers choose lower levels of debt, because customers with investments in relation-specific assets will suffer direct costs if the supplier goes bankrupt (Titman (1984)) and customers are reluctant to deal with supplier who may not have incentives to maintain reputation (Maksimovic and Titman (1991)). Kale and Shahrur (2007) and Banerjee, Dasgupta and Kim (2008) find empirical support for these arguments and show that firms use decreased leverage to commit to business partners who undertake relationship-specific investments. High debt increases the risk of bankruptcy and firm distress costs, so firms choose lower debt to signal their business partners about their financial heath and stability of long-term relationships. In this paper we build up on this literature and focus on the bilateral social connections between executives of customer and supplier firms. Our research question is how social connections to customers who undertake relation-specific investments affect capital structure decisions of suppliers. We focus on studying capital structure decisions of dependent suppliers, because they are much smaller than customers, and the loss of the major customer may substantially damage the dependent supplier financial health.

On one hand, there are several reasons why we may observe the positive effect of connections to major customers with relation-specific investments on the suppliers' capital structure. First, connected suppliers are more likely to pursue riskier financial policies if they know that the relationship with the customer with relation-specific investments is stable. We build our intuition on the vast literature in sociology and economics, which shows that connections can create trust between connected individuals (e.g. Coleman (1988), Nahapiet and Ghosal (1998), Woolcock (1998), Putnam (2000), Karlan, Mobius, Rosenblat, and Szeidl (2009)) through building so-called "social collateral" (or "credit slip"), which serves similar to physical collateral securing borrowing-lending transactions. The break of contracts may incur personal and firm reputational damage (Brass and Labianca (2006), Karpoff and Lott (1993)), so social connections between customer and supplier firms are likely to decrease the probability that each firm will behave opportunistically toward its partner. When social connections promote trust between trading parties, suppliers in multiperiod settings will maintain their reputation for future sales (and, for example, will not reduce the quality of the products), because cheating will have monetary and social costs. Thus, connections allow the suppliers to take more debt, because they are confident in the future stability of the relationship and repayment of the debt. We label this channel as *bonding* channel.

Second, personal connections can mitigate the information asymmetry between parties in supply-chain relationship (Chen, Levy, Martin, and Shalev (2017)) by transmitting hard and soft information and lowering monitoring costs. Moreover, recent studies have provided evidence about the role of social connections in mitigating information asymmetries in financial decisions (e.g. Cohen, Frazzini and Malloy (2008), (2010), Duchin and Sosyura (2013)). Socially connected customer and supplier are likely to interact more frequently than unconnected parties, and more intensively - even outside their formal business relationship. Frequent interactions will facilitate information transfers between parties (e.g. through communication or factory site visits), thereby mitigating information asymmetry. Thus when suppliers have connections to customer firms, the customer firms are likely to have greater access to information about financial health of their suppliers and can better evaluate the risk of potential bankruptcy. If social connections to customers with investments in relation-specific assets reduce costs of monitoring, then dependent suppliers will choose higher level of debt. We refer to this channel as *information asymmetry* channel.

On the other hand, there are reasons to believe that connections to major customers with relation-specific assets may lead to lower debt. This happens, for example, if debt is used to protect profits from expropriation (e.g. Bronars and Deere (1991)). The threat of surplus renegotiation leads to *ex ante* underinvestment in specific assets (Grossman and Hart (1986), Hart and Moore (1990)). Higher debt helps to "shield" profits and reduce the amount of profits that could be expropriated. In our setting, social connections while promoting trust between parties could lower the likelihood of aggressive renegotiation. We label this channel as *bargaining* channel.

We use BoardEx to calculate the connections between senior managers of customer and supplier firms. We consider two people as being connected if they participated in the same organization at the same time in the past. To account for potential reverse causality when business relationship leads to a formation of connections, we focus only on past connections formed at third-party organizations (e.g. universities, past employment). We additionally exclude connections that we formed after the start of the customer-supplier business relationship as a robustness check. We take information from Compustat Segment files and use the combination of manual and automated procedures to identify the major customers (customers with more than 10% of supplier sales).[21]

Using a matched supplier-customer sample of U.S. firms, we find a strong support for a positive effect of social connections on market leverage of suppliers. We document that suppliers connected to key R&D-intensive customers choose higher book and market leverage. The effect of connections to key R&D-intensive customers on the leverage is economically meaningful. We estimate that for a median firm, an increase in market leverage due to connections compensates for approximately the half of the leverage decline due to customers' R&D investments.

Our results hold even after controlling for potential endogeneity concerns. While we use supplier fixed effects to account for supplier-level unobservable factors, one needs to rule out all other potential explanations. For example, the allocation of certain types of suppliers across customer firms is not random, and suppliers' leverage choices could be a function of customer characteristics. Specifically, Demirci (2016), Lian (2017) and Oliveira, Kadapakkam and Beyhaghi (2017) show that customer financial health affects the leverage of the supplier. To address the endogeneity concerns we use two independent approaches. The first one is the event study, when we use turnovers of key executives (CEO, CFO or COO) at the customer firms as exogenous shocks to supplier connections. These shocks are likely to be exogenous to the managers' connections at the supplier firms, because on average the purchases from a particular supplier constitute less than 3% from customer total purchases. The turnovers of key executives at the customer firms are likely to lead to a loss or break of social connections that suppliers have formed with the customer firms. Using difference-in-difference research design, we compare changes in leverage ratios of the connected suppliers that have lost connections to the changes in leverage ratios of the connected suppliers to the *same* customer that did not lose any connections as a result of

[21]Because relationship-specific investments are unobservable, we follow a common approach in the literature and use firm's research and development (R&D) expenditures as a proxy for relationship-specific investments (e.g. Titman and Wessels (1988), Allen and Phillips (2000), Banerjee, Dasgupta and Kim (2008)). R&D expenditures include expenses incurred in research and development of the product, reflecting firm's innovation effort. When a supplier (customer) firm makes relation-specific investments in a partner, it tends to produce unique and customized products that have no close substitutes (Titman and Wessels (1988), Banerjee, Dasgupta and Kim (2008)).

the turnover at the customer firm. Comparing suppliers for the same customer allows us to keep the quality of the customer (observed and unobserved) constant. We show that suppliers with R&D-intensive customers experience significant drops in leverage ratios following the loss of the connections.

The second approach is the propensity score matching, where we match connected and unconnected suppliers to eliminate differences in observable characteristics. We repeat our baseline tests on the sample of suppliers, which are similar across all key characteristics, but differ only in being connected to their customer. We show that our results that connections to R&D-intensive customers positively affect supplier's leverage continue to hold. In addition, we address the potential reverse causality problem, when existing business relationships facilitate the formation of social connections between trading partners. We exclude connections formed after the start of the business relationship between suppliers, and our baseline results continue to hold.

We next study the potential explanations for the positive effect of connections to R&D-intensive customers on leverage. Consistent with the *bonding* channel, connected suppliers are likely to increase leverage when trading relationships are more intense and last longer. To test this channel, we first show that after controlling for firm fixed effects suppliers connected to key customers indeed have higher sales to these customers. In addition, using Cox proportional hazard model we find that business relationships tend to last longer for suppliers connected to key customers. These effects are stronger in the subsamples of suppliers with connections to R&D-intensive customers. Second, we find that the effect of connections to R&D-intensive customers on market leverage is significantly stronger when relationship between supplier and customer is intense and lasts longer. Overall, these results strongly support the bonding channel that connected suppliers are likely to increase debt when they are confident in the stability of the relationship.

We also find support for the *information asymmetry* channel and show that the effect of social connections to R&D-intensive customers is stronger when information asymmetry between customer and supplier is high. We use geographical distance between supplier and customer locations to measure information asymmetry. Higher distance is associated with higher costs of access to information and higher monitoring costs (Giroud (2013), Costello (2013)). Since social connections facilitate communication between parties and help to decrease the information acquisition costs, social connections should be more important when customers and suppliers are located far away from each other. We compute average geographical distance between supplier and its key customers by averaging the distances between the headquarters location of supplier and that of each of its customers. Consistent with our expectations, we find that the positive effect of social connections to R&D-intensive customers on market leverage is significant only when supplier is located far away from the customer. Overall, these results imply that connections may serve a channel for reducing information asymmetry between trading parties.

To provide a better picture of the effect of connections on leverage, we perform a set of tests examining the deviation from the target capital structure. If connections indeed promote bonding and resolve information asymmetry issues, then we might expect that taking extra debt does not "push" the supplier towards financial distress. Consistent with this expectation, we find that suppliers connected to R&D-intensive customers are likely to optimally increase debt. Specifically, we observe that as customers increase R&D investments, connected suppliers significantly reduce underleverage, while unconnected suppliers significantly increase underleverage. Consistent with our channels, we interpret this evidence as connected suppliers being able to move closer to optimal (target) debt levels.

Our study contributes to the emerging research on the role of social connections in customer-supplier relationships. To our knowledge, we are the first to focus on the effect of social connections between customers and suppliers on supplier capital structure decisions. We extend the work of Chen, Levy, Martin, and Shalev (2017), who study how social connections affect the selection of suppliers and contractual terms between suppliers and customers, and the work of Dasgupta, Zhang and Zhu (2017), who study the effect of social connections between customers and suppliers on supplier innovation.

Our study is also related to the stream of research on solutions to hold-up problems in customer-supplier relationships. For example, Johnson, Karpoff and Yi (2015) find that IPO firms being heavily dependent on their business partners benefit from using takeover defenses to show commitment to their business relationships. When a firm goes public it becomes an easy target, especially when it is young and small. In case of takeover the management is usually replaced, what can lead to renegotiation of previous informal agreements. The use of takeover defenses helps the firm to commit to its business strategy, and, moreover, to signal to the partner that it values the relationship. The work of Dass, Kale and Nanda (2014) suggests that trade credit can serve as a commitment device between vertically related firms, which invest in relationship-specific assets. In contrast to these studies, we focus on the role of social connections in bonding to partners' contracts.

3 Sample and Data

3.1 Sample and Variable Construction

To construct the sample, we select all firms covered by the Compustat Industry Segment file during the period from 2000 through 2014. According to SFAS No. 131, firms are required to disclose the identity of the principal customer that account for more than 10% of their total sales, and some firms voluntary report the names of the principal customers when sales are below the threshold. We treat all disclosed customers as the principal customers, but exclude customers, whose names are reported as "Customers", "Companies", "Distributors" or "Not reported". We keep firms with non-missing information on sales to major customers. One difficulty in working with Compustat Segment file is to determine whether the customer firm is covered by Compustat/CRSP files, as customer names are often abbreviated.

In matching disclosed customer names with Compustat/CRSP files we follow (Fee and Thomas (2004)) and use a combination of automated and manual procedures. Specifically, we first match each customer name with several potential Compustat firms, based on customer name spelling. Then we manually check and confirm each match based on corporate names and industry classification. If the customer is a subsidiary of a publicly traded firm, then we assign to the customer the identifier of the parent corporation. We tend to be conservative in our matching of customer names to firm identifiers to ensure that disclosed customers are matched to correct Compustat firms.

Following previous studies of capital structure determinants (e.g. Berger, Ofek and Yermack (1997), Kale and Shahrur (2007)), we exclude financial firms (SIC codes between 6000 and 6999) and utilities (SIC codes between 4900 and 4999). We then require that each customer-supplier pair is present in BoardEx database. BoardEx provides information on work and educational histories, board memberships and non-profit organization memberships, as well as information on bilateral social connections for senior executives. Because prior to 2000 the coverage of BoardEx is limited, we use 2000 as a starting year to mitigate survivorship bias (Engelberg, Gao and Parsons (2013)). We use CIK identifier to match BoardEx and Compustat databases. For cases, when CIK was not provided, we used a string matching procedure to match company names from both databases. To ensure the quality of the matching procedure, we manually checked all matches and made necessary corrections.

Finally, we require that both suppliers and customers have non-missing financial information. Firm-level financial variables are obtained from Compustat and CRSP databases. To eliminate outliers, we trim the sample by excluding observations with market and book leverage greater than 1, firm cash flow (to total assets) greater than 1 or less than -1, firm's Tobin's Q greater 10 and then winsorize all variables at the 1st and 99th sample percentiles. The final sample consists of 1219 unique supplier firms, 493 customer firms and 5374 supplier firm-year observations.[22]

We use two measures of financial leverage as common in the literature (e.g. Baker and

[22]The sample size implies 4.4 observations on average per firm per year. This smaller number of observations relative to the sample duration from 2000 to 2014 is for two reasons. First, the need to match with BoardEx, where we require that both supplier and customer firms not only be present in the database, but the composition of executives be covered in the "Summary" files for both firms in a given year. Our sample size is substantially reduced because for early 2000s the coverage of BoardEx is still limited, and we drop supplier-customer pair in a given year if either firm is not represented in terms of composition of managers. Second, we aggregate the observations by supplier firm for all customers of a given supplier. As a result, our sample is not by pair-level, but by supplier firm-level. Later, in section 3.2.1 we describe our empirical model.

Wurgler (2002), Lemmon, Roberts, and Zender (2008)). The first one, *Market Leverage,* is equal to the sum of book values of long-term debt and debt in current liabilities divided by the sum of book value of debt and market value of common equity. The second one, *Book leverage,* is the sum of book values of long-term debt and debt in current liabilities divided by book value of assets.

The data on social connections are obtained from BoardEx. Following the extensive literature, we base our measure of social connections on employment, educational and social ties between senior managers of supplier and customer firms. We focus only on connections formed between executives that potentially participate in supply chain decisions: specifically, we restrict our attention to connections formed between senior managers (e.g. CEO, CFO, COO), excluding board members for the analysis. For example, besides CEO, CFO and COO, we consider the following titles frequently represented in our sample: "Senior Vice President", "Vice President", "Division VP/President", "General Manager", "Executive VP". We consider two people as being connected if they participated in the same organization at the same time in the past. For example, we would classify two executives as being connected if they both previously worked at the same public or private company. Because the business relationship between customer and supplier may lead to a formation of the connections between them, we require the employment connections be formed only at third-party companies. Similarly, two executives would share an educational connection if they both studied in the same university or were members of professional/social clubs during the same period of time in the past. The overwhelming majority of connections (about 94%) comes from employment or board memberships in public or private companies, about 4% - are educational connections and the remaining connections (about 2%) - are connections formed through memberships in professional organizations and social clubs.

We compute our measure of connections similar to Ishii and Xuan (2014). For each supplier-customer pair we count the number of connected pairs of individuals composed of one member of the supplier firm and one member of the customer firm. Then we compute *Connections to Key Customer* by dividing the number of connected pairs by the total number of pairs that exist between individuals of customer and supplier firms.

3.2 Descriptive statistics

Table 1 shows the summary statistics of variables we used in the empirical analysis. As shown in Panel A the mean market leverage of the supplier is 17% and the share sales to key customers is about 27%. Customers are much greater in size (as measured by book value of assets and market capitalization) than suppliers, and the ratio of the median book assets of the customer to that of the supplier indicates that customer is about 64 times bigger than the median supplier. An average supplier invests about 7% of the book assets in R&D, and average *Key customers R&D* (defined as the sum of R&D-intensities of key customers weighted by the percentage of sales to these customers) is about 0.01 and consistent with the values reported in Kale and Shahrur (2007). Overall, the descriptive statistics of the independent variables show that firms in our sample differ significantly across characteristics of suppliers and their customers.

About 60% of suppliers are connected, and for the sample of pairs of suppliers and customers the average *Connections to Key Customer* is about 0.01 suggesting that on average six connections exist between a typical supplier and customer firms in our sample.[23] In panel B we report the numbers by subsamples based on existence of *Connections to Key Customer* between supplier and customer. We define an indicator variable *Connected* equals one if *Connections to Key Customer* is positive, suggesting that a supplier has a least one connection with its key customer(s). Connected suppliers have higher level of market and book leverage, higher book value of assets, invest more in R&D, are less risky (as measured by standard deviation of ROA for the previous 10 years) than unconnected suppliers. Connected suppliers differ from unconnected suppliers along their customers' characteristics. For example, connected suppliers have higher number of major customers, sell a higher share of their sales to their major customers than unconnected suppliers, and have key customers with greater R&D-intensity. The differences are significant at 1%. The summary statistics suggest that there are significant differences between connected and unconnected suppliers, and in our empirical analysis we account for this differences, first,

[23]Given that the average [median] network size (number of non-board executives) of a supplier firm in our sample is 16 [13], and the average network size of the customer firm is much larger than that of a supplier with the average [median] number of executives of 39 [33].

by explicitly controlling for this differences in our regression analysis and, second, by using propensity-score matching to create similar subsamples of connected and unconnected suppliers across these characteristics.

4 Empirical Strategy and Results

4.1 Univariate Results

Table 2 compares the mean values of measures of financial leverage for the connected and unconnected subsamples. Panel A (B) reports the mean values of market (book) leverage across terciles of *Key Customers R&D* and between connected and unconnected subsamples. There are several observations from this table. First, the market and book leverage almost monotonously decline with the increase in *Key Customers R&D*, consistent that firms decrease leverage when they have customers investing in relation-specific assets (Kale and Shahrur (2007)). The decline in leverage across terciles of *Key Customers R&D* is observed for connected (t=7.49 and t=10.11 for market and book leverage, respectively) and for unconnected suppliers (t=8.25 and t=8.91). Second, in every tercile of *Key Customers R&D* the market leverage for connected suppliers is significantly higher than for unconnected suppliers. The differences persist at 1%. The similar picture is observed for the book leverage. These results suggest that cross-firm social connections are associated with higher debt levels for suppliers whose major customers undertake relation-specific investments.

4.2 Multivariate Analysis

4.2.1. Empirical Model

To test how connections to key customers that undertake relation-specific investments affect the firm leverage, we estimate the following regression model:

$$\begin{aligned} \textit{Supplier Debt}_{it} = \beta_1 \textit{Connections to Key R\&D-intensive Customers}+ \\ +\gamma X_{it-1} + \zeta_i + \delta_t + \epsilon_{it} \end{aligned} \tag{4}$$

where $\textit{Supplier Debt}_{it}$ is a market (book) leverage of supplier i in fiscal year *t*, *Connections to Key R&D-intensive Customers* is the sum of connections between supplier i and each of its key customer weighted by R&D intensities and sales to these customers measured at the fiscal year *t-1*. The regression also includes a set of control variables X_{it-1}, firm fixed effects ζ_i, and year fixed effects δ_t. We include firm fixed effects to account for cross-firm heterogeneity (such as strategy, managerial talent) that could potentially affect the amount of debt the firm takes. The year fixed effects help to account for macroeconomic factors that could affect the leverage decisions of sample firms. Because the unit of observation is supplier firm-year, we adjust standard errors for heteroscedasticity and cluster at firm (supplier) level.

Our main variable of interest is *Connections to Key R&D-intensive Customers* is computed in the following way:

$$\begin{aligned} \textit{Connections to Key R\&D-intensive Customers} = \sum_{j=1}^{n} (\textit{Connections to Key Customer}_j \\ \times \textit{Key Customer R\&D}_j \times \textit{Sales to Key Customer}_j) \end{aligned}$$

here *n* is the number of customer firms, $\textit{Connections to Key Customer}_j$ is the total number of connections between executives of supplier and customer firms scaled by the total number of possible executives' pairs (see the discussion of this measure in section 2.1), $\textit{Key Customer R\&D}_j$ is equal to the R&D expense (scaled by total assets) of the jth customer, $\textit{Sales to Key Customer}_j$ is the percentage of firm's sales to the jth customer.

The intuition behind this measure is similar to that of the measure of weighted R&D intensities of all major customers introduced in Kale and Shahrur (2007). If the supplier expects that customers will undertake relation-specific investments, supplier will choose the level of debt to be dependent on connections *to all* key R&D-intensive customers.

Because Kale and Shahrur (2007) shows that suppliers' leverage depends on R&D intensities of all major customers, we explicitly include this variable in the model (1). *Key Customers R&D* is a sum of sales-weighted R&D intensities of all major customers for a supplier firm in a given year:

$$\textit{Key Customers R\&D} = \sum_{j=1}^{n} (\textit{Key Customer R\&D}_j \times \textit{Sales to Key Customer}_j)$$

Other control variables include variables that are known to affect the leverage (e.g. Berger, Ofek and Yermack (1997), MacKay and Phillips (2005), Kale and Shahrur (2007), Lemmon, Roberts, and Zender (2008)). These variables include: *Size* (natural logarithm of total assets), *ROA* (operating income divided by total assets), *Fixed Assets* (net property, plant and equipment divided by total assets), *R&D* (research and development expenditures divided by total assets), *SGA* (selling, general and administrative expenses divided by total assets), *Tobin's Q* (book value of assets plus the market value of common equity minus the book value of common equity divided by book value of assets), *Volatility* (rolling standard deviation of ROA for the previous 10 years relative to a given year), *Non-Debt Tax Shields* (investment tax credit divided by total assets).

4.2.2. The Effect of Connections to Key R&D-intensive Customers on Dependent Suppliers Leverage: Baseline Results

Table 3 reports the results of estimation of equation (1). First, the results show the coefficient on *Key Customers R&D* is negative and significant at 1%, suggesting that suppliers decrease leverage when they have R&D-intensive customers. This result is similar to Kale and Shahrur (2007), who show that firm's leverage is negatively related to R&D intensities of its customers and suppliers. Second, the connections to R&D-intensive customers increase the leverage. For example, as Panel A column (1) shows the coefficient on *Connections to Key R&D-intensive Customers* is positive and significant at 5%. In column (2) we report the results of regressions, in which industry fixed effects (based on 2-digit SIC industry classification) are added. We include industry fixed effects to account for time-invariant industry differences in leverage. The coefficient on *Connections to Key R&D-intensive Customers* remains positive and becomes significant at 1% (t = 2.73). Column (3) reports the results of regressions with firm fixed effects added. And again, the coefficient on *Connections to Key R&D-intensive Customers* is positive and significant at 1% (t = 2.59). It's worth to note that firm fixed effects can also absorb slow-changing cross-firm differences in corporate governance (investor protection, antitakeover laws, etc.), since R&D expenses can be correlated with the quality of a supplier corporate governance (John, Litov and Yeung (2008), Sapra, Subramanian and Subramanian (2014)).

The effect is economically meaningful. To evaluate the economic significance we first estimate the portion of change in the main explanatory variable *Connections to Key R&D-intensive Customers* due to change in the first component - when *Connections to Key Customer* moves from the 5th percentile value to the 95th percentile value, holding *Key Customer R&D* and *Sales to Key Customer* at their sample means. Next we compute the change in market leverage due to change of *Connections to Key R&D-intensive Customers* caused by change in connections. For example, using the estimated coefficient in column (2), we find that when *Connections to Key Customer* moves from the 5th percentile value to the 95th percentile, the *Connections to Key R&D-intensive Customers* increases by 0.045, what corresponds to leverage increase by 0.01 or by 10% for a median firm. Further, to better evaluate the economic significance, we compute the drop in leverage associated with the change in *Key Customers R&D*. It turns out that when *Key Customers R&D* moves from the 5th percentile value to the 95th percentile value, market leverage declines by 21% for a median firm.[24] Hence an increase in market leverage due to connections covers approximately the half of the leverage decrease due to customers' R&D investments.

Columns (4) - (6) report nearly identical results for the book leverage. Notably, the estimates on other control variables have predicted signs. For example, higher supplier size and fixed assets are positively related to leverage, because larger firms or firms with higher collateral have lower costs in obtaining debt. Firms with more growth opportunities (higher Tobin's Q) and more

[24]The magnitude of the effect is comparable to estimates in Kale and Shahrur (2007).

risky firms (with higher profit volatility) have to maintain lower leverage. Consistent with the bargaining role of debt, suppliers with more concentrated customers (*Key Customers Industry Concentration*) increase leverage (Kale and Shahrur (2007)). Overall, the results in this section suggest that firms choose higher leverage when they have social connections to business partners who undertake relation-specific investments.

4.3 Potential Endogeneity

While the results in Section 3.2.2 show that there is positive relation between connections to key R&D-intensive customers and leverage, this relation is not necessarily causal. In our baseline regression we control for unobserved factors at the supplier level using firm fixed effects. However, there are still some unobserved factors that could confound our results. The allocation of certain types of suppliers and across customer firms is not random, and suppliers' leverage choices could be a function of customer characteristics. Specifically, Demirci (2016), Lian (2017) and Oliveira, Kadapakkam and Beyhaghi (2017) show that customer financial health affects the leverage of the supplier. This leads to a potential endogeneity, which we address in two ways. First, we employ a difference-in-difference framework and use managers' turnovers at customer firms as exogenous shocks to connectivity. As an alternative strategy, we compare changes in leverage using matched firms with similar characteristics.

4.3.1. Event-Study Approach

In the first approach to establish causality, we focus on a subsample of turnovers of senior managers at the customer firms. Senior managers at the supplier firms who have pre-existing social connections with the departing manager at the customer firm are likely to lose a connection with the customer firm. Hence, as a result of the turnover at the customer firm, the supplier firm may lose connection(s) with the customer firm. At the same time, since the average share of purchases from a particular supplier constitute less than 3% from a customer sales, the turnover of the senior manager at the customer firm is likely to be exogenous to the performance of the supplier firm. Therefore, the result that a loss of connection due to plausibly exogenous shock to supplier firm connectivity would lead to a choice of lower leverage by a supplier firm would provide a causal support for the previously shown positive relation between supplier firm connectivity and leverage.

To show that decrease in the supplier firm connectivity due to a manager turnover in a customer firm results in a decrease in supplier leverage, we identify the senior managers' departures at the customer. Among all senior managers we limit our attention to the departures of CEO, CFO and COO, because these executives hold greater responsibility for the supply chain decisions (than other executives), and hence losing connections to them should affect the leverage of a supplier firm to a greater extent. Next, for each supplier that lost connection(s) due to turnovers in a customer firm we find a supplier who has connections to the same customer firm, but was not affected by the turnover at the customer firm. Following Fracassi and Tate (2012) we use difference-in-difference setup, which allows us to compare the leverage of a treatment group - suppliers who lost connection(s) to the customer firm with the leverage of a control group - suppliers who did not lose any connections while still being connected to the same customer firm. The advantage of this approach is that while comparing the leverage of the connected suppliers to the *same* customer firm, we rule out all confounding factors related to the quality of the customer. We estimate the following model:

$$\begin{aligned} \textit{Market Leverage}_{it} = \beta_1 \textit{After} + \beta_2 \textit{After} \times \textit{Lost Connections} + \\ + \gamma X_{it} + \zeta_i + \delta_t + \epsilon_{it} \end{aligned} \tag{5}$$

where *Market Leverage*$_{it}$ is a market leverage of supplier *i* in fiscal year *t*, *After* is a dummy variable that equals one for the fiscal years after the manager turnover at the customer firm, *Lost Connections* is a dummy variable that equals one if the connected supplier lost connection after the turnover. The key variable is *After* $\times$ *Lost Connections*, which captures the difference in differences effect or change in market leverage for a supplier who lost connection to a customer firm. The coefficient on *After* will show the average within-firm changes in leverage for the unaffected suppliers. We control for the same set of control variables as in our baseline model (1) and supplier firm fixed effects. If the firm experiences multiple events, we include firm-years for all events, but correct for repeating firm-years by clustering standard errors at the supplier firm level. We choose a one-year window centered on the event year (the fiscal year of the turnover) to minimize the possibility that other events will confound the tests.

The results of the tests are reported in Table 4. The odd numbers of columns report the estimates for the suppliers, which customers have high R&D expenses (above the sample median), the columns with even numbers correspond to suppliers with customers with low R&D expenses (below the sample median). The estimate in Column (1) show that the coefficient on *After* $\times$ *Lost Connections* is negative and significant at 5% (t = -2.63). This result suggests that suppliers with R&D-intensive customers choose lower levels of debt in the year following the lost of connection(s) with a C-level executive (CEO, CFO, COO) as a result of the turnover at the customer firm. In contrast, in Column (2) the coefficient on *After* $\times$ *Lost Connections* is not significant and close to zero (t = 0.35), suggesting that suppliers with not R&D-intensive customers do not decrease leverage in the next year they lose connection(s) with an "important" executive at the customer firm. The results in the remaining columns imply that this pattern of results holds after adding industry or firm fixed effects.

4.3.2. Propensity-Score Matching

We supplement our event-based tests with a propensity score matching approach and construct samples of connected suppliers with unconnected suppliers with similar observable suppliers (customers) characteristics. We match connected with unconnected suppliers based on the following variables: *Size*, *Firm R&D*, *Key Customers R&D* and *Percent of Sales to Key Customers*. In the matching procedure we use a propensity score obtained from predicted values from the first stage. For each observation from a connected supplier (in a given year) we search an observation from another unconnected supplier that satisfies the caliper of 0.01. In addition, we limit search to the same 3-digit SIC industry of the connected supplier. This procedure yields 1010 firm-years that cover 294 connected (treated) suppliers matched to 286 unconnected (control) suppliers.[25]

Table 5 Panel A reports the descriptive statistics for the matched and control supplier (customer) samples. The results show that after matching the sample of connected suppliers (customers) became much more similar to the sample of unconnected suppliers (customers). For example, for suppliers there are no significant differences between matched and control groups across all factors that are likely to affect leverage. Panel B reports the results of the regression analysis of the model (1) but on the matched sample. Again as in Table 3, we observe a positive and significant effect of connections to key R&D-intensive customers on the leverage of the dependent suppliers. The results hold for the market and for the book leverage.

Overall, the results in this section support a positive causal long-term and short-term relationship of the connections to key R&D-intensive customers on the leverage of the dependent suppliers.

4.4 Channels of the Effect

4.4.1. Bonding Channel

We have established that firms with connections to R&D-intensive partners maintain higher debt. According to our first explanation, which we refer to as bonding channel, connected suppliers are likely to increase debt, because they can better predict the sales coming from the trustworthy customer and they are confident in the stability of the relationship. If connections affect the leverage through bonding partners' commitment, then we might expect that the effect of connections on leverage is stronger, when the trading relationship is intense and has a long duration. In this section, we first show that connections indeed increase the *intensity* and *duration* of the relationship, and then we derive results about the effect of connections on debt depending on the intensity and duration of the relationship.

[25]The reason for the uneven number of connected and unconnected suppliers is because we match firm-year observations.

We start with gauging the effect of connections on the intensity of the relationship. To measure the intensity of relationship we use *Sales to Key Customers* (sum of sales to key customers divided by total supplier sales), which characterizes the importance of relationship as the degree of dependence on major customers increases when suppliers are selling more to customers (e.g. Banerjee, Dasgupta and Kim (2008), Itzkowitz (2013)). Our major explanatory variable, *Connections to Key Customers* is the sum of sales-weighted connections that the particular supplier has with all its key customers in a given year:

$$\textit{Connections to Key Customers} = \sum_{j=1}^{n} (\textit{Sales to Key Customer}_j \times \textit{Connections to Key Customer}_j)$$

here $\textit{Connections to Key Customer}_j$ is the total number of connections between executives of supplier and customer firms scaled by the total number of possible executives' pairs (see the discussion of this measure in section 2.1).

To empirically estimate the effect of connections to key customers on the intensity of the relationship, we regress the measure of intensity of the relationship on *Connections to Key Customers*. Panel A of Table 6 presents the results. Column (1) shows estimates with industry (2-digit SIC) fixed and column (2) - with firm fixed effects to control for the all unobserved time-invariant factors that could bias our results. In all regressions we adjust standard errors for heteroscedasticity and cluster them by firm. The results in column (1) show that connections to key customers significantly increase purchases by key customers (t = 5.37). After adding firm fixed effects, the coefficient on *Connections to Key Customers* remains positive and significant at 1%. In columns (3) and (4) we study how this effect varies with the R&D-intensity of the customer. The results in these columns suggest that suppliers' connections matter for the sales only when customers are highly R&D-intensive (R&D-expenses are above the sample median).

We next study how connections affect the duration of the business relationship. If social connections encourage relation-specific investment, the business relationship is likely to be maintained for a longer time. We follow Fee, Hadlock and Thomas (2006) and use duration analysis to estimate the hazard function describing the length of the relationship. In our estimation procedure we treat the relationships that last until the last year of the sample period as right censored observations, because we know that the relationship lasted at least until this last year. We assume that the relationship starts in the first year the customer-supplier relationship appears in Compustat segment file and ends when the sample period ends (2014).

The estimates reported in Panel B of Table 6 are the coefficients (not hazard rates) from the estimation of Cox proportional hazard model for the sample, where the unit of observation is supplier-customer pair. The dependent variable is the hazard rate that the relationship between customer and supplier will be terminated in the next year. The main explanatory variable is *Connections to Key Customer*, which is the number of connections between customer and supplier scaled by the possible number of pairs of executives that could exit between two companies. We cluster standard errors at the pair level. Column (1) shows that connections between customers and suppliers significantly reduce the hazard rate of the termination of the relationship, suggesting that connections facilitate longer relationships. The effect is significant at 1%. In column (2) we add controls (lagged one year) that could possibly predict the duration of the relation. The coefficient on connections variable maintains the sign and significance (1%) after adding the controls. The coefficients on controls have predicted signs. For example, higher supplier market leverage increases the risk of the relationship termination through increasing the probability of the supplier bankruptcy. Lower supplier ROA significantly reduces the relationship duration. In column (3) we additionally include industry fixed effects (supplier 2-digit SIC) to account for the unobserved industry variation (for example, industry-specific M&A activity) that could affect both the connections and the duration of relationship (Fee and Thomas (2004)). Again, after adding industry fixed effects our results remain significant at 1%. Finally, in column (4) we examine the role of connections to key customer depending on the R&D-intensity of the customer. The results show that the magnitude of the effect is twice higher for the suppliers with highly R&D-intensive customers (when customer R&D intensity is above the sample median).

Overall, the results show that connections to key R&D-intensive customers is an important factor for the intensity and duration of the business relationship. We next measure how the effect of connections on leverage changes depending on the intensity and duration of the trading relationship. We measure the intensity of the relationship by using *Sales to Key Customers* described above, and we measure *Relationship Duration* by computing the number of years the relationship lasts between supplier and customer. Additionally, we compute *Bonding Index*, which combines two previous measures in one index. To construct the index, we, first, average the firm's percentile rankings according to each of the measures, and then, we scale the index value to range from zero (low) to one (high). For each of the three bonding measures, we classify suppliers into suppliers with high or low degree of bonding. We label high- (low-) bonding suppliers to be suppliers, which have value of the measure at the top (bottom) quartile of the sample distribution. We next replicate the Table 3 using created subsamples. The results are reported in Table 7. Across three measures of bonding the effect of connections to R&D-intensive customers on market leverage is positive and significant only in the subsample of suppliers with high degree of bonding. This suggests that connected suppliers choose higher debt only if relationship is intense and/or has long duration. Results of tests of coefficients of interest (Chi^2-statistics) strongly confirm that the effects are different across the corresponding subsamples.

4.4.2. Information Asymmetry Channel

Extensive research on social connections supports the premise that social connections facilitate communication and decrease information acquisition costs (e.g. Cohen, Frazzini and Malloy (2008), (2010), Duchin and Sosyura (2013)). In the context of customer-supplier relationships Chen, Levy, Martin, and Shalev (2017) show that social connections between two trading parties reduce information asymmetry, because business partners are likely to have greater access to more accurate information about financial health of their respective partners. Hence, consistent with Information Asymmetry channel we argue that partners will be able to choose higher level of debt, because this does not necessarily signal about approaching bankruptcy or severe financial distress. If indeed firms increase leverage, because their partner is better informed about their financial health, then we would expect that the effect of connections on leverage is stronger (weaker) in settings characterized by high (low) information asymmetry.

Following the approach widely accepted in literature, we use geographical distance between supplier and customer locations to measure information asymmetry. Higher distance is associated with higher costs of access to information and, hence, with higher information asymmetry (Giroud (2013)). For example, Costello (2013) using geographical distance between customers and suppliers as a proxy for information asymmetry shows that distance increases the probability of using restrictive financial covenants in the supplier contracts, and her evidence suggests that financial covenants can mitigate information asymmetry. Since social connections facilitate communication between parties and help to decrease the information acquisition costs, they also substitute for formal contractual terms (Chen, Levy, Martin, and Shalev (2017)). Therefore, we expect that social connections should be more important when information gaps are larger or, in other words, when customers and suppliers are located far away from each other.

Distance is computed as an average geographical distance between a supplier and its key customers, measured in miles. The average distance is computed by averaging the distances between the headquarters location of supplier and that of each of its customers. We compute the distance using latitude and longitude coordinates for the addresses of the supplier (customer) headquarters obtained from the U.S. Census Bureau's Gazetteer City-State File. We then apply the formula to calculate the distance between two points on Earth's surface. customers. As shown in Table 1, the mean (median) geographical distance between the supplier and customer pair is 970 (738) miles, and the mean (median) distance between supplier and its key customers is 953 (850) miles, what is similar to estimates shown in Chu, Tian and Wang (2018) and Dasgupta, Zhang and Zhu (2017).[26]

Again, we replicate the results of Table (3) by subsamples of suppliers divided by the degree of information asymmetry (measured by distance). Consistent with our expectations, the results in Table 8 show that the coefficient on *Connections to Key R&D-intensive Customers* is significant at 5%, and its magnitude is higher in the subsample of the suppliers located far away from their

[26]For example, Dasgupta, Zhang and Zhu (2017) find that the mean (median) geographical distance between customer and supplier is 984 (772) miles.

major customers. The magnitude of the coefficient is approximately four times larger in the subsample of high-distance suppliers than that in the subsample of low-distance suppliers, and the test of coefficients between two subsamples reveals that the difference between these two coefficients is significant at 10%. Overall, these results provide the evidence that information asymmetry can explain our results.

4.4.2. Leverage Adjustment Analysis

If connections indeed lead to leverage increase through promoting bonding and resolving information asymmetry issues, then we expect that this increase is beneficial for the supplier, because, for example, extra funds allow it to invest more. Hence, in another set of tests we check whether firms increase debt optimally. It has been well established that firms can deviate from the target capital structure, and the leverage deviation is costly for the firms. The commitment role of debt implies that the existence of R&D-intensive customers pushes suppliers to maintain low-leverage policy (Kale and Shahrur (2007), Banerjee, Dasgupta and Kim (2008)), and these lower levels of debt could be suboptimal. If connected suppliers tend to increase debt, then it is natural to study whether they lever up to move close to optimal debt ratios, thereby reducing underleverage caused by the commitment to key R&D-intensive customers.

To measure the leverage deviation from the optimal level, we use a two-step estimation procedure similar to that used in previous studies (e.g. Frank and Goyal (2007), Uysal (2011)). On the first step, we estimate the target ratio by running annual cross-section regressions of market leverage on its determinants widely studied in literature (e.g. Frank and Goyal (2007), Kayhan and Titman (2007), Lemmon, Roberts, and Zender (2008)). On the second step, we compute deviation from the target. We begin by estimating the target leverage by running yearly regressions of market leverage on known determinants:

$$\textit{Market Leverage}_{it} = \beta' X_{it-1} + \epsilon_{1t} \tag{6}$$

The set of control variables X_{it-1} includes: *Industry Leverage* (median industry leverage), *Profitability* (operating income scaled by assets), *Tobins's Q*, *Fixed Assets*, *Size* (the natural logarithm of total assets), *Inflation* (the natural logarithm of CPI), *Depreciation* (depreciation expenses scaled by total assets), *R&D Intensity* (R&D expenses scaled by total assets), *Positive R&D Intensity* (indicator of positive R&D expenses). In estimation we construct separate cross-section samples, consisting of all firms in Compustat universe in a given year. Following previous literature, we exclude foreign firms, subsidiaries of firms, utilities and financial firms. To minimize the effect of outliers on our results, we further drop observations with abnormal cash flows scaled by assets (less than -1 or greater than 1) and Tobin's Q greater than 10. We also winsorize all variables at the 1% and 99% levels.

Next we compute the market leverage deviation defined as the difference between the actual market leverage and the target market leverage. Consistent with the empirical approach adopted in previous studies, the target market leverage is the fitted values from the equation (3). Panel A of Table 9 shows the descriptive statistics for the market leverage deviation. The mean market leverage deviation is negative for the sample firms (-0.024), suggesting that the average sample firm is underleveraged. This is consistent with previous studies showing that many firms follow a low-leverage policy (e.g., Molina (2005), Devos, Dhillon, Jagannathan and Krishnamurthy (2012), Strebulaev and Yang (2013)).

In Panel B of Table 9 we compare the mean deviation from the target for connected and unconnected firms across terciles of customers' R&D. Notably, in the second and third terciles of *Key Customers R&D* connected suppliers are less underleveraged than unconnected suppliers with differences significant in two terciles at 5% and 1% levels respectively. The differences in deviation from target increase with *Key Customers R&D*. As we move from the 1st to the 3rd tercile, we observe two different trends for connected and unconnected firms. Connected firms are able to reduce the deviation (by taking more debt), but unconnected firms, on the other hand, increase the deviation from the target (by reducing debt). The differences between the 1st and the 3rd terciles are significant at 1% level for connected firms. Overall, these results imply that connections between supplier and customer firms are beneficial for supplier firms by allowing them to move closer to the optimal level of debt.

4.5 Reverse Causality

Common concern in studies about personal connections is the reverse causality. In our setting, this suggests that the business relationship facilitates creation of social connections. For example, people knowing each other as executives of trading partners are more likely to interact beyond the business relationship (attend professional conferences, establish personal contact at MBA program, etc.). To address this concern, we eliminate social connections that were formed after the firms became business partners. From Compustat Segments we additionally collect the start dates of the business relationship between customers and suppliers. Using this filter, we drop only 17% of connections, and the overwhelming majority of connections were formed in distant past. After we replicate the results in Table 3. The results reported in Table 10 are very similar to the baseline results in Table 3, implying that reverse causality is unlikely to drive our results.

5 Conclusion

In this paper we study the relation between suppliers' social connections to R&D-intensive customers and suppliers' capital structure decisions. We find that suppliers with social connections to innovative customers choose higher levels of book and market leverage. To provide the causal support for the effect we use customer firms managers turnovers as exogenous shocks to supplier connections. The turnovers of C-level executives at customer firms are likely to lead to loss or break of social connections that suppliers have formed with the customer firms. Using difference-in-difference research design, we compare changes in leverage ratios of the connected suppliers that have lost connections to the changes in leverage ratios of the connected suppliers to the same customer that did not lose any connections as a result of the turnover at the customer firm. We show significant drops in leverage ratios at the supplier firm following the loss of the connections. We support our findings with additional robustness tests based on propensity score matching and with tests addressing reverse causality.

We also examine the potential mechanisms that may explain these results: bonding of suppliers and customers and reduced information asymmetry between suppliers and customers. Our findings provide support for the both mechanisms. In particular, consistent with the bonding channel, connected suppliers are likely to trade more with major R&D-intensive customers, and the business relationship between suppliers connected to R&D-intensive customers lasts significantly longer. Consistent with information asymmetry channel, we find that the effect of social connections to R&D-intensive customers is stronger when information asymmetry between customer and supplier is higher. In addition, we document that social connections allow suppliers to move closer to optimal debt levels. Overall, we show that social connections that have been formed between managers of supplier and customer firms play an important role in capital structure decisions.

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7 Tables

Table 1: Summary Statistics

The table presents summary statistics for the sample of 1219 unique supplier firms and 493 customer firms between 2000 and 2014, which are covered both by Compustat Segments and BoardEx and have non-missing financial information. Panel A shows the financial characteristics of customers and suppliers, and panel B reports the results of univariate comparisons for the sample partitioned based on whether a supplier is connected to at least one of its major customers. All variables are defined in Appendix A. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Suppliers and Customers

Variable	Mean	25th perc.	Median	75th perc.	St. dev.
Supplier Characteristics (5374 obs.)					
Supplier Market Leverage	0.171	0.002	0.102	0.275	0.197
Supplier Book Leverage	0.183	0.003	0.140	0.303	0.186
Supplier Market Value of Assets, $M	4748	178	679	2697	14639
Supplier Book Assets, $M	2491	116	448	1884	6399
Supplier Sales, $M	2518	93	380	1609	6984
Supplier Capital Expenditure/Assets	0.048	0.016	0.028	0.052	0.062
Supplier Tobin's Q	1.908	1.146	1.522	2.187	1.224
Supplier Return on Assets (ROA)	0.077	0.040	0.107	0.159	0.158
Supplier Fixed Assets	0.223	0.067	0.149	0.289	0.219
Supplier R&D Intensity	0.066	0.000	0.020	0.096	0.103
Supplier Tax Credit	0.001	0.000	0.000	0.000	0.003
Supplier Volatility	0.110	0.035	0.067	0.124	0.140
Supplier Industry Concentration	0.080	0.042	0.059	0.107	0.055
Percent of Sales to Major Customers	0.265	0.126	0.200	0.340	0.201
Number of Customers per Supplier	2.203	1.000	2.000	3.000	1.396
Customer Market Value of Assets, $M	123173	20421	53048	182394	163840
Customer Book Assets, $M	75530	10786	28754	109159	114025
Key Customers R&D	0.007	0.000	0.000	0.006	0.016
Key Customers Industry Concentration	0.044	0.011	0.027	0.058	0.051
Key Customers Change in Sales	0.006	0.000	0.003	0.009	0.013
Customer-Supplier Distance (1000 miles)	0.970	0.318	0.738	1.532	0.796
Average Distance to Key Customers	0.953	0.398	0.805	1.389	0.721
Social Connections:					
Proportion of Connected Suppliers	60.3%				
Connections to Key Customer	0.011	0	0	0.004	0.045

Panel B: Connected and Unconnected Suppliers

Variable	Connected	Unconnected	Diff.	T-stat.	
Supplier Market Leverage	0.185	0.158	0.027	4.949	***
Supplier Book Leverage	0.208	0.161	0.047	9.284	***
Key Customers R&D$_{t-1}$	0.008	0.006	0.002	4.960	***
Supplier Firm Size$_{t-1}$	6.726	5.484	1.241	25.218	***
Supplier Return on Assets$_{t-1}$	0.088	0.078	0.010	2.307	**
Supplier R&D Intensity$_{t-1}$	0.069	0.061	0.008	2.876	***
Supplier Tobin's Q $_{t-1}$	2.078	1.954	0.124	3.191	***
Supplier Volatility$_{t-1}$	0.105	0.114	-0.010	-2.531	***
Number of Customers per Supplier	2.298	2.118	0.180	4.735	***
Percent of Sales to Major Customers$_{t-1}$	0.280	0.252	0.029	5.216	***

Table 2: Univariate Results

The table reports differences-in-means estimates across depending on the terciles of *Key Customers R&D* and by subsamples of *Connected* and *Unconnected* suppliers. *Key Customers R&D* is the sum of R&D intensities of all major customers weighted by the proportion of sales to each customer. *Connected* supplier is a supplier that has least one connection to one of its major customers. *Market Leverage* is equal to the sum of book values of long-term debt and debt in current liabilities divided by the sum of book value of debt and market value of common equity. *Book Leverage* is the sum of book values of long-term debt and debt in current liabilities divided by book value of assets. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Supplier Market Leverage

Variable	Connected	Unconnected	Diff.	T-stat.	
Key Customers R&D (tercile)					
1	0.208	0.180	0.028	3.43	***
2	0.204	0.165	0.038	3.44	***
3	0.144	0.111	0.034	3.93	***
(3)-(1)					
T-stat.	7.49***	8.25***			

Panel B: Supplier Book Leverage					
Key Customers R&D (tercile)					
1	0.244	0.183	0.061	7.94	***
2	0.220	0.172	0.049	4.75	***
3	0.158	0.114	0.044	5.42	***
(3)-(1)					
T-stat.	10.11***	8.91***			

Table 3: The Effect of Connections to Key R&D-intensive Customers on the Leverage of Dependent Suppliers

The table presents the results of supplier-level regressions, in which each observation is supplier firm-year. The dependent variable is *Market Leverage* or *Book Leverage*. *Market Leverage* is equal to the sum of book values of long-term debt and debt in current liabilities divided by the sum of book value of debt and market value of common equity. *Book Leverage* is the sum of book values of long-term debt and debt in current liabilities divided by book value of assets. The key explanatory variable, *Connections to Key R&D-intensive Customers*, is the sum of connections to each major customer weighted by R&D intensities and proportion of sales to each major customer, where connections to each major customer is the number of connected pairs divided by the total number of pairs that exist between individuals of customer and supplier firms. *Key Customers R&D* is the sum of R&D intensities of all major customers weighted by the proportion of sales to each customer. All continuous variables are winsorized at 1% and 99% levels. All other variables are defined in Appendix A. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the supplier firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Market Leverage			Book Leverage		
	(1)	(2)	(3)	(4)	(5)	(6)
Connections to Key R&D-int. Customers	0.204**	0.228***	0.150***	0.211*	0.216**	0.150***
	(2.13)	(2.73)	(2.59)	(1.73)	(2.00)	(2.66)
Key Customers R&D$_{t-1}$	-0.638***	-0.689***	-0.515***	-0.778***	-0.811***	-0.567***
	(-3.49)	(-3.86)	(-2.71)	(-3.67)	(-3.82)	(-2.93)
Key Customers Industry Concentration$_{t-1}$	0.403***	0.328***	-0.013	0.518***	0.352***	0.111
	(4.87)	(4.14)	(-0.13)	(6.23)	(4.40)	(1.18)
Key Customers Change in Sales$_{t-1}$	-0.794***	-0.718***	-0.548***	-0.745***	-0.604***	-0.446**
	(-3.97)	(-3.97)	(-3.07)	(-3.65)	(-3.04)	(-2.29)
Supplier Industry Concentration$_{t-1}$	0.223**	0.043	0.064	0.127	-0.038	-0.086
	(2.16)	(0.27)	(0.40)	(1.21)	(-0.25)	(-0.63)
Supplier Size$_{t-1}$	0.021***	0.017***	0.053***	0.028***	0.024***	0.037***
	(7.82)	(6.30)	(5.88)	(10.50)	(8.87)	(4.30)
Supplier ROA$_{t-1}$	-0.242***	-0.233***	-0.154***	-0.203***	-0.181***	-0.110***
	(-8.96)	(-8.66)	(-5.15)	(-7.05)	(-6.33)	(-3.88)
Supplier Fixed Assets$_{t-1}$	0.178***	0.200***	0.154**	0.209***	0.189***	0.082*
	(6.55)	(5.02)	(2.43)	(8.26)	(5.22)	(1.68)
Supplier R&D$_{t-1}$	-0.322***	-0.251***	-0.025	-0.200***	-0.163***	-0.039

	Market Leverage			Book Leverage		
	(1)	(2)	(3)	(4)	(5)	(6)
	(-7.43)	(-5.78)	(-0.46)	(-4.14)	(-3.45)	(-0.64)
Supplier SGA_{t-1}	-0.015	-0.010	0.005	-0.001	0.010	0.029
	(-0.72)	(-0.46)	(0.15)	(-0.07)	(0.40)	(0.60)
Supplier Tobin's Q_{t-1}	-0.027***	-0.028***	-0.008***	-0.006**	-0.010***	-0.002
	(-12.80)	(-12.34)	(-3.47)	(-2.45)	(-4.08)	(-0.77)
Supplier $Volatility_{t-1}$	-0.057**	-0.048**	0.019	-0.035	-0.032	-0.022
	(-2.51)	(-2.10)	(0.49)	(-1.12)	(-1.04)	(-0.56)
Supplier Nondebt Tax $Shields_{t-1}$	-4.067***	-4.145***	-0.962	-4.432***	-4.179***	-0.282
	(-4.41)	(-4.61)	(-1.42)	(-4.08)	(-3.89)	(-0.30)
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE (2-digit SIC)	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
Observations	5374	5374	5374	5374	5374	5374
R-squared	0.28	0.35	0.81	0.25	0.32	0.83

Table 4: Leverage of Dependent Suppliers and Connections to Key R&D-intensive Customers: Event Studies

The table presents the results of the regressions, in which each observation is a pair of supplier-customer firm-year. The dependent variable is *Market Leverage*, which is equal to the sum of book values of long-term debt and debt in current liabilities divided by the sum of book value of debt and market value of common equity. *After* is a dummy variable that equals one for the fiscal years after the manager turnover at the customer firm, *Lost Connections* is a dummy variable that equals one if the connected supplier lost connection after the turnover. The key variable is *After* $\times$ *Lost Connections*, which captures the difference in differences effect or change in market leverage for a supplier who lost connection to a customer firm. If the firm experiences multiple events, all firm-years are included. The estimation is made on a one-year window centered on the event year (the fiscal year of the turnover). *Key Customers R&D* is the sum of R&D intensities of all major customers weighted by the proportion of sales to each customer. The sample is splitted according to high (low) *Key Customers R&D* - when *Key Customers R&D* is above (below or equal) the sample median. Calendar year fixed effects are included in all regressions, industry fixed effects (based on 2-digit SIC industries) are included in columns ((3) and (4) and supplier firm fixed effects are included in columns (5) and (6). All continuous variables are winsorized at 1% and 99% levels. All other variables are defined in Appendix A. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the supplier firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Market Leverage					
	Key Customers R&D					
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
After	0.002	-0.001	-0.004	0.024	0.071	-0.022
	(0.08)	(-0.02)	(-0.13)	(0.56)	(1.55)	(-0.85)
Lost Connections	-0.020	0.004	-0.026	-0.061	omitted	
	(-0.62)	(0.07)	(-0.68)	(-1.38)		
After x Lost Connections	-0.156**	0.039	-0.160**	0.034	-0.164**	0.116
	(-2.63)	(0.35)	(-2.36)	(0.39)	(-2.15)	(1.48)
Customer Industry Concentration$_{t-1}$	0.015	0.273	-0.030	0.047	-1.102	2.974
	(0.08)	(0.98)	(-0.12)	(0.20)	(-0.37)	(1.30)
Customer Change in Sales$_{t-1}$	-0.312	0.446	-0.146	-0.370	-0.479	0.483
	(-0.78)	(0.53)	(-0.28)	(-0.47)	(-0.97)	(1.04)
Supplier Concentration$_{t-1}$	0.139	0.155	1.755	1.745	0.841	-2.356
	(0.33)	(0.18)	(1.43)	(1.40)	(0.46)	(-1.03)

	Market Leverage					
	Key Customers R&D					
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Supplier Firm Size$_{t-1}$	0.011	0.002	0.003	0.003	0.041	0.040
	(0.78)	(0.14)	(0.19)	(0.25)	(0.83)	(0.42)
Supplier Firm ROA$_{t-1}$	-0.333***	-0.346	-0.343***	-0.205	0.079	0.096
	(-4.83)	(-1.56)	(-3.28)	(-1.20)	(0.50)	(0.66)
Supplier Fixed Assets$_{t-1}$	-0.311**	0.306*	-0.289*	0.422*	-0.225	-0.177
	(-2.15)	(1.92)	(-1.78)	(1.90)	(-0.40)	(-0.51)
Supplier Firm R&D$_{t-1}$	-0.139	-0.400	-0.137	-0.201	0.101	-0.029
	(-1.24)	(-1.31)	(-1.06)	(-0.65)	(0.69)	(-0.09)
Supplier Firm SGA$_{t-1}$	-0.137*	-0.297*	-0.158	-0.186	0.114	0.126
	(-1.79)	(-1.74)	(-1.57)	(-1.07)	(1.43)	(0.40)
Supplier Tobin's Q$_{t-1}$	-0.004	-0.013	-0.004	-0.026**	-0.003	0.004
	(-0.84)	(-1.41)	(-0.60)	(-2.59)	(-0.47)	(0.47)
Supplier Volatility$_{t-1}$	-0.112**	-0.126	-0.126**	-0.099	-0.638	-0.266
	(-2.63)	(-0.51)	(-2.51)	(-0.42)	(-1.07)	(-0.68)
Supplier NonDebt Tax Shields$_{t-1}$	3.006	-7.008	3.314	-8.545	-0.325	0.080
	(1.10)	(-1.39)	(1.04)	(-1.27)	(-0.10)	(0.02)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	Yes
Chi^2 statistic	2.75		4.22		26.31	
p-value	0.097		0.039		0.000	
Observations	145	122	145	122	145	122
R-squared	0.38	0.51	0.42	0.68	0.91	0.98

Table 5: Leverage of Dependent Suppliers and Connections to Key R&D-intensive Customers: Propensity-Score Matching

Panel A reports differences-in-means estimates by subsamples of propensity score matched *Connected* and *Unconnected* suppliers. *Connected* supplier is a supplier that has least one connection to one of its major customers. Panel B presents the results of the regression analysis on the propensity-score matched sample of suppliers. *Key Customers R&D* is the sum of R&D intensities of all major customers weighted by the proportion of sales to each customer. *Market Leverage* is equal to the sum of book values of long-term debt and debt in current liabilities divided by the sum of book value of debt and market value of common equity. *Book Leverage* is the sum of book values of long-term debt and debt in current liabilities divided by book value of assets. *Connections to Key R&D-intensive Customers* is the sum of connections to each major customer weighted by R&D intensities and proportion of sales to each major customer, where connections to each major customer is the number of connected pairs divided by the total number of pairs that exist between individuals of customer and supplier firms. Industry fixed effects (based on 2-digit SIC industries) are included in regressions. All continuous variables are winsorized at 1% and 99% levels. All other variables are defined in Appendix A. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the supplier firm level.***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: PSM Matched Sample of Suppliers (1010 obs.)

Variable	Connected	Unconnected	Diff.	T-stat.	
Supplier Market Leverage	0.129	0.098	0.032	3.06	***
Supplier Book Leverage	0.151	0.115	0.035	3.23	***
Control Variables:					
Key Customers R&D$_{t-1}$	0.011	0.009	0.002	1.59	
Supplier Firm Size$_{t-1}$	5.644	5.531	0.113	1.18	
Supplier Return on Assets$_{t-1}$	0.042	0.040	0.002	0.20	
Supplier R&D Intensity$_{t-1}$	0.110	0.113	-0.003	-0.41	
Supplier Tobin's Q$_{t-1}$	2.390	2.245	0.145	1.45	
Supplier Volatility$_{t-1}$	0.164	0.150	0.014	1.33	
Number of Customers per Supplier	2.339	2.245	0.094	1.16	
Percent of Sales to Major Customers$_{t-1}$	0.287	0.300	-0.013	-0.92	

Panel B: Regression Analysis

	Market Leverage (1)	Book Leverage (2)
Connections to Key R&D-int. Customers	0.241**	0.218*
	(2.26)	(1.61)
Key Customers R&D$_{t-1}$	-0.535**	-0.946***
	(-1.98)	(-2.70)
Key Customers Industry Concentration$_{t-1}$	0.333**	0.445**
	(2.31)	(2.32)
Key Customers Change in Sales$_{t-1}$	-0.391	-0.566
	(-1.08)	(-1.48)
Supplier Industry Concentration$_{t-1}$	0.322	-0.029
	(1.12)	(-0.09)
Supplier Size$_{t-1}$	0.015***	0.023***
	(2.89)	(3.93)
Supplier ROA$_{t-1}$	-0.137***	-0.192***
	(-4.25)	(-3.91)
Supplier Fixed Assets$_{t-1}$	0.094	0.121*
	(1.50)	(1.74)
Supplier R&D$_{t-1}$	-0.153***	-0.104
	(-3.20)	(-1.59)
Supplier SGA$_{t-1}$	-0.001	0.014
	(-0.04)	(0.36)
Supplier Tobin's Q$_{t-1}$	-0.017***	-0.001
	(-5.08)	(-0.27)
Supplier Volatility$_{t-1}$	0.010	0.006
	(0.34)	(0.13)
Supplier Nondebt Tax Shields$_{t-1}$	-4.245***	-5.490***
	(-3.54)	(-3.36)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	1010	1010
R-squared	0.39	0.32

Table 6: Social Connections, Intensity and Duration of the Customer-Supplier Relationship

Panel A presents the results of supplier-level regressions, in which each observation is supplier firm-year. The dependent variable is *Supplier Sales to Key Customers*, which is equal to the total sales to key customers divided by the total sales of the supplier. *Connections to Key Customers* is the sum of connections to each major customer weighted by the proportion of sales to each major customer, where connections to each major customer is the number of connected pairs divided by the total number of pairs that exist between individuals of customer and supplier firms. Panel B presents the coefficients of Cox proportional hazards model describing the duration of the relationship between customer and supplier. The unit of observation is the customer-supplier pair, and we treat relationships that last until the last year of the sample period as right censored. *Connections to Key Customer* is the total number of connections between executives of supplier and customer firms scaled by the total number of possible executives' pairs. All explanatory variables are lagged. All other variables are defined in Appendix A. All continuous variables are winsorized at 1% and 99% levels. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the supplier firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Social Connections and Intensity of the Customer-Supplier Relationship

	Supplier Sales to Key Customers			
			Key Customers R&D	
			High	Low
	(1)	(2)	(3)	(4)
Connections to Key Customers	2.358***	2.178***	2.240**	1.970
	(5.37)	(2.72)	(2.29)	(1.32)
Key Customers Ind. Concentration$_{t-1}$	2.029***	1.972***	1.968***	2.010***
	(18.71)	(13.29)	(8.36)	(11.81)
Key Customers Change in Sales$_{t-1}$	2.324***	0.635***	0.579*	0.313
	(7.60)	(2.72)	(1.74)	(0.98)
Supplier Concentration$_{t-1}$	-0.369***	-0.395***	-0.585**	-0.316**
	(-3.24)	(-2.93)	(-2.18)	(-2.23)
Supplier Firm Size$_{t-1}$	-0.011***	0.006	0.010	0.008
	(-4.07)	(0.67)	(0.68)	(0.78)
Supplier Firm ROA$_{t-1}$	0.087***	0.182***	0.201***	0.095*
	(2.70)	(4.31)	(3.47)	(1.86)
Supplier Fixed Assets$_{t-1}$	-0.045	0.030	0.023	0.047
	(-1.57)	(0.60)	(0.26)	(0.94)
Supplier Firm R&D$_{t-1}$	0.388***	0.081	-0.013	0.208**
	(6.96)	(0.97)	(-0.13)	(2.05)
Supplier Firm SGA$_{t-1}$	-0.074***	0.083*	0.114*	0.075
	(-3.21)	(1.86)	(1.70)	(1.61)
Supplier Tobin's Q$_{t-1}$	-0.003	-0.008**	-0.008*	-0.006

Panel A. Social Connections and Intensity of the Customer-Supplier Relationship				
	Supplier Sales to Key Customers			
			Key Customers R&D	
			High	Low
	(1)	(2)	(3)	(4)
	(-1.23)	(-2.57)	(-1.91)	(-1.45)
Supplier Volatility$_{t-1}$	0.100***	0.095	0.062	0.016
	(2.86)	(1.49)	(0.77)	(0.25)
Supplier NonDebt Tax Shields$_{t-1}$	0.392	0.850	1.990	-0.185
	(0.29)	(0.48)	(0.84)	(-0.14)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	No
Firm FE	No	Yes	Yes	Yes
Observations	5374	5374	2687	2687
R-squared	0.51	0.85	0.85	0.89

Panel B: Social Connections and Duration of the Customer-Supplier Relationship					
	Hazard Rate of Relationship Termination				
				Customer R&D	
				High	Low
	(1)	(2)	(3)	(4)	(5)
Connections to Key Customer	-2.049***	-2.068***	-1.869***	-3.282**	-1.614**
	(-2.63)	(-2.79)	(-2.76)	(-2.09)	(-2.05)
Supplier Size$_{t-1}$		0.010	0.001	0.023	0.004
		(0.58)	(0.05)	(0.75)	(0.18)
Supplier ROA$_{t-1}$		-0.638**	-0.679**	-0.648	-0.389
		(-2.15)	(-2.16)	(-1.60)	(-0.84)
Supplier Market Leverage$_{t-1}$		0.478**	0.605***	0.259	0.810***
		(2.48)	(2.96)	(0.81)	(3.19)
Supplier R&D$_{t-1}$		1.448***	1.278***	1.269**	1.707***
		(3.68)	(3.00)	(2.30)	(2.68)
Customer Size$_{t-1}$		-0.064**	-0.070***	-0.050	-0.053
		(-2.57)	(-2.66)	(-1.08)	(-1.58)
Customer ROA$_{t-1}$		0.835*	1.096**	0.616	0.328
		(1.66)	(2.08)	(0.96)	(0.32)
Customer R&D$_{t-1}$		-2.551*	-1.770		
		(-1.90)	(-1.32)		
Customers Ind. Concentration$_{t-1}$		-0.245	-0.359	-2.039**	0.037
		(-0.80)	(-0.98)	(-2.37)	(0.09)
Sales to Customer$_{t-1}$		0.394**	0.347*	0.141	0.616*
		(2.01)	(1.76)	(0.55)	(1.84)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No
Observations	6447	6321	6321	3168	3153

Table 7: Leverage of Dependent Suppliers and Connections to Key R&D-intensive Customers: Bonding Channel

The table presents the results of supplier-level regressions, in which each observation is supplier firm-year. The dependent variable is *Market Leverage*, which is equal to the sum of book values of long-term debt and debt in current liabilities divided by the sum of book value of debt and market value of common equity. *Connections to Key R&D-intensive Customers* is the sum of connections to each major customer weighted by R&D intensities and proportion of sales to each major customer, where connections to each major customer is the number of connected pairs divided by the total number of pairs that exist between individuals of customer and supplier firms. *Key Customers R&D* is the sum of R&D intensities of all major customers weighted by the proportion of sales to each customer. The sample is splitted according to whether the value of bonding measures is in the top (bottom) quartile of sample distribution. *Supplier Sales to Key Customers* is equal to the total sales to key customers divided by the total sales of the supplier. *Relationship Duration* is the average duration of the relationship between customer and all its suppliers in years. *Bonding Index* combines *Supplier Sales to Key Customers* and *Relationship Duration* in one index. To construct the index we first average the firm's percentile rankings according to each of the measures, and then scale the index to range from zero (low) to one (high). All continuous variables are winsorized at 1% and 99% levels. All other variables are defined in Appendix A. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the supplier firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Measure	Supplier Sales to Key Customers		Relationship Duration		Bonding Index	
Degree	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Connections to Key R&D-int. Customers	0.254***	-0.145	0.559***	0.159	0.413***	-0.036
	(2.97)	(-1.02)	(3.09)	(1.49)	(3.17)	(-0.26)
Key Customers R&D$_{t-1}$	-0.474**	0.103	-1.832**	-0.536**	-0.717**	-0.474
	(-2.51)	(0.13)	(-2.13)	(-2.09)	(-2.09)	(-0.67)
Key Customers Industry Concentration$_{t-1}$	0.274**	-0.032	0.497***	0.234*	0.356**	0.072
	(2.52)	(-0.09)	(2.85)	(1.94)	(2.42)	(0.37)
Key Customers Change in Sales$_{t-1}$	-0.648***	-1.584	-0.796**	-0.135	-0.968***	0.539
	(-2.92)	(-1.27)	(-2.13)	(-0.37)	(-3.49)	(0.63)
Supplier Industry Concentration$_{t-1}$	-0.040	-0.294	-0.139	0.045	0.385	0.226
	(-0.12)	(-1.06)	(-0.38)	(0.16)	(1.19)	(0.78)
Supplier Size$_{t-1}$	0.024***	0.009**	0.022***	0.017***	0.023***	0.008**

Measure	Supplier Sales to Key Customers		Relationship Duration		Bonding Index	
Degree	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
	(4.96)	(2.00)	(3.81)	(4.98)	(4.08)	(2.01)
Supplier ROA_{t-1}	-0.170***	-0.294***	-0.312***	-0.202***	-0.246***	-0.239***
	(-4.38)	(-5.28)	(-3.93)	(-5.33)	(-3.99)	(-5.01)
Supplier Fixed $Assets_{t-1}$	0.282***	0.170***	0.370***	0.193***	0.319***	0.203***
	(3.48)	(2.89)	(4.24)	(4.72)	(3.91)	(3.97)
Supplier $R\&D_{t-1}$	-0.148***	-0.367***	-0.191	-0.303***	-0.262***	-0.353***
	(-2.61)	(-4.02)	(-1.27)	(-4.86)	(-2.98)	(-4.04)
Supplier SGA_{t-1}	0.029	-0.057	0.023	-0.018	0.007	-0.075**
	(0.93)	(-1.64)	(0.42)	(-0.60)	(0.19)	(-2.16)
Supplier Tobin's Q_{t-1}	-0.017***	-0.033***	-0.056***	-0.023***	-0.026***	-0.029***
	(-4.40)	(-8.08)	(-6.39)	(-7.58)	(-4.95)	(-7.80)
Supplier $Volatility_{t-1}$	-0.025	-0.128**	0.048	-0.077***	0.052	-0.116**
	(-0.83)	(-2.26)	(0.57)	(-2.65)	(0.97)	(-2.57)
Supplier Nondebt Tax $Shields_{t-1}$	-3.443**	-4.879***	-6.690**	-2.867**	-5.091**	-4.198***
	(-2.33)	(-2.78)	(-2.57)	(-2.43)	(-2.53)	(-2.69)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2 statistic	10.81		5.44		7.74	
p-value	0.001		0.020		0.005	
Observations	1343	1344	1198	1367	1309	1345
R-squared	0.40	0.39	0.37	0.37	0.40	0.38

Table 8: Leverage of Dependent Suppliers and Connections to Key R&D-intensive Customers: Information Asymmetry Channel

The table presents the results of supplier-level regressions, in which each observation is supplier firm-year. The dependent variable is *Market Leverage*, which is equal to the sum of book values of long-term debt and debt in current liabilities divided by the sum of book value of debt and market value of common equity. *Connections to Key R&D-intensive Customers* is the sum of connections to each major customer weighted by R&D intensities and proportion of sales to each major customer, where connections to each major customer is the number of connected pairs divided by the total number of pairs that exist between individuals of customer and supplier firms. *Key Customers R&D* is the sum of R&D intensities of all major customers weighted by the proportion of sales to each customer. *Distance* is the average distance between a supplier and its key customers, measured in miles. The *Distance* is computed by averaging the distances between the headquarters location of supplier and that of each of its customers. The sample is splitted according to value of *Distance* is in the top (bottom) quartile of sample distribution. All continuous variables are winsorized at 1% and 99% levels. All other variables are defined in Appendix A. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the supplier firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Measure	Distance	
Degree	High	Low
	(1)	(2)
Connections to Key R&D-int. Customers	0.278**	0.063
	(2.18)	(0.53)
Key Customers R&D$_{t-1}$	-0.679***	-0.688**
	(-2.67)	(-2.06)
Key Customers Industry Concentration$_{t-1}$	0.482***	0.221
	(3.11)	(1.10)
Key Customers Change in Sales$_{t-1}$	-0.708**	0.132
	(-2.08)	(0.28)
Supplier Industry Concentration$_{t-1}$	-0.643	0.033
	(-1.59)	(0.11)
Supplier Size$_{t-1}$	0.009**	0.034***
	(2.03)	(5.66)
Supplier ROA$_{t-1}$	-0.110***	-0.251***
	(-2.68)	(-3.92)
Supplier Fixed Assets$_{t-1}$	0.192***	0.174***
	(2.77)	(2.68)
Supplier R&D$_{t-1}$	-0.153**	-0.212**
	(-2.55)	(-1.97)
Supplier SGA$_{t-1}$	-0.030	0.030
	(-0.96)	(0.60)

Measure	Distance	
Degree	High	Low
	(1)	(2)
Supplier Tobin's Q_{t-1}	-0.021***	-0.033***
	(-6.89)	(-5.75)
Supplier $Volatility_{t-1}$	-0.001	-0.051
	(-0.02)	(-1.05)
Supplier Nondebt Tax $Shields_{t-1}$	-2.201*	-1.688
	(-1.90)	(-0.78)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Chi^2 statistic	3.08	
p-value	0.079	
Observations	1302	1306
R-squared	0.43	0.41

Table 9: Supplier Market Leverage Adjustment Analysis

Panel A presents the summary statistics. *Market Leverage Deviation* is the difference between the actual market leverage and the target leverage, where the target leverage is computed as the predicted value from yearly regressions of market leverage on its determinants: *Industry Leverage* (median industry leverage), *Profitability* (operating income scaled by assets), *Tobins's Q*, *Fixed Assets*, *Size* (the natural logarithm of total assets), *Inflation* (the natural logarithm of CPI), *Depreciation* (depreciation expenses scaled by total assets), *R&D Intensity* (R&D expenses scaled by total assets), *Positive R&D Intensity* (indicator of positive R&D expenses). Panel B presents the univariate results, comparing connected and unconnected suppliers across terciles of *Key Customers R&D*. *Key Customers R&D* is the sum of R&D intensities of all major customers weighted by the proportion of sales to each customer. *Connected* supplier is a supplier that has least one connection to one of its major customers. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Summary Statictics (4150 obs.)

Variable	Mean	25th perc.	Median	75th perc.	St. dev.
Supplier Market Leverage Deviation	-0.024	-0.135	-0.053	0.053	0.163

Panel B: Univariate Results (4150 obs.)

Supplier Market Leverage Deviation

Variable	Connected	Unconnected	Diff.	T-stat.	
Key Customers R&D (tercile)					
1	-0.0195	-0.0273	0.008	1.056	
2	-0.0200	-0.0425	0.023	2.205	**
3	0.0044	-0.0453	0.050	5.273	***
(3)-(1)					
T-stat.	2.82***	2.06**			

Table 10: Leverage of Dependent Suppliers and Connections to Key R&D-intensive Customers: Reverse Causality

The table presents the results of supplier-level regressions from Table 3. The connections variable is adjusted to address reverse causality by dropping connections formed after the formation of business relationship. All continuous variables are winsorized at 1% and 99% levels. All variables are defined in Appendix A. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the supplier firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Full Sample

	Market Leverage			Book Leverage		
	(1)	(2)	(3)	(4)	(5)	(6)
Connections to Key R&D-int. Customers	0.276**	0.293***	0.230***	0.292**	0.282**	0.176**
	(2.44)	(2.92)	(3.57)	(2.18)	(2.40)	(2.39)
Key Customers R&D$_{t-1}$	-0.677***	-0.721***	-0.556***	-0.823***	-0.846***	-0.576***
	(-3.63)	(-3.97)	(-2.79)	(-3.81)	(-3.94)	(-2.91)
Key Customers Industry Concentration$_{t-1}$	0.403***	0.327***	-0.014	0.518***	0.352***	0.111
	(4.87)	(4.14)	(-0.13)	(6.23)	(4.40)	(1.18)
Key Customers Change in Sales$_{t-1}$	-0.793***	-0.716***	-0.548***	-0.743***	-0.603***	-0.446**
	(-3.96)	(-3.96)	(-3.07)	(-3.64)	(-3.03)	(-2.29)
Supplier Industry Concentration$_{t-1}$	0.223**	0.043	0.062	0.127	-0.038	-0.088
	(2.17)	(0.27)	(0.39)	(1.22)	(-0.25)	(-0.64)
Supplier Size$_{t-1}$	0.021***	0.017***	0.053***	0.028***	0.024***	0.037***
	(7.82)	(6.31)	(5.87)	(10.51)	(8.90)	(4.29)
Supplier ROA$_{t-1}$	-0.243***	-0.234***	-0.155***	-0.203***	-0.182***	-0.110***
	(-9.02)	(-8.71)	(-5.16)	(-7.09)	(-6.37)	(-3.88)
Supplier Fixed Assets$_{t-1}$	0.177***	0.199***	0.154**	0.208***	0.188***	0.082*
	(6.52)	(5.01)	(2.43)	(8.23)	(5.21)	(1.68)
Supplier R&D$_{t-1}$	-0.324***	-0.253***	-0.025	-0.202***	-0.164***	-0.038
	(-7.49)	(-5.82)	(-0.46)	(-4.18)	(-3.48)	(-0.62)
Supplier SGA$_{t-1}$	-0.016	-0.011	0.005	-0.002	0.009	0.028
	(-0.73)	(-0.48)	(0.13)	(-0.08)	(0.38)	(0.58)
Supplier Tobin's Q$_{t-1}$	-0.027***	-0.028***	-0.009***	-0.006**	-0.010***	-0.002

Panel A: Full Sample

	Market Leverage			Book Leverage		
	(1)	(2)	(3)	(4)	(5)	(6)
	(-12.81)	(-12.35)	(-3.50)	(-2.46)	(-4.09)	(-0.79)
Supplier Volatility$_{t-1}$	-0.057**	-0.048**	0.019	-0.035	-0.032	-0.023
	(-2.51)	(-2.10)	(0.48)	(-1.12)	(-1.04)	(-0.58)
Supplier Nondebt Tax Shields$_{t-1}$	-4.108***	-4.180***	-0.986	-4.476***	-4.213***	-0.279
	(-4.45)	(-4.65)	(-1.47)	(-4.12)	(-3.92)	(-0.30)
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE (2-digit SIC)	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
Observations	5374	5374	5374	5374	5374	5374
R-squared	0.28	0.35	0.81	0.25	0.32	0.83

8 Appendix A. Variables Definitions

- *Market Leverage* - equal to the sum of book values of long-term debt and debt in current liabilities divided by the sum of book value of debt and market value of common equity.
- *Book leverage* - the sum of book values of long-term debt and debt in current liabilities divided by book value of assets.
- *Market Leverage Deviation* - the difference between the actual market leverage and the target leverage, where the target leverage is computed as the predicted value from yearly regressions of market leverage on its determinants: *Industry Leverage* (median industry leverage), *Profitability* (operating income scaled by assets), *Tobins's Q*, *Fixed Assets*, *Size* (the natural logarithm of total assets), *Inflation* (the natural logarithm of CPI), *Depreciation* (depreciation expenses scaled by total assets), *R&D Intensity* (R&D expenses scaled by total assets), *Positive R&D Intensity* (indicator of positive R&D expenses).
- *Size* - natural logarithm of total assets.
- *ROA* - operating income divided by total assets.
- *Fixed Assets* - net property, plant and equipment divided by total assets.
- *R&D intensity* - research and development expenditures divided by total assets. Following the literature, we set missing values of research and development expenditures to equal zero.
- *SGA* - selling, general and administrative expenses divided by total assets.
- *Tobin's Q* -book value of assets plus the market value of common equity minus the book value of common equity divided by book value of assets.
- *Volatility* - rolling standard deviation of ROA for the previous 10 years relative to a given year.
- *Non-Debt Tax Shields* - investment tax credit divided by total assets.
- *Industry Concentration* - the sum of squared market shares in sales. Industry is defined using two-digit SIC code.
- *Key Customers R&D* - the sum of R&D intensities of all major customers weighted by the proportion of sales to each customer.
- *Key Customers Industry Concentration* - the sum of industry concentration of all major customers weighted by the proportion of sales to each major customer.
- *Key Customers Change in Sales* - the sum of changes in sales of all major customers weighted by the proportion of sales to each major customer. Change is sales is computed as percentage difference in sales (scaled by assets) between the current and the previous year.

- *Connections to Key Customer* - the total number of connections between executives of supplier and customer firms scaled by the total number of possible executives' pairs.
- *Connections to Key Customers* - the sum of connections to each major customer weighted by the proportion of sales to each major customer, where connections to each major customer is the number of connected pairs divided by the total number of pairs that exist between individuals of customer and supplier firms.
- *Connections to Key R&D-intensive Customers* - is the sum of connections to each major customer weighted by R&D intensities and proportion of sales to each major customer, where connections to each major customer is the number of connected pairs divided by the total number of pairs that exist between individuals of customer and supplier firms.
- *Supplier Sales to Key Customers* - total sales to key customers divided by the total sales of the supplier.
- *Relationship Duration* - the duration of the relationship between customer and supplier measured in years. We consider the year of start of the relationship as the first year the supplier-customer relationship appears in Compustat segment file.
- *Bonding Index* - combines *Supplier Sales to Key Customers* and *Relationship Duration* in one index. To construct the index we first average the firm's percentile rankings according to each of the measures, and then scale the index to range from zero (low) to one (high).
- *Distance* - average geographical distance between a supplier and its key customers, measured in miles. The average distance is computed by averaging the distances between the headquarters location of supplier and that of each of its customers. We compute the distance using latitude and longitude coordinates for the addresses of the supplier (customer) headquarters obtained from the U.S. Census Bureau's Gazetteer City-State File. We then apply the formula to calculate the distance between two points on Earth's surface.

CHAPTER 3: SOCIAL CONNECTIONS AND INNOVATION IN DIVERSIFIED CONGLOMERATES

1 Abstract

Using a hand-collected sample on divisional managers in S&P500 diversified conglomerates, we study the effect of divisional manager-CEO social connections on the scale and success of corporate innovation activities. Divisional managers who previously worked or studied with CEO file a greater number of patents during their tenure at the segment. These patents receive more citations in future and represent a greater scientific and economic value. To provide causal support for our findings, we exploit plausibly exogenous variation in connections caused by CEO non-performance related retirements. The difference-in-difference estimation shows that after the CEO leaves the office, connected segments experience drop in a quantity and quality of innovation activities. These findings can imply that socials connections help to mitigate adverse selection problems associated with R&D investments.

2 Introduction

Do personal connections affect innovation in conglomerates? Current research on innovation in diversified conglomerates supports the view that diversification leads to both less innovation and innovation of lower quality (Seru (2014)). Because of the information asymmetries between corporate headquarters and divisional managers, the allocation of research and development (R&D) resources is susceptible to supply-demand mismatches, leading to lower innovation. At the same time, it is hard to not recognize that personal connections being woven at all levels of organizational hierarchy are important for firm performance. A large body of work on the role of social connections in financial decisions suggests that social connections facilitate information transfers and information sharing (e.g. Cohen, Frazzini, and Malloy (2008, 2010), Duchin and

Sosyura (2013)), but little is known about the role of social connections in innovation activities in conglomerates.

This question becomes particularly important given that it is well established that innovation fosters economic growth (Romer (1986)), and diversified conglomerates make up a significant part of U.S. economy (Montgomery (1994)). In this paper we study how the findings of Seru (2014) that diversified firms are less innovative will change in the presence of social connections inside these firms. We focus on social connections between corporate headquarters and divisions, because information frictions that exist between these levels of organizational hierarchy could impede innovation. More specifically, our main question is how social connections between CEO and divisional managers in diversified conglomerates affect conglomerates' innovative activities. We are also interested to know whether conglomerates with a higher proportion of divisional managers connected to CEO generate more innovation.

In forming our hypothesis we substantially build on the intuition of Seru (2014). It is well understood that R&D projects are characterized by high uncertainty about eventual outcomes. Moreover, there are large information asymmetries between divisional managers responsible for the innovative projects and headquarters who provide financing for these projects. Divisional managers knowing ahead that the financing of their divisions depends on the success of the R&D project have a substantial discretion over the information they provide to CEO about the prospects of the project. We hypothesize that personal connections may mitigate internal information asymmetry between divisional managers and CEO. Therefore, divisions run by managers with social connections to CEO will be more productive in terms of internal quantity and quality of generated innovation.

There are two ways how social connections may help in reducing information asymmetry between divisional managers and CEO. First, social connections facilitate the transmission of the valuable information through the network of top executives (e.g. Cohen, Frazzini, and Malloy (2008, 2010), Duchin and Sosyura (2013)). Hence, divisional managers with connections to CEO are more likely to provide more rich and precise information about the prospects of innovative projects. Second, social connections formed in the past may be relevant for building good reputation, and divisions run by managers with good reputation will be more trustworthy and in future face less information problems (Diamond (1989)).[27]

We combine segment data from Compustat Segment files with hand-collected data on identities of divisional managers. We use BoardEx to calculate the connections between CEO and divisional managers. We consider CEO as being connected to divisional manager if they studied or worked together at the same time in the past. We count only connections formed during previous employment or education. We obtain innovation data from Kogan, Papanikolaou, Seru and Stoffman (2017) patents dataset, which is based on U.S. Patent and Trademark Office (USPTO) data from 1926-2010. Following Seru (2014), we distribute 46,534 patents produced by the sample firms across conglomerate divisions by matching the patent technology class with the three-digit SIC code of the division industry. We measure the scale of innovation by the natural logarithm of one plus the total number of patents applied (citations received by these patents) during a given fiscal year. We measure the scientific success of innovation by focusing on the patents that are cited in the 50th percentile (and above) of the citation distribution within their technology class-year. We measure the economic success of innovation by using the dollar value of each patent as reported in the Kogan, Papanikolaou, Seru and Stoffman (2017) and estimated using the stock market response to news about the patent.

Our baseline results show that segments run by divisional managers connected to CEO are associated with greater number of applied patents, more citations generated by these patents, higher probability to file highly scientifically important patents, higher number of scientifically important patent applications and higher economic value of this patents as measured by market valuations of the applications (Kogan, Papanikolaou, Seru and Stoffman (2017)). The magnitude of the effects is substantial: one additional connection to CEO is associated with next year increase in patents' applications by 24.10%, in future citations received by the patents - by 27.10% , in high-impact patents as measured by technology class citations in the 50th percentile - by 31.04%,

[27] In addition, a threat of losing a connection to an important and influential CEO may ex-ante mitigate possible negative behavior (e.g. Boot, Greenbaum and Thakor (1993), Brass and Labianca (2006)).

and, finally, in patents economic value - by 21.10%.[28] The results are robust to controlling for unobserved time-invariant firm-level factors (by including firm fixed effects) and controlling for overall divisional managers' connectedness.

To provide a causal support for the effects we use plausibly exogenous CEO non-performance related retirements as exogenous shocks to managers' connections. CEO departures due to planned retirements are likely to lead to a loss of connection(s) with the divisional managers these CEOs were previously connected. Using a difference-in-difference setup, we show that following a plausibly exogenous CEO turnover segments that switched from connected to unconnected CEO experience a significant decrease in innovation outcomes.

After establishing the results at the segment-level, we turn to the firm-level analysis. Specifically, we study whether conglomerates with a higher proportion of divisional managers connected to CEO generate more innovation. To mitigate the endogeneity concerns, we estimate regressions with variables represented as annual changes. This approach cancels all firm-invariant factors. We find that when the firms increase the proportion of divisional managers connected to CEO, they file more patents and patents of higher economic value. Taken together, our segment- and firm-level results suggest that connections to CEO have a innovation-enhancing role in conglomerates.

Our study contributes to the emerging research on the innovation in conglomerates. Seru (2014) using plausibly exogenous variation in the merger outcomes due to failed mergers shows that firms completed diversified mergers produce subsequently less amount of innovation and innovation of less quality relative to firms that did not complete the mergers. He concludes that the observed drop in innovation can be explained by the existence of information asymmetries between CEO and divisional managers. Anjos and Fracassi (2015) view conglomerates as possessing informational advantage compared to single-segment firms and show that conglomerates participating in more informationally-central industries (relative to single-segment firms) produce more patents and better patents. Anjos (2018) builds on Seru (2014) and theoretically studies the

[28]The reported percentage increases are in logarithmic values.

innovation behavior of conglomerates. He provides an explanation for the result of Seru (2014) that conglomerates innovate less by focusing on the existence of knowledge spillovers that allow for information exchange between divisions. He shows that in the presence of these knowledge spillovers conglomerates can innovate less compared to single-segment firms. We complement these findings by providing evidence that is consistent with the view that reduced innovation outcomes of conglomerates relative to single-segment firms can be caused by information problems. Because personal connections between CEO and divisional managers can alleviate the internal information problems, we show that conglomerates with such connections are associated with greater and more successful innovation.

We also add to the research examining the effect of external connectivity of managers on innovation. For example, Faleye, Kovacs, and Venkateswaran (2014) find that firms with better-connected CEOs are associated with more R&D investments and greater number and higher quality patents. Consistent with our paper, their findings imply that personal connections alleviate the access to valuable information and thereby reduce the CEOs' reluctance upon taking risky innovative projects. Kang, Liu, Low and Zhang (2018) find that firms with CEOs socially connected with board members produce more patents and citations. Their findings are also consistent with the information role of personal connections, specifically, that connections facilitate more productive exchange of information between CEO and board members who provide CEO with industry expertise about innovation projects. We complement this literature by focusing on CEO connections to divisional managers, and our results are consistent with the information role of personal connections.

3 Sample and Data

3.1 Segments Data

Our sample is based on the Compustat Segment files and covers the 8-year period from 2003 to 2010. Our sample ends in 2010, because it is the last year for which the innovation data is available.

The sample selection procedure is as follows. First, we select all the companies that enter S&P500 for one or more years within the sample period of 2006-2013. We then exclude financial and utilities companies leaving 507 companies. We next require that conglomerates operate in industrial segments, that segments have non-missing SIC values, that firms have at least 2 business segments with non-missing values for segment assets and segment capital expenditures, and that the sum of segment sales does not deviate more than 5% from the total firm sales. These filters produce 237 firms. We then randomly select 100 firms out of those 237 firms with information for all divisional managers for these firms. If a firm doesn't provide information on all divisional managers, we replace the firm with another firm from our sample of multisegment firms. To avoid the reduction of the sample size due to missing financial data, we additionally hand-collect missing financial data (operating profit and segment assets) from 10-K annual reports for our sample of firms with information about divisional managers. Since the sample period starts from 2003, we complement the existing dataset of divisional managers starting from 2006 by additionally hand-collecting the identities of divisional managers for 2003-2005 years.

We define a segment's industry based on its primary 3-digit SIC code (sics1). Following Cohen and Lou (2012) and Schneider and Spalt (2016), we define conglomerate firms as firms operating in more more than one industry.[29] For 100 firms for which we collected information on divisional managers, we aggregate segment data by reportable segments (identifier sid) by industries or three-digit SIC code. Our final sample utilized in regressions consists of 1030 segment-year-observations, which cover 232 unique divisions (based on industries)[30] and 79 companies.[31] We report summary statistics on firms and segments in our sample in Panel A Table 1. An average conglomerate has book assets valued at $22.8 billion, has annual R&D expenses of 2% of book assets and operates in 3.15 distinct three-digit SIC industries.

[29]As in Schneider and Spalt (2016), we treat firms as single-segment firms if they: 1) operate in one three-digit SIC code and 2) appear in Compustat Fundamentals Annual database but not in the segment data.

[30]Henceforth, we will use segments and divisions interchangeably and refer to segments based on three-digit SIC classification.

[31]21 firms out of randomly selected 100 firms dropped from the sample as a result of data aggregation by industries as opposed by reportable segments.

3.2 Innovation Data and Measures

We obtain innovation data from Kogan, Papanikolaou, Seru and Stoffman (2017) (henceforth KPSS) patents dataset, which is based on U.S. Patent and Trademark Office (USPTO) data from 1926-2010. For each firm in the dataset we can observe the number of patents filed with the USPTO, the number of citations each filed patent received and the estimated market value of each patent. Kogan, Papanikolaou, Seru and Stoffman (2017) obtain the entire history of U.S. patent documents from Google Patents, and match the patent data to corporations covered in CRSP database. The matched firms in KPSS can be identified by CRSP PERMNO identifiers. Using these identifiers, we augment the innovation dataset by matching the financial information for sample firms from Compustat.

However, the KPSS dataset provides the innovation data only at the aggregated firm level without distribution of the patents applied by a specific segment of the conglomerate. To distribute 46,534 patents produced by the sample firms across segments we follow the algorithm suggested in Seru (2014). Specifically, for each patent we use the technology class the patent was filed in and match it to the three-digit SIC code of the segment industry. We obtain the matching table between technology classes and SIC codes from USPTO website. If the patent cannot be assigned to a unique division, we divide the patent equally among the possible candidates.[32]

To measure different dimensions of innovation activity we construct several variables. Following the innovation literature (e.g. Trajtenberg (1990), Griliches (1990), Hall, Jaffe and Trajtenberg (2005)), we use simple patent counts to measure the amount of innovation and citations counts to measure the quality of innovation. Following a common approach in innovation studies, we use the patent application date to assign patents to fiscal years. For each conglomerate segment we find the aggregate number of patents produced in a given fiscal year, and *Patents* is equal to the natural logarithm of one plus the total number of patents applied during a given fiscal year. Similarly, *Citations* counts the total number of citations generated by patents filed in

[32] Around 30% of patents are assigned using this approach. Seru (2014) additionally uses the state of location of inventors and state of the subsidiary to assign patents to divisions, and we leave it for future work.

a given fiscal year and is equal to the natural logarithm of one plus the total number of citations received for patents applied during a given fiscal year.

A common concern in innovation literature is so-called truncation bias, which appears because of the average two-year lag between the patent application time and patent approval time. As a result patents and citations diminish towards the end of the sample. We address the truncation bias by scaling patents (citations) by average patents (citations) granted in the same year and in the same technology class (variables *Scaled Patents* and *Scaled Citations*, respectively) as in Seru (2014) and Bernstein (2015). Moreover, as recommended in Hall, Jaffe and Trajtenberg (2001) we include year dummies in all regressions. Additionally, in robustness regressions we exclude two last years restricting our sample to patents filed up to 2007, considering that patents applied after 2007 may not appear in the sample.

To capture the novelty dimension of innovation, we construct *High Impact Patents* in the spirit of the measure used by Acemoglu, Akcigit and Celik (2014)) , which focuses on the patents that are cited in the 50th percentile (and above) of the citation distribution within their technology class-year. Similarly, we construct *High Impact Innovation*, which is a dummy variable equal to one if any of the firm's patents are cited in the 50th percentile (and above) of the citation distribution within their technology class-year. To measure the economic value of innovation, we use the market value of each patent as reported in the KPSS dataset. KPSS dataset provides the dollar value of each patent, estimated using the stock market response to news about the patent. Using this data, we compute *Patents Value* as the natural logarithm of one plus the dollar value of all patents applied for during a given year.

3.3 Managers and Connections

Our sample includes 495 unique divisional managers and 110 CEOs. To identify the divisional manager responsible for the business segment, we follow the procedure of data collecting described in Duchin and Sosyura (2013). We read biographical histories of the firm's executives in the annual reports (both types of reports - "for investors" and 10-Ks) and proxy statements. In addition to these sources we use biographical information in BoardEx database and other publicly available sources of information: Bloomberg Executive directory, Reuters and companies press releases. Divisional managers typically hold the following titles: “Executive Vice President”, “Senior Vice President”, “Divisional President” or “Chief Executive Officer” (of the corresponding subsidiary). We select only the managers who are responsible for a particular business segment. We disregard managers who are responsible for a functional area across all or many segments (such as senior vice president of finance, senior vice president of marketing), because it is not possible to establish a clear match between these managers and particular business segments.

In matching managers to segments we consider only the highest-level executive responsible for a business segment in a given period of time. In some cases the segment names in Compustat and in annual reports disagree. For example, the segments reported by Compustat are sometimes more aggregated than divisions reported in the annual report. In this situation, we match the segment with the highest-level manager among all the managers responsible for the segment as reported by Compustat. In addition, we collect starting and ending dates of the managers’ tenure in the position. If a segment changes its manager during the fiscal year we assign both old and new managers to the segment in this year.

We consider two managers to be socially connected if at one moment in their past they participated in the same organization. In our approach of measuring connections we require that participation in the same organization has *time overlaps*. This stricter approach in measuring connections allows us to better account for actual interaction between two people in the past. Arguably, just having the same organization in their CV’s does not guarantee that two managers were at one place in any period of time in the past.

We obtain data on social connections from the BoardEx database. BoardEx provides information on pairwise connections, based on their educational, employment and non-professional background. For each pair of people we have dates of their overlap in the same organization, type of organization and the persons’ roles in that organization during the connection period. Each divisional manager-CEO pair we consider being connected if they both studied or worked in the organization, which is not the current conglomerate firm, during the same time in the past. To mitigate reverse causality issues, we count only one earliest connection between two managers irrespective of when and where it was established, and drop all observations that represent duplicate connections between the same pair of managers. We find that 12% of divisional managers have connections to CEO in our sample.

We use the measure of social connections, developed in previous studies (Gaspar and Massa (2011), Duchin and Sosyura (2013)). We define *Connections to CEO* as the the fraction of connected managers (to CEO) out of the total number of managers responsible for the segment minus the average value of this fraction of connected managers (across all firm segments) in a given firm-year. This firm-adjusted measure allows us to capture the relative connectedness of each segment in conglomerate relative to other segments in conglomerate. We use the following formula:

$$\textit{Connections to CEO}_i = \textit{Connection}_i - \frac{\sum_{j=1}^{n} \textit{Connection}_j}{n} \tag{7}$$

here *Connection*$_i$ denotes the fraction of connected managers (to CEO) out of the total number of managers responsible for the segment i, and n denotes the number of segments (three-digit SIC industries) in conglomerate in a given year.

3.4 Additional Variables

In our regressions we include the standard control variables used in the conglomerate and innovation literature. Specifically, we control for *Segment Sales* (ratio of segment sales to firm sales), *Segment Size* (natural logarithm of segment assets), *Segment Relative Size* (ratio of segment assets to total conglomerate assets), *Segment Relative Q* (demeaned Tobin's Q for conglomerate three-digit SIC industry), *Segment CapEx* (ratio of segment capital expenditures to segment assets), *R&D Expenses* (ratio of firm R&D expenses to firm assets), *ROA Volatility* (rolling standard deviation of ROA for the previous 10 years relative to a given year) and *CEO Ownership* (percent of the firm's outstanding stock hold by CEO). We winsorize all continuous variables at 1% and 99% levels to mitigate the effect of outliers.

We also control for manager ability and formal influence in order to isolate these two effects from the role of manager's connections. For example, McNeil and Smyth (2009) find that manager's formal influence distorts capital allocation efficiency, because more powerful managers obtain more capital. Specifically, to control for the formal influence we use the average company tenure of managers responsible for segment (*Tenure*) and proportion of managers (out of all managers responsible for the segment) in senior status as identified by BoardEx role title (*Senior*). To control for ability and/or skill, we use the proportion of managers graduated Ivy League universities (*Ivy League*) and proportion of managers that have Ph.D. degree (*PhD*).

4 Empirical Strategy and Results

4.1 Univariate Results

Table 1 Panel B compares the measures of innovation activity taken at the time of filing for the connected and unconnected segments. Since R&D investments may require time to produce patents, we sort segments into connected and unconnected subsamples based on connections in one year prior to filing. We define *Connected* segments as segments where the majority of the managers are connected to CEO, or in other words, the proportion of connected managers is greater (or equal) 0.5 and *Unconnected* segments as segments where the proportion of connected managers is less than 0.5. We observe that connected segments generate greater number of patents (scaled patents) than unconnected segments, with difference significant at 5%. The same observation is true for other measures of innovation activity - citations (scaled citations), high impact patents and patents value. Taken together, these results give a preliminary picture that segments run by divisional managers connected to CEO are associated with greater amount and higher quality of innovation.

Looking at other segment characteristics, we find no significant differences (at most marginal differences) in segment sales (as measured ratio of segment sales to firm sales), size, relative size (ratio of segment assets to total conglomerate assets), relative Tobin's Q (demeaned across segments' Q). However, connected segments have a lower proportion of divisional managers in senior status and higher proportion of managers having a PhD degree.

4.2 Multivariate Analysis

To test how connections to CEO affect the segments' innovation outcomes, we estimate the following regression model:

$$\begin{aligned} \mathit{Innovation}_{it+1} = \alpha + \beta \mathit{Connections\ to\ CEO}_t + \gamma X_{it} + \mathit{Industry}_n + \mathit{Industry}_i \\ + \mathit{Year}_t + \epsilon_{it} \end{aligned} \tag{8}$$

where $\mathit{Innovation}_{it+1}$ is an innovation outcome of segment i in fiscal year $t+1$. We examine the innovation outcomes in the next year, because it takes time for the R&D investments to produce patents. *Connections to CEO* is the connections measure for segment i computed as shown in equation (1) above. The regression also includes a set of control variables X_{it}, firm industry and segment industry fixed effects (based on 2-digit SIC codes) and year fixed effects. Additionally, we include firm fixed effects to account for time-invariant industry differences across firms (such as strategy, managerial talent) that could potentially affect segments' innovation activity. We adjust standard errors for heteroscedasticity and cluster at firm level.

Table 2 reports the results of estimation of equation (2). The results show that across all specifications the coefficient on *Connections to CEO* is positive and significant at 5% or better. The results in column (1) suggest that segments run by divisional managers who have connections to CEO file more patents in the following year. In column (2) we add firm fixed effects to the regression, and our results remain unchanged (t = 2.68, coefficient significant at 1%). The positive and significant coefficients in columns (3) and (4) indicate that connections to CEO are associated with increased citations. The estimates in columns (5) and (6) tell us that connections to CEO are associated with the greater amount of novel innovation, measured by higher number of generated patents, which are cited in the 50th percentile (and above) of the citation distribution within their technology class-year. The results from logit regression in column (7) suggest that connections to CEO are associated with the significantly higher probability of filing patents that are more novel in nature. Finally, columns (8) and (9) show that connections to CEO are associated with more commercially successful patents. The economic significance of the results is substantial. Specifically, in the column (1) the coefficient on *Patents* of 0.514 tells us that for a mean firm (with the average of *Patents* equal to 1.03) an increase by one connection to CEO is associated with 24.10% increase in *Patents* in the next year.[33] Further, the coefficients in the columns (3), (5) and (8) imply that for a mean firm one additional connection to CEO is associated with increase in *Citations* - by 27.10% , with increase in *High Impact Patents* - by 31.04%, and, finally, with increase in *Patents Value* - by 21.10%. It is worth to note that the estimates on other control variables have predicted signs. For example, higher CEO ownership is negatively related to innovation outcomes, because CEO may be reluctant on taking risky innovative projects. We also find that firms with more volatile ROA are associated with more segment-level innovation.

In Table 3 we examine the robustness of our baseline results. In the first set of tests we account for truncation bias. Our results continue to hold if we: 1) use *Scaled Patents* and *Scaled Citations* as dependent variables, as shown in columns (1) and (2) respectively; 2) we restrict our sample to patents filed up to 2007, considering that patents applied after 2007 may not appear in the sample as shown in columns (3) and (4). We next control for overall connectedness of divisional managers, since Faleye, Kovacs, and Venkateswaran (2014) show that better-connected CEOs are associated with more and higher quality patents. We measure the overall connectedness of divisional managers by using the concept of degree centrality as in El-Khatib, Fogel and Jandik (2015). Degree centrality measures the total number of social connections a given manager has to all other executives within the whole BoardEx network of North America executives. As common

[33]Increase by one connection to CEO translates into increase in our demeaned measure *Connections to CEO* by 0.48, multiplying coefficient of 0.514 by 0.48 gives 0.248 increase in the log-patents variable *Patents*, what corresponds the percentage increase of 24.10% for a mean firm in a sample - with a mean value of *Patents* equal to 1.03.

in literature, *Centrality* is expressed in percentiles (1st percentile – least central, 100th percentile – most central), which capture the relative position of the manager in the entire network of BoardEx executives. After calculating the degree centrality for all managers, we compute the relative centrality using the equation (1) above (variable *Centrality*). Columns (5) and (6) show that our results remain unchanged after controlling for overall connectedness of divisional managers. Finally, in columns (7) and (8) we repeat analysis by replacing *Connections to CEO* with the dummy variable *Connected* to compare connected and unconnected segments, and our results continue to hold.

Taken together, the results in this section suggest that segments operated by divisional managers with connections to CEO are associated with higher quality and quantity of innovation.

4.3 Potential Endogeneity

While the results in the previous section show that there is positive relation between connections to CEO and innovation outcomes, this relation is not necessarily causal. In our baseline regression we control for unobserved factors at the firm level using firm fixed effects. However, there are still some unobserved segment-level factors that could drive both - innovation outcomes and connections to CEO.

We address potential endogeneity using a difference-in-difference estimation. Following a large body of work on social connections (e.g. Duchin and Sosyura (2013), Fracassi and Tate (2012)), we use CEO planned retirements as exogenous shocks to connections of divisional managers to CEO.[34] Specifically, we focus on a subsample of CEO turnovers caused by CEO plausibly exogenous retirements. Divisional managers who are connected with the departing CEO are likely to lose this connection(s) after the CEO departure. Hence, as a result of the CEO turnover the segment run by connected divisional manager may lose connection(s) with CEO. Therefore, the observed decrease in the innovation outcomes as a result of a loss of connection due to plausibly exogenous CEO turnovers would provide a causal support for the previously shown

[34] We have only one CEO death during the sample period, so we focus only on CEO retirements.

positive relation between segment connections and innovation.

We identify CEO turnovers due to deaths or planned retirements at the sample firms. Using Execucomp, we focus on a subset of CEO departures with codes for the reason "Deceased" and "Retired". To identify non-performance related retirements, we require the executive to have age exceeding 60 years at the year of the departure (Huson, Parrino and Starks (2001), Parrino (1997)). We next check each potential retirement using firms' press releases and media articles. If we find a press-release about the planned CEO retirement, we classify the potential retirement as a retirement, otherwise - we label this departure as non-retirement and later exclude this CEO departure from the sample of retirements. Using this process, we identify 38 CEO turnovers with 23 CEO retirements (including one death) and 15 CEO departures (non-retirements) during the sample period.

In a difference-in-difference setup we define a treatment group (*Connected CEO* = 1) - segments in which a connected CEO was replaced by a unconnected CEO due to an exogenous turnover and control group (*Connected CEO* = 0) - segments in which a unconnected CEO was replaced by a unconnected CEO due to an exogenous turnover. In other words, in this approach we are comparing the innovation outcomes of the treated segments - segments that lost connection(s) due to exogenous CEO departure with control segments - segments that did not lose any connections as a result of the CEO departure. We remove turnovers when the connected CEO was replaced by a connected CEO or unconnected CEO was replaced by a connected CEO. We run the tests with commonly used 7-year and 5-year investigation-windows (e.g. Fracassi and Tate (2012)) centered on the CEO departure year and remove two confounding turnovers in these 7(5)-year windows. Since in our sample the number of control segments significantly dominate the number of treated segments, we follow Seru (2014) and conduct our analysis by randomly selecting five control segments (without replacement) for every treated segment. Our final sample consists of five treated segments and twenty five control segments, yielding 130 firm-segment-year observations for a 7-year window centered on the CEO retirement event. We estimate the following model:

$$\textit{Innovation Outcome}_{it} = \alpha + \beta_1 \textit{After} + \beta_2 \textit{Connected CEO} + \beta_3 \textit{After} \times \textit{Connected CEO} \\ + \textit{Industry}_n + \textit{Industry}_i + \textit{Year}_t + \epsilon_{it} \quad (9)$$

where *Innovation Outcome*$_{it}$ is an innovation outcome of segment *i* in fiscal year *t*, *After* is a dummy variable that equals one for the fiscal years after the exogenous CEO departure, *Connected CEO* is a dummy variable that equals one if the segment lost connection after the exogenous CEO turnover. The key variable *After* $\times$ *Connected CEO* captures the difference in differences effect or change in innovation outcome for a segment that lost connection to CEO as a result of the exogenous CEO turnover. The coefficient on *After* shows the average changes in innovation outcome for the unaffected segments. We control for the same set of control variables as in our baseline model (2) taken at the year prior to filing. As previously, we cluster standard errors at the firm level.

The results of the tests are reported in Table 4. The estimates in Column (1) show that the coefficient on *After* $\times$ *Connected CEO* is negative and significant at 5% (t = -2.74), suggesting that after the segment files significantly less patents in the year following the departure of the connected CEO. The results in the remaining columns paint the similar picture: decrease in other innovation outcomes after the CEO departure due to planned retirement.[35]

4.4 Firm-Level Innovation

So far, we documented that there is a positive effect of social connections on the innovation outcomes at the segment level. In this section we study if such effects exist at firm level. We use the measure of firm-level patents by aggregating patents filed at the segment level. Similarly to segment-level patents variable, we define *Firm Patents* as the natural logarithm of one plus the total patents filed by all firm segments. We are also interested in the firm-level value of patents filed by all segments, and *Firm Patents* is equal to the natural logarithm of one plus the

[35]In unreported analysis, we repeat the estimation using *Scaled Patents*, *Scaled Citations* and controlling for *Centrality*. We obtain quantitatively similar results.

total dollar value patents filed by all firm segments. To mitigate omitted variable concerns, we perform regressions in yearly changes. This approach allows to cancel all time-invariant firm-level factors. Specifically, the dependent variable is the change in *Firm Patents* from the previous year, and the main independent variable is the change is the change in *Firm Connectedness* from the previous year. *Firm Connectedness* is a firm-level connections measure and is equal to asset-weighted average of the proportion of divisional managers connected to CEO.

Table 5 presents the results. Column (1) shows estimates for firm patents and column (2) - for firm-level patents value. In all regressions we adjust standard errors for heteroscedasticity and cluster them by firm. The positive (and significant at 5%) coefficient on *Firm Connectedness* in both columns indicates that when connections to CEO increase, the firm files more patents and the economic value of the patents increase. The results suggest that connections to CEO matter for firm innovation at aggregate firm-level irrespective of how relatively connected the individual segments are.

5 Conclusion

In this paper we study the how connections to CEO affect conglomerates' innovation outcomes. We find that segments operated by divisional managers who have past educational or employment overlaps with CEOs are associated with greater number of filed patents, more highly cited patents and higher probability to file novel and highly scientifically valuable patents. Importantly, these higher quantity of patent applications translates into subsequent higher market valuations of these applications suggesting the economic success of inventions. The observed relationships are robust to controlling for unobserved time-invariant firm-level factors (by including firm fixed effects) and controlling for overall divisional managers' connectedness.

To provide a causal support for the effects we use exogenous CEO turnovers as exogenous shocks to managers' connections. CEO departures due to planned retirements are likely to lead to a loss of connection(s) with the divisional managers these CEOs were previously connected.

Using a difference-in-difference setup, we show that following a CEO turnover segments that switched from connected to unconnected CEO experience a significant decrease in innovation outcomes. At firm level, we show that firms with greater proportion of divisional managers connected to CEO are associated with superior innovation outcomes. Overall, our results suggest that connections to CEO have a innovation-enhancing role in conglomerates.

6 References

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7 Tables

Table 1: Summary Statistics

The table reports summary statistics for firms (Panel A) and segments (Panel B. The sample is 79 randomly selected S&P industrial conglomerates between 2003 and 2010, which operate in at least two business segments, have non-missing operating profit and segment assets and disclose identity of divisional managers. Innovation data is from Kogan, Papanikolaou, Seru and Stoffman (2017) patents dataset. The financial information is from merged Compustat and Compustat Historical Segments, identities of divisional managers' are collected from 10-K annual reports and data on divisional managers' personal characteristics and connections is from BoardEx.

Panel A: Firms

	All Firms		
Variable	Mean	Median	SD
Book assets, $millions	22768	13922	44680
Firm R&D	0.020	0.016	0.023
Market value, $millions	29614	15857	51147
Number of 3-digit SIC segments	3.148	3.000	1.105
Sales, $millions	22096	11026	24440
ROA volatility	0.027	0.021	0.020
CEO ownership	0.011	0.001	0.033
Patents	1.432	0.000	1.993
Citations	1.226	0.000	1.972
Patents Value	2.483	0.000	3.080
High Impact Patents	0.949	0.000	1.537
Firm Connectedness	0.003	0.000	0.049

Panel B: Segments

	All Firms		Connected (Prop >= 0.5)	Unconnected (Prop < 0.5)		
Variable	Mean	SD	Mean	Mean	Difference	
Innovation Measures at Patent Application Year						
Patents	1.031	1.551	1.478	1.003	0.475	**
Scaled Patents	0.681	1.075	0.961	0.663	0.298	**
Citations	0.860	1.539	1.299	0.833	0.466	**
Scaled Citations	0.904	1.538	1.281	0.880	0.401	**
High Impact Patents	0.626	1.131	0.931	0.607	0.324	**
High Impact Innovation	0.313	0.464	0.417	0.306	0.111	*
Patents Value	1.956	2.621	2.759	1.906	0.853	**
Independent Variables in One Year Before Patent Application						
Connections to CEO	0.001	0.157	-	-	-	
Segment Sales	1.502	0.994	1.694	1.490	0.204	
Segment Size	7.998	1.203	7.759	8.012	-0.253	*
Segment Relative Size	0.341	0.237	0.348	0.340	0.008	
Relative Q	-0.016	0.332	0.030	-0.019	0.049	
Segment CapEx	0.048	0.048	0.037	0.048	-0.011	*
Tenure (yrs.)	14.081	10.442	4.551	14.656	-10.105	
Senior	0.494	0.477	0.267	0.508	-0.241	***
Ivy League	0.225	0.38	0.237	0.224	0.013	
PhD	0.041	0.173	0.114	0.037	0.077	***

Table 2: Connections to CEO and Innovation Outputs

The table presents the results of segment-level regressions of innovation measures on social connections measure, segment and manager controls. The innovation variables are taken at year t+1. All other variables are measured at year t. All continuous variables are winsorized at 1% and 99% levels. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable	Patents (t+1)		Citations (t+1)		High Impact Patents (t+1)		High Impact Innovation (t+1)	Patents Value (t+1)	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Connections to CEO	0.514***	0.486***	0.482**	0.407**	0.402***	0.346**	1.054**	0.854**	0.848**
	(2.68)	(2.68)	(2.55)	(2.24)	(2.69)	(2.15)	(2.19)	(2.18)	(2.60)
Segment Sales	0.421***	0.169**	0.407***	0.173**	0.315***	0.134**	0.733**	0.624***	0.267*
	(4.61)	(2.06)	(4.50)	(2.25)	(4.32)	(2.29)	(2.47)	(4.57)	(1.95)
Segment Size	0.322***	0.214	0.304***	0.252*	0.239***	0.194*	0.742***	0.643***	0.326
	(3.41)	(1.45)	(3.64)	(1.81)	(3.58)	(1.93)	(2.82)	(4.42)	(1.25)
Segment Rel. Size	-0.553	-0.157	-0.525	-0.297	-0.384	-0.212	-0.888	-1.411***	-0.146
	(-1.59)	(-0.32)	(-1.66)	(-0.65)	(-1.55)	(-0.63)	(-0.98)	(-2.69)	(-0.18)
Segment Rel Q	0.236***	0.165*	0.215**	0.166*	0.182***	0.140*	0.721***	0.378**	0.227
	(2.84)	(1.79)	(2.51)	(1.68)	(2.78)	(1.84)	(3.52)	(2.49)	(1.52)
Segment CapEx	2.263*	2.848**	2.778**	2.839**	1.827**	2.190***	11.080**	5.112**	5.066**
	(1.92)	(2.50)	(2.41)	(2.63)	(2.08)	(2.80)	(2.15)	(2.42)	(2.46)
R&D Expenses	8.923*	-2.337	6.662	-3.000	5.558*	-4.783	23.825**	15.817**	9.056
	(1.94)	(-0.31)	(1.57)	(-0.28)	(1.76)	(-0.63)	(2.10)	(2.35)	(0.74)
CEO Ownership	-8.483*	-15.438**	-11.413**	-19.052***	-7.365**	-12.876***	-157.526***	-16.582*	-24.839**
	(-1.91)	(-2.53)	(-2.36)	(-2.73)	(-2.25)	(-2.80)	(-3.12)	(-1.98)	(-2.26)
ROA volatility	14.977***	20.087**	13.467***	22.867**	9.822***	13.344*	-4.675	21.237**	30.262**
	(3.03)	(2.07)	(2.70)	(2.24)	(2.67)	(1.80)	(-0.30)	(2.39)	(2.05)
Tenure	0.017**	0.002	0.012*	-0.002	0.010**	-0.001	0.043***	0.022**	0.005

Dependent Variable	Patents (t+1)		Citations (t+1)		High Impact Patents (t+1)		High Impact Innovation (t+1)	Patents Value (t+1)	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(2.43)	(0.43)	(1.87)	(-0.44)	(2.04)	(-0.18)	(2.92)	(2.11)	(0.68)
Senior	-0.445***	-0.007	-0.379***	0.035	-0.292***	0.033	-1.178***	-0.563**	0.006
	(-3.40)	(-0.05)	(-3.26)	(0.24)	(-3.36)	(0.31)	(-2.81)	(-2.34)	(0.03)
Ivy League	0.376***	0.165	0.295**	0.095	0.237**	0.074	0.908***	0.530**	0.275
	(2.68)	(1.40)	(2.33)	(0.84)	(2.52)	(0.93)	(2.63)	(2.18)	(1.35)
PhD	-0.031	-0.492	0.058	-0.346	-0.022	-0.332	0.521	0.148	-0.425
	(-0.11)	(-1.31)	(0.21)	(-0.98)	(-0.10)	(-1.14)	(0.47)	(0.31)	(-0.83)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Industry FE	Yes	No	Yes	No	Yes	No	Yes	Yes	No
Segment Industry FE	Yes	No	Yes	No	Yes	No	No	Yes	No
Firm fixed effects	No	Yes	No	Yes	No	Yes	No	No	Yes
N	1030	1030	1030	1030	1030	1030	779	1030	1030
Adj. R^2	0.57	0.66	0.54	0.63	0.53	0.62	N/A	0.57	0.65

Table 3: Connections to CEO and Innovation Outputs: Robustness

The table presents the results of segment-level regressions of innovation measures on social connections measures, segment and manager controls. All continuous variables are winsorized at 1% and 99% levels. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Scaled		Restricted Sample		Controlling for Centrality		Connections Dummy	
Dependent Variable	Patents (t+1)	Citations (t+1)	Patents (t+1)	Citations (t+1)	Patents (t+1)	Citations (t+1)	Patents (t+1)	Citations (t+1)
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Connections to CEO	0.446***	0.593***	0.640**	0.659**	0.614***	0.523***		
	(3.24)	(3.17)	(2.61)	(2.59)	(3.09)	(3.08)		
Connected (>= 0.5)							0.500**	0.444**
							(2.42)	(2.04)
Segment Sales	0.309***	0.408***	0.574***	0.580***	0.275***	0.226***	0.416***	0.403***
	(4.66)	(4.52)	(4.71)	(4.71)	(3.34)	(3.18)	(4.61)	(4.48)
Segment Size	0.211***	0.315***	0.461***	0.478***	0.220**	0.181**	0.323***	0.305***
	(2.98)	(3.44)	(3.09)	(3.44)	(2.43)	(2.47)	(3.46)	(3.68)
Segment Rel. Size	-0.261	-0.582*	-0.755	-0.776	-0.489	-0.460	-0.563	-0.534*
	(-0.99)	(-1.68)	(-1.38)	(-1.49)	(-1.36)	(-1.57)	(-1.61)	(-1.68)
Segment Rel Q	0.176***	0.209**	0.383***	0.359***	0.177**	0.147**	0.229***	0.209**
	(2.94)	(2.29)	(3.03)	(2.85)	(2.35)	(2.00)	(2.76)	(2.46)
Segment CapEx	1.197	2.967**	3.284*	4.016**	1.389	1.386*	2.367*	2.859**
	(1.44)	(2.55)	(1.93)	(2.31)	(1.40)	(1.80)	(1.95)	(2.44)
R&D Expenses	6.122*	7.571	11.171	8.555	10.212**	6.485*	8.822*	6.583
	(1.78)	(1.61)	(1.65)	(1.41)	(2.29)	(1.98)	(1.94)	(1.58)
CEO Ownership	-4.968*	-10.645**	-7.903	-12.504	0.674	-2.125	-8.326*	-11.277**
	(-1.73)	(-2.29)	(-0.99)	(-1.51)	(0.15)	(-0.61)	(-1.92)	(-2.35)
ROA volatility	9.876***	12.199**	11.306*	12.659**	12.563**	6.066	14.127***	12.716**
	(2.85)	(2.56)	(1.76)	(2.15)	(2.41)	(1.56)	(2.82)	(2.60)

	Scaled		Restricted Sample		Controlling for Centrality		Connections Dummy	
Dependent Variable	Patents (t+1)	Citations (t+1)	Patents (t+1)	Citations (t+1)	Patents (t+1)	Citations (t+1)	Patents (t+1)	Citations (t+1)
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tenure	0.013**	0.014**	0.019**	0.014	0.021***	0.015***	0.018***	0.013**
	(2.58)	(2.14)	(2.06)	(1.60)	(3.28)	(3.06)	(2.69)	(2.09)
Senior	-0.301***	-0.388***	-0.578***	-0.505***	-0.324***	-0.272***	-0.428***	-0.364***
	(-3.25)	(-3.22)	(-2.74)	(-2.66)	(-2.71)	(-3.30)	(-3.29)	(-3.12)
Ivy League	0.269***	0.319**	0.515**	0.460**	0.341***	0.251***	0.370***	0.289**
	(2.69)	(2.47)	(2.42)	(2.30)	(2.81)	(2.81)	(2.67)	(2.30)
PhD	-0.050	-0.024	-0.128	-0.140	-0.463	-0.415	-0.057	0.036
	(-0.23)	(-0.09)	(-0.34)	(-0.38)	(-1.46)	(-1.62)	(-0.20)	(0.13)
Centrality					-0.005	-0.003		
					(-1.54)	(-1.22)		
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Segment Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1030	1030	667	667	729	729	1030	1030
Adj. R^2	0.54	0.53	0.63	0.60	0.48	0.38	0.57	0.54

Table 4: Connections to CEO and Innovation Outputs: Difference-in-Difference Estimation

The table presents the estimation results of the following equation:

$$Innovation\ Outcome_{it} = \alpha + \beta_1 After + \beta_2 Connected\ CEO + \beta_3 After \times Connected\ CEO + Industry_n + Industry_i + Year_t + \epsilon_{it}$$

where *Innovation Outcome*$_{it}$ is an innovation outcome of segment *i* in fiscal year *t*, *After* is a dummy variable that equals one for the fiscal years after the exogenous CEO departure, *Connected CEO* is a dummy variable that equals one if the segment lost connection after the exogenous CEO turnover. *After* × *Connected CEO* captures the difference in differences effect or change in innovation outcome for a segment that lost connection to CEO as a result of the exogenous CEO turnover. The coefficient on *After* shows the average changes in innovation outcome for the unaffected segments. We control for the same set of control variables as in Table 2 taken at the year prior to filing. All continuous variables are winsorized at 1% and 99% levels. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable	Patents	Scaled Patents	Citations	Scaled Citations	High Impact Patents	Patents Value	Patents	Scaled Patents	Citations	Scaled Citations	High Impact Patents	Patents Value
	[-3,3]						[-2,2]					
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
After	0.226	0.146	0.321	0.352*	0.234*	0.006	0.247	0.188	0.331*	0.301	0.276**	-0.107
	(1.44)	(1.33)	(1.69)	(1.97)	(1.85)	(0.02)	(1.22)	(1.35)	(2.09)	(1.75)	(2.15)	(-0.22)
Connected CEO	1.092***	0.837***	1.338***	1.362***	0.942***	1.915***	1.059***	0.829***	1.336***	1.387***	0.925***	1.924***
	(4.16)	(3.11)	(5.06)	(3.53)	(4.53)	(3.15)	(4.46)	(3.40)	(4.20)	(3.19)	(4.22)	(3.02)
After x Connected CEO	-0.658**	-0.532***	-0.872***	-1.015**	-0.695***	-1.011*	-0.730***	-0.576***	-1.016***	-1.153***	-0.796***	-1.234**
	(-2.74)	(-4.05)	(-4.79)	(-2.78)	(-3.48)	(-1.83)	(-3.20)	(-4.42)	(-5.45)	(-3.42)	(-4.03)	(-2.69)
Segment Sales	0.416***	0.356***	0.339**	0.323*	0.363**	0.672***	0.483***	0.391***	0.404**	0.407**	0.380**	0.840***
	(3.24)	(3.17)	(2.32)	(1.81)	(2.59)	(3.70)	(3.93)	(3.71)	(2.72)	(2.26)	(2.53)	(3.44)
Segment Size	1.094***	0.801***	0.946***	0.993***	0.878***	1.215***	1.158***	0.839***	1.018***	1.104***	0.890***	1.421***
	(5.01)	(5.35)	(4.55)	(3.68)	(4.92)	(3.11)	(5.89)	(4.92)	(4.78)	(4.74)	(5.20)	(3.98)
Segment Rel. Size	-3.586***	-2.765***	-3.169***	-2.896***	-3.056***	-3.938**	-4.224***	-3.073***	-3.827***	-3.836***	-3.343***	-5.416***

Dependent Variable	Patents	Scaled Patents	Citations	Scaled Citations	High Impact Patents	Patents Value	Patents	Scaled Patents	Citations	Scaled Citations	High Impact Patents	Patents Value
	[-3,3]						[-2,2]					
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(-5.29)	(-6.45)	(-5.07)	(-3.22)	(-5.58)	(-2.88)	(-9.75)	(-8.26)	(-5.20)	(-6.68)	(-8.47)	(-4.41)
Segment Rel Q	0.019	0.042	0.141	0.305	0.203	0.173	0.073	0.148	0.188	0.214	0.281	0.243
	(0.06)	(0.19)	(0.49)	(0.94)	(0.82)	(0.27)	(0.18)	(0.57)	(0.70)	(0.73)	(1.16)	(0.30)
Segment CapEx	1.342	-0.382	0.432	2.747	0.125	-7.337	1.662	0.319	0.595	2.758	0.554	-7.563
	(0.41)	(-0.20)	(0.13)	(0.84)	(0.05)	(-0.74)	(0.59)	(0.13)	(0.15)	(0.75)	(0.17)	(-0.92)
R&D Expenses	18.065*	15.088**	19.116**	15.656*	9.189	28.496	5.495	4.892	6.661	6.269	-2.388	16.312
	(2.07)	(2.41)	(2.53)	(1.91)	(1.32)	(1.66)	(0.80)	(1.17)	(0.86)	(0.99)	(-0.39)	(0.89)
CEO Ownership	-108.0***	-84.1***	-124.5***	-89.9**	-103.1***	-155.9**	-114.6***	-79.7***	-131.5***	-103.8***	-98.7***	-187.5**
	(-3.04)	(-4.06)	(-3.00)	(-2.48)	(-3.51)	(-2.17)	(-3.80)	(-4.33)	(-3.48)	(-4.00)	(-3.70)	(-2.75)
ROA volatility	37.191*	30.932*	52.086**	48.425*	32.017*	55.669	14.265	16.834	25.216	26.229	13.334	17.333
	(1.84)	(2.05)	(2.46)	(2.11)	(1.83)	(1.68)	(0.99)	(1.57)	(1.38)	(1.49)	(0.90)	(0.60)
Tenure	0.006	0.011	0.009	0.014	0.013	0.003	0.008	0.011	0.015	0.015	0.020	0.007
	(0.36)	(0.92)	(0.48)	(0.72)	(0.94)	(0.09)	(0.52)	(0.98)	(1.03)	(0.85)	(1.48)	(0.21)
Senior	0.152	0.126	-0.196	0.112	0.016	0.472	0.299	0.230	0.188	0.290	0.300	0.620
	(0.80)	(1.05)	(-1.01)	(0.61)	(0.09)	(1.03)	(1.50)	(1.48)	(0.54)	(0.91)	(1.06)	(1.29)
Ivy League	-0.181	-0.213	-0.502	-0.193	-0.283	-0.537	-0.360	-0.297	-0.762**	-0.530**	-0.447*	-0.932
	(-0.59)	(-1.10)	(-1.55)	(-0.65)	(-1.18)	(-1.06)	(-0.94)	(-1.04)	(-2.73)	(-2.29)	(-2.05)	(-1.50)
PhD	0.029	0.080	0.142	-0.078	0.090	-0.042	0.229	0.194	0.280	0.160	0.203	0.502
	(0.16)	(0.60)	(0.60)	(-0.35)	(0.63)	(-0.10)	(1.31)	(1.46)	(1.07)	(0.88)	(1.46)	(1.16)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Segment Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	130	130	130	130	130	130	106	106	106	106	106	106
Adj. R^2	0.95	0.95	0.94	0.94	0.94	0.91	0.96	0.96	0.96	0.96	0.96	0.93

Table 5: Firm Connectedness and Firm-Level Innovation

The table presents the results of regressions in first-differences, in which the dependent variable is the annual change in firm-level innovation measures. All continuous variables are winsorized at 1% and 99% levels. t-statistics, reported in parentheses, are based on standard errors that allow for clustering at the firm level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable	ΔFirm Patents	ΔFirm Patents Value
Model	(1)	(2)
ΔFirm Connectedness	0.558**	0.912**
	(2.23)	(2.11)
ΔR&D Expenses	11.229*	22.867*
	(1.90)	(1.82)
ΔCEO Ownership	-20.072***	-31.649**
	(-2.94)	(-2.39)
ΔNumber of Segments	0.098	0.330
	(1.20)	(1.40)
ΔFirm Sales	-0.127	-0.153
	(-0.56)	(-0.32)
ΔROA volatility	0.106	-5.216
	(0.01)	(-0.35)
Year FE	Yes	Yes
N	359	359
Adj. R^2	0.09	0.08