ESSAYS IN EMPIRICAL CORPORATE FINANCE AND INSTITUTIONAL OWNERSHIP

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Farooq Durrani

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Examining Committee Members:

Lalitha Naveen, Advisory Chair, Department of Finance
Ronald Anderson, Department of Finance
Gurdip Bakshi, Department of Finance
Kose John, External Member, Department of Finance, New York University.

ABSTRACT

My dissertation consists of two chapters which explores various aspects of empirical corporate finance and institutional ownership.

In the first chapter, I examine whether common owners – an institution with holdings in both the distressed and the lending firm – ameliorates this conflict given that common owners should seek to maximize the equity value of both firms. The results show that when a common owner holds a stake in both the borrowing and lending firm, distressed firms are over 3.3-times more likely to file for Chapter 11 freefall bankruptcy (rather than prepack) as compared to borrowing-lending firms without a common owner. Using ownership of passive funds as an instrument for the presence of a common owner, I provide evidence of a causal relation between common ownership and bankruptcy filing choice. Overall, the analysis indicates that common ownership in both financially distressed borrowing firms and their lending firms leads to a greater likelihood of Chapter 11 freefall bankruptcy filing; suggesting that common owners typically side with creditors to maximize their combined equity value in both the borrowing and lending firm.

Next, I examine the effect of CEO social connections on stock returns. An equally weighted (value weighted) long-short portfolio strategy earns investors excess returns of 5.39% (4.44%) per year. Three potential reasons explain the relation between CEO social connections and excess returns; better firm performance, investor information asymmetry, and/or greater investor risk-bearing. Our analysis provides evidence consistent with CEO connections both increasing firm risk and improving firm performance.

DEDICATION

This dissertation is dedicated to the memory of my beloved father, Abdul Hameed Durrani, who died due to cancer before I started my doctoral studies.

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CHAPTER 1

COMMON OWNERSHIP AND BANKRUPTCY

Introduction

Over the last several decades, equity ownership of U.S. publicly traded firms has shifted from retail investors to institutional investors. Institutional investors such as Fidelity, Blackrock, and Vanguard now own over 60% of the total equity in U.S. firms. The growth in institutional equity ownership distances individual investors from their holdings but also potentially allows institutions to wield influence in firm decision making. Importantly, most institutional investors own large stakes in multiple firms, many of which can be competitors, have a supplier-customer relationship, or have a borrower-lender relationship. For example, AQR Capital Management Inc. holds large stakes in both Exide Technologies (borrowing firm) and Wells Fargo & Co (lending institution). Figure 1 shows a graphical representation of the structure of common ownership. I refer to institutions holding stakes across multiple firms as common ownership. Existing studies find that common ownership strengthens the customer-supplier relationship by increasing innovative and financial collaboration (Freeman, 2018), and leads to lower interest rates for borrowing firms by reducing information asymmetry and frictions (Ojeda, 2019). Matvos and Ostrovsky (2008) document that a large fraction of the negative returns for acquiring firms in an M&A transaction involve a common owner holding stakes in both bidding and target firms. Azar, Schmalz and Tecu (2018) find that common ownership reduces market competition, leading to higher prices for consumers without an accompanying increase in consumer demand.

A unique type of common ownership arises when institutions hold equity stakes in both a firm seeking bankruptcy protection and in the banks that lend to these distressed firms. The decision to enter bankruptcy presents an inherent conflict between the borrowing and the lending firm's objectives. Each firm seeks to safeguard their shareholders' value in different ways: Lending firms or banks prioritize recovering the promised interest and principal payments, whereas distressed borrowers seek to renegotiate loan terms or even default on the loan to protect valuable resources from creditors. The difference in borrowers' and lenders' objective functions creates a moral hazard in that each party may seek to take actions that protect their interests at the expense of the other party. However, a common institutional owner could potentially ameliorate the moral hazard by acting as a neutral agent that seeks to maximize both the borrower's and the lender's equity values so as to enhance or maximize value for its own shareholders. PG&E's (Pacific Gas and Electric) recent problems illustrate the struggle between creditors and incumbent managers to control the bankruptcy process and the manner in which institutional investors ameliorate the conflict. In this case, PG&E's managers and the firm's creditors (PIMCO, Elliott Management Co.) fiercely argued that each should maintain control of the bankruptcy process to ensure a speedy and less expensive workout. The presence of a common shareholder in both PG&E and the creditors arguably mitigates that conflict as the institution will seek to maximize their portfolio value.[1]

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[1] See *The Wall Street Journal*, August 17, 2019: PG&E Stays in Charge of Mega-Billion-Dollar Bankruptcy Exit Plan.

To investigate the effect, if any, of common ownership on the relation between lending and borrowing firms, I examine the type of bankruptcy that financially distressed companies choose for creditor protection. Distressed firms can seek protection by filing either a Chapter 11 "freefall" bankruptcy or a Chapter 11 prepackage ("prepack") bankruptcy. Prepack bankruptcies require that borrowers reach an agreement with two-thirds (or more) of their creditors prior to filing a reorganization plan. Borrowers maintain a distinct advantage over lenders with prepacks because this process tends to be quicker and less expensive than freefalls, provides the flexibility of out-of-court restructurings, and perhaps most importantly, increases borrower control relative to that of the lender because the borrowing firm develops the work-out plan (John, Mateti and Vasuden 2012).

Although borrowers prefer prepacks, extant literature indicates that lenders maximize their own equity value by pursuing freefall bankruptcies. In freefall, the distressed company immediately files for bankruptcy and only thereafter, commences negotiations with its stakeholders. Freefalls present advantages to lenders along at least four different lines. First, freefalls adhere more strictly to absolute priority rights (APR) than prepacks (Bharath, Panchapegesan, and Werner 2010). Second, freefalls provide lenders with more equity and control when the borrower exits bankruptcy relative to borrower-initiated bankruptcies (Weiss 1990; Gilson et al. 1990; Tashijan, Lease and McConnell 1996). Third, freefalls yield higher overall financial recovery for the distressed firms' stakeholders versus prepack filings. Finally, the freefall process results in larger bond payoffs for firm debt holders than prepacks (John, Mateti and Vasuden 2012). Overall, these arguments indicate that, *ceteris paribus*, distressed borrowing firms maximize their equity value through prepacks while lending institutions can maximize their equity values through freefalls, suggesting a potential conflict of incentives in resolving financial distress.

Intuitively, the common owner may influence or pressure the borrowing or lending firm to seek to seek a particular form of bankruptcy, i.e., freefall or prepack. The common owner's decision to intervene arguably rests on the absolute dollar value invested into the borrower versus the lender. For instance, a common owner with a large dollar value equity stake in JPMorgan or Citibank (the lender) versus a small dollar value stake in a Gymboree (distressed firm) suggests that the institutional owner prefers a free-fall bankruptcy filing over a prepack. The main research question that I address centers on whether common ownership influences the type of protection or bankruptcy choice that creditors pursue.

Using the UCLA-LoPucki Bankruptcy Database (BRD), I obtain data on 1,040 bankruptcy filings spanning from 1990 to 2018. After removing firms that are not matched in DealScan and Compustat, I am left with 292 bankruptcy filings, of which 80 firms (28%) have a common institutional owner that holds equity stakes in both the borrower and the lender.[2] The remaining 212 firms (72%) do not have a link through a common equity holder. For those borrower-lender combinations with a common owner, the common owner holds, on average, 18% and 9% of the distressed firm and lending firm, respectively. On an absolute dollar basis, this translates into an equity stake of $44.0 million in the borrowing firm and $31.6 million in the lending firm.

For the empirical analysis, I measure common ownership in three ways. First, I use a binary variable that equals one when the borrower-lender combination has a common

[2] My sample construction closely resembles that of Ivashina, Iverson and Smith (2016) who also lose a large fraction of firms after merging with Compustat and Deal Scan.

institutional owner and zero otherwise. Second, following Hansen and Lott (1996), I use the ratio of the product of shares held by common owner in the borrowing firm and the lending firms to the product of shares outstanding of borrower and lender. Last, I adopt Anton and Polk (2014) measure based on the ratio of sum of market values of shares held by the common owner in the borrowing and lending firm to the sum of market value of borrower and lenders. In establishing a common ownership threshold, I do not place a minimum equity holding for either the borrower or lender but rather that the common owner maintains an equity stake at the time of bankruptcy filing.

The univariate results indicate that borrower-lender combinations with common owners file for freefall bankruptcies, on average, in 75% of the cases. Whereas borrower-lenders with no common ownership file for freefall bankruptcies 50% of the time. This difference in filing is significant at the 1% level or better, suggesting that common ownership influences the bankrupt filing choice.

In multivariate analysis, after controlling for borrower and lender size, performance, liquidity, leverage, concentration of syndicated debt, and industry and time effects, I find that borrower-lenders with a common owner are about 3.33 times more likely to file for freefalls as compared to borrower-lender combinations without a common owner. Additional analysis indicates that a one percent increase in common ownership when measured in terms of number of shares (value of shares) increases the likelihood of borrowing firm filing for Chapter 11 freefall bankruptcy by 7.04% (1.97%). Overall, the analysis provides evidence consistent with the argument that common owners influence the borrower’s bankruptcy filing choice.

Many institutions such as pension and retirement funds maintain common ownership stakes across many borrower-lender combinations but are passive owners. As passive investors, these institutions hold stakes across broad asset classes to meet the strictures of their investment guidelines and thus, may have little incentive to intervene when firms face financial distress. To address this concern, I segregate common owners into passive and non-passive institutions such as endowment funds, educational trust, and retirement funds (Azar, Raina, and Schmalz, 2016; Ojeda, 2019). For this sample, I find that firms are 3.33 -times more likely to file for freefall bankruptcies than prepacks. Further analysis indicates that a one percent increase in common ownership when measured in terms of number of shares (value of shares) increases the likelihood of borrowing firm filing for Chapter 11 freefall bankruptcy by 33.57% (3.64%). The analysis provides evidence consistent with the argument that common owners influence the borrower's bankruptcy filing choice and this effect is stronger for non-passive owners.[3]

My results are plausibly driven by firms filing for Chapter 11 where institutional investors hold large stakes in both the equity and debt of the distressed company, i.e., institutions maintain dual holdings. Institutional owners with these dual holdings potentially influence managers and/or creditors to pursue one type of bankruptcy over the other to maximize the total value of their firm investment. To investigate this possibility, I eliminate common institutional owners with dual holdings from the sample and reconduct my analysis. The results continue to indicate that firms with common owners are more likely to file for freefall bankruptcy rather than prepacks. A one percent increase in the

[3] Due to data issues that I discuss in the data section, I cannot reliably separate passive funds such as retirement funds, education funds and endowment funds from the non-passive funds that is why I do not present results for the sample with passive funds.

market value (shares) of common ownership is associated with 2.18% (6.08%) increase in distressed firms filing for freefall versus prepack bankruptcies. Using the other measures of common ownership, I find similar results, suggesting that my results are robust to institutions with dual holdings.

Another potential concern focuses on whether common owners' absolute dollar investment in the borrower and lender influence bankruptcy type. A common owner for instance, with a disproportionately larger investment in the distressed firm versus that of the lender, may seek to maximize the soon to be bankrupt firm's equity value and thus influence managers to pursue a prepack rather than a freefall filing (or vice versa). To investigate this explanation, I examine the difference in market value of the common owners' stake in the lender less the stake in the borrower. The analysis indicates that freefall filings are more likely to occur (versus prepacks) when common owners maintain larger stakes in the lender than in the borrower. A one standard deviation increase in the log difference in the market value of the stake between the lender and borrower is associated with a 9.0% increase in the likelihood of a freefall bankruptcy. Consistent with Matvos and Ostrovsky (2008) findings that common owners' absolute dollar investment in borrower and lenders influence M&A transactions, my analysis suggests that value of the investment affects bankruptcy filing choice.

My sample suffers from a potential selection bias in that I only observe firms filing for bankruptcy protection. Some firms in financial distress that choose alternate paths such as acquisition, closure, and/or assets sales do not appear in the sample, suggesting a selection bias and inconsistent estimators. Using a Heckman probit selection model (Van de Ven and Van Praag 1981), I find no evidence of a correlation between the error terms in the main equation and selection equation, suggesting consistent estimates from the primary analysis and further indicating that common ownership influences bankruptcy filing type.

The analysis implicitly assumes that investors are fully informed on firm performance and ownership structure. In contrast, Gilje, Gormley, and Levit (2019) argue that not all investors are fully informed with some investors paying less attention and other investors paying more attention. Gilje et al. (2019) develop measures of common ownership that account for the attention that institutions allocate towards the firms in which they invest. Using four proxies of common ownership that control for investor attention, I continue to find that increases in common ownership increase the likelihood of firms opting for Chapter 11 freefall bankruptcy.

My analysis potentially suffers from an unobservable or latent variable problem in that the firm and/or management likely play a role bankruptcy filing choice. Hedge fund managers for instance, may engage in strategic investments in borrowing and lending firms to arbitrage pay-offs. A strategic investor with a pre-existing equity stake in a lending firm that holds a large, concentrated debt claim in the financially distressed firm may decide to also take a large stake in the borrowing firm to influence the bankruptcy decision or vice-versa. PG&E's recent issues with bankruptcy illustrates the issue. Baupost Group with a pre-existing stake in PG&E also bought PG&E debt claims to hedge any losses associated with the bankruptcy and also to increase their voice and control in the reorganization process. To address such endogeneity concerns, I follow Azar, Raina, and Schmalz (2016) and Ojeda (2019) and use the variation in ownership of passive index funds in the borrowing and lending firms as an instrument for common ownership. Intuitively, such funds follow a strategy of investing in a market-wide basket of firms and do not implement or follow strategic investment philosophies. When instrumenting for common ownership with index fund holdings, I find that Chapter 11 freefall bankruptcies are significantly more likely to occur when the borrower and lender have a common owner versus no common owner.

My research contributes to bankruptcy, corporate governance and common ownership literatures. To the best of my knowledge this is the first study to examine and document the relationship between common ownership between borrower and lenders on the type of bankruptcy decision filed by the borrower. This paper differs from existing studies of bankruptcy and ownership because I study the effect of third-party ownership (the common owner) rather than holders of debt and stock in either the lender or the borrower. This study further, contributes to the governance literature by showing that common ownership appears to mitigate agency problems between borrowers and lenders arising from differences in their objective functions.

I also contribute to the bankruptcy literature by documenting that the type of ownership affects the decision to file for Chapter 11 freefall bankruptcy. Existing studies examine the costs associated with each types of bankruptcy (Bris, Welch and Zhu 2006), the effect of bankruptcy type on equity holders (Ebherhart, Altman, and Aggarwal 1999), and the macroeconomic factors that contribute towards the decision to file for bankruptcy (Maksimovic and Phillips 1998). Recent studies also document the relation between dual holding of debt and equity and the probability of filing for bankruptcy as compared to pursuing out-of-court restructurings (Chu et al. 2018; Jian, Li, and Shao 2010). Similarly, Ivashina, Iverson and Smith (2016) document the effect of debt concentration on bankruptcy decisions. This paper contributes to this literature stream by showing that type of ownership increases the likelihood of filing for Chapter 11 freefall bankruptcy.

From a policy perspective, my analysis contributes to the growing debate about the role proxy voting firms play in advising institutional investors' voting on corporate proposals. In a recent ruling, the SEC urged investment advisors to undertake greater diligence when voting for various policy proposals and required more transparency in proxy voting firms such as Glass Lewis and Institutional Shareholder Services. Already, firms such as Vanguard maintain their own voting-service departments that examine policy proposals and votes after carefully examining the impact of these proposals on their portfolio value.

The rest of the paper is organized as follows. Section 2 discusses data sources and sample construction for both bankruptcy data and common ownership variables. Section 3 discusses methodology, and empirical findings. Section 4 discusses various robustness tests. Section 5 talks about instrumental variable results. Section 6 concludes the paper.

Data and Sample Selection

To study the impact of common ownership on bankruptcy filing type, I use bankruptcies filed by publicly traded firms from 1990 to 2018. The data comes from the UCLA-LoPucki Bankruptcy Research Database (BRD), which covers bankruptcies of publicly traded firms with a market value of $100 million or more, measured in 1980 dollars (about $305 million in 2018). This dataset provides information on bankruptcy filing date, type of bankruptcy, debtor-in-possession (DIP) financing, economy's gross domestic product (GDP) at time of bankruptcy, and the outcome of the bankruptcy process.

Data on the bankrupt firms' lenders comes from Thomson Reuters DealScan. DealScan provides data on different types of syndicated loans such as revolving credit, and project financing. Syndicated loans are identified using a Facility ID that links lender information to a single borrower. Lender information includes lender role (lead agent or a participant) and the amount of the loan. I only include transactions that include the amount of the loan. To merge the DealScan data with Compustat data, I use links provided by Chava and Roberts (2008) and Schwert (2019).

I obtain institutional shareholding data from Thomson Reuters SEC13F. Firms exercising investment discretion of $100 million or more must file Form 13F with the SEC each quarter, listing their equity holdings. Thomson Reuters assigns Manager Number as an ID for each fund or manager. Using Thomson Reuters CUSIP identifier, I match 13F institutional ownership data to the borrowers and lenders for firms filing for bankruptcy.

I start with 1,040 bankruptcy cases for bankruptcies filed from 1990 to 2018 having value of more than $100 million as per dollar value in 1980. After matching with DealScan and Compustat, I am left with 292 observations. Ivashina, Iverson and Smith (2016) also lost around 70% of their observations when their study merged Bankruptcy data with Deal Scan data. They were left with 119 observations for the sample period of bankruptcies filed between 1998 and 2009.

Out of 292 observations, 80 (28%) firms have common owners, and the remaining 212 (72%) firms that filed for bankruptcy do not have common owner, these statistics are similar to Freeman's (2018) findings in his study regarding impact of common ownership on customer-supplier relationship.

Construction of Common Owner Variable

I use three different measures of common ownership. The first measure is a dummy variable that equals one when the lender-borrower combination in the bankruptcy filing have at least one common owner, and zero otherwise. This constitutes the most basic measure of common ownership.

$$Common_{(blt)} = 1\{Investor_{(bt)} \cap Investor_{(lt)} \neq \emptyset\} \tag{1}$$

where $Investor_{(bt)}$ is the institutional investor(s) that hold shares in borrower b at time t and similarly $Investor_{(lt)}$ is the institutional investor(s) that hold shares in lenders l at time t that extended funding to a borrower at the time when institutions held shares in both borrower and lender. I compute this measure of common ownership one quarter before the borrowing firm files for bankruptcy. For example, if the firm filed for bankruptcy on April 23, then I will use data for the quarter ending on March 31st of that year.

The second proxy of common ownership is the sum of the market value of stock held by a common owner in the borrower and lender combination, scaled by the total market capitalization of the borrower and lender (Anton and Polk, 2014). Specifically, this second measure is;

$$Co-Value_{bLt} = \frac{\sum_{f=1}^{F}(S_{b,t}^{f}P_{b,t}+\sum_{l=1}^{L}S_{l,t}^{f}P_{l,t})}{S_{b,t}P_{b,t}+\sum_{l=1}^{L}S_{l,t}P_{l,t}} \tag{2}$$

$S_{b,t}^{f}$ denotes the number of shares owned by fund *f* in borrowing firm b at time t at one quarter before the firm files for bankruptcy. $P_{b,t}$ denotes the price of the borrowing firm at time *t*. $S_{l,t}^{f}$ denotes the number of shares owned by fund *f* in lenders *l* at time *t*, where fund f is the common owner in the borrowing and lending firm. $P_{l,t}$ denotes the price of the lending firm at time *t*. My measure varies from Anton and Polk (2014) because of multiple lenders to for a single borrower; therefore, I sum the dollar value investment of fund *f* in all lenders at time *t.*

As an illustration, assume borrower B has two lenders (L1 and L2) and two common owners (F1 and F2) at the time of bankruptcy. The market value of borrower B is $100, and those of L1 and L2 are $500 and $800, respectively. F1 invests $20, $80, and $100 in B, L1, and L2, respectively. Similarly, fund F2 invests $10, $160, and $120 in B, L1, and L2, respectively. *Co-Value* for firm B at time *t* is calculated as follows:

$$Co - Value_{bLt} = \frac{(20+10)+(80+100+160+120)}{100+500+800} = 0.408$$

The third measure of common ownership is the product of the proportion borrower shares held by the common owner and the proportion of lender shares held by the common owner (Hansen and Lott, 1996). The measure is.

$$Co - Share_{bL,t} = \frac{\sum_{f=1}^{F} S_{b,t}^{f}}{S_{b,t}} \times \sum_{l=1}^{L} \frac{\sum_{f=1}^{F} S_{l,t}^{f}}{S_{l,t}} \quad (3)$$

$S_{b,t}^{f}$ and $S_{l,t}^{f}$ denote the number of shares owned by fund *f* in borrowing firm *b* and lenders *l* at time *t* respectively, where fund *f* is the common owner in the borrowing firm and the lenders.

Descriptive Statistics

Table 1 breaks down the number of bankruptcies on a yearly basis from 1990 through 2018 with a value of $100 million or greater in 1980 dollars. Chapter 11 prepack bankruptcies increase after 2005 due to the introduction of the Bankruptcy Abuse Prevention and Consumer Protection that incentivizes managers to opt for prepacks by placing limits on Key Management Retention Programs (so-called "KERPs") and severance packages, and by limiting debtors' exclusive rights to file to 18 months. Prior to the 18-month limit, debtors could file at any time, thereby reducing management leverage in bankruptcy process. Table 1 shows a steady increase in both prepack bankruptcies and the faction of prepacks as a proportion of total bankruptcies.

Table 2, Panel A reports difference in mean test for main variables for both Freefall and Prepack bankruptcies. Column I reports the mean value of variables for firms that filed for freefall bankruptcies, whereas column II reports the mean value for firms that filed for prepack bankruptcies. The t-tests reported in column IV indicate that both main measures of Common Ownership, *Co-Value* and *Co-Share*, are significantly higher for freefall bankruptcies as compared to prepack bankruptcies. Similarly, we observe that the ratio of the dollar value of investment by the common owner in the lender to borrower is also significantly higher for firms that file for freefall bankruptcies as compared to prepack bankruptcies. However, we observe that common owners maintain greater shareholdings for firms that file for freefall bankruptcy as compared to firms that file for prepack bankruptcy and this difference is significant at 0.1% level. Like earlier findings by John et. al (2012), we find that firms that file for freefall bankruptcy have worse operating performance as compared to firms that file for prepack bankruptcy. I use return on asset as a proxy for operating performance and observe that firms that file for freefall bankruptcy have an average ROA of -9.61%, whereas firms that file for prepack bankruptcy have an average ROA of -0.01%. However, I observe that firms with freefall bankruptcy use less leverage, on average, as compared to firms that file for prepack bankruptcy. Firms filing for freefall bankruptcy are larger and more liquid (defined as cash and cash equivalents), as compared to firms that file for prepack bankruptcy.

After examining the mean values of both proxies of common ownership and financial variables based on type of bankruptcy, we now report the mean of financial variables based on presence of common ownership in panel B of Table 2. Column I reports the mean values for borrowing firms that have a common owner, whereas column II reports the mean values for borrowing firms without a common owner. Values from panel B of Table 2 show that borrowing firms that filed for bankruptcy that do not have a common owner have better operating performance, higher assets, leverage and liquidity as compared to firms with a common owner. These results show that financially constrained firms without a common owner perform better financially compared to firms with a common owner.

Thus far, we have examined mean values of proxies of common ownership and financial variables based on type of bankruptcy and presence of common ownership. Panel C of Table 2 shows that borrower-lender combinations with common owners file for Chapter 11 freefall bankruptcies in 75% of cases on average, whereas borrower-lenders with no common ownership file for Chapter 11 freefall bankruptcies in 52% of cases. Results from Panel C clearly shows that a presence of a common owner result in more freefall bankruptcies as compared to prepack bankruptcies.

Table 3 reports descriptive statistics for the proxies of common ownership, *Co-Value* and *Co-Share*, and financial variables for firms that filed for bankruptcy. Panel A reports descriptive statistics for firms that file for chapter 11 prepack bankruptcies whereas

Panel B reports descriptive statistics for firms that file for freefall bankruptcies. *Co-Value* and *Co-Share* are the two main measures of common ownership used in this study along with *Common* to examine the relationship between common ownership and bankruptcy decision. Overall mean for the *Co-Value* and *Co-Share* is similar to earlier studies of common ownership found (Ojeda, 2019; Anton and Polk, 2014; Hansen and Lott, 1996; Freeman, 2018). However, the mean common ownership is higher when firms opt for freefall bankruptcy compared to prepack bankruptcy. Similarly, the dollar value of common owners is higher in lenders compared to borrowers, and this difference is greater in firms that opt for freefall relative to prepack bankruptcy. On average, firms that opt for prepacks have better operating performance measured in terms of ROA compared to firms that opt for freefalls. The mean results we observe of financial variables for firms that opted for freefall and prepack bankruptcy support earlier findings by John et al. (2012).

Panels D and E reports the descriptive statistics for borrower who filed for Chapter 11 bankruptcy without and with common owner respectively. We observe that in my sample of 292 firms, the firms that do not have a common owner have positive operating performance, higher leverage, assets, and liquidity as compared to firms that do have a common owner.

Growth in Common Ownership

Results from Tables 2 and 3 show that, on average, financial variables are different for firms that have a common owner versus firms that do not have a common owner. Figure 2 depicts the growth in institutional common ownership from 1990 through 2018 for firms appearing in CRSP. I use data from Thomson Reuters 13F filings to compute the level of common ownership. Common ownership has grown from around 40% in 1980 to around

65% by 2018, indicating a grow rate of over 50% in institutional ownership over the 37 years.

Figure 3 reports institutional common ownership in lenders and borrowers or firms that appear in Thomson Reuters DealScan dataset. This dataset contains data of syndicated loans, which is one of the major types of lending arrangement among financial institutions and borrowers. Figure 3 shows a similar pattern of growth of common ownership to that observed in Figure 2. Common ownership grew from around 46% in 1990 to 64% in 2017. This growth is concentrated among firms using syndicated lending arrangements. Importantly, DealScan does not capture other lending arrangements such as bonds and trade credit. Figures 2 and 3 indicate a substantial growth institutional common ownership over the last 30 years. Although this type of ownership has grown, figures 2 and 3 indicate a dip in the early 2000's. The dip corresponds to a Thomson Reuter's data recording issue where some institutions were not included in the database. Ben-David, Franzoni and Moussawi (2012) also note this issue and WRDS tried to correct this problem by supplementing some of the data but bias still exists. Just to give an indication of the issue at hand, WRDS used actual 13F filings to compute institutional ownership and find that institutional ownership for 2015 is around 70%, whereas institutional ownership for 2015 using Thomson Reuters data is around 60%. So, using this dataset our results are somewhat more conservative. I address this concern is by using year dummies. Looking at Figures 2 and 3, we infer the growth in common ownership of institutional investors and the power yielded in firm policies as a result of this ownership. A prime example is Blackrock Inc. pushing companies to contribute to CSR in order to receive financial support from Blackrock.

Methodology and Empirical Results

My primary interest lies in the relation between institutional common ownership and borrower-lender decisions to file for freefall or prepack bankruptcy. Bankruptcy presents a scenario where both the borrower and the lender, *ceterris paribus*, arguably have differing preferences for the type of bankruptcy filing. Lenders' seek to recover their principal and interest payments. Borrowers' however seek to mitigate shareholder wealth destruction and quickly resolve the bankruptcy process. All else equal, borrowers prefer prepack relative to freefall bankruptcies (Chatterjee et al., 1996; Gilson et al.,1990). On the other hand, lenders prefer freefalls because these provide more control over the bankruptcy process and tend to limit deviations from APR (Bharath, Panchapegesan, and Werner, 2010).

To examine the effect, if any, on the relation between between common ownership and bankruptcy filing type, I use the following probit model.

$$\Pr(freefall = 1|Common) = \varphi(\beta_0 + \beta_1 Common\ Ownership_{t-1} + \beta_2 ROA_{t-1} + \beta_3 Leverage_{t-1} + \beta_4 Size_{t-1} + \beta_5 Cash\ and\ Cash\ Equivalent_{t-1} + \beta_6 Credit\ Concentration_{t-1} + \beta_7 Delaware_{t-1}) \quad (4)$$

where *Common*, *Co-Value*, and *Co-Share* are proxies for *Common Ownership*. These three proxies of *Common Ownership* are the main variables of interest. The main outcome variable is *freefall,* which equals one if the firm opts for freefall bankruptcy and equals zero if the firm opts for prepackaged bankruptcy.

I control firm specific variables in multivariate regression analysis, which have been shown to affect the outcome of bankruptcy decision. Earlier work by Moulton and

Thomas (1993) and Campbell (1996) find that the size of the firm and its profitability are key variables that affect decision of bankruptcy filing. I proxy for size and firm profitability by using logarithm of total asset and return of assets respectively. I computed return on assets by dividing Earnings before Interest Taxes and Depreciation by Total Assets. Furthermore, I also control for credit concentration of syndicated loans participated by banks and financial institutions. Ivashina, Iverson and Smith (2016) identify credit concentration as a variable that affect bankruptcy outcome. I measured syndicated debt credit concentration by calculating standardized Herfindahl-Hirschman Index for syndicated loans. I also controlled for liquidity by using log of cash and cash equivalent as a proxy. To address concern of any effects due to industry and time, I introduce Fama-French 10 industry and year fixed dummies as well.

Base line results

This analysis focuses on the three main proxies of *Common Ownership*, an indicator variable equal to one if there was a common owner at the time of bankruptcy filing(*Common)*, proportion of shareholding of common owners (*Co-Share*), and proportion of market value owned by common owners (*Co-Value*). Table 4 reports the result of the main Probit model. Using all three proxies, I find that common ownership increases the probability of a firm filing for Chapter 11 freefall bankruptcy. Panel A reports univariate results, and Panel B reports multivariate results. In panel B, I control for firm performance, size, liquidity, leverage, credit concentration, and whether the bankruptcy was filed in the state of Delaware as well as for industry and year fixed effects.

Univariate results show that the presence of common owners increases the likelihood of a firm filing for chapter 11 freefall bankruptcy by 26%. Similarly, 1%

increase in *Co-Value (Co-Share)* is associated with an increase in likelihood of firm opting for Chapter 11 freefall bankruptcy by 1.87% (3.74%), and it is significant at 1% (5%) level. These results show that common ownership is associated with an increase in likelihood of firm opting for Chapter 11 freefall bankruptcy.

In multivariate settings, when I control for firm size, profitability, leverage, credit concentration, and liquidity, I find the 1% increase in *Co-Value (Co-Share)* is associated with an increase in likelihood of firm opting for Chapter 11 freefall bankruptcy by 2.052% (7.175%). These results are significant at minimum 5% level of significance. Similarly, the presence of common owner in borrower-lender relationship increases the likelihood that the borrowing firm files for Chapter 11 freefall bankruptcy by 27%.

Results from the main Probit Model show that an increase in common ownership is associated with increase in the probability of a firm opting for Chapter 11 freefall bankruptcy. These results indicate that borrowing firms that share common owners with the lending firm are more likely to opt for Chapter 11 freefall bankruptcy.

There are couple of plausible explanation for the results we observe. First, summary statistics from Table 2 and 3 show that common owner have more dollar value invested in lender firms as compared to borrowing firm at the time of bankruptcy and this difference is greater in firms filing for Chapter 11 freefall bankruptcy. These findings suggest that common owner are more concerned about their dollar investment in lending firm as compared to borrowing firms and so they force borrowing firms to opt for Chapter 11 freefall bankruptcy, which increases not only their control over the whole processes but that of the lender as well. Second plausible explanation can be that they are not satisfied from the way the firm is being run and would like to exert more control and influence over the firm. In a way they want more control over the bankruptcy process because they believe management of the firm might start taking on more risk, which can than decrease the value of the assets of the firm. Just like what happened with bankruptcy of Sears, in which the Sears Inc filed a lawsuit against its former CEO for allegedly destroying the value of the company and its assets.

Non-Passive Funds

The primary analysis indicates that financially constrained firms with common owners are more likely to opt for freefall rather than prepack bankruptcies. One plausible explanation for this finding focuses on common owners exerting control during the bankruptcy process to maximize their combined borrower-lender investment. To provide insights into this explanation, I remove passive common owners from my sample and reconduct the analysis. Passive owners such as index funds, education endowments, and trusts arguably maintain little interest in intervening in the outcome of bankruptcy filings. The remaining institutional owners thus represent those characterized as taking a more active role in corporate oversight and performance.

Table 5 reports probit model results with my three primary measures of common ownership when excluding passive institutional investors. Similar to the results in the previous analysis, I continue to find that the presence of a commoner owners is associated with a significantly greater likelihood of distressed firms opting for freefall bankruptcies over prepack bankruptcies. Notably, the coefficient estimates on the three measure of non-passive common ownership tend to be substantially larger relative to full sample of institutional owners. The marginal effects of the two continuous measures of of common ownership, Co-Share and Co-Value, are 29.164 (7.04) and 3.300 (1.97) for the non-passive (all) institutions. Because the estimates come from separate regressions, the coefficients are not statistically comparable to one another. To directly assess the effect of all institutions versus non-passive institutions on bankruptcy choice, I conduct a difference in coefficient test by introducing a dummy variable, which finds that Co-Share is significantly higher for non-passive funds as compared to the whole sample.

The analysis thus far illustrates that an increase in common ownership in borrowing and lending firms increases the likelihood of freefall rather than prepack bankruptcy. Further, the results indicate that this relation appears strongest with non-passive institutions relative to passive institutions, providing evidence that common owners maintain an important voice in the bankruptcy filing type.

Non-Dual Holdings

Existing studies document that lending firms assume equity positions when distressed firms emerge from bankruptcy and the lending firm's equity position is larger when the borrower files for a freefall bankruptcy (Ivashina, Iverson, and Smith, 2016). Similarly, Chu et al. (2018) find that when institutions maintain concurrent debt and equity holdings in distressed firms (i.e., dual holdings), the workout resolution is more likely to involve an out-of-court restructuring versus a court ordered restructuring. These prior studies suggest that the presence of dual holders, rather than common owners, influence bankruptcy filing choice. To address this concern, I remove common owners maintaining both debt and equity stakes in firms seeking bankruptcy protection.

Table 6 displays the results of the non-dual holding analysis. After controlling for the effect of institutions holding both equity and debt in the distressed firm, I continue to find that borrowing firms with common owners are more likely to opt for freefall rather than prepack bankruptcies. An increase of 1% of the common owners' value (shares) in the borrower-lender combination is associated with a 2.184% (6.086%) increase in the likelihood of a freefall bankruptcy filing. Similarly, when using the binary to denote the presence of a common owner, I continue to find that when institutions hold stakes in both borrowing and lending firms that distressed firms are more likely to file for freefall bankruptcies versus prepack bankruptcies.

These results show that our main findings are robust to non-dual holding of debt and equity firms. Although the marginal effect is lower than the marginal effect we observed for a sample of non-passive funds, it is still significant at the minimum 5% level for all three proxies of common ownership. These results clearly support our main findings that the increase in common ownership increases the likelihood of firm filing for chapter 11 free fall bankruptcy. Furthermore, this finding further supports the argument that common owners exert more control over the bankruptcy process to protect their investment.

Robustness

Common Owner Investment in Lender vs. Borrower

The measures of common ownership used so far do not provide information about the dollar value investment of common owner in the lender as compared to the borrower. The main objective of common owners in this scenario is to maximize their portfolio value. Hence, it is important for us to know the amount of exposure common owner has in lender firms as compared to borrowing firms because this would shape the decision common owner would make. For example, if common owners have more investment in borrowing firm, they will try to influence a decision that favors the borrower and vice versa. As shown by Matvos and Ostrovsky (2008), institutional investors voted for merger even though it had negative announcement effect on acquirer because these owners gained more from the price gain in their investment in target. So, their attitude towards acquisition is determined from the impact of acquisition on dollar value investment in target and then overall portfolio.

To address this concern, I introduce another measure to capture the difference in the dollar value investment of common owner in the lender and borrower. As we can see from Tables 2 and 3, common owners have more dollar value investment in lenders as compared to borrowers, and the difference is greater for observations in which borrower files for Chapter 11 freefall bankruptcy. I hypothesize that *difference* should be associated with higher likelihood of firms opting for Chapter 11 freefall bankruptcy as common owners would try to protect their investment in lenders against any negative impact of bankruptcy. The lender's main objective is to recover their principal amount as well as the interest/coupon on the loan. We use the following Probit model to study the relationship between dollar value investment of common owner in lender on decision on bankruptcy.

$$\Pr(freefall = 1|Diff) = \varphi(\beta_0 + \beta_1 Diff_{t-1} + \beta_2 ROA_{t-1} + \beta_3 Leverage_{t-1} + \beta_4 Size_{t-1} + \beta_5 Cash\ and\ Cash\ Equivalent_{t-1} + \beta_6 Credit\ Concentration_{t-1} + \beta_7 Delaware_{t-1}) \quad (5)$$

where

$$Diff_{blt} = \ln\left(\sum_{f=1}^{F} \sum_{l=1}^{L} S_{lt}^{f} P_{lt}\right) - \ln\left(\sum_{f=1}^{F} S_{bt}^{f} P_{bt}\right) \quad (6)$$

$S_{b,t}^{f}$ and $S_{l,t}^{f}$ denotes the number of shares owned by fund *f* in borrowing firm *b* and lenders *l* at time *t* respectively, where fund *f* is the common owner in borrowing firm and lenders and $P_{b,t}$ and $P_{l,t}$ denotes the price of borrowing and lending firm at time t.

Table 7 reports the result of the above mentioned Probit model. Looking at both columns 1 and 2, we find that the increase in the difference in the dollar value of investment between lender and borrower is associated with an increase in the likelihood of borrowing firms opting for Chapter 11 freefall bankruptcy. For the subsample of non-passive funds reported in column 3, we find that a one standard deviation increases in log of difference in lender and borrower investment of common owner results in an increase in probability of firm opting for Chapter 11 freefall bankruptcy by 11%. Similarly, for subsample where common owners only hold equity stake in both borrower and lender, we find that an increase in log difference between dollar investment in lender and borrower increases the likelihood of firms filling for Chapter 11 freefall bankruptcy.

These result supports our earlier findings that common owners are trying to protect their interest in lending firms and are forcing borrowing firms to opt for Chapter 11 freefall bankruptcy giving more control to themselves as well as lenders for the whole process of bankruptcy and curtail any deviations from Absolute Priority Rule(APR). Additionally, these results also support the notion that common owner opts for Chapter 11 freefall bankruptcy in order to gain control so they can protect their investment in creditors and mitigating difference in objective problem as depicted by recent bankruptcy filing of Sears.

This result is similar to findings of Matvos and Ostrovsky (2008), who explained negative announcement return of acquirer through cross ownership of equity holding in targets. They find that cross equity owners are better off in a merger because they gain more through positive announcement return from target as compared to loss, they face from negative announcement return from investment in acquirer.

Selection Bias

One of the main issues with our results is that we only have those financial constrained firms in our sample that opted for Chapter 11 bankruptcy. However, there are other financial constrained firms that did out of court restructuring of debt and did not file for chapter 11 bankruptcy, which can lead to a sample selection bias. Sample selection bias can make our main estimator inconsistent and our results unreliable. To address the concern related to sample selection bias, I follow Van de Ven and Van Praag (1981) and use the Heckman Probit method.

The main question we examine in this study is whether common ownership affects the decision by the borrower to file for Chapter 11 freefall bankruptcy. We will use the following equation to examine our main research question, which will be known as main equation.

$$\Pr(freefall = 1|Common\ Ownership) = \varphi(\beta_0 + \beta_1 Common\ Ownership_{t-1} + \beta_2 ROA_{t-1} + \beta_3 Leverage_{t-1} + \beta_4 Size_{t-1} + \beta_5 Cash\ and\ Cash\ Equivalent_{t-1} + \beta_6 Credit\ Concentration_{t-1} + \beta_7 Delaware_{t-1} + u) \quad (7)$$

$$\Pr(bankruptcy = 1|Common\ Ownership) = \varphi\Big(\propto_0 + \propto_1 Common\ ownership_{t-1} + \propto_2 ROE_{t-1} + \propto_3 Leverage_{t-1} + \propto_4 Size_{t-1} + \propto_5 \left(\frac{Net\ Working\ Capital}{Total\ Assets}\right)_{t-1} +$$

$$\propto_6 \left(\frac{Retained\ Earning}{Total\ Asset}\right)_{t-1} + \propto_7 \left(\frac{Earning\ before\ Interest\ and\ Taxes}{Total\ Assets}\right)_{t-1} +$$

$$\propto_8 \left(\frac{Sales}{Total\ Assets}\right)_{t-1} + \propto_9 Operating\ Margin_{t-1} + v\Big) \quad (8)$$

where Common Ownership is measured as follows

$$Co_{Value_{bLt}} = \frac{\sum_{f=1}^{F}(S_{b,t}^{f} P_{b,t} + \sum_{l=1}^{L} S_{l,t}^{f} P_{l,t})}{S_{b,t}P_{b,t} + \sum_{l=1}^{L} S_{l,t}P_{l,t}}$$

$$Co_{Share_{bL,t}} = \frac{\sum_{f=1}^{F} S_{b,t}^{f}}{S_{b,t}} \times \sum_{l=1}^{L} \frac{\sum_{f=1}^{F} S_{l,t}^{f}}{S_{l,t}}$$

Equation 7 is the main equation whereas equation 8 is the selection equation, which examines the variables that affect the decision to file for Chapter 11 bankruptcy. We follow Altman (1968) in selecting the variables that predict the decision by the firm to file for Chapter 11 bankruptcy.

Null hypothesis is that the correlation between error term, *u* and *v*, of both Probit models is equal to zero ($\rho = Corr(u, v) = 0$). If the correlation between error term is not equal to zero, then the error terms in both Probit models might contain some common omitted variables, which can imply that there may be a case for a serious sample selection bias, resulting in an inconsistent estimates of coefficients of our proxies of common ownership, *Co-Value* and *Co-Share*, in the main equation.

Following Van de Ven and Van Praag (1981), I use Heckman Probit method to address concerns of selection bias. For the model to be well identified the selection equation should have at least one variable that is not in the main equation. As you can see that variables ROE, $\frac{Networking\ Capital}{Total\ Assets}$, $\frac{Retained\ Earning}{Total\ Assets}$, $\frac{EBIT}{Total\ Assets}$, $\frac{Sales}{Total\ Assets}$, and

Operating Margin are only in the selection equation and are not in the main equation. The dependent variable in the selection equation is bankruptcy, which is equal to 1, if the firm files for bankruptcy otherwise equal to 0.

To address concerns of selection bias, I construct a sample by merging data of firms that filed for bankruptcy with all Compustat firms. I remove firms whose data was not available in Thomson Reuters Deal Scan dataset. I assign value of zero for firm-year observations whose data did not match with Thomson Reuters 13F Filling dataset. I only compute *Co-Value* and *Co-Share* for borrower and lender at the beginning of each year.

Results of the Heckman Probit are reported in panel A of Table 8. They show that a 1% increase in *Co-Value* increases the probability of firm filing for Chapter 11 freefall bankruptcy by 1.15%; likewise, a 1% increase in *Co-Share* increases the probability of a firm filling for Chapter 11 freefall bankruptcy by 3.76%. These results are analogous to our earlier findings. Furthermore, results from the Heckman model shows that an increase in profitability and leverage increases the probability of prepack bankruptcy, whereas an increase in size increases the probability of freefall bankruptcy.[4]

To examine our main hypothesis, we look at results of Wald test reported in panel D of Table 8. As we can see that both Arthro and the Wald test are not significant, which means we fail to reject the null hypothesis that the correlation between error term of main

[4] Results of Heckman Probit model are reported in Table 8. Panel A reports marginal effect of the main equation, whereas Panel B reports the coefficients for selection equation of Heckman Probit. Panel C reports the result of significance of correlation between error term of main and selection equation.

equation and selection equation is zero. The result Heckman Probit shows that selection bias is not a concern and does not affect our main findings that given firms file for Chapter 11 bankruptcy, the increase in common ownership increases the likelihood of firms opting for freefall bankruptcy as compared to prepack bankruptcy.

GGL Proxies of Common Ownership

The measures of common ownership we have used in this study assumes that investors are fully informed. Gilje, Gormley, and Levit (2019) (GGL from hereon) argued that not all investors are fully informed: some investors pay less attention, and some investors pay more attention. They developed a measure of common ownership that considered the attention allocated by the investor to the companies they invest in. The following is the functional form of GGL measure of common ownership.

$$GGL(A,B) = \sum_{i=1}^{l} \alpha_{i.A} g(\beta_{i,A}) \alpha_{i,B} \qquad (9)$$

where

$$GGL(A,B)_{FullAttention}: g = 1 \qquad (9A)$$

$$GGL(A,B)_{Linear}: g\big(\beta_{i,A}\big) = \big(\beta_{i,A}\big) \qquad (9B)$$

$$GGL(A,B)_{Convex}: g\big(\beta_{i,A}\big) = \beta_{i,A}^{2} \qquad (9C)$$

$$GGL(A,B)_{Concave}: g\big(\beta_{i,A}\big) = \beta_{i,A}^{0.5} \qquad (9D)$$

GGL's measure of common ownership is flexible based on the attention of the common owners. For common owners that are completely inattentive g= 0, which means *GGL(A,B) = 0*. However, if common owners that are perfectly informed, one would set g

=1 for all investors than $g(\beta_{i,A}) = (\beta_{i,A})$. On the other hand if $g(\beta_{i,A})$ is convex (concave), then firms receive more (less) attention than the relative share of the firm in their portfolio. Gilje, Gormley, and Levit (2019) also use voting behavior of common owners to measure for attention. They follow Iliev and Lowry (2015) and proxy for investor attention using a dummy variable to indicate whether the investor reject the advice Institutional Shareholder Services for voting. If investors are more attentive, then they are more likely to form their own opinion regarding various corporate proposal and not rely on the ISS to inform their voting decision. Gilje, Gormley, and Levit (2019) find that the estimated attention function for an average institutional investor has a concave shape and has more of a concave function suggesting, an increase in attention diminishes with the increase in portfolio weight. GGL called this measure a *fitted* measure of common ownership.

I compute common ownership of borrower with all its lenders at the time the firm filed for bankruptcy. So, I have one borrower with multiple lenders. To compute GGL measure of common ownership for all the lenders with the borrower, Gilje, Gormley, and Levit (2019) show that one can take the simple mean of all the above proxies of common ownership to compute GGL for lenders with the borrower who filed for Chapter 11 freefall/prepack bankruptcy. All borrower-lender combination who were not matched in data were assigned a value of 0.

I obtain data of GGL measure from the data posted by Gilje, Gormley, and Levit (2019) via WRDS. They compute common ownership for each pair of stock for all variation based on attention of the common owner on an annual basis and not on quarterly basis. I merge the common ownership data with one year previous from the year when the firm file for bankruptcy. For example, if the bankruptcy was filed in 2011, then I will use GGL common ownership data from 2010, as it would be the common ownership value for a pair of stock for the year ending 2010. Similarly, we use one-year prior accounting and financial data in our Probit model. For example, if a firm filed for bankruptcy in 2011, then we use accounting data for the fiscal year ending 2010 in our Probit model. GGL measure for all pair of companies is available till 2012, so for this analysis we only use bankruptcy that were filed till 2013.

We use the following Probit model to study whether common ownership affects the decision by the borrower to file for Chapter 11 freefall or prepack bankruptcy and we measure common ownership using the measure proposed by GGL.

$$\Pr(freefall = 1|GGL) = \varphi(\beta_0 + \beta_1 GGL_{t-1} + \beta_2 ROA_{t-1} + \beta_3 Leverage_{t-1} + \beta_4 Size_{t-1} + \beta_5 Cash\ and\ Cash\ Equivalent_{t-1} + \beta_6 Credit\ Concentration_{t-1} + \beta_7 Delaware_{t-1}) \qquad (10)$$

where GGL is computed as discussed earlier from equation 9(A) to 9(D).

The marginal effect from the Probit model using four variations of GGL model is reported in Table 9. The marginal effect of common ownership when investor have linear, full, fitted, and concave attention is positive and significant, suggesting that probability of firms filing for Chapter 11 Freefall increases with an increase in common ownership. Marginal effect for other control variables is similar to my main earlier findings as well. Like the main results, I use both year and Fama-French 10 industry dummies as well. These results support my main findings that an increase in common ownership increases the likelihood of firm opting for Chapter 11 freefall bankruptcy. They also support our main conclusion that borrower-lender combination with common owners more likely to opt for Chapter 11 freefall bankruptcy because common owner wants to exert more control over the whole bankruptcy process and protect their dollar value investment in the lender.

Instrumental Variable

A potential concern with this research is that my results could be biased due to presence of endogeneity, which can arise due to unobservable or latent variable problem. For example, hedge fund managers for instance, may engage in strategic investments in borrowing and lending firms to arbitrage pay-offs. A strategic investor with a pre-existing equity stake in a lending firm that holds a large claim in the financially distressed firm may decide to also take a large stake/claims in the borrowing firm to influence the bankruptcy decision. PG&E’s recent issues with bankruptcy illustrates the issue. Baupost Group with a pre-existing stake in PG&E also bought PG&E debt claims to hedge any losses associated with the bankruptcy and to increase their voice and control in the reorganization process. If this happens, then I should see an increase in correlation and the effect we are seeing is not due to common ownership.

Following Azar et al. (2016) and Ojeda (2019), I use variations in common ownership driven by index funds such as Vanguard, Invesco's PowerShares, and Fidelity's Spartan in borrower and lenders as an instrument. The idea for using variation in common ownership driven by index funds as an instrument is as follows. Index funds are operated under certain rules and set investment objectives, growth in index funds is a result of increase in savings of individuals and their investment in these funds. These index funds are less likely to invest in borrowing and lending firms in order to take strategic advantage stemming from more control in the borrowing firm, through acquiring equity in both borrowing firm and lender firm.

I use the following equation for the 2SLS approach.

$$Common\ Ownership_{t-1} = \gamma_0 + \gamma_1 Common\ Ownership\ of\ Index\ Funds\ _{t-1} + \gamma_2 ROA_{t-1} + \gamma_3 Leverage_{t-1} + \gamma_4 Size_{t-1} + \gamma_5 Cash\ and\ Cash\ Equivalent_{t-1} + \gamma_6 Credit\ Concentration_{t-1} + \gamma_7 Delaware_{t-1} \quad (11)$$

$$Freefall_i = \beta_0 + \beta_1 Common\ \widehat{Ownership}_{t-1} + \beta_2 ROA_{t-1} + \beta_3 Leverage_{t-1} + \beta_4 Size_{t-1} + \beta_5 Cash\ and\ Cash\ Equivalent_{t-1} + \beta_6 Credit\ Concentration_{t-1} + \beta_7 Delaware_{t-1} \quad (12)$$

In the above equation, we use *Co-Share* and *Co-Value*, which are computed using equation (2) and (3), as proxy for *Common Ownership.* I constructed $Common\ Ownership\ of\ Index\ Funds$ using common ownership of the index funds in borrower and lenders using the proportion of value of shares, *Co-Value*, and number of shares held, *Co-Share*, by index funds. These measures of common ownership are similar to those used to compute common ownership for the whole sample using equations 2 and 3.

$$Co_{Value_{Index}\,bLt} = \frac{\sum_{f=1}^{F}(S_{b,t}^{f} P_{b,t} + \sum_{l=1}^{L} S_{l,t}^{f} P_{l,t})}{S_{b,t} P_{b,t} + \sum_{l=1}^{L} S_{l,t} P_{l,t}} \quad (13)$$

$$Co_{Share_{Index}\,bL,t} = \frac{\sum_{f=1}^{F} S_{b,t}^{f}}{S_{b,t}} \times \sum_{l=1}^{L} \frac{\sum_{f=1}^{F} S_{l,t}^{f}}{S_{l,t}} \quad (14)$$

The result of the 2SLS are reported in Table 10. Dependent variable is the dummy variable for freefall, if firm opted for Chapter 11 freefall bankruptcy it is equal to 1 and if firm opts for Chapter 11 prepack bankruptcy than freefall is equal to 0. Column 2 reports result when I use the proportion of shares owned as a measure of common ownership and variation in proportion of shares owned by index funds as an instrument. The results from column 2 of Table 10 demonstrate the causal relationship between common ownership and the decision to file for Chapter 11 freefall bankruptcy, and the main variable for interest *Co-Share* is significant at 5%. Furthermore, Column 4 reports the results when I use proportion of market value as a measure of common ownership and variation in proportion of market value by index funds as an instrument. These results show that the coefficient of *Co-Value* is significant at 1% level.

These results show causal relationship between common ownership and decision to file for the type of bankruptcy and support our earlier findings that increase in common ownership increases the likelihood of firm opting for Chapter 11 Freefall bankruptcy.

Announcement Return

Existing studies by Chatterjee et al. (1996) and Gilson et al. (1990) find that Chapter 11 prepack bankruptcies have a less negative impact on equity prices compared to when firms opt for Chapter 11 freefall bankruptcies. These studies also find that impact on equity is least negative when firms can do an out of court restructuring instead of going for Chapter 11 bankruptcy, whether it is prepack or freefall. These findings clearly show that equity holder would prefer an out of court restructuring, if not possible so than their preferred plan of action would be to go for Chapter 11 prepack bankruptcy.

However, lenders prefer Chapter 11 freefall bankruptcy as compared to Chapter 11 prepack bankruptcy for two reasons. First, Chapter 11 freefall bankruptcy would give lenders more control over the process because in Chapter 11 freefall bankruptcy lenders can also present their own plan and borrowing firm management has at most 18 months to present their plan for voting. Second, Chapter 11 freefall bankruptcy is associated with less Absolute Priority Rule (APR) deviations, which benefits the lender. Notably, we do understand the announcement effect of Chapter 11 prepack and freefall bankruptcy on lenders. I hypothesize that because lenders prefer Chapter 11 freefall bankruptcy over prepack bankruptcy, the announcement effect of Chapter 11 freefall bankruptcy will be greater than that of Chapter 11 prepack bankruptcy.

Table 11 reports results of announcement effect for both lenders and borrowers. In my study Lenders are syndicated loan lenders and it does not include trade creditors and bond holders and all the bankruptcies are greater than $100 million, in 1980-dollar value (equivalent to $308 million today). I find that Lenders associated with borrowers who file for Chapter 11 freefall bankruptcy have a positive announcement effect around day 0 and day +1 and CAR is 0.12% over this time period. However, Lenders whose borrowers have filed for Prepack bankruptcy has a negative announcement effect with CAR of -0.30% for day 0 and day +1. Here day 0 is the filing date of bankruptcy. These results further strengthen our earlier findings that shareholders of Lending institutions prefer Chapter 11 freefall bankruptcy over Chapter 11 prepack bankruptcy because they perceive the former as more lender friendly option.

Like earlier studies by Chatterjee et al. (1996) and Gilson et al. (1990), I also find that Chapter 11 freefall bankruptcy has more negative announcement return for equity holder as compared to Chapter 11 prepack bankruptcy. This finding supports the notion that Chapter 11 prepack bankruptcy are more equity friendly and less negative impact can also be associated with less time in bankruptcy.

To further understand the economic impact of announcement-return on the dollar investment of common owner in lenders and borrowers, I compute the impact of impact of return on filing date on mean dollar investment in lender and borrower for both types of bankruptcy. Table 12 reports the result of impact of announcement return on mean dollar investment of common owner in lender and borrower. Results from Table 11 show that despite the negative announcement effect for Chapter 11 freefall bankruptcy is greater than Chapter 11 prepack but the loss is offset from the gain common owners make through their dollar investment in lenders.

These results provide further evidence that common owners perform better when the borrowing firms opt for Chapter 11 freefall bankruptcy. They can influence the borrowing firm in making this decision because of their power as shareholders.

Conclusion

Institutional ownership has increased from 42% in 1980 to around 65% in 2018, which has resulted in greater influence of institutional owners in terms of the decisions made by the firms. Similarly, institutional ownership also grew from 40% to 60% for lenders and borrowers who utilized syndicated loans over the same time period. Bankruptcy is a major decision made both by borrowing and lending institutions, and this decision presents an agency problem that originates from the conflict of objectives between the borrowing and lending firms. Everything else being constant, Chapter 11 prepack bankruptcy is equity friendly or borrower friendly, whereas Chapter 11 freefall bankruptcy is more lender friendly.

I measure common ownership in three different ways. First, I measure common ownership as a presence of common owner, second, I measure common ownership as a proportion of shares owned by common owner in both borrower and lender, and last, I measure common ownership as a proportion of value of shares owned by common owner in borrower and lenders. Although these measures capture common ownership between borrower and lenders but does not give us any clue about how much more ownership they own in lender as compared to borrower. To address this concern, I introduce another measure which is difference between the log value of the dollar value investment of the common owner in both the lender and borrower.

In this study, I examine the impact of common ownership between borrower and lenders on the type of bankruptcy filed by the borrowing firm. Using a sample of public bankruptcy of more than $100 million (in 1980 dollars) from 1990 to 2018, I find that an increase in common ownership is associated with an increase in the likelihood that the borrowing firm opts for Chapter 11 freefall bankruptcy.

The univariate results indicate that borrower-lender combinations with common owners file for freefall bankruptcies, on average, in 75% of the cases. Whereas borrower-lenders with no common ownership file for freefall bankruptcies 50% of the time. In multivariate analysis, after controlling for borrower and lender size, performance, liquidity, leverage, concentration of syndicated debt, and industry and time effects, I find that borrower-lenders with a common owner are about 3.33 times more likely to file for freefalls as compared to borrower-lender combinations without a common owner

Additionally, I find that as the difference in common owners' investment in lender with borrower increases, so does the likelihood of borrowing firm opt for Chapter 11 freefall bankruptcy. Furthermore, I find that the coefficient of all measures of common ownership increase when I remove passive funds such as endowment funds, retirement funds, and index funds from the sample. These findings support the notion that common owners have more dollar investment in lenders compared to borrowers, and they prefer Chapter 11 freefall bankruptcy to protect their dollar investment in lending institutions. Additionally, Chapter 11 freefall bankruptcy is more lender friendly compared to prepack bankruptcy due to less deviation from APR (Bharath, Panchapegesan, & Werner, 2010), which gives lenders further incentive to favor freefall bankruptcy over prepack bankruptcy.

Following Van de Ven and Van Praag (1981), I use the Heckman Probit model to address concerns related to sample selection bias, which can cause the estimator to be inconsistent. Results from the Heckman Probit model show that I fail to reject the null hypothesis, i.e., that the error term between the main equation and selection equation are correlated and findings of the study are not affected by selection bias. The results of this study are also robust to the proxies of common ownership developed by Gilje, Gormley, and Levit (2019), who consider the investor attention function. This further strengthens the main findings of the study that increases in common ownership likewise increase the likelihood of firms opting for Chapter 11 freefall bankruptcy.

Overall, this study contributes to both bankruptcy and common ownership literatures. To the best of my knowledge this is the first study to examine and document the relationship between common ownership between borrower and lenders on the type of bankruptcy decision filed by the borrower. This study shows that common ownership appears to mitigate agency problem between borrower and lender, which exists due to the inherent difference in their objective function. My paper also contributes to the bankruptcy literature by showing that the type of ownership affects the decision to file for Chapter 11 freefall bankruptcy.

This study also contributes to the growing debate about the role of proxy firms in advising institutional investors about various voting proposals put forth by the firms. Vanguard which is one of the largest institutional investors already maintains its own voting services department that examine each policy proposal and votes carefully after considering the impact of its vote on portfolio value of their firm. Recent rulings by the SEC, which require more transparency from proxy voting firms in their decision making, has led investment managers to not rely solely on proxy voting firm advice for voting and do their own due diligence. These changing dynamics further increase the role of investment managers in the major policy decisions made by the firm.

Fig 1 – Graphical Example Common Owner

This figure shows a graphical example of common owner

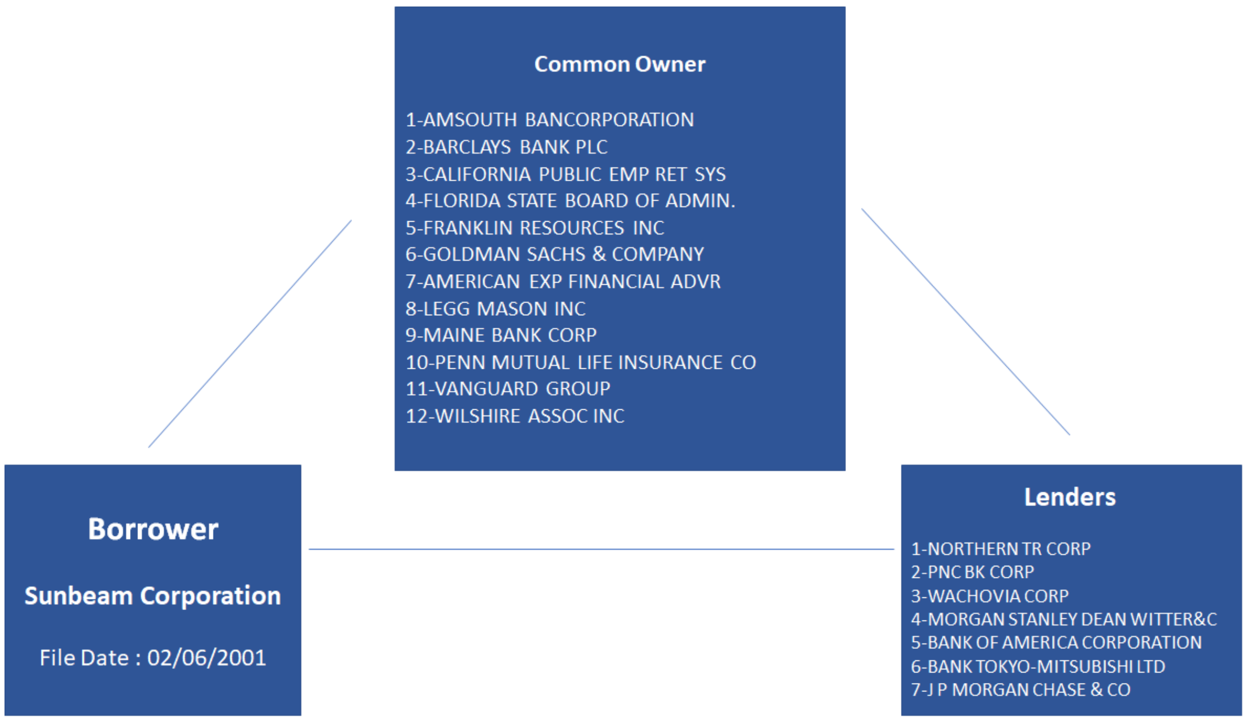


Fig 2 – Market Value of and Overall Percent of Shares held by Institutional Investors

This figure shows on the left axis the average fraction of a public firm owned by institutional investors of all the firms with data available in CRSP.

Fig 3- Market Value of and Overall Percent of Shares held by Institutional Investors (DealScan)

This figure shows on the left axis the average fraction of a public firm owned by institutional investors of all the firms with data available in CRSP and firms that shows up on DealScan.

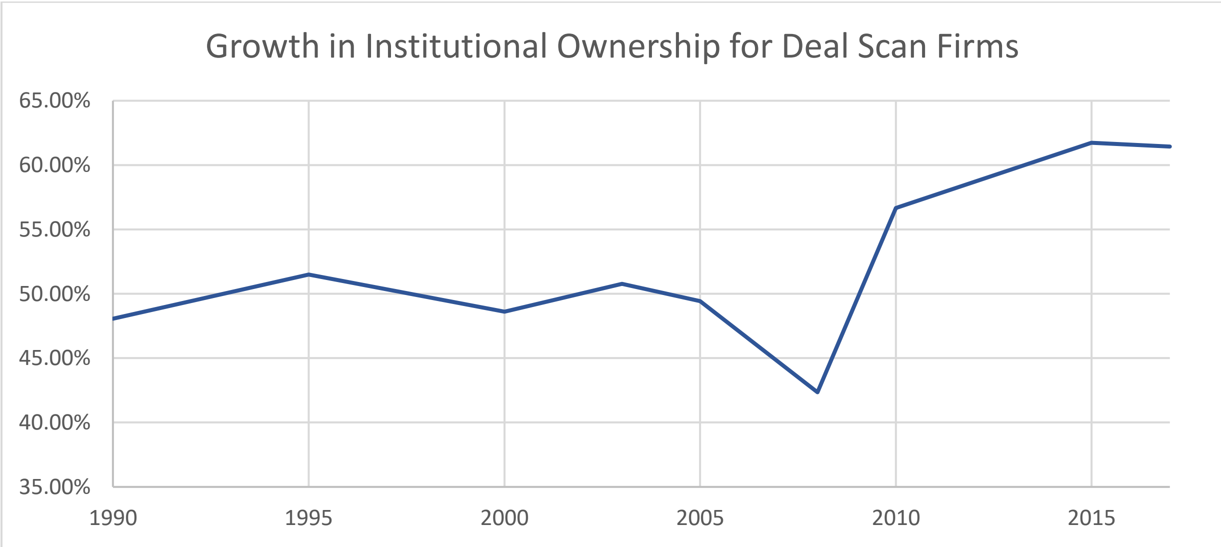


Table 1 – Bankruptcies by Year

Year	Total Bankruptcy	Freefall Chapter 11	Prepack Chapter 11	Fraction of Prepack to Total Bankruptcy
1990	30	28	2	7%
1991	41	35	6	15%
1992	32	21	11	34%
1993	25	13	12	48%
1994	12	6	6	50%
1995	19	14	5	26%
1996	16	8	8	50%
1997	17	10	7	41%
1998	31	22	9	29%
1999	45	30	15	33%
2000	80	63	17	21%
2001	97	76	21	22%
2002	83	49	34	41%
2003	57	43	14	25%
2004	29	16	13	45%
2005	25	21	4	16%
2006	14	9	5	36%
2007	13	9	4	31%
2008	39	29	10	26%
2009	91	53	38	42%
2010	36	15	21	58%
2011	23	13	10	43%
2012	24	15	9	38%
2013	26	10	16	62%
2014	17	8	9	53%
2015	25	13	12	48%
2016	43	18	25	58%
2017	30	14	16	53%
2018	18	9	9	50%

This table reports the number of Chapter 11total bankruptcies, Chapter 11 freefall bankruptcies, and Chapter 11 prepack bankruptcies each year from 1990 to 2018. All the bankruptcies are of public firm and are more than $100 million , in 1980 dollar value (currently equal to $308 million).

Table 2 – Difference in Mean Test

Panel A: Freefall vs Prepack

Variable	Mean (Freefall)	Mean (Prepack)	Difference	t-test	Mean (Full Sample)
Co-Value	0.0351	0.0114	0.0081	3.41	0.0248
Co-Share	0.0108	0.0027	0.0236	2.48	0.0073
Difference in Common Owner Investment in Lender vs. Borrower	3.01	1.23	1.78	3.98	2.24
Proportion of Shareholding owned in Borrower	0.075	0.017	0.058	3.96	0.050
ROA	-0.0961	-0.0001	-0.0960	-0.86	-0.0547
Leverage	0.1498	0.2882	-0.1383	-3.93	0.2095
Cash and Cash Equivalent	312.76	181.82	130.94	1.68	256.26
Assets	3510.043	2595.14	914.90	0.77	3115.25

Panel B: Presence of a Common Owner

Variable	Mean (With Common Owner)	Mean (Without Common Owner)	Difference	t-test	Mean (Full Sample)
ROA	-0.193	-0.002	-0.191	-1.55	-0.054
Leverage	0.169	0.224	-0.209	-1.37	0.2095
Assets	1865.81	3586.74	-1720.93	-1.32	3115.25
Cash and Cash Equivalent	193.76	279.84	-86.08	0.995	256.26

Panel C: Common Owner and Chapter 11 Freefall Bankruptcy

	No Common Owner	Common Owner	Total
Chapter 11 Prepack	107	19	**126**
Chapter 11 Freefall	105	61	**166**
Total	**212**	**80**	**292**

This table reports difference in mean test of proxies of common ownership and firm characteristics of borrowing firms that filed for bankruptcy during the time period from 1990 to 2018. Panel A reports difference in mean test for Chapter 11 prepack bankruptcy vs freefall bankruptcy, whereas Panel B reports difference in mean test for lender-borrower combination with and without common owner. Panel C reports the number of Chapter11 prepack and freefall bankruptcies by presence of a common owner. ROA is computed by dividing operating income before taxes and depreciation by total assets, Leverage is computed by dividing long term debt by total assets, and Size is computed as Log of total assets. Common ownership variables Co-Value is computed as the proportion of value of shares owned by common owners to total market value of shares of lenders and borrowers and Co-Share is computed as the proportion of number of shares owned by common owners to total number of shares of lenders and borrowers.

Table 3- Summary Statistics.

	Mean	Std. Dev	Median	Maximum	Minimum
Panel A: Chapter 11 Prepack Bankruptcy					
Co-Value	0.0114	0.0404	0	0.3211	0
Co-Share	0.0026	0.0161	0	0.1691	0
Dollar Investment in Lender (Million)	**22,600**	**40,800**	**660**	**150,000**	**15.8**
Dollar Investment in Borrower (Million)	**7.80**	**14.8**	**1.826**	**58.5**	**0.00305**
Log Difference in Investment in Lender vs Borrower	1.23	3.11	0	14.90	0
ROA	-0.001	0.319	0.061	0.428	-2.79
Leverage	0.288	0.351	0.154	1.397	0
Assets (Million)	2595.14	7420.25	720.41	60029.1	106.168
Cash (Million)	222.196	40.572	40.57	9825.9	0.167
Panel B: Chapter 11 Freefall Bankruptcy					
Co-Value	0.035	0.0693	0	0.374	0
Co-Share	0.011	0.034	0	0.323	0
Dollar Investment in Lender (Million)	**35,400**	**63,700**	**10,800**	**387,000**	**17.2**
Dollar Investment in Borrower (Million)	**60.6**	**292**	**2.51**	**2230**	**0.001**
Log Difference in Investment in Lender vs Borrower	3.01	4.22	0	13.36	0
ROA	-0.008	0.216	0.030	0.305	-1.338
Leverage	0.149	0.248	0.019	1.39	0
Assets (Million)	3510.043	11468.28	964.483	136295	0.862
Cash (Million)	510.764	2916.659	61.685	36730	0.001
Panel C: Full Sample					
Co-Value	0.0248	0.0596	0	0.3742	0
Co-Share	0.0073	0.0279	0	0.3230	0
Dollar Investment in Lender (Million)	**32,300**	**59,100**	**9140**	**387000**	**1580**
Dollar Investment in Borrower (Million)	**48.1**	**256**	**1.94**	**2230**	**0.0013**
Log Difference in Investment in Lender vs Borrower	2.24	3.87	0	14.9	0
ROA	-0.0004	0.222	0.041	0.355	-1.338
Leverage	0.207	0.295	0.064	1.397	0
Assets (Million)	3115.26	9921.25	829.39	136295	0.862
Cash (Million)	386.245	2279.38	48.22	36730	0.001

Table 3, continued

	Mean	Std. Dev	Median	Maximum	Minimum
Panel D: Firms without Common Owner					
ROA	0.004	0.214	0.041	0.355	-1.339
Leverage	0.221	0.292	0.086	1.397	0
Assets (Million)	3586.74	11325.74	856.83	136295	53.69
Cash (Million)	454.74	2638.73	58.56	36730	0.052
Panel E: Firms with Common Owner					
ROA	-0.193	0.243	0.036	0.355	-1.338
Leverage	0.169	0.304	0.011	1.438	0
Assets (Million)	1865.812	4218.667	727.655	35862	0.862
Cash (Million)	204.723	703.513	25.637	5616	0.001

This table reports summary statistics of firm characteristics of borrowing firms that filed for bankruptcy during the time period from 1990 to 2018. This table also reports summary statistics for measure of common ownership. Panel A and B reports summary statistics for firms that opted for Chapter 11 Prepack bankruptcy and Chapter 11 freefall bankruptcy, whereas Panel C reports summary statistics for the whole sample. Panel D and E report summary statistics for firms with common owner and without common owner respectively. ROA is computed by dividing operating income before taxes and depreciation by total assets, Leverage is computed by dividing long term debt by total assets, and Size is computed as Log of total assets. Common ownership variables Co-Value is computed as the proportion of value of shares owned by common owners to total market value of shares of lenders and borrowers and Co-Share is computed as the proportion of number of shares owned by common owners to total number of shares of lenders and borrowers.

Table 4 – Probit Model for Whole Sample

Panel A – Univariate Probit Model

	(1) freefall	(2) freefall	(3) freefall
Common	0.260***		
	(3.28)		
Co_Share		3.745*	
		(1.99)	
Co_Value			1.872**
			(3.01)
Diff			
Constant	0.529	0.523	0.547
	(0.76)	(0.75)	(0.78)
Observations	292	292	292
Pseudo R^2	0.19	0.17	0.18

Table 4, continued

Panel B – Multivariate Probit Model

	(1) freefall	(2) freefall	(3) freefall
$Common_i$	0.266***		
	(3.11)		
Co_Share_i		7.175***	
		(2.62)	
Co_Value_i			2.052***
			(3.06)
ROA_i	-0.296*	-0.359**	-0.341**
	(-1.83)	(-2.12)	(-2.00)
$Leverage_i$	-0.363***	-0.369***	-0.363***
	(-2.97)	(-2.83)	(-2.85)
$Size_i$	0.083*	0.095**	0.087**
	(1.88)	(2.20)	(1.99)
$Cash_i$	0.022	0.006	0.009
	(0.86)	(0.27)	(0.37)
Credit $Concentration_i$	0.912*	0.974*	0.891*
	(1.85)	(1.87)	(1.81)
$Delaware_i$	-0.179**	-0.204**	-0.202***
	(-2.39)	(-2.79)	(-2.74)
Industry and Year Dummy	Yes	Yes	Yes
Constant	-1.179	-1.428	-1.25
	(-1.26)	(-1.54)	(-1.36)
Observations	292	292	292
Pseudo R2	0.26	0.25	0.25

This table reports the Probit model of probability of filing for Chapter 11 freefall bankruptcy. Dependent variable is *Freefall* which is equal to 1 if the firm filed for Chapter 11 freefall bankruptcy and 0 if the firm filed for Chapter 11 prepack bankruptcy. The main variable of interest are four measure of common ownership; *Common, Co_Share,* and *Co_Value*, Panel A reports Univariate Probit model results whereas Panel B reports Multivariate Probit Model results. *Common* is a dummy variable which is equal to 1 if borrower and lender shared a common owner one quarter before the borrowing firm filed for Chapter 11 bankruptcy. *Co_Share* is computed as $\frac{\sum_{f=1}^{F} S_{b,t}^{f}}{S_{b,t}} \times \sum_{l=1}^{L} \frac{\sum_{f=1}^{F} S_{l,t}^{f}}{S_{l,t}}$, where$S_{b,t}^{f}$ and $S_{l,t}^{f}$ denotes the number of shares owned by fund *f* in borrowing firm *b* and lenders *l* at time t respectively, where fund *f* is the common owner in borrowing firm and lenders. *Co_Value* is computed as $\frac{\sum_{f=1}^{F}(S_{b,t}^{f} P_{b,t} + \sum_{l=1}^{L} S_{l,t}^{f} P_{l,t})}{S_{b,t} P_{b,t} + \sum_{l=1}^{L} S_{l,t} P_{l,t}}$,where $S_{b,t}^{f}$ denotes the number of shares owned by fund *f* in borrowing firm *b* at time *t*, which is at one quarter before the firm files for bankruptcy and $P_{b,t}$ denotes the price of borrowing firm at time t. *ROA* is computed by dividing operating income before taxes and depreciation by total assets, *Leverage* is computed by dividing long term debt by total assets, and *Size* is computed as Log of total assets. In Panel B, I control for Fama French 10 Industry and Year fixed effect. Results shown in Panel A and B uses common ownership from all categories of investors, such as institutions, individuals and endowment and college funds. *t* statistics in parentheses *, **, and *** represents significance at 10%,5% and 1% level.

Table 5- Probit Model for Sample of Non-Passive Funds

	(1) freefall	(2) freefall	(3) freefall
Common $_i$	0.268***		
	(3.01)		
Co-Share $_i$		33.569*	
		(1.94)	
Co-Value $_i$			3.637***
			(2.94)
ROA $_i$	-0.253*	-0.297**	-0.281**
	(-1.82)	(-2.11)	(-2.01)
Leverage $_i$	-0.363***	-0.367***	-0.368***
	(-3.00)	(-2.84)	(-2.91)
Size $_i$	0.074*	0.087**	0.078*
	(1.66)	(2.01)	(1.77)
Cash $_i$	0.024	0.011	0.016
	(0.89)	(0.45)	(0.62)
Credit Concentration $_i$	0.908*	0.881*	0.871*
	(1.87)	(1.85)	(1.81)
Delaware i	-0.187**	-0.193**	-0.197**
	(-2.50)	(-2.68)	(-2.68)
Constant	-1.138	-1.333	-1.175
	(-1.24)	(-1.44)	(-1.27)
Industry and Year Dummy	Yes	Yes	Yes
Observations	292	292	292
Pseudo R2	0.27	0.27	0.27

This table reports the Probit model of probability of filing for Chapter 11 freefall bankruptcy. Dependent variable is *Freefall* which is equal to 1 if the firm filed for Chapter 11 freefall bankruptcy and 0 if the firm filed for Chapter 11 prepack bankruptcy. The main variable of interest are four measure of common ownership; *Common*, *Co_Share*,*Co_Value*, and *Diff*. *Common* is a dummy variable which is equal to 1 if borrower and lender shared a common owner one quarter before the borrowing firm filed for Chapter 11 bankruptcy. *Co-Share* is computed as $\frac{\sum_{f=1}^{F} S_{b,t}^{f}}{S_{b,t}} \times \sum_{l=1}^{L} \frac{\sum_{f=1}^{F} S_{l,t}^{f}}{S_{l,t}}$, where$S_{b,t}^{f}$ and $S_{l,t}^{f}$ denotes the number of shares owned by fund *f* in borrowing firm *b* and lenders *l* at time t respectively, where fund *f* is the common owner in borrowing firm and lenders. *Co-Value* is computed as $\frac{\sum_{f=1}^{F}(S_{b,t}^{f} P_{b,t} + \sum_{l=1}^{L} S_{l,t}^{f} P_{l,t})}{S_{b,t} P_{b,t} + \sum_{l=1}^{L} S_{l,t} P_{l,t}}$,where $S_{b,t}^{f}$ denotes the number of shares owned by fund *f* in borrowing firm *b* at time *t*, which is at one quarter before the firm files for bankruptcy and $P_{b,t}$ denotes the price of borrowing firm at time t. *ROA* is computed by dividing operating income before taxes and depreciation by total assets, *Leverage* is computed by dividing long term debt by total assets, and *Size* is computed as Log of total assets. I control for Fama French 10 Industry and Year fixed effect. Results shown excludes common ownership of index funds and non-passive funds classified as Category 5 in Thomson Reuters 13F Dataset. *t* statistics in parentheses *, **, and *** represents significance at 10%,5% and 1% level.

Table 6 - Probit Model for Sample of Non-Dual Holding Common Owners

	(1) freefall	(2) freefall	(3) freefall
Common $_i$	0.271**		
	(3.11)		
Co-Share $_i$		6.086**	
		(2.54)	
Co-Value $_i$			2.184**
			(3.05)
ROA $_i$	-0.256*	-0.323**	-0.310**
	(-1.86)	(-2.54)	(-2.11)
Leverage $_i$	-0.357***	-0.323**	-0.354***
	(-2.92)	(-2.19)	(-2.79)
Size $_i$	0.073	0.364***	0.080**
	(1.61)	(2.82)	(1.80)
Cash $_i$	0.031	0.011	0.015
	(1.08)	(0.46)	(0.57)
Credit Concentration $_i$	0.892*	0.888*	0864*
	(1.85)	(1.84)	(1.80)
Delaware $_{t-1}$	-0.178**	-0.202***	-0.201***
	(-2.37)	(-2.78)	(-2.73)
Constant	-1.235	-1.423	-1.285
	(-1.35)	(-1.54)	(-1.39)
Industry and Year Dummy	Yes	Yes	Yes
Observations	292	292	292
Pseudo R2	0.26	0.25	0.25

This table reports the Probit model of probability of filing for Chapter 11 freefall bankruptcy. Dependent variable is *Freefall* which is equal to 1 if the firm filed for Chapter 11 freefall bankruptcy and 0 if the firm filed for Chapter 11 prepack bankruptcy. The main variable of interest are four measure of common ownership; *Common*, *Co_Share*,*Co_Value*, and *Diff*. *Common* is a dummy variable which is equal to 1 if borrower and lender shared a common owner one quarter before the borrowing firm filed for Chapter 11 bankruptcy. *Co_Share* is computed as $\frac{\sum_{f=1}^{F} S_{b,t}^{f}}{S_{b,t}} \times \sum_{l=1}^{L} \frac{\sum_{f=1}^{F} S_{l,t}^{f}}{S_{l,t}}$, where$S_{b,t}^{f}$ and $S_{l,t}^{f}$ denotes the number of shares owned by fund *f* in borrowing firm *b* and lenders *l* at time t respectively, where fund *f* is the common owner in borrowing firm and lenders. *Co_Value* is computed as $\frac{\sum_{f=1}^{F}(S_{b,t}^{f} P_{b,t} + \sum_{l=1}^{L} S_{l,t}^{f} P_{l,t})}{S_{b,t} P_{b,t} + \sum_{l=1}^{L} S_{l,t} P_{l,t}}$,where $S_{b,t}^{f}$ denotes the number of shares owned by fund *f* in borrowing firm *b* at time *t*, which is at one quarter before the firm files for bankruptcy and $P_{b,t}$ denotes the price of borrowing firm at time t. *ROA* is computed by dividing operating income before taxes and depreciation by total assets, *Leverage* is computed by dividing long term debt by total assets, and *Size* is computed as Log of total assets. I control for Fama French 10 Industry and Year fixed effect. Results shown common owners who also own debt in the borrowing firm. *t* statistics in parentheses. *, **, and *** represents significance at 10%,5% and 1% level.

Table 7 – Common Owner Investment in Lender vs. Borrower

	(1) Freefall Univariate	(2) Freefall Multivariate	(3) Freefall Non-Passive	(4) Freefall Non-Dual
Diff $_i$	0.0277***	0.029***	0.027***	0.031***
	(2.92)	(2.90)	(2.77)	(2.97)
ROA $_i$		-0.325**	-0.271**	-0.282**
		(-1.99)	(-2.01)	(-2.08)
Leverage $_i$		-0.375***	-0.372***	-0.365***
		(-3.10)	(-3.10)	(-3.03)
Size $_i$		0.083*	0.075*	0.069
		(1.84)	(1.65)	(1.50)
Cash $_i$		0.023	0.026	0.035
		(0.90)	(0.97)	(1.22)
Credit Concentration $_i$		0.905*	0.945*	0.875*
		(1.80)	(1.88)	(1.80)
Delaware $_i$		-0.178**	-0.183**	-0.176**
		(-2.35)	(-2.43)	(-2.31)
Constant	0.548	-1.191	-1.142	-1.203
	(0.79)	(-1.29)	(-1.23)	(-1.31)
Industry and Year Dummy	No	Yes	Yes	Yes
Observations	292	292	295	292
Pseudo R2	0.19	0.25	0.25	0.26

This table reports the Probit model of probability of filing for Chapter 11 freefall bankruptcy. Dependent variable is *Freefall* which is equal to 1 if the firm filed for Chapter 11 freefall bankruptcy and 0 if the firm filed for Chapter 11 prepack bankruptcy. The main variable of interest is *Diff*, which is computed as the difference between log of market value of ownership of common owners in lenders and borrowers. *ROA* is computed by dividing operating income before taxes and depreciation by total assets, *Leverage* is computed by dividing long term debt by total assets, and *Size* is computed as Log of total assets. I control for Fama French 10 Industry and Year fixed effect. Results shown excludes common ownership of index funds and non-passive funds such as Endowment Funds and Retirement Funds and funds classified as Category 5 in Thomson Reuters 13F Dataset. Column 1,2,3, and 4 reports results from univariate, multivariate, sample of non-passive funds, and sample of Non-Dual Holdings respectively. *t* statistics in parentheses *, **, and *** represents significance at 5%,1% and 0.1% level.

Table 8 – Selection Bias

Panel A – Marginal Effect of Main Equation

	(1) $Freefall_i$	(2) $Freefall_i$
$Co-Value_i$	1.15**	
	(2.11)	
$Co-Share_i$		3.763***
		(2.83)
ROA_i	-0.503**	-0.551**
	(-2.12)	(-2.29)
Lvg_i	-0.545***	-0.544***
	(-3.84)	(-3.87)
$Size_i$	0.116***	0.113***
	(2.59)	(2.53)
$Cash_i$	0.016	0.017
	(0.55)	(0.66)
$Credit\ Concentration_i$	0.632	0.621
	(1.27)	(1.24)
$Delaware_i$	-0.214***	-0.220***
	(-2.74)	(-2.85)
Industry and Year Dummy	Yes	Yes
Observations	281	281

This table reports the Heckman Probit model of probability of filing for Chapter 11 freefall bankruptcy. Dependent variable in main equation is *Freefall* which is equal to 1 if the firm filed for Chapter 11 freefall bankruptcy and 0 if the firm filed for Chapter 11 prepack bankruptcy. However, dependent variable in selection equation is *Bankruptcy* which is equal to 1 if firm filed for bankruptcy and 0 otherwise. The main variables of interest are *Co-Value* and *Co-Share*. *Co-Share* is computed as $\frac{\sum_{f=1}^{F} S_{b,t}^{f}}{S_{b,t}} \times \sum_{l=1}^{L} \frac{\sum_{f=1}^{F} S_{l,t}^{f}}{S_{l,t}}$, where$S_{b,t}^{f}$ and $S_{l,t}^{f}$ denotes the number of shares owned by fund *f* in borrowing firm *b* and lenders *l* at time t respectively, where fund *f* is the common owner in borrowing firm and lenders. *Co-Value* is computed as $\frac{\sum_{f=1}^{F}(S_{b,t}^{f} P_{b,t} + \sum_{l=1}^{L} S_{l,t}^{f} P_{l,t})}{S_{b,t} P_{b,t} + \sum_{l=1}^{L} S_{l,t} P_{l,t}}$,where $S_{b,t}^{f}$ denotes the number of shares owned by fund *f* in borrowing firm *b* at time *t*, which is at one quarter before the firm files for bankruptcy and $P_{b,t}$ denotes the price of borrowing firm at time t. *ROA* is computed by dividing operating income before taxes and depreciation by total assets, *Leverage* is computed by dividing long term debt by total assets, and *Size* is computed as Log of total assets. I control for Fama French 10 Industry and Year fixed effect. Panel A reports marginal effect of the main equation (equation 8), Panel B reports coefficient value from Heckman Probit for Selection Equation respectively. Panel C reports the result of Wald test *t* statistics in parentheses *, **, and *** represents significance at 10%,5% and 1% level.

Table 8, continued

Panel B – Coefficient of Selection Equation

	(1) $bankruptcy_t$	(2) $bankruptcy_t$
$Co-Value_{t-1}$	-1.969***	
	(-8.99)	
$Co-Share_{t-1}$		-3.830***
		(-6.58)
Lvg_{t-1}	-0.659***	-0.663***
	(-3.98)	(-3.98)
$Size_{t-1}$	0.0763***	0.0734***
	(9.54)	(9.15)
$\left(\frac{Net\ Working\ Capital}{Total\ Assets}\right)_{t-1}$	-0.0184**	-0.0177**
	(-2.15)	(-2.02)
$\left(\frac{Retained\ Earning}{Total\ Asset}\right)_{t-1}$	0.0103***	0.00989***
	(3.18)	(3.07)
$\left(\frac{Earning\ before\ Interest\ and\ Taxes}{Total\ Assets}\right)_{t-1}$	-0.0941***	-0.0925***
	(-4.52)	(-4.49)
$\left(\frac{Sales}{Total\ Assets}\right)_{t-1}$	0.0231***	0.0221***
	(3.93)	(3.79)
$Operating\ Margin_{t-1}$	0.00260*	0.00258*
	(1.79)	(1.75)
ROE_{t-1}	0.000308**	0.000312**
	(2.49)	(2.52)
Constant	-3.402***	-3.399***
	(-9.79)	(-9.98)
Industry and Year Dummy	Yes	Yes
Constant	-0.877	-0.983
	(-1.43)	(-1.48)
Observations	116714	116714

Panel C – Test of Independence of Equations

	Coefficient	**Standard Error**	**t-stat**	**p-value**
Athrho	-0.724			-0.837

<u>Wald Test of Independence Equations ($\rho = Corr(u, v) = 0$)</u>

Chi- square value	1.60
p-value	1.73

Table 9 – GGL Measure

	(1) $Freefall_i$	(2) $Freefall_i$	(3) $Freefall_i$	(4) $Freefall_i$
$GGL_{Linear(i)}$	0.412***			
	(7.07)			
$GGL_{Full\ Attention(i)}$		0.012***		
		(5.85)		
$GGL_{Fitted(i)}$			0.009***	
			(4.23)	
$GGL_{Concave(i)}$				0.012***
				(5.23)
ROA_i	-0.259*	-0.296	-0.335	-0.292
	(-1.27)	(-1.21)	(-1.40)	(-1.27)
$Leverage_i$	-0.177*	-0.235*	-0.206*	-0.196*
	(-1.81)	(-1.91)	(-1.94)	(-1.83)
$Size_i$	0.019	0.034	0.017	0.011
	(0.60)	(0.76)	(0.45)	(0.28)
$Cash_i$	-0.006	-0.005	-0.004	-0.006
	(-0.32)	(-0.20)	(-0.21)	(-0.28)
$Credit\ Concentration_i$	0.355*	0.566**	0.474*	0.447*
	(1.99)	(2.14)	(1.95)	(1.92)
$Delaware_i$	-0.075	-0.128*	-0.087	-0.086
	(-1.35)	(-1.70)	(1.34)	(-1.34)
Industry and Year Dummy	Yes	Yes	Yes	Yes
Observations	272	272	272	272

This table reports the Probit model of probability of filing for Chapter 11 freefall bankruptcy. Dependent variable is *Freefall* which is equal to 1 if the firm filed for Chapter 11 freefall bankruptcy and 0 if the firm filed for Chapter 11 prepack bankruptcy. The main variables of interest are GGL_{Linear}, $GGL_{FullAttention}$, GGL_{Fitted}, $GGL_{Concave}$, and GGL_{Convex}. *ROA* is computed by dividing operating income before taxes and depreciation by total assets, *Leverage* is computed by dividing long term debt by total assets, *Size* is computed as Log of total assets, *Cash* is calculated as log of Cash and investments, and *Credit Concentration* is the Herfindahl Index of syndicated loan outstanding . I control for Fama French 10 Industry and Year fixed effect.

t statistics in parentheses *, **, and *** represents significance at 5%,1% and 0.1% level.

Table 10 – Instrumental Variable Regression

	(1) Co_Share	(2) Freefall	(3) Co_Value	(4) freefall
Index-Co-Share$_i$	13.26***			
	(4.26)			
Co-Share$_i$		4.68**		
		(1.96)		
Index-Co-Value$_i$			3.42***	
			(9.36)	
Co-Value$_i$				1.449**
				(2.67)
ROA$_i$	0.00471	-0.272*	-0.00713	-0.253*
	(1.04)	(-2.17)	(-0.76)	(-2.21)
Leverage$_i$	-0.00153	-0.334***	-0.00660	-0.293***
	(-0.49)	(-3.44)	(-1.18)	(-3.01)
Size$_i$	0.000581	0.0752*	0.00363	0.054
	(0.43)	(2.25)	(1.21)	(1.62)
Cash$_i$	0.0000230	0.00597	-0.00146	0.013
	(0.04)	(0.31)	(-0.92)	(0.65)
Credit Concentration$_i$	-0.00552	0.795*	0.0170	0.712**
	(-0.58)	(2.24)	(0.83)	(1.97)
Delaware$_i$	0.000	-0.136*	-0.005	-0.136**
	(0.00)	(-2.39)	(-1.28)	(-2.37)
Constant$_i$	-0.00559	0.202	-0.0340	0.230
	(-0.59)	(0.82)	(-1.30)	(0.93)
Industry and Year Dummy	Yes	Yes	Yes	Yes
N	292	292	292	292
R2	0.42	0.29	0.69	0.30

This table reports instrumental variable regression of *freefall* on measures of common ownership, *Co_Share* and *Co_Value*. I use variation in Common Ownership due to Index Funds such as Vanguard, Invesco's PowerShares, and Fidelity's Spartan in borrower and lenders as an instrument. Following Azar et. al (2016) and Ojeda (2019), I compute *Co_Share* and *Co_Value* using sample of Index Funds. I use *Co_Share* and *Co_Value* computed using Index Funds to estimate value for *Co_Share* and *Co_Value* for Sample of whole sample. *Co_Share* is computed as $\frac{\sum_{f=1}^{F} S_{b,t}^{f}}{S_{b,t}} \times \sum_{l=1}^{L} \frac{\sum_{f=1}^{F} S_{l,t}^{f}}{S_{l,t}}$, where $S_{b,t}^{f}$ and $S_{l,t}^{f}$ denotes the number of shares owned by fund *f* in borrowing firm *b* and lenders *l* at time t respectively, where fund *f* is the common owner in borrowing firm and lenders. *Co_Value* is computed as $\frac{\sum_{f=1}^{F}(S_{b,t}^{f} P_{b,t} + \sum_{l=1}^{L} S_{l,t}^{f} P_{l,t})}{S_{b,t} P_{b,t} + \sum_{l=1}^{L} S_{l,t} P_{l,t}}$, where $S_{b,t}^{f}$ denotes the number of shares owned by fund *f* in borrowing firm *b* at time *t*, which is at one quarter before the firm files for bankruptcy and $P_{b,t}$ denotes the price of borrowing firm at time t. *ROA* is computed by dividing operating income before taxes and depreciation by total assets, *Leverage* is computed by dividing long term debt by total assets, and *Size* is computed as Log of total assets. I control for Fama French 10 Industry and Year fixed effect. Results shown common owners who also own debt in the borrowing firm. *t* statistics in parentheses. *, **, and *** represents significance at 10%,5% and 1% level. Column 1 and 3 report results of 1st stage whereas column 2 and 4 report result of second stage least square.

Table 11 – Announcement Return

	Sample	Day	CAR	Z test Value	Sign Test
Lender	Freefall	(0,+1)	0.12%	Significant at 1%	Significant at 5%
	Prepack	(0,+1)	-0.30%	Significant at 5%	
Borrower	Freefall	(0,+1)	-18.48%	Significant at 1%	Significant at 1%
	Prepack	(0,+1)	-6.83%	Significant at 1%	

This table reports the results of cumulative abnormal return (CAR) around day 0 and day +1, where day 0 is the filing date for the type of bankruptcy and day +1 is the next day, for both lender and borrower and for the type of bankruptcy filled by the firm. CAR is computed using market adjusted model.

Table 12 – Economic Impact of Announcement Return

	Chapter 11 Prepack Bankruptcy			**Chapter 11 Freefall Bankruptcy**		
	Mean Value	**CAR (0,+1)**	**Impact**	**Mean Value**	**CAR**	**Impact**
Lender	20,400,000,000.00	-0.30%	-61,200,000.00	35,300,000,000.00	0.12%	42,360,000.00
Borrower	7,147,337.00	-6.83%	-488,163.12	57,200,000.00	-18.48%	-10,570,560.00
Overall Impact for Common Owner			-61,688,163.12			31,789,440.00

This table reports the impact of cumulative abnormal return (CAR) around day 0 and day +1, where day 0 is the filing date for the type of bankruptcy and day +1 is the next day, on both lender and borrower and for the type of bankruptcy filled by the firm. CAR is computed using market adjusted model.

CHAPTER 2

CEO SOCIAL CONNECTIONS AND SHAREHOLDER WEALTH

Introduction

Social networks constitute the web of personal and professional relations or resources that surround individuals, groups or organizations and the characteristics of these relationships (White 2002). An individual's social network size proxies for social capital that captures the difference in individuals' power (Fowler 1997). Similarly, social networks can help individuals achieve their interests and goals (Coleman 1988). Earlier research in finance finds that directors' social networks are linked with lower bond yields through greater media coverage and more ties to financial firms (Chuluun, Prevost and Puthenpurackal 2014) and that director social capital is positively related to corporate disclosure quality (Reeb and Zhao 2013). Similarly, Coles, Daniel, Naveen, and Durrani (2019) find that connections of directors with outside members act as a proxy for advising quality and that as firm complexity increases so does board advise quality. These findings support the belief that highly connected directors provide resources to the firm such as legitimacy, skills, information and links to capital providers, suppliers, customers and other relevant entities. Hillman and Dalziel (2003) claim that these resources are beneficial for firms as they lower transaction costs while improving the likelihood of firms' long-term viability.

Social connections developed by CEOs, throughout their careers, can help to obtain information at a lower cost that potentially enhances firm value (Burt 1997; Tsai and Ghoshal 1998; Bajo, Chemmanur, Simonyan, and Tehranian 2016). Engelberg, Gao, and

Parsons (2012 and 2013) find that firms with CEOs with large networks earn significantly greater profits than those with smaller networks and that these connections help firms obtain debt at lower interest rates and with less restrictive covenants. Similarly, existing research shows that mutual fund returns improve when fund managers maintain connections to directors at invested firm (Cohen, Frazzini, and Malloy, 2008). However, as argued by Mizruchi (1982), these social connections potentially make CEOs more influential, weakening corporate governance and resulting in corporate policies that are in the interest of the CEO rather than shareholders. Francassi and Tate (2012) find that connections between the CEO and directors weaken the effectiveness of board monitoring resulting in lower firm value. Similarly, Hwang and Kim (2009) document that CEOs earn greater compensation and exhibit weaker turnover-performance sensitivity when CEOs maintain connection to the firm's directors. El-Khatib, Fogel, and Jandik (2015) find that highly socially connected CEOs engage in more mergers and acquisitions (M&A's) relative to less well-connected CEOs and the deals carry greater value losses to the acquirer and the combined firm. Overall, prior research provides evidence that CEO social connections influence firm decision-making and arguably affect firm value and thus, shareholders.

We examine whether CEO social connections influence firm stock-market returns. Our results show that firms with well-connected CEOs strongly outperform the market. In our tests, we calculate abnormal stock returns using the Carhart four-factor model for value-weighted and equal-weighted portfolios based on CEO connections. An investment strategy that buys an equally weighted portfolio of stocks with the highest level of CEO connections and simultaneously shorts an equally-weighted portfolio with the lowest level of CEO connections earns abnormal returns of about 5.26% per year (excluding portfolio rebalancing costs). Similarly, an equally weighted (value weighted) long-only portfolio earns excess returns of 3.98% (4.61%) per year. We obtain similar results in a multivariate setting with industry and firm-year fixed effects as well as with Fama-MacBeth regressions.

We use two measures of CEO connectedness – *degree*, and *closeness* – based on an extensive literature from sociology (Freeman 1977; Demarzo et al. 2003; Ballester et al. 2006). These measures capture CEOs' experiences from serving on the boards of other institutions. *Degree* is the number of connections that a CEO maintains with outside board members irrespective of the importance of the connection, arguably capturing the level of information flow. *Closeness* captures the notion that CEO may be well-connected to directors serving on other boards and this allows the CEO to obtain information at a lower cost relative to distant relationship with an outside director. A high closeness score indicates that the CEO receives information in a short time span (Bajo et al. 2016; El-Khatib, Fogel, and Jandik 2015). Importantly, in both the factor model specifications and the multivariate specifications, we find that firms with better connected CEOs earn significantly greater returns than the market portfolio and that a long only strategy yields profits to investors.

We identify three potential explanations for observing that firms with well-connected CEOs earn significantly higher returns than firms with non- or poorly-connected CEOs. The first explanations centers on a market efficiency or information asymmetry argument. Specifically, well-connected CEOs are better informed about the value of those connections and their impact on firm value relative to outside investors and their knowledge of the value these connections (Engelberg, Gao, and Parsons 2013; Larcker, So, & Wang 2013). This difference in knowledge creates information asymmetry between corporate insiders and outside investors leading to an under-reaction when well-connected CEOs assume their positions. If markets are not fully efficient, then CEO connectedness may not be completely reflected in prices, resulting in subsequent positive abnormal returns.

The second explanation focuses on well-connected CEOs enhancing firm performance. CEOs with strong social connections to other executives and directors arguably accrue and hold better information sets than less well-connected CEOs. Better data and information potentially lead to systemically better decision-making that improves firm performance and returns relative to firms with weaker information sets (Larcker, So, & Wang 2013). Similarly, CEOs with better networks may be able to act more quickly in investment and financing decisions that provides a competitive advantage to less well-connected firms. The second explanation thus asserts that the positive effects from CEO connections are not fully priced and lead to positive abnormal returns for the firm and outside shareholders.

The two previous explanations rely on at least some small level of market inefficiency in pricing CEO connectedness into stock prices. That is, outside investors fail to completely understand and price the effects on connections into stock prices. Our third explanation centers on the notion that outside investors are fully aware of CEO connections and demand extra compensation for holding shares in firms with well-connected CEOs. Intuitively, CEOs with substantial social connections arguably possess more bargaining power and influence and thus, will be more immune to governance controls and systems relative to poorly connected executives, e.g., powerful and entrenched management. With well-connected CEOs, outside shareholders bear a risk that executives will extract private benefits from the firm at the expense of shareholders. If so, investors will demand a higher return on their shares for bearing this risk.

To provide insights into which explanation, if any, better explains the relation between CEO connectedness and stock price returns, we conduct additional testing. We begin with the firm performance argument (second explanation) by examining the relation between CEO connections and leading changes in return on assets (ΔROA_{t+1}). Following Lilienfeld-Toal and Ruenzi (2014) and Larcker, So, and Wang (2013) we use ΔROA_{t+1} as a proxy for firm operating performance. A positive impact on ΔROA_{t+1} for highly connected CEO firms supports the hypothesis that CEO social connections enhance firm value. On the other hand, CEO connections negatively affecting ΔROA_{t+1} supports the argument that social connections detract from firm performance. The analysis indicates that firms with well-connected CEOs exhibit greater excess returns than firms with less well-connected CEOs.

To provide insights into the risk-based argument for well-connected CEOs systematically exposing shareholders to a priced risk, we example the impact of CEO social connections on volatility of returns. Prior literature documents risk can be defined as volatility of returns (Baker, Bradley, and Wurgler 2011; Dutt, and Humphery-Jenner 2013). Furthermore, Giroud and Mueller (2011) argues that capital expenditure may not be good proxy for firms whose investment activity is mainly driven by mergers. Dutt, and Humphery-Jenner (2013) shows that a negative relation exists between firm operating performance and stock volatility and Baker, Bradley, and Wurgler (2011) shows that stocks with low volatility is associated with firm with higher stock performance. Based on the results of existing studies we thus expect to observe a negative relation between CEO connections and stock volatility, which would then support that excess return we observe is mainly due to firm performance. On the other hand, if we observe positive association between CEO connections based on board directorship and stock volatility, which would than support the risk-based explanation for observing excess returns. We use standard deviation of returns as proxy for risk and find that firms with highly connected CEO's are associated with negative impact on stock market volatility. This finding supports compliments findings of earlier studies that show association between high operating performing firms with low stock market volatility. Furthermore, these findings support the notion that highly connected CEO's improve firm performance and at the same time has negative affect on volatility of returns most probably stemming from better operating performance.

To provide additional evidence on the market efficiency explanation, we examine the effect of CEO connections on analyst forecast errors. If firms with well-connected CEOs exhibit a greater likelihood or propensity to miss analyst forecasts, then this would be consistent with an explanation that these firms (or outside shareholders) suffer from a greater asymmetric information problem than firms with weakly-connected CEOs (Krishnaswami & Subramaniam, 1999). Our analysis indicates that CEO social connections appear to have no effect on analyst forecast errors or the dispersion of analyst estimates; suggesting that well-connected firms appear to exhibit the same level of information asymmetry as poorly-connected CEO firms, e.g., similar levels of market efficiency.

Overall, we find that firms with highly connected CEOs earn excess return and that this excess return remains consistent over the entire sample period. Three possible explanations for observing a positive relation between CEO connections and excess returns are; information asymmetry, better firm performance, and greater risk-bearing by outside shareholders. Our analysis does not provide evidence that firms with well-connected firms suffer from greater information asymmetry than less well-connected firms.

Our analysis further indicates that well-connected CEOs appear to be associated with lower risk, which is stemming from better operating performance, which enables these shareholders to earn a greater return on their investment. The risk-connection relation holds through the entire sample period. In sum, the results appear to support a performance-based explanation for observing positive excess returns in firms with well-connected CEOs.

We contribute to three strands of finance literature. To the best of our knowledge, this is the first study that examines the relation between excess returns and CEO social connections. Our analysis lends strong evidence to notion that firms with well-connected CEOs systematically outperform the market with a simple long position and that investors can earn better returns (3.91% per year) when pursing a long-short strategy. Second, our study suggests that the better returns stem from two primary channels; firms with better connected CEO exhibit better accounting performance, which in turn shows that highly connected CEO's are also associated with low stock return volatility. Second, we contribute to the literature that shows the importance of social connections in finance (Francassi and Tate 2012; Cao, Dhaliwal, Li and Yang 2015; Chulun, Prevost and Puthenpurackal 2014; Cohen, Frazzini, and Malloy 2008; Bajo, Chemmanur, Simonyan and Tehranian 2016; Engelberg, Gao, and Parsons 2012). Finally, we add to growing the literature that examines corporate governance through an asset pricing perspective (Larcker, So, & Wang 2013; Liliand-Toal & Ruenzi 2014; Eisfeldt & Papnikolaou 2013). Shareholders show deep concern on the returns of their investments versus accounting or valuation metrics. Our analysis using three and four factor portfolios shows that investors while bearing a risk to well-connected CEOs can earn returns that outpace the overall stock market.

The remainder of the paper is organized as follows. In Section 1, we discuss our sample selection procedure and describe how we calculate our proxy of social connection of CEO. In Section 2, we present Carhart 4 factor model results and characteristic adjusted return results in multivariate settings. In Section 3, we further study all three potential explanations for observing abnormal returns. Section 4 concludes.

Data and Sample Selection

The sample period for this study is from 2000 to 2012. I obtain the information about connections of CEO and all other board information from BoardEx. From 2007 onwards BoardEx has information about boards beyond S&P 1500 firms. Prior to 2007 BoardEx had information about S&P 1500 firms only. We include only those firms from BoardEx whose data was also available in Compustat and CRSP. We include those firms in our analysis whose CEO at least sit one outside board per year. After these selection criteria we are left 6173 firm year observations for characteristic adjusted return analysis.

We obtained characteristics-based benchmark and return from Daniel, Grinblatt, Titman, and Wermers (1997), accounting data is gathered from Compustat, analyst earnings forecast data is obtained from IBES, and stock returns data is gathered from CRSP. We obtain the factor data and 48 industry codes from Kenneth French's website.

Table 13 shows the summary statistics of all the main variables. There are total of 6173 firm year observation in our sample from 2000 to 2012. Average asset size of the firm in the sample is 8,281 million. Size is the natural log of market capitalization of the firm, average size of the firm in our sample is 7.41. Leverage is defined as the sum of total long-term liabilities and portion of long-term liabilities for current year divided by total assets. On average the firms in our sample has a leverage of 22% with maximum value of 72%. On average firms in our sample has a CEO who has *degree* score of 21.76, which means that on average a CEO in our sample has 22 outside connections.

Figure 4 and 5 shows mean score of *degree* and *closeness* by year wise. *Degree*, and *closeness* score is calculated based on outside board connections per year. For example, if CEO is sitting on outside board B1 in year 2007 and 2008 but does not sit on any board other than his own company in year 2009 and 2010, his *degree* and *closeness* score will be calculated based on connections with board members of board B1 for year 2007 and 2008 and he will not be in our analysis for year 2009 and 2010. This approach is adopted for characteristic adjusted analysis, performance valuation and forecasting error analysis.

As we can see the mean score of *degree* and *closeness* remain stable over the years. However, if we look at the number of CEOs having outside connections each year increases till 2007 and after that it starts to decrease. One of the reasons for the increase in outside connection can be improvement in the dataset over time. But the reason for decline can be attributed to the 2007-08 crises that is why we see a decline in outside connections in 2009 and 2010, however outside connections start to increase in 2011 and 2012.

Measure of Social Connection

According to Jackson (2010) individuals are connected to other individuals through links and nodes, which then form a network. Individual is more socially connected if he is connected to more individuals, to more powerful individual in the network and connected to individuals to a shortest path within the network (Padgett and Ansell,1993).

To capture these different dimensions of social network connectedness of CEO, we measure them using *degree*, and *closeness*, measure of social network connectedness. First, we capture the number of connections that a CEO has with outside board members in a given year regardless how closer or important that connection is. This would capture the flow of information through many channels. *Degree centrality* would measure this dimension of connectedness. $\delta(i, j)$ denote the connection that exist between a CEO of company *i* and outside board member of company *j*. For example, if a CEO of company *A*, sits on board of company *B and C*, and on both company *B* and *C* each have 3 and 5 board members than the degree score for company *A* CEO will be 8 for that year.

$$Degree_i = \sum_{j \neq i} \delta(i, j) \qquad (1)$$

Second, a CEO may be well connected if he is closer to other people who are sitting on other board, if that happens than it will help CEO in obtaining information at a lower cost. To capture this dimension of CEO social connectedness we use CLOSENESS measure of social connectedness. A higher normalized CLOSENESS score means that an individual in the network is shortest on path to collect information and disseminate it, suggesting he is more connected. Information arrives to him in the shortest time span.

Empirical Analysis

We study the relationship between social connection of CEOs and stock market performance by first conducting portfolio analysis using characteristic adjusted return in multivariate analysis as well as Carhart four factor model and then investigate the explanation of these results.

Portfolio Construction

We construct portfolio based on the lagged *degree*, and *closeness* score of social connectedness. For example, we will use *degree*, and *closeness* score of year 2007 to create portfolio for year 2008. Each year we divide firms into four quartiles based on *degree*, and *closeness* score of their CEO. Firms in quartile 4 has the CEO with the most outside connections and firms in quartile 1 has CEO with least outside connection.

For characteristic adjusted return analysis, we construct portfolio each June. Each June we distribute firms into four quartiles based on *degree*, and *closeness* score. The firms with most connected CEO are in quartile 4 while firms with the least connected CEO are in quartile 1. As stated earlier we follow Daniel et al. (1997) in calculating characteristic adjusted return, which is calculated as the difference between firm's cumulative return and the value weighted average portfolio of firms matched by size, book to market and momentum where both returns are measured over the same holding period.

When we conduct portfolio analysis using Carhart (1997) four factor model we construct portfolio each January. The firms can move between different portfolios based on *degree*, and *closeness* score of their CEO. We construct both equally weighted and value weighted portfolio for four quartiles. Value weighted portfolio is calculated according to the market capitalization of the companies. The long only portfolio contains only stocks in quartile 4 whereas long-short portfolio is the difference in excess return of stocks in quartile 4 with excess return of stocks in quartile 1.

DGTW Characteristic Adjusted Return

Prior literature has shown that several firm characteristics can affect firm stock returns (Brenna, Chordia, and Subrahmanyam 1998). To explore whether these firm characteristics are affecting excess return results where firms that have highly connected CEO earn significant abnormal return, we employ multivariate regression and control for various firm characteristics.

$$Characteristic\ Adjusted\ Return_{i,t} = \alpha_i + \beta_1 Centrality_{i,t-1} + \beta_2 ROA_{i,t-1} + \beta_3 \text{assets}_{i,t-1} + \beta_4 \text{size}_{i,t-1} + \beta_5 lvg_{i,t-1} + \beta_6 RND_{i,t-1} + \beta_7 lbm_{i,t-1} + + \beta_8 Board\ Connection_{\ i,t-1} + \beta_9 Percentage\ of\ Independent\ Director_{i,t-1} + \beta_{10} CEO\ Age_{i,t-1} + \varepsilon_{i,t} \qquad (4)$$

Following Larcker, So, and Wang (2013) and Hoitash and Mkrtchyan (2017) we use pooled OLS regression with industry and year fixed effect. Dependent variable is characteristic adjusted excess return, which is calculated by subtracting firm's return from value weighted portfolio return which is matched by size, book-to-market and momentum, over the same holding period (Daniel, Grinblatt, Titman and Wermers 1997). Following Daniel et. al (1997), we assign firms based on characteristics portfolios based on first size, second on book-to-market and last on momentum. This results in 125 portfolios. The benchmark returns, and firms assigned to each portfolio based on size, book-to-market and momentum is obtained from Daniel et. al (1997). Firms are assigned to portfolio each June of each year. Firms are divided into quartile based on *degree,* and *closeness* score. Firms are assigned to quartiles each June. The main independent variable or variable of interest is the quartile rank based on *degree,* and *closeness* score. We control for size, assets, sales, research and development, past profitability, book to market ratio (LBM), and leverage (LVG). Size is calculated as the natural log of market capitalization, sales is the natural log of sales, assets is the natural log of total assets, leverage is calculated by dividing total debt by total assets and LBM is calculated by 1 + book to market ratio.

Table 14 reports the characteristic adjusted return for each quartile based on *degree* and *closeness* score of CEO social connections. We can see a monotonic increase in the characteristic adjusted return as we move from firm with least connected CEO to most connected CEO and the difference between the characteristic adjusted return of firms with the most and the least connected CEO is significant at 5% level. This result finds that firms with highly connected CEO's have positive affect on the shareholder wealth.

Next, we perform multivariate analysis and Table 15 reports the regression result of one year ahead characteristics adjusted return on quartile ranks for *degree*, and *closeness,* measure of network centrality. t-statistics are reported in parenthesis and we use cluster standard errors around industry. Table 15 Panel A show results from pooled OLS regression with industry and year fixed effect and Panel B show results from Fama-Macbeth regression. Both OLS and Fama-Macbeth models clearly show that social connections have positive effect on stock returns. According to Fama-Macbeth regression firms whose CEOs are in the highest quartile earn abnormal return of 2.10% per year as compared to firms whose CEOs are in the lowest quartile based on *degree* score. We find similar results with *closeness* score as well.

Results from pooled OLS regression with industry and year fixed effect show that both measures of network centrality are significant at 1% level. Consistent with our hypothesis, we find that firms who have CEO in the highest quartile earn 2.10% (based on *degree* score), and 2.70% (based on *closeness* score) excess return as compared to firms who have CEO in the lowest quartile.

Factor Model

As a robustness test, we use Carhart (1997) four factor model, which controls for risk, outperformance of small versus big companies, the outperformance of high book to market versus small book to market companies, and momentum factors. The first three factors are discovered by Fama and French (1993) and momentum factor is developed by Jegadeesh and Titman (1993).

$$R_{i,t} - R_{b,t} = \alpha_i + \beta_{i,M} * mktrf_t + \beta_{i,hml} * hml_t + \beta_{i,smb} * smb_t + \beta_{i,umd} * umd_t + \varepsilon_{i,t} \quad (3)$$

The dependent variable is difference between return of portfolio *i* in month *t*, $R_{i,t}$, from its benchmark, $R_{b,t}$. In case of long only portfolio, return on benchmark portfolio is the risk-free rate and in case of long-short portfolio the return on benchmark is the return on short portfolio over the same time period. We have discussed earlier about how we constructed both long and short portfolios. $mktrf_t$ denotes the difference between market portfolio and risk-free rate for time period *t*, hml_t is return difference between high and low book to market stocks, smb_t is return difference between small and large capitalization stock portfolio, and umd_t is the return difference between high past and low past returns stocks.

Table 16 panel A reports the results where the dependent variable is excess return of equally weighted long only portfolio when we use *degree* score as a measure of CEO centrality. As we can see from column (1), alpha is positive and significant at 1% level. In this regression we are using monthly returns. The results show that long only portfolio of companies who have CEOs who are most connected earn 4.06% annualized abnormal return. Next, to make sure that our results are consistent over time and are not driven by single year we divide the sample into two time periods, one from 2000 to 2007 and other from 2008 to 2012. Results are reported in column 2 and 3 and we find that alpha is positive and both statistically and economically significant. The results in column 2 and 3 shows that firms that have highly connected CEO earn abnormal return of 3.21% and 3.46% on annualized basis in the two time periods.

Column 4 to 6 shows the results when the dependent variable is excess return of value weighted long only portfolio. Here the weights are given based on the market capitalization of the firm in the portfolio. We see that same results hold, and the excess return earned by stocks in highly connected stocks is both economically and statistically significant over time. Value weighted long only portfolio earn abnormal return of 4.71% on annualized basis over the full sample period. These results along with results from equally weighted portfolio shows that our results are not driven by small number of very large firms.

Table 16 panel B presents results of long only portfolio when we use *closeness* as a measure of CEO centrality. We obtain similar results what we obtained earlier with *degree* as a measure of CEO centrality. Equally weighted (value weighted) Long only portfolio earns an abnormal return of 3.77% (4.34%) per year. Like results in panel A, we also observe that results are consistent over time when we divide the sample period into two sub periods.

So far, we have examined stock performance of firms in long only portfolio, which have highly connected CEOs. We now examine the long-short strategy that goes long on stocks that are in the highest quartile based on *degree*, and *closeness* score of CEO centrality and short on firms in the lowest quartile based on *degree*, and *closeness* score of CEO centrality. In this analysis dependent variable is difference between return of long and short portfolio. Results from the long-short portfolio are reported in table 16 panel C, and D. The first (last) 3 columns shows the results from equally weighted (value-weighted) portfolios. The equally weighted results are somewhat stronger as compared to long only portfolio results. For example, long-short equally weighted portfolio based on *degree (closeness)* score earns alpha of 0.439% (0.413%) per month whereas alpha for long only equally weighted portfolio based on *degree(closeness)* score of CEO centrality is 0.332% (0.309%) per month. The abnormal return on monthly basis for *degree (Closeness)* score of CEO centrality is almost 33% (33%) higher for long-short strategy as compared to long only strategy and these results are consistent even when we break down sample period into two time periods.

However, in case of value weighted portfolio results do not differ a lot between long only and long-short portfolio strategy. Abnormal return for value weighted long-short strategy based on *degree (Closeness)* score of CEO centrality is 0.363% (0.332%) per month. However, for value weighted long only portfolio earns an abnormal return based on *degree (Closeness)* score of CEO centrality of 0.384% (0.355%) per month. However, as we observe in table 4 panel D in which we use *degree* score for CEO centrality, when we break down the time period into two sub sample periods, we observe that alpha for long short strategy for time period from 2008 to 2012 is 42% higher than for long only strategy. These results show that in time period from 2008 to 2012 underperformance of firms with low socially connected CEOs lead to even higher abnormal return for firms with high socially connected CEOs.

Overall result from table 16 shows that firms who have highly socially connected CEOs as compared to firms with low socially connected CEOs earn both statistically and economically significant abnormal return even after controlling for market risk, size, value and momentum factors. Moreover, we find similar results for both equally weighted and value weighted portfolios and the results remain consistent when we divide the sample period into two sub periods. These results show that firms with highly socially connected firms significant excess returns, but we do not find strong evidence that firms with CEO in the lowest quartile negatively affect returns of the firm.

Our results of excess return both using Carhart (1997) four factor model and DGTW multivariate regression show that firms with most connected CEO earn abnormal return as compared to firms in the lowest quartile and it is consistent over time period.

Why Do Highly Connected CEO Firms Deliver Abnormal Return?

There are three potential explanations for the abnormal return earned by firms who have highly connected CEO. One of the plausible explanations is based on performance. Secondly, we can associate abnormal return with risk-based explanation and last, it is plausible that these abnormal returns are due to the information asymmetry caused by the connections. We will analyze all three explanation and try to find which explanation is consistent with our findings of abnormal returns.

Explanation Based on Future Operating Profitability

We first study the operating performance-based explanation. We argue that it is the positive impact connections of CEOs have on firm operating performance that leads to excess returns earned by these firms.

To examine whether social connections of CEO lead to change in the fundamentals of the firm we regress firms future operating profitability proxied by change in return on assets on quartile score based on *degree,* and *closeness*. For dependent variable we take the difference between ROA of year *t+1* from ROA of year *t*. Return on assets (ROA) is calculated by dividing operating income by total assets. This would give us an idea how the connections of CEO would impact future operating profitability. The results of this regression are reported in table 17, just like the earlier regression we include industry and year fixed effects and use clustered standard errors around firm. We control for size, research and development, past profitability, book to market ratio (LBM), outside connections of board and leverage (LVG). Size is calculated as the natural log of market capitalization, assets is the natural log of total assets, leverage is calculated by dividing total debt by total assets and LBM is calculated by 1 + book to market ratio.

$$\Delta ROA_{i,t} = \alpha_i + \beta_1 Centrality_{i,t-1} + \beta_2 ROA_{i,t-1} + \beta_3 \text{assets}_{i,t-1} + \beta_4 \text{size}_{i,t-1} + \beta_5 lvg_{i,t-1} + \beta_6 RND_{i,t-1} + \beta_7 lbm_{i,t-1} + \beta_8 Board\ Connection_{i,t-1} + \beta_9 Proportion\ of\ Independent\ Director_{i,t-1} + \beta_{10} CEO\ Age_{i,t-1} + \varepsilon_{i,t} \qquad (5)$$

The result of the regression shows that firms who have CEO in highest quartile earn higher profitability as compared to firm who have CEO in the lowest quartile on when we use our both proxies of connections of CEO i.e, *degree* and *closeness* Moreover, firm in the highest quartile earn 0.456% (degree) future change in ROA as compared to firm with CEO in the lowest quartile.

These results show that performance-based explanation is consistent with abnormal returns earned by firms having highly connected CEOs.

Explanation Based on Future Stock Return Volatility

Now we examine whether excess return earned by highly socially connected CEO firms is attributable to risk generated by CEOs of these firms. To study the risk-based explanation we examine the impact these connections have on standard deviation of return, which we proxy for risk. We posit if highly connected CEOs improve firm operating performance than it should result in lower standard deviation, which will explain the presence of excess return earned by firm with highly connected CEO's. This will support our operating performance-based explanation. However, on the other hand highly connected CEO's can also expose shareholders to risk by doing empire building and taking on more risky projects, which would show a positive association between CEO social connections and volatility of returns.

To examine the impact of connections of CEO on risk we employ pool regression with the following specification. The sample period is from 2000 to 2012 and we include both year and industry dummies. Standard errors are clustered around firm. We include all public firms that are in BordEx.

$$Volatility\ of\ Return_{i,t} = \alpha_i + \beta_1 Centrality_{i,t-1} + \beta_2 ROA_{i,t-1} + \beta_3 \text{assets}_{i,t-1} + \beta_4 \text{size}_{i,t-1} + \beta_5 lvg_{i,t-1} + \beta_6 RND_{i,t-1} + \beta_7 lbm_{i,t-1} + \beta_8 Board\ Connection_{i,t-1} + \beta_9 Proportion\ of\ Independent\ Director_{i,t-1} + \beta_{10} CEO\ Age_{i,t-1} + \varepsilon_{i,t} \qquad (6)$$

Where we volatility of return is proxy for risk. Centrality is the social connection score measured by *degree* and *closeness* centrality which have been defined earlier. Results of the pooled regression are reported in table 18 which shows that CEO centrality is negatively and significantly associated with standard deviation of returns and it is the same for both proxies of centrality. The results show that increase in CEO social connection reduces firm's risk as measured by standard deviation of return. This result when paired with earlier findings, where we observed association between increase in CEO social connections with firm operating performance supports the notion that shareholders are earning excess return due to firm performance.

The results coupled with earlier result indicate highly connected CEOs are associated with better operating performance and low risk as depicted by negative relationship with standard deviation of returns. These results are consistent with highly connected CEO firms earning excess return and

Explanation Based on Information Asymmetry

We now study the market information asymmetry explanation. It is plausible that market is unaware of the impact of social connections of CEO and the value it brings to the firm. We posit that for information asymmetry explanation to be consistent with excess return we should see an effect of firms with highly socially connected firms on information asymmetry. We proxy information asymmetry by analyst forecast errors, and dispersion of analyst forecast

$$Analyst\ Forecast\ Errors_{i,t} = \alpha_i + \beta_i Centrality_{i,t-1} + \beta_i Growth_{i,t-1} + \beta_i \text{Young}_{i,t-1} + \beta_i \text{size}_{i,t-1} + \beta_i Net\ \ Income_{i,t-1} + \beta_i No.of\ \ Analyst_{i,t-1} + \varepsilon_{i,t} \quad (7)$$

$$Dispersion\ of\ analyst\ forecast_{i,t} = \alpha_i + \beta_i Centrality_{i,t-1} + \beta_i Growth_{i,t-1} + \beta_i \text{Young}_{i,t-1} + \beta_i \text{size}_{i,t-1} + \beta_i Net\ \ Income_{i,t-1} + \beta_i No.of\ \ Analyst_{i,t-1} + \varepsilon_{i,t} \quad (8)$$

We calculate *analyst forecast error* as the difference between realized earning per share and consensus analyst forecast earnings per share divided by total assets. One criticism of analyst forecast error is that may capture the riskiness of the firm (Krishnaswami and Subramaniam, 1999). So, we also use analyst forecast dispersion as proxy. *Analyst forecast dispersion* is calculated as the standard deviation of all earning forecast made. All these measures are leading measures.

We report the result of pooled OLS regression of various proxies of information asymmetry on quartiles of centrality of CEOs of firm measured by *degree*, and *closeness* score in table 5, we control for industry and year fixed effect. If firm is in quartile 4, it has the most connected CEO and vice versa. Growth and Young are dummy that equals 1 if the firm is in the lowest tercile of book to market and age respectively. Age is defined as when the firm first appeared in CRSP. Size is the log of market cap. We also control for the number of analysts covering the firm, and firm net income as well.

Table 19 Column 1-2 report the result when the dependent variable is forecasted error, we find that analyst forecast errors are not significantly associated with degree and closeness measure of network connectedness of CEO. Column 3-4 show the result with analyst dispersion of earnings as the dependent variable and our results are the same as with analyst forecast error.

Over all the results clearly show that abnormal return earned by firms with highly connected CEO is not consistent with information asymmetry hypothesis. These results show that analysts adjust their forecasts and impound the impact of connections in their forecast of earnings.

Instrumental Variable Regression

One of the main concerns about our results is that it can suffer from endogeneity which is caused by reverse causality. For example, it is hard to say that firms that are bigger in size and more profitable can recruit more connected CEOs or better performance of the firms is due to the connections of CEO. To address concerns related to endogeneity I use *degree score* of CEO based on board connections within 100 miles of the zip code of the headquarter of firm as an instrument for my main variable of *degree.* The idea behind using *degree* score within 100 miles is that it is based on the number of firms within 100 miles, which should not affect the firm performance but can affect the number of connections of CEO. So, if there are more firms than the CEO will have more connections, so it will affect the connections but not the firm performance.

$$Degree\ Connections_{i,t} = \alpha_i + \beta_1 Degree\ Score\ within\ 100\ miles_{i,t-1} +$$

$$\beta_2 ROA_{i,t-1} + \beta_3 \text{assets}_{i,t-1} + \beta_4 \text{size}_{i,t-1} + \beta_5 lvg_{i,t-1} + \beta_6 RND_{i,t-1} + \beta_7 lbm_{i,t-1} +$$

$$\beta_8 Board\ Connection_{i,t-1} + \beta_9 Proportion\ of\ Independent\ Director_{i,t-1} + \beta_{10} CEO\ Age_{i,t-1} + \varepsilon_{i,t} \quad (9)$$

$$\Delta\ ROA_{i,t} = \varphi_i + \mu_1 \widehat{Degree\ Score}_{\ i,t-1} + \mu_2 ROA_{i,t-1} + \mu_3 \text{assets}_{i,t-1} + \mu_4 \text{size}_{i,t-1} + \mu_5 lvg_{i,t-1} + \mu_6 RND_{i,t-1} + \mu_7 lbm_{i,t-1} + \mu_8 Board\ Connection_{i,t-1} + \mu_9 Proportion\ of\ Independent\ Director_{i,t-1} + \mu_{10} CEO\ Age_{i,t-1} + v_{i,t} \quad (10)$$

Results from 2 stage least square regression are reported in table 8. Column I report results of first stage whereas column 20 reports results of second stage regression. We use both industry and time fixed effects in instrumental variable regression and use clustered standard errors around the firm. Results from 2SLS regression clearly show that connections of CEO through sitting on other boards affects the performance of the firm positively or it improves the operating performance of the firm and when connections move from 25th percentile to 75th percentile it improves performance by 1.8%. F-stat which is not reported is greater than 10 which shows that the instrument is valid. The results from instrumental variable regression supports our main findings that social connections of CEO which are developed by sitting on other boards positively affects the operating performance of the firm and our instrument provides causal evidence of the said relationship.

Conclusion

Social network formed by CEO over the years provide an important channel through which he can gather information and use those connections to benefit firm by raising debt at lower cost (Engelberg, Gao, & Parssons, 2012). Similarly, these connections can help CEO to market the firm eventually benefitting the shareholders wealth.

Conversely, CEO can use his connections to garner power and engage in empire building through value destroying acquisitions (El-Khatib, Fogel & Jandik, 2015). So, far existing literature has examined relationship of CEO within the firm and with its board holders or outside the world with creditors. However, this study focuses on the connections of CEO with outside world and gives a holistic picture of the impact of CEO connections on firm stock performance.

In this study we study the impact CEO social connections with outside world by sitting on other boards on firm stock performance. We find that CEO social connections are associated with earning future excess return. In an equally weighted (value weighted) long only portfolio firms with most connected CEOs earn abnormal return of 4.06% (4.741%) per year. Similarly, in an equally weighted (value weighted) long-short portfolio strategy result in an abnormal return of 5.39% (4.44%) per year, where we go long on firms in the highest quartile of centrality of CEO and short on firms in lowest quartile based on centrality of CEO. We observe similar results when we use *closeness* as a measure of CEO centrality. Similarly, we follow Daniel et al. (1997) to calculate characteristic adjusted return and use them in multivariate analysis and find that highly connected CEO firms earns abnormal returns.

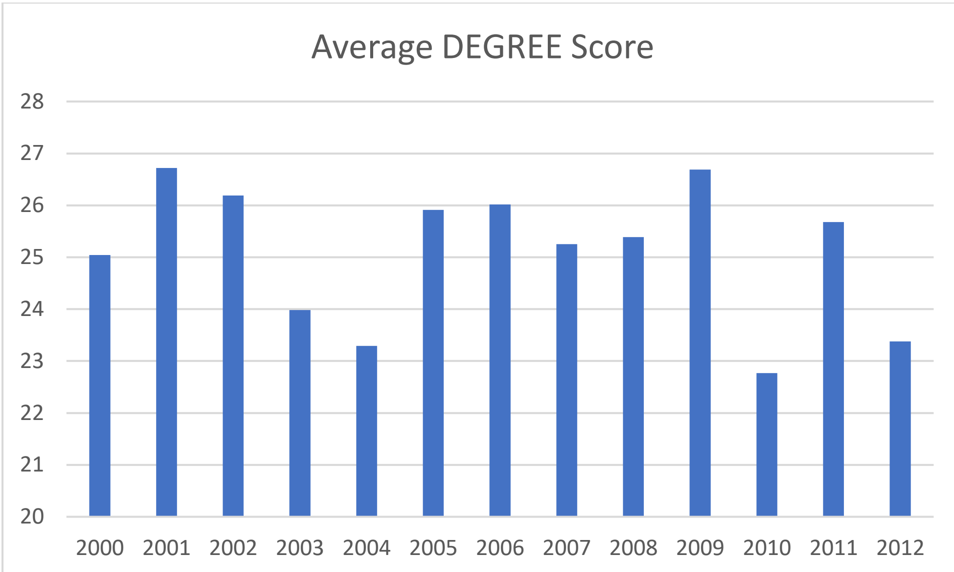
There are three potential explanation for observing excess returns: information asymmetry, operating performance, and risk. We than examine all three potential explanations and find out which is consistent with our primary results. One potential explanation for observing excess return can be that market participants such as analysts are not aware of the connections of CEO and do not impound the impact of these connections in their forecast which can lead to excess return (Larcker, So, & Wang, 2013). This explanation means that markets are inefficient. To examine whether markets are inefficient, we study the impact of connections on analyst forecast errors and analyst forecast dispersion and find that centrality of CEO is not significantly related to both analysts forecast errors and analyst forecast dispersion. This result shows that excess return earned by highly connected CEO firms cannot be explained by information asymmetry.

Next, we examine whether firms with highly connected CEOs earn excess returns due to improvement in their operating performance. We measure operating performance as change in return on assets (ΔROA_{t+1}) (Lilienfeld-Toal & Ruenzi, 2014). We measure return on assets by dividing operating income by total assets. We find that for the overall sample period change in return on assets (ΔROA_{t+1}) is significantly positively associated with *degree and closeness* centrality of CEOs

Last, we examine whether shareholder demand excess returns due to the risk caused by increase in volatility of monthly return by highly connected CEOs. To examine this relationship, we employ pooled OLS model and find that CEO centrality is negatively associated with year ahead standard deviation of monthly return. These results indicate that CEOs who are highly socially connected are associated with low stock return volatility and positive firm performance.

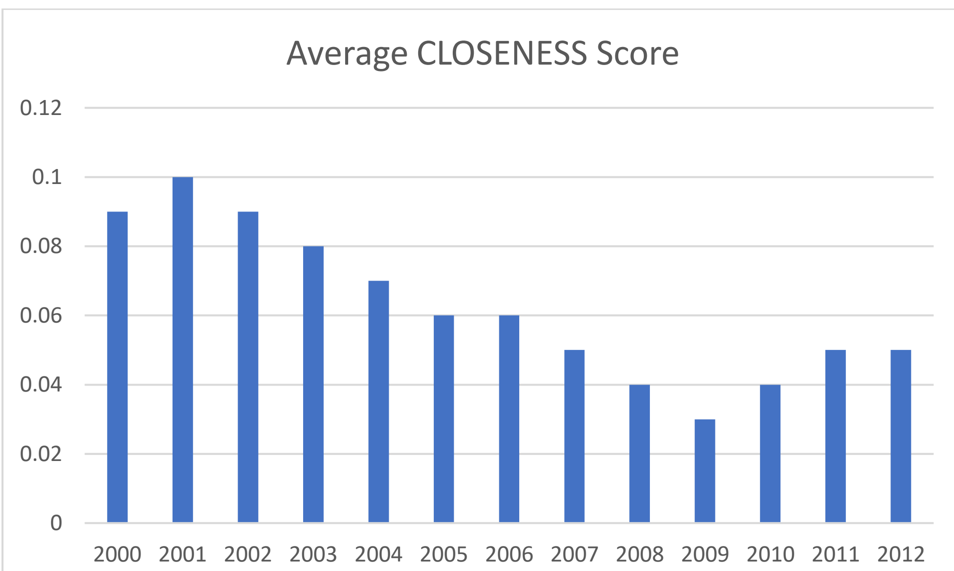
Overall, we find that CEO social connections by sitting on other boards has a positive effect on stock performance and this effect is consistent. We use both Carhart (1997) four factor model and characteristic adjusted return in multivariate analysis and find that firms with highly connected CEOs earn abnormal return. We posit that there are three potential explanations, information asymmetry, performance and risk, to explain the presence of abnormal returns earned by highly connected CEO firms. After examining all three-potential explanation, we find that performance-based explanation is consistent with the excess returns earned by the firms.

Figure 4: Average DEGREE score of CEO per year



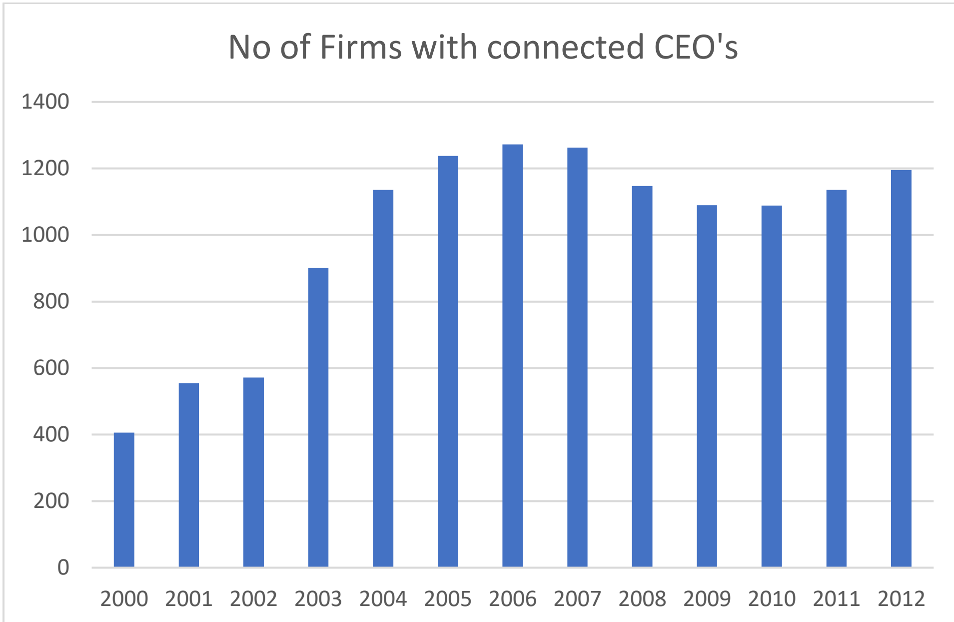
This figure shows the mean DEGREE score of CEO who are connected each year over the sample period from 2000 to 2012.

Figure 5: Average CLOSENESS score of CEO per year



This figure shows the mean CLOSENESS score of CEO who are connected each year over the sample period from 2000 to 2012.

Figure 6: Number of Firms with CEO having social connections per year



This figure shows the number of firms with CEO who are sitting on other boards per year during the sample period from 2000 to 2012.

Table 13: Descriptive Statistics

	Mean	Median	Standard Deviation	Max	Min
Degree	21.52	15	19.78	131	4
Closeness	0.05	0.04	0.03	0.19	0.02
DGTW Return	2.96%	-0.71%	32.07%	131%	-62.5%
Change of ROA	-0.011%	0.10%	5.74%	23.94%	-21.82%
LBM	1.52	1.44	0.37	3.10	0.95
Market Cap ($ Million)	7.62	7.60	1.79	12.01	3.33
Assets ($ Million)	8281	2165	19623	275644	5.049
Leverage	0.22	0.21	0.17	0.72	0
RND	0.11	0.01	0.45	3.96	0
SD return	0.10	0.09	0.06	0.35	0.02
Number of directors	9.6	9	2.35	22	4
Proportion of Independent Director	82.4%	86%	9.05%	94.11%	28.57%
CEO Age	56.83	57.1	6.73	40.7	74.5

The data includes all firms in Compustat, CRSP, and BoardEx from 2000 to 2012. Sales, Net Income and Asset is in millions of dollars. Size is the natural log of market capitalization calculated on June 30 of each year, when portfolios are formed. Operating income is defined as operating income before depreciation and I use OIBDP compustat variable. LBM is defined as (1 + Book to Market). Return on Assets is defined as operating income divided by total assets. DEGREE and CLOSENESS score are calculated for each CEO each year and is based connections developed by sitting on other boards. All variables are winsorized at 1%.

Table 14: Characteristic Adjusted Return by quarter

	Characteristic Adjusted Return	
	Degree	**Closeness**
Quartile 4 (Most Connected)	0.043	0.038
3	0.035	0.035
2	0.027	0.033
Quartile 1 (Least Connected)	0.015	0.012
High – Low	0.027*	0.026*
t-test	(2.36)	(2.23)

Table 2 reports the results DGTW characteristic adjusted return for both proxies of centrality, *degree* and *closeness*, per quartile of centrality.

Table 15: Characteristic Adjusted Return

Panel A

	(1) $DGTW\ Return_t$	(2) $DGTW\ Return_t$
$Degree_{t-1}$	0.00839*	
	(2.19)	
$Closeness_{t-1}$		0.0082**
		(2.45)
LBM_{t-1}	-0.0899***	-0.0896***
	(-3.93)	(-3.88)
$Size_{t-1}$	-0.0770***	-0.0774***
	(-5.96)	(-6.04)
ΔROA_{t-1}	0.0571	0.0586
	(0.99)	(1.02)
$Assets_{t-1}$	0.0640***	0.0640***
	(4.80)	(4.87)
$Leverage_{t-1}$	-0.0157	-0.0142
	(-0.44)	(-0.40)
RND_{t-1}	-0.00293	-0.00298
	(-0.29)	(-0.30)
$Board\ Connection_{t-1}$	0.000729	0.000736
	(1.02)	(1.02)
$Prop\ of\ Independent\ Director_{t-1}$	-0.0530	-0.0526
	(-0.88)	(-0.87)
$CEO\ Age_{t-1}$	-0.000666	-0.000570
	(-0.95)	(-0.85)
Intercept	0.406***	0.403***
	(4.56)	(4.54)
Industry and Year Fixed Effect	Yes	Yes
N	6173	6173
Adj R-Square	0.026	0.026

Panel A present results from regressing firm-specific one-year-ahead characteristic adjusted returns (RET1Y) on the quartile ranks of two measures of board centrality; *degree* and *closeness*. Quartiles are formed each June of each year when the portfolios are formed based on *degree* and *closeness* score of CEO centrality. Firms assigned the rank of 4 are in the highest quartile and 1 are in the lowest quartile. Both industry and year fixed effects are included and clustered standard errors around firm is used. *t-statistics* are shown in the parenthesis and level of significance is specified by *, **, and *** for 10%,5%, and 1% respectively. For industry we use Fama French 49 industry codes based on 2-digit SIC codes. Characteristic-adjusted returns are calculated as of July 1st of each year as the difference between a firm's cumulative return and the value-weighted average portfolio of firms matched by size, book-to-market, and momentum, where both returns are measured over identical holding periods. LBM equals one plus the firm's book to market ratio. SIZE equals the log of market capitalization. Leverage is defined as the sum of total long-term liabilities and portion of long-term liabilities for current year divided by total assets. ROA is

Table 15, continued

calculated as operating income divided by total assets. RND is calculated by dividing R&D expense by Sales.

Panel B: Fama Macbeth Regression

	(1) $DGTW\ Return_t$	(2) $DGTW\ Return_t$
$Degree_{t-1}$	0.00913***	
	(3.23)	
$Closeness_{t-1}$		0.00694**
		(2.50)
ΔROA_{t-1}	0.0101	0.0117
	(0.11)	(0.12)
$Assets_{t-1}$	0.0229	0.0238
	(1.80)	(1.87)
$Size_{t-1}$	-0.0341*	-0.0348*
	(-2.38)	(-2.43)
$Leverage_{t-1}$	0.0457	0.0458
	(1.22)	(1.19)
RND_{t-1}	-0.0409	-0.0407
	(-1.60)	(-1.60)
LBM_{t-1}	-0.0421*	-0.0424*
	(-3.03)	(-2.95)
$Board\ Connection_{t-1}$	0.000989	0.00106
	(1.77)	(1.91)
$Prop\ of\ Independent\ Director_{t-1}$	0.000602	-0.0000928
	(0.01)	(-0.00)
$CEO\ Age_{t-1}$	-0.000441	-0.000340
	(-0.65)	(-0.52)
Intercept	0.159*	0.156*
	(2.36)	(2.33)
N	6173	6173
Adj. R-Square	0.056	0.056

Panel B presents results of Fama Macbeth regression one ahead characteristic adjusted return for each quartile based on *degree* and *closeness* over the sample period. All variables are winsorized at 1%.

Table 16: Carhart 4 Factor Model

Panel A: Long Only - Degree						
	Dependent Variable: Excess Return					
	Equally Weighted			Value Weighted		
	(1)	(2) 2000-2007	(3) 2008-2012	(4)	(5) 2000-2007	(6) 2008-2012
Alpha	0.332***	0.264**	0.284*	0.384***	0.320**	0.326**
	(2.88)	(1.98)	(1.85)	(3.51)	(2.48)	(2.26)
Market	1.008***	1.091***	0.987***	1.004***	1.079***	0.990***
	(25.44)	(25.54)	(28.32)	(26.39)	(26.08)	(29.26)
Size	0.310***	0.270***	0.451***	0.278***	0.243***	0.403***
	(6.67)	(5.44)	(6.64)	(6.05)	(4.85)	(6.49)
Value	0.163**	0.272***	-0.0664	0.141	0.236**	-0.075
	(2.00)	(3.76)	(-0.61)	(1.81)	(3.24)	(-0.77)
Momentum	-0.015	0.036	-0.106***	-0.007	0.045	-0.097***
	(-0.42)	(0.80)	(-3.77)	(-0.20)	(1.03)	(-3.90)
N	156	96	60	156	96	60

Panel A shows the results of Carhart (1997) four factor model for portfolio containing stocks in Quartile 4 based on CEO connection calculated by *degree and closeness* score. Dependent variable is excess return which is calculated as the difference between monthly return on portfolio of stock in Quartile 4 from risk free rate. We assign stocks in each portfolio based on *degree* and *closeness* score each January. We use monthly stock returns. Quartile 4 includes stocks with the highest scores in *degree* and *closeness.* Column 1 and columns 4 shows the results for full sample. Column 2 and 5 show results for sub sample period from 2000 to 2007. Column 3 and 6 shows results for sub sample period from 2008 to 2012. Column 1 to 3 calculates portfolio based on equal weights whereas we use value weighted portfolios in column 4 to 6. *t-statistics* are shown in the parenthesis and level of significance is specified by *, **, and *** for 10%,5%, and 1% respectively.

Table 16, continued

Panel B: Long Only - Closeness						
	Dependent Variable: Excess Return					
	Equally Weighted			Value Weighted		
	(1)	(2) 2000-2007	(3) 2008-2012	(1)	(2) 2000-2007	(3) 2008-2012
Alpha	0.309***	0.262**	0.289**	0.355***	0.305**	0.345**
	(3.12)	(2.06)	(2.00)	(3.74)	(2.49)	(2.53)
Market	1.013***	1.081***	0.991***	1.009***	1.073***	0.986***
	(32.07)	(31.52)	(28.45)	(33.07)	(32.23)	(30.01)
Size	0.379***	0.366***	0.435***	0.337***	0.324***	0.394***
	(9.55)	(7.05)	(7.72)	(8.31)	(6.21)	(7.22)
Value	0.110	0.191*8	-0.0418	0.0845	0.154**	-0.0520
	(1.62)	(2.62)	(-0.49)	(1.29)	(2.11)	(-0.65)
Momentum	-0.042*	-0.0031	-0.106***	-0.036	0.006	-0.101***
	(-1.88)	(-0.12)	(-4.81)	(-1.49)	(0.24)	(-4.89)
N	156	96	60	156	96	60

Panel B shows the results of Carhart (1997) four factor model for portfolio containing stocks in Quartile 4 based on CEO connection calculated by *closeness* score. Dependent variable is excess return which is calculated as the difference between monthly return on portfolio of stock in Quartile 4 from risk free rate. We assign stocks in each portfolio based on *closeness* score each January. We use monthly stock returns. Quartile 4 includes stocks with the highest scores in *closeness*. Column 1 and columns 4 shows the results for full sample. Column 2 and 5 show results for sub sample period from 2000 to 2007. Column 3 and 6 shows results for sub sample period from 2008 to 2012. Column 1 to 3 calculates portfolio based on equal weights whereas we use value weighted portfolios in column 4 to 6. *t-statistics* are shown in the parenthesis and level of significance is specified by *, **, and *** for 10%,5%, and 1% respectively.

Table 16, continued

Panel C: Long-Short - *Degree*						
Dependent Variable: Return on Long Potfolio (Q 4) – Return on Short Portfolio (Q1)						
	Equally Weighted			Value Weighted		
	(1)	(2) 2000-2007	(3) 2008-2012	(4)	(5) 2000-2007	(6) 2008-2012
Alpha	0.439***	0.354**	0.531**	0.363***	0.276*	0.462**
	(3.65)	(2.34)	(2.53)	(3.17)	(1.90)	(2.34)
Market	-0.102***	-0.103***	-0.0985	-0.114***	-0.119**	-0.107
	(-3.19)	(-2.77)	(-1.50)	(-3.73)	(-3.24)	(-1.74)
Size	-0.582***	-0.591***	-0.540***	-0.592***	-0.588***	-0.585***
	(-10.50)	(-9.72)	(-4.62)	(-11.28)	(-10.00)	(-5.41)
Value	0.171***	0.190**	0.126	0.158***	0.172**	0.127
	(3.57)	(3.02)	(1.28)	(3.66)	(3.03)	(1.44)
Momentum	0.045	0.049	0.033	0.047	0.050	0.038
	(1.51)	(1.70)	(0.65)	(1.70)	(1.79)	(0.79)
N	156	96	60	156	96	60

Panel C shows the results of Carhart (1997) four factor model. Dependent variable is the difference between return of portfolio of stocks in quartile 4 (highest) and return of portfolio of stocks in quartile 1 (lowest). We assign stocks in each portfolio based on *degree* score each January. We use monthly stock returns. Column 1 and columns 4 shows the results for full sample. Column 2 and 5 show results for sub sample period from 2000 to 2007. Column 3 and 6 shows results for sub sample period from 2008 to 2012. Column 1 to 3 calculates portfolio based on equal weights whereas we use value weighted portfolios in column 4 to 6. *t-statistics* are shown in the parenthesis and level of significance is specified by *, **, and *** for 10%,5%, and 1% respectively.

Table 16, continued

Panel D: Long-Short - *Closeness*						
Dependent Variable: Return on Long Potfolio (Q 4) – Return on Short Portfolio (Q1)						
	Equally Weighted			Value Weighted		
	(1)	(2) 2000-2007	(3) 2008-2012	(4)	(5) 2000-2007	(6) 2008-2012
Alpha	0.413**	0.328**	0.520**	0.332***	0.246	0.453**
	(3.23)	(2.07)	(2.14)	(2.71)	(1.58)	(2.06)
Market	-0.0756**	-0.106***	-0.0494	-0.0886***	-0.116***	-0.0676
	(-2.22)	(-2.71)	(-0.66)	(-2.76)	(-2.96)	(-0.99)
Size	-0.464***	-0.440***	-0.521***	-0.478***	-0.446***	-0.557***
	(-7.45)	(-5.89)	(-4.69)	(-8.01)	(-6.21)	(-5.42)
Value	0.147***	0.124**	0.166	0.129***	0.101	0.164*
	(3.20)	(2.32)	(1.51)	(2.99)	(1.98)	(1.70)
Momentum	0.014	0.011	0.019	0.010	0.011	0.015
	(0.47)	(0.36)	(0.35)	(0.37)	(0.38)	(0.29)
N	156	96	60	156	96	60

Panel D shows the results of Carhart (1997) four factor model. Dependent variable is the difference between return of portfolio of stocks in quartile 4 (highest) and return of portfolio of stocks in quartile 1 (lowest). We assign stocks in each portfolio based on *closeness* score each January. We use monthly stock returns. Column 1 and columns 4 shows the results for full sample. Column 2 and 5 show results for sub sample period from 2000 to 2007. Column 3 and 6 shows results for sub sample period from 2008 to 2012. Column 1 to 3 calculates portfolio based on equal weights whereas we use value weighted portfolios in column 4 to 6. *t-statistics* are shown in the parenthesis and level of significance is specified by *, **, and *** for 10%,5%, and 1% respectively.

Table 17: Changes in ROA

	(1) ΔROA_t	(2) ΔROA_t
$Degree_{t-1}$	0.00135**	
	(2.46)	
$Closeness_{t-1}$		0.00186***
		(3.17)
LBM_{t-1}	-0.0110**	-0.0110**
	(-2.79)	(-2.79)
$Size_{t-1}$	-0.00450*	-0.00456*
	(-1.75)	(-1.78)
ΔROA_{t-1}	-0.147***	-0.147***
	(-7.12)	(-7.10)
$Assets_{t-1}$	0.00213	0.00200
	(0.76)	(0.72)
$Leverage_{t-1}$	0.0146**	0.0151**
	(2.38)	(2.43)
RND_{t-1}	0.000680	0.000645
	(0.42)	(0.41)
$Board\ Connection_{t-1}$	0.000147*	0.000129
	(1.68)	(1.52)
$Prop\ of\ Independent\ Director_{t-1}$	-0.0208**	-0.0200**
	(-2.46)	(-2.43)
$CEO\ Age_{t-1}$	-0.000214**	-0.000205**
	(-2.39)	(-2.31)
Intercept	0.0141	0.0141
	(1.40)	(1.40)
Industry and year dummies	Yes	Yes
N	6173	6173
Adj. R-Square	0.055	0.055

The table reports regression results of one year ahead change in ROA on Quartile based on degree and closeness score. Change in ROA is calculated by subtracting FY1 ROA from FY0 ROA Firms assigned the rank of 4 are in the highest quartile and 1 are in the lowest quartile. Both industry and year fixed effects are included and clustered standard errors around firm is used. *t-statistics* are shown in the parenthesis and level of significance is specified by *, **, and *** for 10%,5%, and 1% respectively. For industry I use Fama French 49 industry codes based on 2-digit SIC codes. LBM equals one plus the firm's book to market ratio. SIZE equals the log of market capitalization. Leverage is defined as the sum of total long-term liabilities and portion of long-term liabilities for current year divided by total assets. ROA is calculated as operating income divided by total assets. RND is calculated by dividing R&D expense by Sales. All variables are winsorized at 1%.

Table 18: Standard Deviation of Returns

	(1) SD_Return_t	(2) SD_Return_t
$Degree_{t-1}$	-0.00260**	
	(-2.96)	
$Closeness_{t-1}$		-0.00152*
		(-2.15)
LBM_{t-1}	0.000164	0.0000279
	(0.03)	(0.01)
$Size_{t-1}$	-0.0169***	-0.0168***
	(-4.55)	(-4.46)
ΔROA_{t-1}	-0.0196	-0.0198
	(-1.69)	(-1.71)
$Assets_{t-1}$	0.00601	0.00578
	(1.68)	(1.58)
$Leverage_{t-1}$	0.00840	0.00839
	(0.85)	(0.85)
RND_{t-1}	0.0200***	0.0201***
	(6.11)	(6.11)
$Board\ Connection_{t-1}$	0.000149	0.000109
	(1.00)	(0.73)
$Prop\ of\ Independent\ Director_{t-1}$	-0.0223*	-0.0209
	(-2.21)	(-1.97)
$CEO\ Age_{t-1}$	-0.000203	-0.000246
	(-1.22)	(-1.42)
Intercept	0.233***	0.233***
	(13.13)	(13.02)
Industry and Year Dummies	Yes	Yes
N	6299	6299
Adj. R- Square	0.389	0.388

The table reports regression results of one year ahead *standard deviation of returns* on Quartile based on *degree* and *closeness* score. S*tandard deviation of returns* is calculated by standard deviation of monthly returns during a fiscal year of the firm. Firms assigned the rank of 4 are in the highest quartile and 1 are in the lowest quartile based on CEO Social Connections. Both industry and year fixed effects are included and clustered standard errors around firm is used. *t-statistics* are shown in the parenthesis and level of significance is specified by *, **, and *** for 10%,5%, and 1% respectively. Column 1 shows the result when we use *degree* as proxy for CEO Social Connections and column 2 show the results when we use *closeness* as proxy for CEO Social Connections. LBM equals one plus the firm's book to market ratio. SIZE equals the log of market capitalization. Leverage is defined as the sum of total long-term liabilities and portion of long-term liabilities for current year divided by total assets. ROA is calculated as operating income divided by total assets. For industry we use Fama French 49 industry codes based on 2-digit SIC codes. All variables are winsorized at 1%.

Table 19: Information Asymmetry

	(1)	(2)	(3)	(4)
	Forecast Error	*Forecast Error*	*Analyst Dispersion*	*Analyst Dispersion*
$Degree_{t-1}$	0.000150		0.00417	
	(0.34)		(0.48)	
$Closness_{t-1}$		-0.000154		0.00566
		(-0.37)		(0.70)
$Growth_{t-1}$	-0.00182	-0.00184	-0.0479*	-0.0480*
	(-0.98)	(-0.99)	(-2.66)	(-2.64)
$Young_{t-1}$	0.000608	0.000552	0.0326	0.0327
	(0.63)	(0.57)	(1.35)	(1.37)
$Net\ Income_{t-1}$	-0.00***	-0.000***	-0.00	-0.00
	(-3.59)	(-3.57)	(-0.50)	(-0.50)
$No\ of\ analyst_{t-1}$	-0.000***	-0.000***	0.000848***	0.000848***
	(-4.20)	(-4.25)	(3.76)	(3.73)
$Size_{t-1}$	0.00567***	0.00576***	-0.0274*	-0.0280*
	(8.33)	(8.88)	(-2.64)	(-2.68)
Intercept	-0.0552***	-0.0552***	0.465***	0.466***
	(-10.21)	(-10.25)	(5.78)	(5.86)
Year and Industry Dummies	Yes	Yes	Yes	Yes
N	4197	4197	4211	4211

The table reports regression results analyst consensus forecast errors on Quartile based on degree and closeness score. The dependent variable in column 1 and 2 is one year ahead analyst consensus forecast error which is calculated by subtracting Conesus forecast earnings per share from realized earning per share divided by total assets per share. Dependent variable in column 3 and 4 is dispersion of analyst forecast calculated as standard deviation of analyst forecast. Firms assigned the rank of 4 are in the highest quartile and 1 are in the lowest quartile. Both industry and year fixed effects are included and clustered standard errors around firm is used. *t-statistics* are shown in the parenthesis and level of significance is specified by *, **, and *** for 5%,1%, and 0.1% respectively. For industry we use Fama French 49 industry codes based on 2-digit SIC codes. Growth and Young are dummy that equals 1 if the firm is in the lowest tercile of book to market and age respectively. Age is defined as when the firm first appeared in CRSP. Size is the log of market cap. All variables are winsorized at 1%.

Table 20: Instrumental Variable Regression

	First Stage	Second Stage
	$Degree_t$	ΔROA_t
$Degree_{t-1}$		.007**
		(2.13)
$Degree\ Score\ within\ 100\ miles_{t-1}$	0.156***	
	(15.88)	
LBM_{t-1}	0.039	-0.011**
	(0.65)	(-2.87)
$Size_{t-1}$	-0.066**	-0.004*
	(-2.10)	(-1.95)
ΔROA_{t-1}	0.188	-0.147***
	(0.86)	(-6.06)
$Assets_{t-1}$	0.253***	0.0008
	(7.96)	(0.35)
$Leverage_{t-1}$	-0.228**	0.016**
	(-2.13)	(2.12)
RND_{t-1}	-0.012	0.0009
	(-0.42)	(0.20)
$Board\ Connection_{t-1}$	0.034***	-0.000
	(16.50)	(-0.38)
$Prop\ of\ Independent\ Director_{t-1}$	-1.24***	-0.012
	(-7.36)	(-1.22)
$CEO\ Age_{t-1}$	0.021***	-0.0003**
	(10.34)	(-2.48)
Intercept	-0.066	0.0501**
	(-0.18)	(2.75)
Industry and year dummies	Yes	Yes
N	6173	6173
R- Square	0.25	0.05

The table reports regression results of instrumental variable regression. Degree score of CEOs within 100 miles of head office of the firm is used as an instrument for the degree score of CEO. Firms assigned the rank of 4 are in the highest quartile and 1 are in the lowest quartile based on CEO Social Connections. Both industry and year fixed effects are included and clustered standard errors around firm is used. *t-statistics* are shown in the parenthesis and level of significance is specified by *, **, and *** for 5%,1%, and 0.1% respectively. Column 1 shows the result when first stage and column 2 show the results of second stage. LBM equals one plus the firm's book to market ratio. SIZE equals the log of market capitalization. Leverage is defined as the sum of total long-term liabilities and portion of long-term liabilities for current year divided by total assets. ROA is calculated as operating income divided by total assets. For industry we use Fama French 49 industry codes based on 2-digit SIC codes. All variables are winsorized at 1%.

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